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A synoptic land change assessment of Ethiopia's Rainfed Agricultural Area for evidence-based agricultural ecosystem management

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Abstract

This paper demonstrates synoptic ways of presenting and characterizing land change processes across Ethiopia's large, complex Rainfed Agricultural Area (RAA). We translated pixel-level detected changes into neighbourhood-level changes that are useful to decision-makers. First, we identified pixel-level changes without and with type/direction of change, based on land cover maps from the years 1986 and 2010. For type-/direction-based characterization, we sorted observed transitions into four categories of prominent land change processes ("forest degradation", "deforestation", "afforestation", and "no change"). Adopting appropriate window sizes for identified ecoregions in the study area, we ran a focal statistics summation operator separately on the two change rasters (with/without consideration of direction of change). The results obtained by applying the approach can be described in relative terms as well as

qualitative terms, using ranges of change values that can be further classified using qualitative terms, i.e. ranging from “no change” to “high/substantial change”. Our non-directional change assessment result showed that approximately 6% of the RAA is characterized by substantial change, whereas 40% appears stable (“no change”). Based on the directional-change assessment results, 3% of deforestation, 4% of forest degradation, and 3% of revegetation processes were found to constitute “high/substantial change”. The types and intensity of landscape transformations display distinct spatial patterns linked to agro-ecological belts and socio-economic dynamics. Minimal reverse changes were observed on some severely degraded lands in the highlands, but the overall per cent cover remains relatively small. Overall, vegetation *degradation* still exceeds *regeneration* by more than half a per cent. Relatively lower altitudes and middle altitudes exhibit higher transformation. The presented approach and resulting outputs can provide planners and decision-makers with a synoptic view of land change processes. It can support policy formulation of sustainable land management and rehabilitation activities of the agricultural ecosystem at national and regional scales.

Keywords: Geography, Geoscience

1. Introduction

Generating information and knowledge on the intensity, direction, drivers, and impacts of Land Use and Land Cover (LULC) change remains an important goal in the field of land change science (Loveland et al., 2002; Sandewall et al., 2001; Turner et al., 2007). Such information is highly valuable to countries like Ethiopia that heavily depend on subsistence agriculture (Crummey, 2009). Ethiopia’s Rainfed Agricultural Area (RAA) is the main source of livelihood for 89% of the population, while contributing 39% of the country’s gross domestic product (CSA, 2014; Teshome, 2014). RAA landscapes are areas where the occurrence/prevalence of dependable rainfall is sufficient to support crop and crop-livestock mixed production systems. The term rainfed agriculture is broadly used to describe any farming practices that rely on rainfall (Wani, et al., 2009). However, a wide range of agricultural practices may be implied, including those focused on crop, forestry, or livestock production. Despite the importance of Ethiopia’s RAA, there is a lack of comprehensive, spatially explicit evidence on the distribution, use, and management of RAA natural resources over time/space and at the required level (Arsano and Tamrat, 2005; Crummey, 2009; Kassawmar et al., 2018). Often, national- and regional-scale interventions are made based on patchy local-level studies and/or global datasets (Crummey, 2009; Muluneh and Arnalds, 2010; Netzel and Stepinski, 2015; Sandewall et al., 2001). Lack of good data compromises efforts to identify and

implement sustainable development interventions and equitable resource-sharing arrangements among riparian countries situated in transboundary geographic settings (Arsano and Tamrat, 2005; Crummey, 2009). Ethiopia is known for its transboundary river-basin systems, in particular the Upper Eastern Nile Basin (UENB), the Omo Gibe Basin (OGB), and the Wabishebele and Genale Dawa Basin. Documenting land change processes at the right spatial and temporal scale thus represents a pressing task for researchers in the field (Kassawmar et al., 2018). In Ethiopia, various studies on the evolution of the RAA – sometimes referred to as “the highlands” or highland landscapes – have been conducted, adopting diverse temporal scales ranging from centuries (McCann, 1997, 1990; Jan Nyssen et al., 2004; Nyssen et al., 2009) to decades (Muluneh and Arnalds, 2010; Teferi et al., 2013). However, the long-period (particularly century-level) change estimates are qualitative and very general, as they stem predominantly from travellers’ accounts and oral reports. Indeed, there is a lack of spatially explicit historical input data (McCann, 1997, 1990; Jan Nyssen et al., 2004; Nyssen et al., 2009). Since the advent of spatial technology – mainly after the 1950s when aerial photographs and satellite images became available – decadal-scale change assessment studies have become very common (Muluneh and Arnalds, 2010). However, depending on the study area, knowledge and information on overall landscape transformations often remains very general, inconsistent, and even contradictory.

Land change information generated for large areas can provide comprehensive knowledge on land change processes occurring at various scales – from the local to the regional – and under varying socio-economic, political, and ecological situations. Nevertheless, many difficulties arise when analysing multiple/long periods as well as complex types of change. Indeed, it is no small task to detect/generate land change information at the national/sub-national level according to appropriate spatial and temporal scales (Kassawmar et al., 2016). In the era of remote-sensing technology, producing multi-temporal LULC maps with many thematic layers for large areas nevertheless remains challenging for experts in the field (Giri, 2005). Besides the difficulties of producing multi-temporal LULC maps, it is very challenging to find the right approach to present and characterize land change processes over large, complex areas like Ethiopia’s RAA (Kassawmar et al., 2018). Regarding change-detection methods, post-classification-based change characterization using pixel-level detected changes from multi-temporal LULC maps has been commonly used in the field of land change studies (Pontius and Cheuk, 2006). The relative simplicity and capability for implementation regardless of image variation (in terms of spectral/spatial resolution used to produce the LULC maps) makes this method of change characterization preferable (Netzel and Stepinski, 2015; Pontius and Cheuk, 2006). The cross-tabulation matrix provided by post-classification comparison makes it possible to study transitions and trajectories and improves our understanding of land dynamics (Pontius and Cheuk, 2006; Teferi et al., 2013). However, from

the perspective of guiding sustainable land management policy and strategies, pixel-level detected changes and corresponding statistics/maps have several limitations. In particular, it can be difficult for non-experts and policymakers to interpret and use the information, especially when the study area is complex and large (Kassawmar et al., 2018).

Researchers in the field have suggested approaches such as landscape-level (Riitters et al., 2009b) and neighbourhood-level (Kassawmar et al., 2018) analysis as ways of overcoming some of the limitations of pixel-level change information. Theobald (2010) demonstrated generation of landscape-level land information as a means of estimating the proportion of a cover type (i.e. natural) within a spatial neighbourhood as well as characterizing compositional/structural aspects of natural landscapes. Riitters et al. (2009a) showed how additional patterns and composition indicators of land cover change can be derived using a landscape approach that enables assessment of pixel-level changes within their context. Such approaches, which aggregate pixel-level change information, can employ a *moving window* tool and generate various metrics (Gustafson, 1998). To minimize the limitations of pixel-based change information, Kassawmar et al. (2018) recommend translating the pixel-level information by examining groups of neighbouring pixels, enabling change description at the neighbourhood level rather than according to individual pixels (Hett et al., 2012). These metrics/outputs (amount, density, and patterns of change) can explain land change processes in a more meaningful way than pixel-level information (Gustafson, 1998; Riitters et al., 2009a; Theobald, 2010). The neighbourhood approach can provide metrics varying depending on the input data and the objective of the study (Griffith, 2004; Riitters et al., 2009a). For the purpose of presenting and characterizing land change processes, the present paper refers to amount and pattern of change. *Amount* of change is expressed in terms of per cent or the number of changed pixels per a defined neighbourhood. *Pattern* of change describes the nature (type, size, density) of change in terms of its spatial arrangement. Importantly, however, complex, large-area land change characterization employing a neighbourhood approach requires multi-scale analysis (Cain et al., 1997; Kassawmar et al., 2016; Wu, 2004).

The overarching aim of the present study was to implement synoptic ways of detecting, presenting, and characterizing land change processes across Ethiopia's large, complex RAA. Individual objectives were: (1) to estimate the overall amount of change at appropriate scale using both pixel-level and neighbourhood-level change estimates, including production of two time step, detailed and accurate LULC maps (1986 and 2016) from medium-resolution Landsat satellite images (also detecting pixel-level changes and understanding their limitations for regional-scale land change presentation and characterization); (2) to identify the different land change types/directions at neighbourhood level and estimate the amount and patterns of

change; (3) to understand and characterize landscape-transformation process using amount and patterns of change for selected major land change processes. Characterization was determined vis-à-vis different biophysical and socio-economic conditions related to specific regional-scale human–nature interactions. The generated information can help to facilitate planning and implementation processes of land management over multifarious, extensive regions.

1.1. Study area description

The present study was conducted over Ethiopia's RAA, which comprises an area measuring approximately 667,923 km² (Fig. 1). The boundaries of the RAA overlap, at least in part, all political administrative regions of the country. Notably, the RAA boundaries encompass the main parts and the majority of Ethiopia's river basins. In particular, the RAA fully covers the UENB, which contributes more than 86% of the Nile River flow despite only accounting for 12% of the larger Nile Basin in terms of geographic area (Arsano and Tamrat, 2005). The UENB unites the riparian countries of the Nile Basin – Ethiopia, South Sudan, Sudan, Eritrea, and Kenya – making it crucial hydrologically in the east African region. The RAA features complex, diverse landscapes with altitudes ranging 350–4,540 meters above sea level (masl). Thus, in many aspects – e.g. biophysical setting and socio-economic condition – the study area is representative of the Ethiopian landscape. For a better understanding of land change within the RAA, we adapted the categorization of major

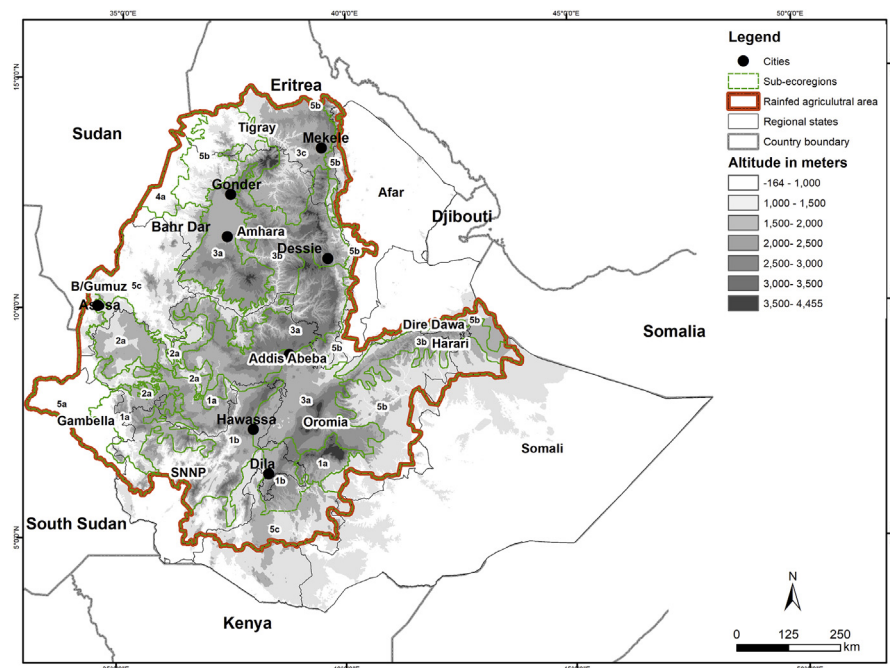


Fig. 1. The study area boundaries showing Ethiopia's RAA and the ecoregions.

ecoregions and sub-ecoregions made by [Kassawmar et al. \(2018\)](#). Detailed description of the ecoregions is presented in [Table 1](#) and [Fig. 1](#).

The identified ecoregions feature inner variation in altitude, since they are primarily distinguished according to similar farming systems, livelihood zones, and land cover/use. Each ecoregion displays a distinct altitude belt and is distinguished by differing climate, land use, and soil conditions, thereby exhibiting variations in landscape transformations. [Table 2](#) shows the altitudinal belts and corresponding traditional Agro-Ecological Belts (AEB) adapted from [Hurni \(1998\)](#).

The RAA has been continually transforming due to various interlinked and complex change drivers. However, the nature (type, extent and density) of the changes considerably vary in time and space. Sub-ecoregion 1a and part of sub-ecoregion 2a of the RAA ([Fig. 1](#)) are dominated by natural high forest and dense woody vegetation. Sub-ecoregion 2a comprises complex mosaics of trees mixed with crops such as cereals, coffee, banana, and false banana. Three decades ago, this area was covered by dense vegetation ([Dessaiegn, 2003](#)), but its favourable agro-climatic

Table 1. Identified and mapped ecoregions featured in the Rainfed Agricultural Area (RAA) of Ethiopia.

| Major ecoregions | Sub-ecoregions | Codes | Ecoregion divides |
|---|--|-------|-------------------|
| Forestry- and semi-agroforestry- dominated ecoregions | Natural high forest, protected areas, national forest reserves, areas of coffee cultivation and other silvo-cultural practices | 1a | Highlands |
| Agroforestry- dominated ecoregions | Distinct agroforestry system and mosaic of croplands with trees and high rainfall areas | 1b | |
| Mixed agricultural system (moderately cultivated) ecoregions | Disturbed forest, artificial forest, mosaic of crops with high trees, high-potential and high-rainfall areas | 2a | |
| Mixed agricultural system (intensively cultivated) ecoregions | Intensively cultivated, high-potential, and high-rainfall areas | 3a | |
| | Intensively cultivated, low-potential, and moderate-rainfall areas | 3b | |
| | Intensively cultivated, low-potential, and low-rainfall areas | 3c | |
| Agro-pastoralist system (lightly cultivated) ecoregions | Lightly cultivated, moderate-potential, lowland, and low-rainfall areas | 4a | Lowlands |
| Dominantly pastoralist ecoregion | Wooded land in the lowlands and moderate-rainfall areas where slash-and-burn cultivation is rarely practiced | 5a | |
| | Wooded land in the lowlands and low rainfall areas where slash-and-burn cultivation is rarely practiced | 5b | |
| | Wooded land in the lowlands and high rainfall areas where slash-and-burn cultivation is rarely practiced | 5c | |

Table 2. Altitudinal ranges (meters) and corresponding traditional Agro-Ecological Belts (AEB) in the study area.

| Altitude range | 500–1,000 | 1,000–1,500 | 1,500–2,000 | 2,000–2,300 | 2,300–3,000 | 3,000–3,700 | >3,700 |
|-----------------------------------|-------------|-------------|------------------|------------------|-------------|-------------|--------|
| Traditional agro-ecological names | Lower Kolla | Upper Kolla | Lower Woyna Dega | Upper Woyna Dega | Lower Dega | High Dega | Wurch |
| Proportional area coverage (%) | 17 | 26 | 30 | 11 | 14 | 2 | 0.2 |

conditions and the presence of extensive cultivable areas attracted people from sub-ecoregions 3a–c (Dessaiegn, 2003). As a result, the landscapes of sub-ecoregion 2a have been actively transformed into cropland mosaics. Sub-ecoregions 3a–c (Fig. 1) are dominated by intensively cultivated landscapes and degraded land comprising scattered shrub and bush vegetation.

2. Materials and methods

2.1. Datasets (data sources)

In the present assessment, we used both primary and secondary vector and raster datasets, acquired from different sources. To assess and characterize land change processes at the neighbourhood level, our proposed approach requires a minimum of two land cover datasets. Before the production of LULC maps, we consulted previous raster-based LULC datasets produced by the following institutions: (1) the Ethiopian Ministry of Agriculture (MoA) for the 1970s covering all of Ethiopia at a scale of 1: 1,000,000; (2) the Woody Biomass Inventory and Strategic Planning Project (WBISPP) using Landsat TM data for 1990s; and, (3) most recently, by the United Nations Food and Agriculture Organization (FAO) in 2013 for forest inventory purposes. These datasets have several limitations, including spatial resolution mismatch, accuracy/quality issues, and variable classification schemes. As a result, we needed to produce our own detailed LULC maps of the RAA for two different years – 1986 and 2016 – from Landsat TM data at 30 m spatial resolution. However, we used the secondary data sources named as reference data during our image-classification process. In addition, we incorporated information about farming systems and livelihood zones developed by the FAO, data on settlement and population distribution provided by the Central Statistical Agency (CSA), data from the ASTER digital elevation model (<http://glovis.usgs.gov>) to derive segments, and high-resolution Google Earth images to label classes and verify our classification.

LULC mapping of large geographic areas is typically challenging when the process involves combining different scenes of images (Fleischmann and Walsh, 1991; Verburg et al., 2011). In particular, it is difficult to detect second-level classes from medium-/moderate-resolution satellite images, such as Landsat time series, for mapping of large geographic areas. As such, available LULC datasets produced by combining different scenes were inaccurate and insufficiently detailed, and displayed few general classes as they were produced using *Level I* LULC classes (Table 3). General LULC maps that ignore patchy minority classes cannot portray Ethiopia's complex landscape and are of limited use in presenting land change process that commonly involve smaller LULC classes. Thus, this study sought to capture these classes using a *Level II* LULC classification scheme (Table 3). Producing the desired LULC maps required a context-oriented classification approach capable

Table 3. The classification scheme applied to map the two categories of LULC (I and II) for the two periods.

| I level classes | SN | II level classes | Brief description of the classes | Code | I level classes | SN | II level classes | Description of the classes | Code |
|-------------------------|----|----------------------|---|------|-----------------|----|-------------------------------|---|--------|
| Water body | 1 | Water body | Lakes and Ponds | WB | Agroforestry | 24 | Agroforestry 7 | Dominantly Mango and other fruit system | AFma |
| Settlement and built-up | 2 | Settlement | All urban and dense rural settlements mixed with several lands cover and uses | ST | | 25 | Agroforestry 8 | Dominantly Banana, mango and other fruit tree system | AFBm |
| | 3 | Homestead plantation | Dense plantations around rural settlements | HP | | 26 | Agroforestry 9 | Enset-Banana and Mango mixed system | AFenbm |
| | 4 | Built-up (concrete) | Only concert part of the settlement | BU | Grassland | 27 | Grassland (Drained) | Drained and dry grasslands found around farm borders and sloping landscapes | GD |
| Forest | 5 | High forest | Moist ever green forests | HF | | 28 | Grassland (Wet or un-drained) | Often found along water course, water bodies and upland depressions | GW |
| | 6 | Dry Forest | Deciduous dry region forests (lowlands of the country) | DF | | 29 | Savanna grassland | Tall and extensive found in dry and flat terrain | SG |
| | 7 | Riverine Vegetation | Any type of woody vegetation exist following the river courses | RV | Wetland | 30 | Swamp | All the time wet, often covered by grass, found along riversides, lakes | SW |
| | 8 | Mixed Forest | Enriched degraded natural forest | MF | | 31 | Marshland | Intermittently flooded and muddy | ML |
| | 9 | Church Forest | Protected patches of forests in religious sites | CF | Cropland | 32 | Large scale farm (commercial) | Agricultural lands owned by non-substance or smallholder farms | LSI |
| Woodland | 10 | Plantation forest | Private and community forests dominantly Eucalyptus | PF | | 33 | Shifting Cultivation | Cleared/burnt woodland for crop production managed by smallholders | SC |
| | 11 | Bamboo Forest | Perineal grass plant community having hollow circular stems | BF | | 34 | Cropland with trees | Croplands with scattered trees managed by smallholders | CT |
| | 12 | Dense Woodland | Densely spaced trees but dominated by single species, largely found in | WLd | | 35 | Croplands (with no trees) | Open crop fields managed by smallholders | CWOT |

(continued on next page)

Table 3. (Continued)

| I level classes | SN | II level classes | Brief description of the classes | Code | I level classes | SN | II level classes | Description of the classes | Code |
|------------------------|----|----------------------------|--|-------|-----------------|----|------------------------------|--|------|
| | | | the lowlands | | | | | | |
| | 13 | Open Woodland | A woodland but degraded and has very scattered trees | WLo | | 36 | Croplands (in hilly terrain) | Intermittently cultivated often in a rugged terrain | CH |
| Shrubland/ Bushland | 14 | Dense Shrub and Bush | Non-tree but woody plants often < 5m height, densely spaced, found in inaccessible highland upslope and arid areas | SBd | | 37 | Irrigated fields Croplands | Managed for dry season crop production | IF |
| | 15 | Open Shrub and Bush | Exist as scattered plant community and often as mosaic with grass plants | SBo | Barren land | 38 | Degraded hills | Highly degraded lands with exposed rock or soil | DH |
| Afro-alpine vegetation | 16 | Sub-afro Alpine Vegetation | Dominated by woody vegetation (Eg.Erica bush) | AAbs | | 39 | Exposed Rock | Landscapes with exposed rocks and little bit covered by annual grass species | ER |
| | 17 | Afro Alpine Vegetation | Dominated by herbaceous vegetation (Grass) | AAg | | 40 | Extensive unpalatable | Herbs A landscape covered by unpalatable herbaceous species | HS |
| Agroforestry | 18 | Agroforestry 1 | Enset dominating system | AFen | | 41 | Salt Flat Deposition | Extensive salt depositions exposed on the surface | SFd |
| | 19 | Agroforestry 2 | Crop mixed with Khat-system | AFck | | 42 | Construction sites | Mining, quarry and other construction site | MS |
| | 20 | Agroforestry 3 | Enset mixed with Khat system | AFek | | 43 | Exposed Sand | Exposed surface commonly sandy surface | ES |
| | 21 | Agroforestry 4 | Dominantly Coffee system | AFcof | | 44 | Exposed surface | Exposed surface but the type of surface cover is unknown | ESc |
| | 22 | Agroforestry 5 | Enset and Coffee system | AFec | River bed | 45 | Wider river course | Intermittently covered by water, boulders and gravels | RC |
| | 23 | Agroforestry 6 | Dominantly Banana system | AFba | Others | 46 | Others | Any other LULC which is not identifiable by Landsat images | OT |

of capturing very small, patchy classes. Kassawmar et al. (2016) recommends reducing landscape heterogeneity by dividing larger areas into smaller homogenous classification units improves classification accuracy and allow to capture patchy and small classes. Ethiopia's RAA can be subdivided by applying the concept of finding homogeneity in heterogeneity and vice versa (Messerli et al., 2009). In Ethiopia, the spatial distribution of LULC types is linked to various environmental gradients such as rainfall patterns, altitude, soil/geology, and farming systems. These facts required a classification approach capable of considering the extreme heterogeneity of the study area, while limiting combination of adjacent scenes. In order not to avoid the spectral difference between scenes and within scenes, we first subdivided the RAA into different polygons based on biophysical similarity. This was done by superimposing several geospatial datasets, including satellite imagery. In another words, we developed polygons within the RAA boundaries that display similarity under different biophysical conditions in order to understand the heterogeneity of the area for classification.

Besides avoiding combination of adjacent scenes for classification, achievement of the intended detail of LULC maps required us to apply a sub-scene classification approach. Thus, prior to labelling, we subdivided every Landsat scene into smaller homogenous segments as a key pre-classification step. Segmentation was done integrating the non-spectral datasets to identify major ecological zones (rainfall, vegetation types, soil/geology, topography) according to Lowry et al. (2007) and using spectral properties according to Bisquert et al. (2015). Further we grouped together similar farming systems/livelihood zones with similar socio-economic activities and biophysical characteristics. Subsequently, the spectral information from the raw satellite images was used to further subdivide each scene into more homogenous segments. The process was iteratively validated using local area knowledge until each segment represented a homogeneous landscape (Kassawmar et al., 2016). The delimitation process resulted in a varying number of segments for each Landsat scene/footprint. For the entire RAA, about 23 Landsat scenes were used, and, for each scene, an average of 20 classification segments was generated. Next, an unsupervised clustering was applied to each homogeneous segment, followed by a supervised visual interaction-based class assignment. Experts who know the area well oversaw the latter step, so as to capitalize on local specialist knowledge. Fig. 2 presents the two LULC maps.

Given that the larger and complex Ethiopia's RAA, which comprises spectrally differing classes over time and space, attention was paid to properly identify mappable classes. Characteristically, the LULC classes in the Ethiopia's RAA are very patchy with varying spectral character that exist as mosaic in the smallholder plots. Therefore, if detailed level of classification and accurate land change assessment is envisioned, identification of smaller but mappable classes need to be performed. This particular study envisioned to produce LULC maps applying a second level

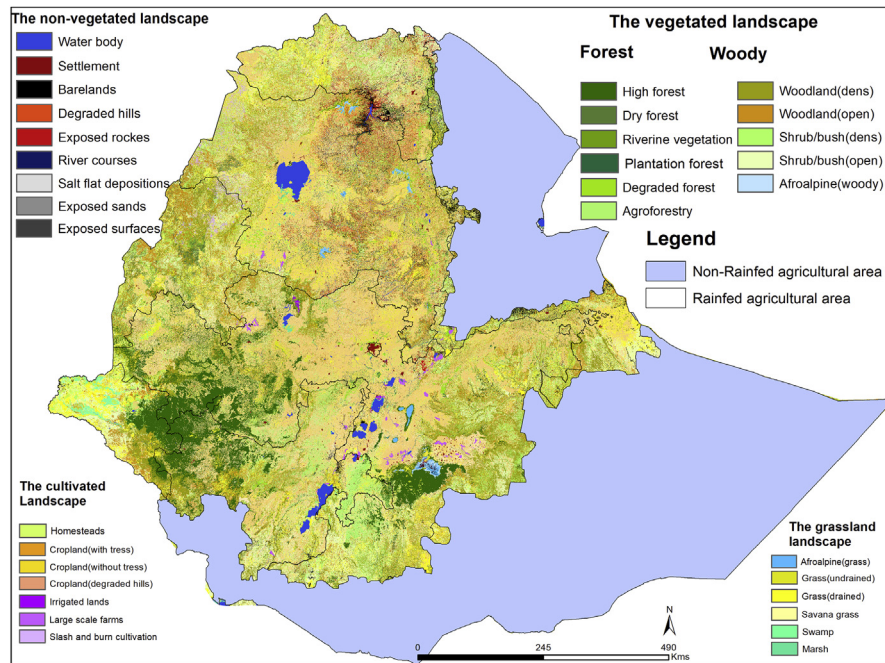


Fig. 2. Detailed Level II LULC map produced for the present assessment.

LULC classification scheme. To do so an exhaustive identification and characterization of LULC classes was performed prior to classification. The classes were identified considering the mapping potential of Landsat images and must fulfil to capture the local level land change processes. To ensure consistent classification, at the beginning, a classification legend was prepared after adapting [Anderson et al., 1976](#) and [Loveland et al., \(2002\)](#) classification scheme to fit with the study area context ([Table 2](#)). As depicted in [Table 3](#), the classification legend consists of ten major categories of LULC classes when applying a first level classification scheme and forty-six sub-categories when a second level classification scheme is applied. For the land change assessment, for simplicity, we used the first classification scheme LULC maps having 10 major LULC classes, namely: water body, settlement, forest, cropland, grassland, woodland, shrub/bushland, bare land, wetland, and Afro-alpine ([Fig. 2](#)). Map produced using a second level classification scheme is available in the supplemental material (SM).

According to [Shao and Wu \(2008\)](#), for LULC datasets to be used in land change assessments that employ landscape-level or neighbourhood-level analysis, they must fulfil the following criteria: (a) consistency of classification accuracy, (b) consistency of spatial resolution, and (c) seasonal consistency of the images. The two maps ([Fig. 3](#)) selected for our neighbourhood-level change assessment fulfilled these important criteria. Firstly, they accurately depict important classes of interest within the complex landscape of the study area, with an overall average accuracy of 85% for

the *level two* classification scheme, and over 87% for the *level one* classification scheme. Given the vastness and heterogeneity of the study area, the achieved accuracy of classification is very good. Secondly, the two maps were produced from images derived from the same sensor (Landsat TM) with the same spatial resolution (30 m). Thirdly, in the production of the two maps, seasonal consistency was maintained, i.e. all the images used were captured in dry-season periods. Moreover, as the two LULC maps were produced by the same experts whose goal was to use the maps for change detection, consistency was maintained in terms of terminology, method of classification, and the type as well as the number of classes detected (Dale and Kline, 2013).

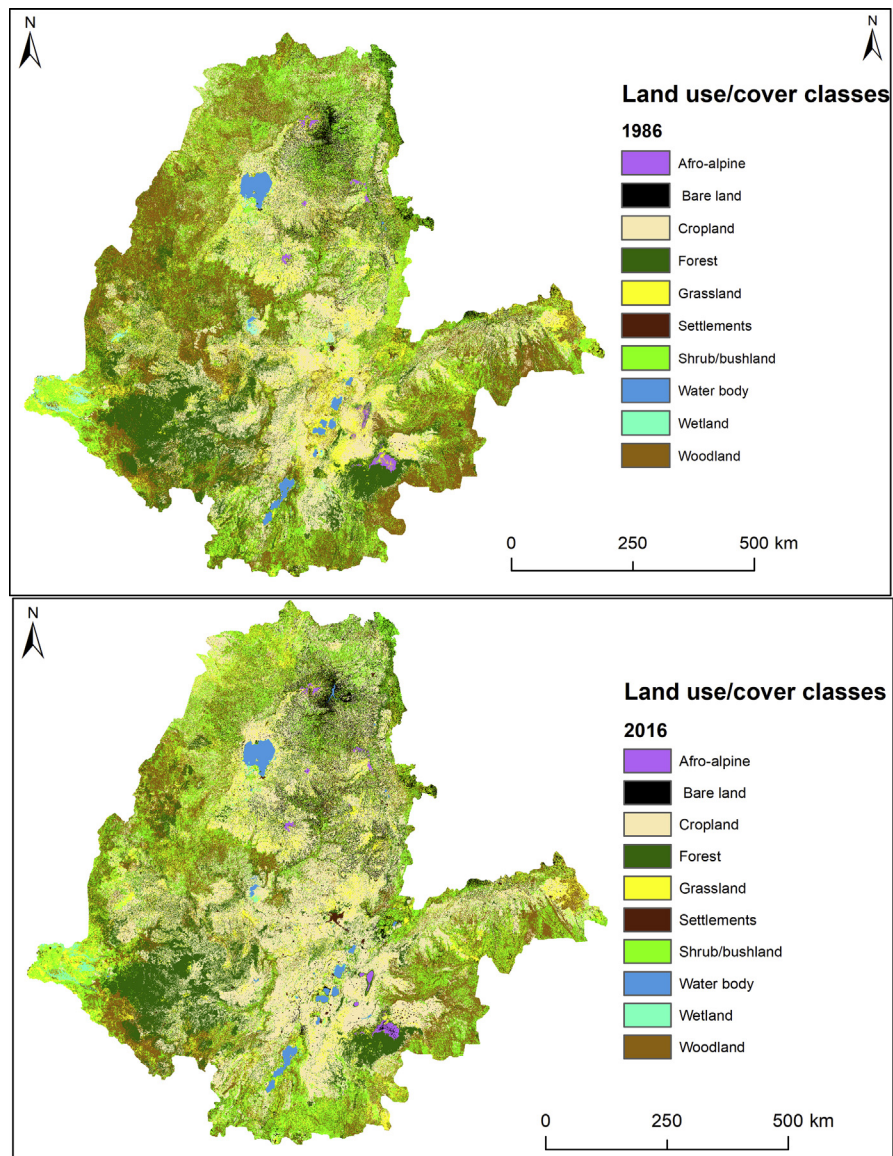


Fig. 3. Generalized (Level II) LULC maps used for the present assessment.

2.2. Approach

In the present assessment, three major steps were followed, each representing one of the objectives of the study: (1) We detected changes using two period maps and further translated pixel-level detected changes into neighbourhood-level changes using selected scales of analysis. (2) We identified four major types of change and separately calculated the amount and patterns of change for each of the identified change types. (3) We characterized land change using neighbourhood-level generated statistics and raster maps that depict the pattern and overall density of changes. Schematic representation of the steps adhered to and detailed descriptions of the approach are presented in Fig. 4 and described in subsequent sections.

2.2.1. Detecting pixel-level changes

In our first objective, we detected pixel-level changes using the two LULC maps (1986 and 2016). The change-detection *confusion matrix* (10*10 classes) resulted in 100 transitions including “no-change” transitions. The resulting pixel-level change information was used for comparison to characterize change over the study area.

2.2.2. Validating the detected changes

Verifying change maps is highly difficult. As a suitable alternative, we sought to validate our estimates. For validation of the pixel-level detected changes, we employed two approaches: (i) using the *accuracy value* of each period of the LULC maps (based on the method of Yuan et al., 1999) and (ii) using *basis of comparison* (Lowell, 2001). In traditional accuracy assessment, error matrices have been commonly used (Lowell, 2001). However, the method was developed for single-period maps only and separately assesses accuracy for individual classification layers.

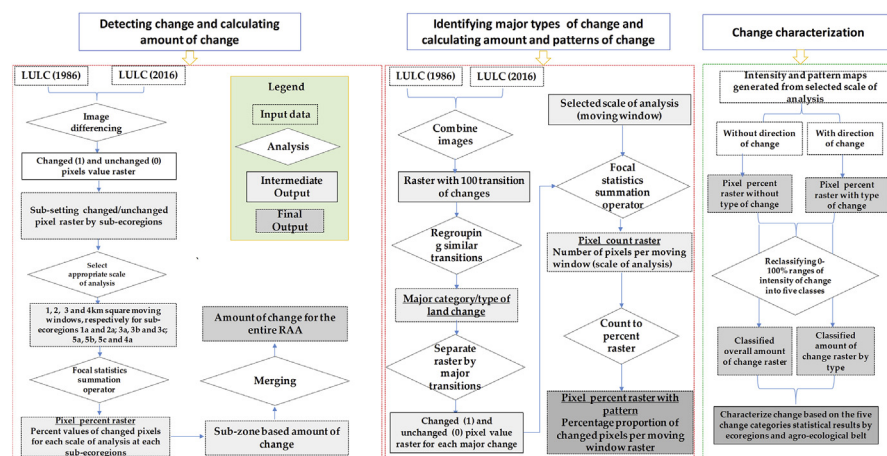


Fig. 4. Schematic representation of the workflow

As cited in (Li and Zhou, 2009), Yuan et al., 1999 suggest using individual single-date classification accuracies to judge the accuracy of change maps. However, this approach is affected by the correlation existing between the individual single-date classification layers (Li and Zhou, 2009). Assuming that each layer of a four-period LULC change assessment exhibits no correlation and is produced with the same level of accuracy (e.g. 90%), the accuracy level of the change map would be the result of multiplying all four accuracy values (i.e. $0.9*0.9*0.9*0.9 = 66\%$). On the other hand, if all four layers are completely correlated – and have the same accuracy value – the aggregated accuracy of the change map would be 90%. This implies that the change map accuracy ranges between 66% and 90%. The challenge of using this approach is that one cannot determine the aggregated accuracy without knowing the correlation between the single-date layers. Otherwise, the approach is useful from an operational feasibility perspective, since obtaining true reference change data is very difficult in particular for large and heterogeneous landscapes. Regarding the basis for comparison approach, several randomly distributed scientific studies have already been conducted in our study area by other researchers. We assumed that the change estimates derived from these independent studies were more or less sufficient for use in validating our change estimates according to the basis for comparison concept of Lowell (2001). To this end, 14 independent case studies were selected (Table 4 and Fig. 5). Eq. (1) was used to apply the basis of comparison.

$$WC_p = \frac{\sum_{i=1}^n Cs * \frac{TAs}{TAS}}{n} \quad (1)$$

Where:

Cs = Percentage of change estimated by a study

TAs = Total area of a study

TAS = Total area of the RAA

n = Number of study sites

WCp = Weighted average change represented by the study periods considered

2.2.3. Translating pixel-level changes to the neighbourhood level

The present study sought to characterize change after translating pixel-level detected changes to neighbourhood-level changes (Kassawmar et al., 2018). This can be done using a moving window that defines the neighbourhood (the context size) based on users' interest (Hagen-Zanker, 2016) or the context of the change process (Kassawmar et al., 2018; Messerli et al., 2009). The moving window decodes clusters of neighbouring pixels and produces a new raster map featuring decoded neighbourhood-level change information. Neighbourhood-level analyses are scale dependent (Wu, 2004) and researchers in the field (Šimová and Katerina, 2012;

Table 4. Independent LULC change scientific studies conducted across the study area (RAA) (AP refers aerial photographs and SI refers satellite images).

| Validation site codes | Authors | Study area/location | Method of study | Area (km ²) | Period of analysis |
|-----------------------|----------------------------|--|--|-------------------------|--------------------|
| 1 (1a) | (Abate, 1994) | The southwest natural forest of Ethiopia (Metu) Dizi catchment | AP of 1957, 1976, 1982, and 1990 | 7 | 1957–1990 |
| 2 (1a) | (Abate, 1994) | The southwest natural forest of Ethiopia (Metu) Gey catchment | AP of 1957, 1976, 1982 and 1990 | 10 | 1957–1990 |
| 3 (1a, 5c, 2a) | (Reusing, 2000) | Southwest/Baro Akobo Basin | AP of 1971 & 1975 and SI of 1986 & 1990 | 30,000 | 1973–1990 |
| 4 (1a) | (Tefera and Sterk, 2008) | Fincha Watershed/Blue Nile Basin | AP for 1957 & 1980 and SI of 2001 | 1318 | 1957–2001 |
| 5 (3a) | (Minale, 2013) | Gilgel Abay/Blue Nile Basin | AP of 1957 & 1975 and SI of 1986 & 2009 | 4570 | 1957–2009 |
| 6 (3a) | (Teferi et al., 2013) | Jedeb/Blue Nile Basin | AP of 1957 & 1975 and SI of 1986 & 2009 | 296 | 1957–2009 |
| 7 (3a) | (Zelege and Hurni, 2001) | Demebecha woreda/Blue Nile Basin | AP of 1957 & 1982 and SI of 1995 | 271 | 1957–1995 |
| 8 (3b) | (Wondie et al., 2015) | Blue Nile Basin, Tara Gedam catchment | AP of 1957 & 1975 and SI of 1986 & 2009 | 9 | 1957–2009 |
| 9 (3c) | (Haregeweyn et al., 2015) | Gilgel Tekeze catchment | SI of 1986, 1995 & 2010 | 352 | 1976–2008 |
| 10 (3c) | (Gebresamuel et al., 2010) | Maileba and Gumselassa catchment, Tigray | AP of 1964 & 1994 and field survey of 2006 | 40.8 | 1964–2006 |
| 11 (3c) | (Gebresamuel et al., 2010) | Maileba and Gumselassa catchment, Tigray | AP of 1964 & 1994 and field survey of 2006 | 40.8 | 1964–2006 |
| 12 (4a and 5c) | (Alemu et al., 2015) | The western Ethiopia Humera district, Tigray | SI of 1986, 1995 & 2010 | 3806, 6328 & 3518 | 1986–2010 |
| 13 (4a and 5b) | (Alemu et al., 2015) | The western Ethiopia Metema district, Amhara | SI of 1986, 1995 & 2010 | 3806, 6328 & 3518 | 1986–2010 |
| 14 (5b) | (Alemu et al., 2015) | The western Ethiopia Guba district, B/Gumz | SI of 1986, 1995 & 2010 | 3806, 6328 & 3518 | 1986–2010 |

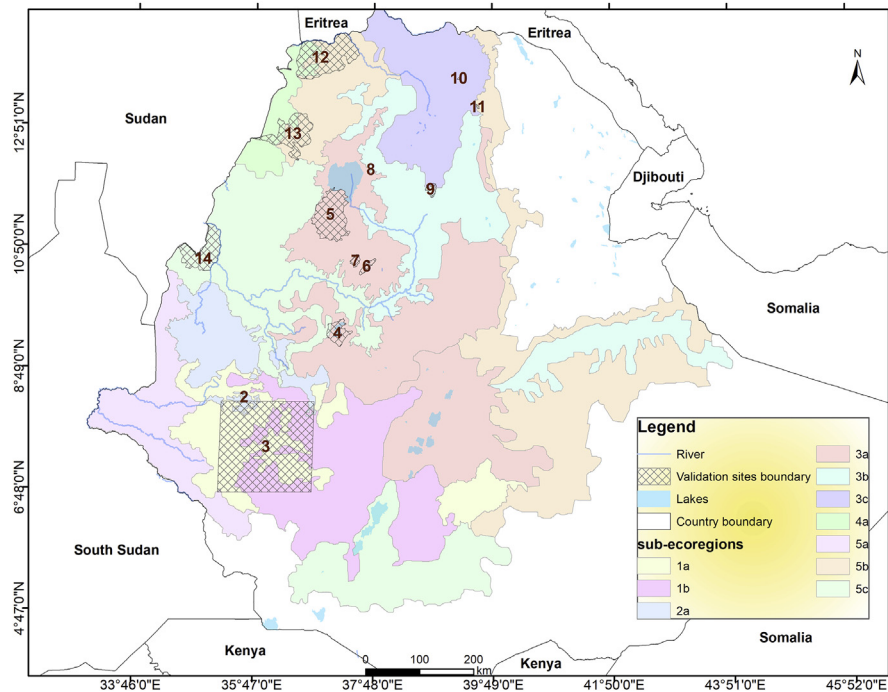


Fig. 5. Location and extent of selected independent LULC change research studies used to validate our change estimates.

Wu, 2004) recommended identifying the appropriate window size before applying the approach (Wu, 2004). According to Riitters et al. (2009a), the size of the targeted object/feature for detection should determine the size of the window (Saura, 2002). For example, the appropriate window size could be set based on the geographic reach of a specific human activity (Heinimann, 2006; Hett et al., 2012; Messerli et al., 2009). Indeed, several studies have used the average reach of land practices among rural actors to define the appropriate size of the moving window (Hurni et al., 2013; Messerli et al., 2009). Further, Kassawmar et al. (2018) concluded that a multi-scale approach is appropriate for large, complex areas like Ethiopia's RAA. In heterogeneous regions, the appropriateness of the size of the moving window should be determined based on the nature of the prevailing changes (Kassawmar et al., 2018; Wu, 2004). The nature of changes — expressed in terms of type, size, and density of change in the study area — is depicted with the Landsat TM data used to produce the land cover datasets (Fig. 6). In the highland portion of Ethiopia's RAA, which comprises ecoregions intensively cultivated by smallholders, there are many changes linked to afforestation practices, communal area closures, and rehabilitation of degraded areas (Muluneh and Arnalds, 2010). In these parts of the study area, relevant land-cover changes are often no bigger than one-quarter of a hectare because of small individual landholding sizes (~1 ha). As depicted in Fig. 6, large-scale and small-scale afforestation-driven land changes were identified as important change types in sub-ecoregions 3a1, 3a4, and 3a5 of the study

area. Also common in the study area are extensive deforestation (3a3 and 3b1), as well as restoration of degraded vegetation based on area closures (5b and 3b2). Finally, change types such as large-scale water infrastructure developments (in 3c and 2a), conversion of extensive vegetated area to mechanized large-scale farming (in 2a), and conversion of extensive grasslands and croplands to built-up areas (in 3a2) occur in the study area to varying extents.

On the other hand, in the low-lying areas of Ethiopia's RAA, large-scale mechanized farming and smallholder-driven slash-and-burn land use practices have become common over the last two decades, and the average minimum dimensions of such changes span hundreds of hectares. In such settings, changes occur at varying spatial extent and are heterogeneous in type depending on the nature and size of changes, which in turn vary with the reach of relevant actors' practices. Thus, a minimum scale of analysis must be set to capture all these types of changes. In sum, it may not always be feasible to choose a single scale of analysis in such cases, and a multi-scale analysis is needed (Cain et al., 1997; Kassawmar et al., 2018; Wu, 2004). Nevertheless, applying multi-scale analysis over large areas requires proper selection of several scales according to the study objective or the land change processes to be characterized (Riitters et al., 2009a; Wu, 2004). The scales of analyses must accurately represent the area in which land use-related land cover changes have been occurring (Hurni et al., 2013; Messerli et al., 2009). The minimum scale of analysis is determined by the quality and resolution of the input data used to produce the LULC maps, which largely decides the size of detectable features. Thus, in our case, the smallest scale of analysis had to be larger than the pixel size of the LULC

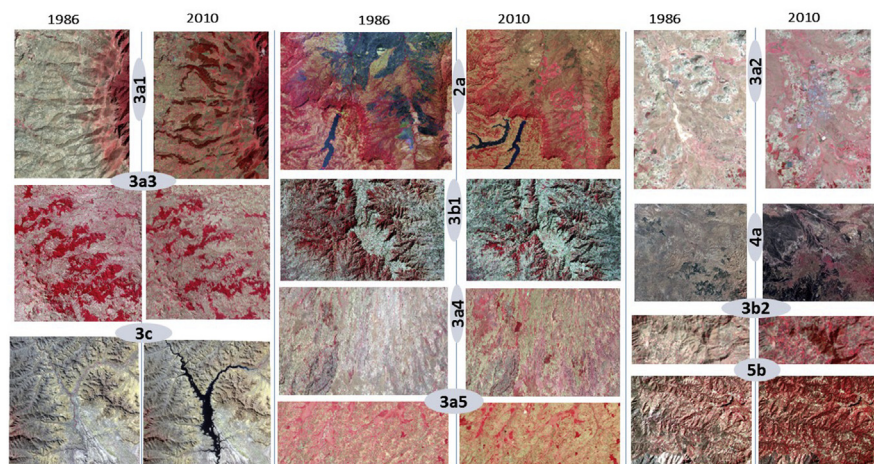


Fig. 6. The nature of commonly occurring changes (Landsat TM images with false colour composite 4-3-2; codes refer to sub-ecoregions described in Fig. 1). 3b1 & 3b2 = Large-scale afforestation/regeneration of degraded (crop)lands; 3c & 2a = Construction of hydro dams (large-scale changes) and dense burning of woody vegetation for shifting cultivation; 3a3 = Large-scale deforestation of natural forest; 3a4, 3a5, & 3a2 = Small-scale afforestation and deforestation; 5b = Small-scale deforestation for cropland expansion; 4a = Extensive burning of wood/shrub land for shifting cultivation.

maps used for the analysis – i.e. 30 m by 30 m (Riitters et al., 2009b). At the same time, it was necessary to select the upper limit/the maximum scale, considering the nature of changes under study. This requires assessing the effect of different moving window sizes on outputs in terms of properly estimating amount, and representing patterns of change, by cross-checking the outputs with known changes. Our assessment revealed that the optimal moving window size can be selected following a rule of thumb set after understanding the nature of change and the effect of scale in estimating the amount of change and presenting the patterns of change across the large and complex RAA. Specifically: (1) the moving window size must be chosen such that changes of interest occurring at a smaller spatial extent are retained, and changes of interest occurring at a larger extent are not exaggerated; (2) the optimal moving window size should be selected for areas with homogenous landscapes in terms of type, size, and density of change. This can be done by subdividing the area into homogenous eco-regions, in which the nature of change is relatively homogenous. According to our assessment results, optimal window sizes for the RAA should range between 1 ha and 10,000 ha. Finally, a 1 km-by-1 km moving window was selected for sub-ecoregions 1a, 2a, 3a; a 2 km-by-2 km window was selected for sub-ecoregions 3b, 3c, and 5b; and, lastly, a 3 km-by-3 km window was selected for sub-ecoregions 4a, 5a, and 5b.

2.2.4. Estimating amount of change

In section 2.2.1 above, we described our identification of pixel-level changes using the two LULC maps from 1986 and 2016. The 100 identified change transitions were regrouped into two categories: *changed* and *unchanged*. This resulted in a single binary raster map with value “0” representing unchanged pixels and “1” representing changed pixels. To translate the pixel-level detected changes into neighbourhood-level metrics on the binary raster map, we applied a moving-window-based focal statistics analysis using the summation operator available in ArcGIS 10.4 ESRI software. This was done based on the appropriate scale selected for each ecoregion. The analysis resulted in a raster file with colour values that define the number or per cent of changed pixels per window. We called this “amount of change”, referring to the number or per cent of changed pixels per area during the assessed period. The specific equations described in (Kassawmar et al., 2018) were adapted to translate the pixel-level detected changes to the neighbourhood level.

2.2.5. Detecting the type/direction of change and estimating intensity of change

In line with our first objective, we identified changed pixels and calculated the amount of change per window. For our second objective, however, we sought to distinguish not only the amount, but also the *pattern* of change based on the type/

direction of change that occurred during the periods assessed. To this end, the LULC datasets from 1986 and 2016 were combined in ArcGIS to generate a change raster map. This resulted in a raster map and change matrix indicating 100 (10×10) change transitions. Characterizing the pattern of change for every individual transition would be exceedingly difficult and not necessarily useful. Thus, we sought to synthesize and regroup these numerous, complex transitions into a limited number of meaningful categories. For that purpose, we identified four main indicators of land change processes (see Table 5).

The four major land change process may be further understood using our conceptual model depicted in Fig. 7. The model shows which transition belongs to which major category of land change process (Table 5), and how the overall landscape transformation process can be interpreted based on the two periods of LULC datasets.

In our model, similar types and directions of change were arranged and grouped together. While landscape transformation is a continual process, human-driven changes often initially become visible as forest degradation (FD) and are frequently referred to as modification (Turner et al., 2007). The continuation of modification processes, or FD, in turn leads to conversion processes, e.g. transformation of vegetated landscape to non-vegetated landscape, or deforestation (DF). In our model, each corner represents the culmination stage of one process and the start of another process. Further, the lower-right and lower-left triangles represent forward and reverse transitions of land change, respectively. In this context, a *forward*

Table 5. The four main types/descriptions of landscape transformation, identified based on consolidation of observed transitions.

| Type of landscape transformation | Code | Description |
|----------------------------------|----------|---|
| Forest degradation | FD | Change transitions characterized by modifications of forest landscape, e.g. from forest to woodland or from woodland to shrubland/bushland. |
| Deforestation | DF | Transitions characterized by conversion of vegetated landscape to non-vegetated landscape. In addition, transitions that induce further land degradation, such as change from cropland to barren lands or conversions of grasslands into wetlands |
| Re-afforestation or Regeneration | RA or RG | Change characterized by forest regrowth due to strict forest protection policies (e.g. in the south), or due to restoration efforts or use changes (e.g. area closures in the north and northeast; afforestation practices on state and communally owned lands in the central region). Also included are transitions linked to wetland restoration. |
| Persistence | P | All pixels that represent no change. |

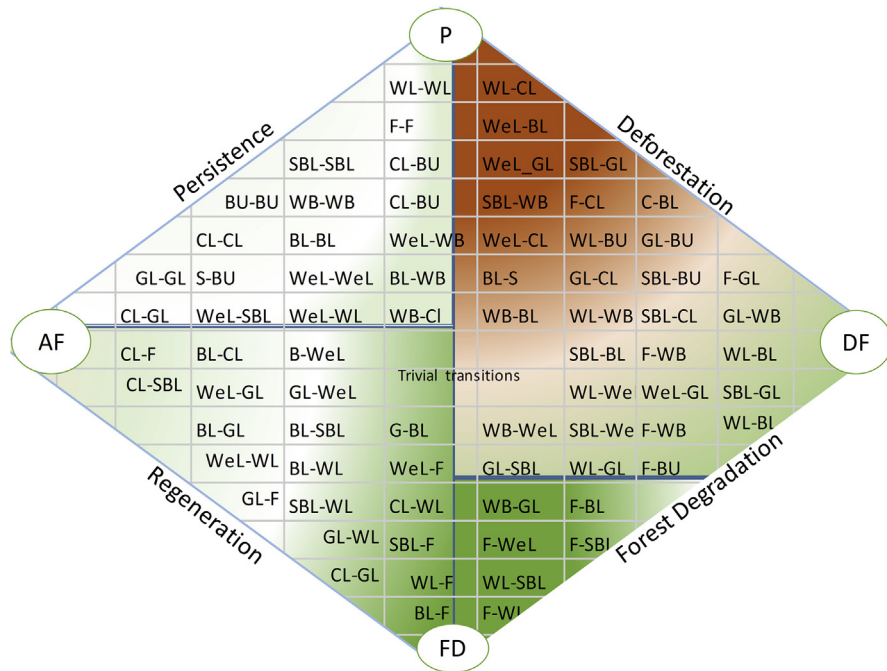


Fig. 7. A four-quadrant conceptual model produced from the change matrix used to describe the type/ direction of landscape transformations: forest degradation (FD), deforestation (DF), persistence (P), and afforestation (AF). F=Forest, WL = Woodland, SBL = Shrubland/Bushland, CL = Cropland, GL = Grassland, BL = Bare land, WeL = Wetland, WB = Waterbody, and BU = Built-up

transformation corresponds to degradation or, in the worst case, destruction of natural landscape – mainly vegetated landscape – whereas the *reverse* corresponds to the rehabilitation of degraded or deforested natural landscape, i.e. regeneration (RG). The varying size and colour gradients of the triangles represent the diversity of the transitions as well as the density and direction of change, together depicting each type of landscape transformation. The deep-green-coloured map areas represent reverse/natural landscape-restoration processes, while lighter-green-coloured map areas represent forward/natural landscape destruction (DF). Finally, persistent landscape (P) is represented with the colour grey. Accordingly, all 100 transitions obtained from post-classification comparison of the change matrix were reclassified into four major types of land change: FD, DF, P, and RG (see Table 5 and Fig. 8). From the reclassified raster, we produced four separate binary “0”-and-“1” raster maps representing each major change type. Finally, we ran a summation focal statistics operator separately for each of the four raster using a moving window, as noted in section 2.2.4. This resulted in amount, density, and patterns of change for the four separate raster maps each representing the type/direction of change.

2.2.6. Characterizing change

Our change characterizations were derived from statistics of changed pixels and their pattern generated within a spatial neighbourhood indicating both the amount and

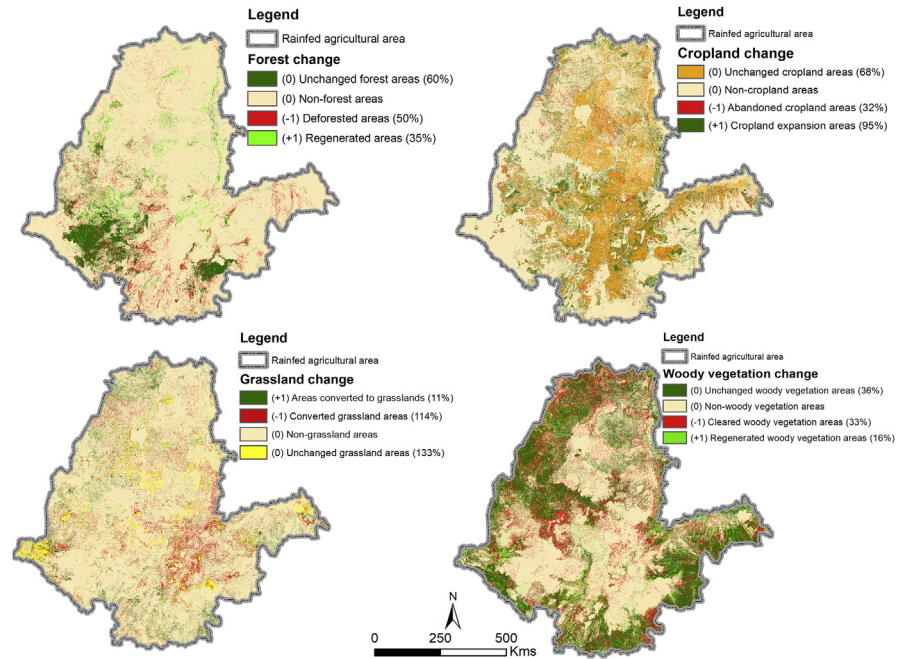


Fig. 8. Pixel-based changes summarized for major ecosystems (upper left, forest ecosystems; upper right, cropland ecosystems; lower left, grassland ecosystems; lower right, non-woody vegetation ecosystems).

density of change with and without the direction of change. Neighbourhood-level change figures and quantitative information may be scientifically valuable, but still may not provide information of use to non-specialists and policymakers unless they are described in a qualitative way (Kassawmar et al., 2018). From the perspective of national- and regional-level change characterization, the large information content of neighbourhood-level change statistics can be cumbersome to work with (Kassawmar et al., 2018). Reclassifying and sorting such data into a handful of meaningful qualitative categories can make neighbourhood-level change information more useful. Therefore, we reclassified our data based on the per cent of change raster map produced on behalf of objective two (with values ranging from 0 to 100). Initially, the breakpoints applied to classify our data were determined using Jenks optimization method or natural breaks available in ArcGIS. Finally, we arrived at the following five classes and corresponding per cent change: “no change” (0–10%), “slight change” (10–25%), “moderate change” (25–50%), “high change” (50–75%), and “substantial change” (>75%). These classes were further simplified into two qualitative landscape transformation indicators – “hot” and “cold” spots of change – for use in prioritizing land management options. This was done based on the amount and degree of change. We designated areas exhibiting higher density of change as *hot-spots* (i.e. high/substantial change classes) and areas exhibiting lower density of change as *cold spots* (i.e. slight/moderate change classes). Finally, based on the

resulting maps and metrics, we characterized landscape transformation in Ethiopia's RAA with and without direction/type of change.

3. Results

3.1. Validating detected changes

The input data used for the assessment were validated using two approaches (see section 2.2.2): (i) using the *accuracy value* of each period of the LULC maps and (ii) using *basis of comparison*. Based on our first validation approach, the accuracy of our change estimates can range between 75–87%. This is because our two period LULC maps have an overall accuracy of 87%. According to the assumption in validation option one, i.e. assuming the two data are not correlated, the accuracy of the change map would range between 75% and 87%, respectively. Taken together, the average accuracy value of the detected changes is 82%. In line with our second validation approach, we compared our change estimates with 14 selected scientific studies. The nature and amount of land change in the present study and reference studies vary considerably according to location, analysis periods, and analysis methods (data used). The details of the assessment are presented in ST 3. Overall, change estimates obtained from the present study ranged from 9% (validation code 8) to 51% (validation code 12). The weighted area percentage of change obtained from the present study was 27%, whereas the “basis for comparison” was found to be 24%. Taken together, our estimates exceeded the estimates obtained from the reference study sites by 7% on average.

As depicted in Table 6, there is considerable variation between the overall amount of land change estimated in the present study versus that of selected reference studies, depending on the study location as well as periods of analysis. For instance, for validation site codes 4, 6 and 9, the estimates of the present study are lower compared to those of the respective reference studies. By contrast, for validation site codes 12, 13 and 14, the change estimates of the present study are higher than those of the reference studies. Among the validation sites considered, smaller variation is observed in sub-ecoregions 2a and 5b, while higher variation is found for verification code 6. Based on the comparison, we can assume that our estimates exaggerate changes in the lowlands and underestimate changes in the highlands. In terms of periods of analysis, among the four category of change analysis periods considered (Table 6), a higher percentage of overall change is recorded between the 1980s and the 1990s (i.e. 31%) for all validation sites. The change has been reduced by half in recent periods (after the 1990s). Overall, change estimates obtained from the present study range from 9% (validation code 8) to 51% (validation code 12). The weighted area percentage of change obtained from the present study is 27%, whereas that of

Table 6. Summary of overall land change statistics estimated by the present study and selected scientific studies.

| Validation site codes | Representing ecoregion | Overall land change estimates (in %) for each period of analysis | | | | | | Variation (on overlapping periods) |
|-----------------------|------------------------|--|-----------|--------------------------|-------------|-------------|------------|------------------------------------|
| | | Present study estimates | | Reference data estimates | | | | |
| | | Total area (km ²) | 1986–2010 | Before 1980s | 1980s–1990s | 1990s–2000s | 1980s–2010 | |
| | | | | 1957–1982 | 1982–1990 | | | |
| 1 | 1a _i | 7 | 23 | 30 | 50 | | | |
| 2 | 1a _{ii} | 9 | 17 | 25 | 30 | | | |
| | | | | | 1971–1997 | | | |
| 3 | 1a _{iii} | 160,000 | 17 | | 27 | | | |
| | | | | 1957–1980 | | | 1980–2001 | |
| 4 | 2a _i | 1318 | 38 | 48 | | - | 43 | -5 |
| | | | | 1974–1986 | 1986–1995 | 1995–2010 | 1986–2010 | |
| 5 | 3a _i | 4570 | 23 | 22 | 8 | 10 | 18 | +5 |
| | | | | 1972–1986 | 1986–1994 | 1994–2009 | | |
| 6 | 3a _{ii} | 296 | 18 | 38 | 29 | 25 | 54 | -26 |
| | | | | 1957–1982 | 1982–1995 | | | |
| 7 | 3a _{iii} | 271 | 9 | 68 | 14 | | | |
| | | | | 1957–1986 | 1986–1995 | 1995–2011 | 1986–2011 | |
| 8 | 3b _i | 9 | 22 | 91 | 10 | 10 | 20 | +2 |
| | | | | 1976–1986 | | | 1986–2008 | |

(continued on next page)

Table 6. (Continued)

| Validation site codes | Representing ecoregion | Overall land change estimates (in %) for each period of analysis | | | | | | Variation (on overlapping periods) |
|---------------------------------------|------------------------|--|-----------|--------------------------|-------------|-------------|------------|------------------------------------|
| | | Present study estimates | | Reference data estimates | | | | |
| | | Total area (km ²) | 1986–2010 | Before 1980s | 1980s–1990s | 1990s–2000s | 1980s–2010 | |
| 9 | 3b _{ii} | 352 | 21 | 43 | - | - | 16 | +14 |
| | | | | 1964–1994 | - | 1994–2006 | | |
| 10 | 3c _i | 24 | 25 | 28 | - | 25 | | |
| 11 | 3c _{ii} | 17 | 35 | 10 | - | 38 | | |
| | | | | | 1985–1995 | 1995–2010 | 1985–2010 | |
| 12 | 4a _i | 3806 | 51 | | 19 | 26 | 47 | +4 |
| 13 | 5b _i | 6328 | 42 | | 13 | 23 | 37 | +5 |
| 14 | 5c _i | 3518 | 33 | | 10 | 35 | 45 | +8 |
| Weighted average percentage of change | | | 27 | 8 | 31 | 14 | 24 | +3 |

the “basis for comparison” is 24%. This implies that our estimates exceed those of the reference study sites by 3%.

3.2. Pixel-level changes

3.2.1. Pixel-level identified transitions that induced landscape transformation

To better understand the nature of landscape transformation, it is of paramount importance to present and describe the pixel-level detected changes prior to neighbourhood-level based change assessment. Table 7 summarizes key transitions (e.g. forest to cropland; shrubland/bushland to cropland) responsible for measured changes, selected based on the amount of change they induced and their importance in changing the landscape. Out of 100 possible transition types, we found that the 30 most-frequent types were sufficient to characterize land change across all ecoregions because they represented more than 97% of the detected changes in the study area. Seven transition types, in particular, occurred in all ecoregions: WL–CL, GL–CL, WL–SBL, GL–SBL, SBL–WL, SBL–GL, and WL–GL.

The entries in Table 7 show the proportional area of change measured for each transition within a particular ecoregion (columns 1a–5c) calculated out of the total changed pixels in the same ecoregion (last row). On the one hand, 17 transitions were *forward* transformations (i.e. deforestation and degradation processes) and accounted for 70% of the observed land change dynamics. On the other, 13 transitions were *reverse* processes (i.e. regeneration of vegetation), accounting for the remaining 30% of the observed change processes. Among the transitions identified in agropastoralist areas (sub-ecoregion 4a), the largest shares of change were due to the *forward* landscape transformation processes of SBL–CL (26%) and SBL–GL (13%). In intensively cultivated ecoregions (3a–c), the most substantial transformations were observed in sub-ecoregion 3c (39% of pixels showing change) with SBL–BL (29%), a *forward* transformation, and SBL–WL (10%), a *reverse* transformation, accounting for the biggest proportions of change. In this way, sub-ecoregions 3a–c exhibited transitions of deforestation and forest degradation that are frequently found in relatively inaccessible areas. Other observed transformations (e.g. degraded to vegetated landscape, croplands to barren lands, and conversion to plantation and mixed forest) were important in the intensively cultivated ecoregions (sub-ecoregions 3a–c) and especially in low-potential areas (sub-ecoregion 3c). Overall, pixel-level detected changes were summarized (Fig. 8) for four major ecosystems: forest, cropland, grassland, and woody vegetation.

The maps depicted in Fig. 8 are important to understand the nature of change as the pixel-level detected changes can show where particular types of change occur. At the same time, it reveals the limitations of the data in terms of characterizing change

Table 7. The most-frequent transitions occurring in each ecoregion and their class-level proportional area coverage.

| Transition type | Trajectory | Direction | Occurrence and density of transitions in each sub-ecoregion | | | | | | | | | | |
|-----------------|------------|-----------|---|-----|------|------|------|------|------|------|------|------|------|
| | | | 1a | 1b | 2a | 3a | 3b | 3c | 4a | 5a | 5b | 5c | RAA |
| WL-F | RG | RLT | 21.1 | 0.5 | 6.1 | 1.9 | 2.1 | 0.7 | | 1.6 | 0.2 | 6.3 | 4.4 |
| SBL-F | RG | RLT | 15.1 | 0.2 | 9.5 | 6.2 | 2.1 | 0.2 | 0.1 | | 0.1 | 0.8 | 3.8 |
| CL-F | RG | RLT | 1.8 | 0.2 | 3.9 | 2.2 | | 0.1 | | | 0.04 | 0.4 | 0.9 |
| F-WL | FD | FLT | 10.7 | 4.1 | 6.3 | 2.4 | | 0.2 | | 4.9 | 0.6 | 6.3 | 3.5 |
| F-CI | DF | FLT | 0.5 | 6.4 | | | | | | | | | |
| WL-CL | DF | FLT | 9.5 | 3.2 | 31.3 | 13.6 | 5.8 | 0.9 | 8.6 | 1.1 | 3.1 | 10.3 | 9.5 |
| GL-CL | DF | FLT | 7.5 | 5.1 | 12.4 | 28.1 | 6.4 | 2 | 3.6 | 0.6 | 3.8 | 3.6 | 6.4 |
| WL-SBL | FD | FLT | 6.3 | 3.3 | 5.8 | 5.2 | 12.1 | 21.4 | 12.8 | 17.6 | 32.1 | 34.1 | 16.4 |
| WL-GL | DF | FLT | 5.1 | 1.4 | 4 | 1.9 | 2.5 | 1.1 | 9.1 | 7.2 | 7.1 | 6.8 | 5.0 |
| F-SBL | DF | FLT | 4.8 | 0.6 | 1.4 | 1 | 0.8 | 0.2 | | 1.3 | 0.7 | 1.4 | 1.3 |
| GL-WL | RG | RTL | 3.3 | | 1.1 | | | | 1 | 7.2 | 2.5 | 0.8 | 1.8 |
| GL-SBL | RG | RTL | 2.3 | | 1 | 1.4 | 1.1 | 0.4 | 3.5 | 8.9 | 2.2 | 1.3 | 2.5 |
| F-GL | DF | FLT | 1.8 | 1.4 | 1.3 | 1 | | 0.1 | | 0.6 | 0.1 | | 0.5 |
| GL-F | RG | RTL | 2.8 | | | 1.8 | 1.5 | 0.1 | | | 0.03 | 0.1 | 0.7 |
| SBL-F | RG | RTL | 2.6 | | 1.8 | | | 0.6 | | | 0.1 | 0.8 | 0.7 |
| SBL-WL | RG | RTL | 3.4 | | 1 | 2 | 9.1 | 10.9 | 3.6 | 10.1 | 10.3 | 6.7 | 6.3 |
| SBL-GL | DF | FLT | 1.4 | 3.0 | 1.3 | 6.3 | 4 | 7.4 | 13.8 | 14.8 | 15.2 | 9.1 | 8.5 |

(continued on next page)

Table 7. (Continued)

| Transition type | Trajectory | Direction | Occurrence and density of transitions in each sub-ecoregion | | | | | | | | | | | |
|--|------------|-----------|---|-----|-----|-----|------|------|------|-----|-----|-----|-----|-----|
| | | | 1a | 1b | 2a | 3a | 3b | 3c | 4a | 5a | 5b | 5c | RAA | |
| CL–WL | RG | RTL | 1.1 | | 1.1 | | | | | | | 0.6 | 2.1 | 0.5 |
| SBL–CL | DF | FLT | 1.8 | 3.2 | 3.8 | 7.5 | 8.1 | 8.9 | 26.1 | 0.7 | 6.5 | 4.4 | 7.7 | |
| CL–GL | RG | RTL | | | 1.8 | 2.5 | 4.1 | 0.7 | 8.7 | | 3.2 | 0.9 | 2.4 | |
| WeL–GL | DF | FLT | | | 1.7 | 2.6 | | | | | | | 0.5 | |
| GL–F | RG | RTL | | | 1.0 | | | | | | | | 0.1 | |
| CL–SBL | RG | RTL | | | 1.0 | 1.6 | 1.19 | 0.9 | 5.8 | 1.2 | 14 | 1.5 | 3.0 | |
| GL–BL | DF | FLT | | | | 2 | | | 0.4 | | 1.3 | | 0.4 | |
| CL–WL | RG | RTL | | | | 1.8 | | 0.3 | 1.1 | | | | 0.4 | |
| SBL–BL | DF | FLT | | | | 1.4 | 12.5 | 28.8 | 1.5 | | 5.1 | 0.4 | 5.5 | |
| F–BL | DF | FLT | | | | 1.2 | 1.2 | 1.6 | | | 0.1 | 0.3 | 0.5 | |
| WL–BL | DF | FLT | | | | 1.1 | 4.2 | 2.9 | 0.2 | | 1.7 | 0.5 | 1.2 | |
| SBL–F | RG | RTL | | | | 1.1 | 3.7 | | | 0.7 | | | 0.6 | |
| CL–BL | DF/FD | FLT | | | | 0.8 | 6.1 | 2.4 | | | 1.0 | 0.3 | 1.2 | |
| Proportion of changed pixels in each sub-ecoregion (in per cent) | | | 21 | | 41 | 24 | 36 | 36 | 59 | 40 | 58 | 43 | 39 | |

FD = Forest Degradation, D = Deforestation, RG = Regeneration, P = Persistence, FLS = Forward Landscape Transformation, and RLT = Reverse Landscape Transformation

across the entire study area and confirms the importance of neighbourhood-level change information as described in section 2.2.3.

3.3. Neighbourhood-level change assessment

3.3.1. Neighbourhood-level amount of change

The neighbourhood-level estimated amount of change, summarized for each sub-ecoregion, is presented in Table 8 and Fig. 9. As shown in Fig. 9, the amount and density of change vary across the ecoregions.

In Table 8, ecoregions falling in the first category (Code 1) display no change (stable landscape), while those falling in the second two categories (Codes 2–3) display slight or moderate change. These may be considered “cold spots” of landscape transformation. The remaining two classes (Codes 4–5) display high or substantial change, making them “hotspots” of landscape transformation. According to our estimates, in the period between 1986 and 2010, 38% of Ethiopia’s RAA was highly or substantially transformed, i.e. a hotspot of landscape transformation. Areas that experienced substantial transformation over the study period include sub-ecoregions 4a (16% change), 5b (10%), 5a (6%), and 2a (9%). By contrast, the *least* amount of transformation occurred in ecoregions 3a and 1a. The patterns of change produced using the five change categories are illustrated on the maps in Fig. 9. Deep-green areas represent stable landscapes, while light-green and yellow patterns correspond to slight and moderate transformation (cold spots); they are geographically concentrated in the southern, central, and eastern parts of the RAA. At the other extreme, orange and red patterns indicate highly and substantially transformed

Table 8. Neighbourhood-level amount of change (number or per cent of change per window) summarized for the nine sub-ecoregions (statistics derived from Fig. 7).

| Code | Change category | Amount of change (in %) for each ecoregion | | | | | | | | | | Average for the RAA |
|------|----------------------------------|--|-----|-----|-----|-----|-----|-----|-----|-----|-----|---------------------|
| | | 1a | 1b | 2a | 3a | 3b | 3c | 4a | 5a | 5b | 5c | |
| 1 | Not transformed (<10%) | 59 | 44 | 52 | 56 | 45 | 40 | 13 | 33 | 28 | 30 | 40 |
| 2 | Slightly transformed (10–25%) | 11 | 21 | 21 | 14 | 22 | 25 | 41 | 25 | 26 | 28 | 23 |
| 3 | Moderately transformed (25–50%) | 7 | 15 | 12 | 10 | 15 | 15 | 41 | 22 | 29 | 28 | 19 |
| 4 | Highly transformed (50–75%) | 7 | 11 | 13 | 9 | 13 | 14 | 4 | 13 | 15 | 11 | 11 |
| 5 | Substantially transformed (>75%) | 17 | 9 | 2 | 12 | 5 | 6 | 0 | 6 | 2 | 4 | 6 |
| | Total | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

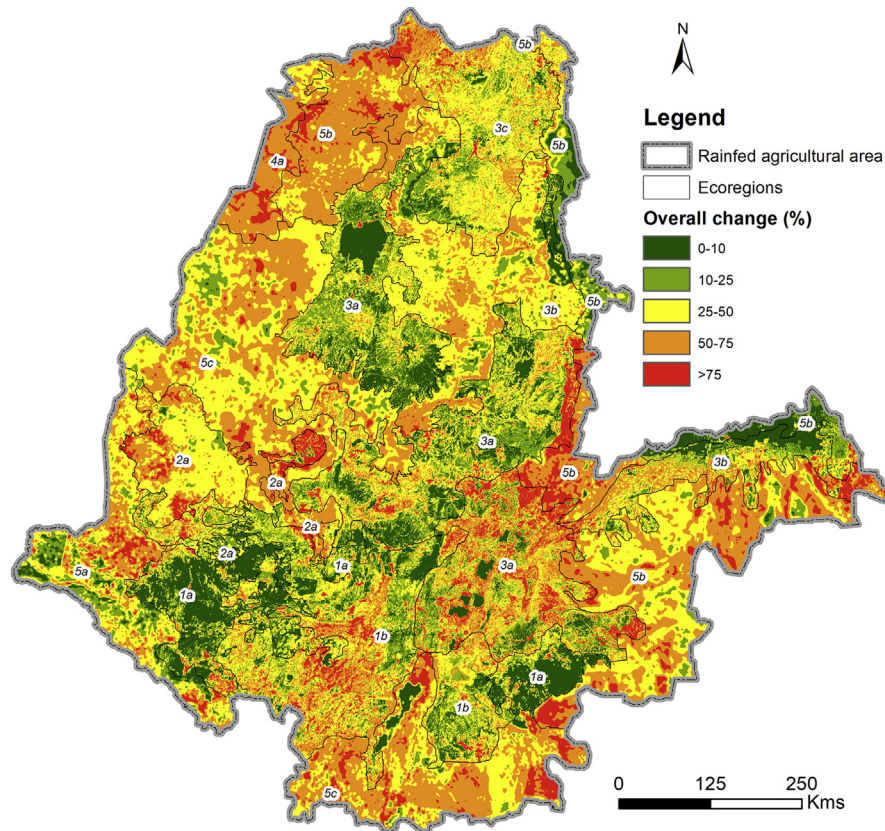


Fig. 9. Amounts and patterns of landscape transformation, measured based on a merger of multi-scale analyses that proved well suited to depicting changes in different ecoregions.

ecoregions (hotspots), respectively; large areas of these transformations may be seen in the north-western (low-lying) portion of Ethiopia's RAA.

3.3.2. Neighbourhood-level detected patterns and direction of change

In addition to identifying the four types of landscape transformation (e.g. forest degradation) and the *direction* of change (e.g. forward or reverse towards less or more vegetation), we further assessed and described the type and direction of landscape transformation using amount and patterns of change (Fig. 10).

Table 9 shows the proportional area coverage (in per cent) of change amounts for each type of landscape transformation occurring at different altitudes (extracted from Fig. 10). Column one lists the four types of landscape transformation. Column two displays the change category and corresponding densities of change. The remaining columns summarize the per cent changes for different agro-ecological belts (AEB). The values were calculated by taking the total changed area in each change category and dividing it by the total area of each AEB.

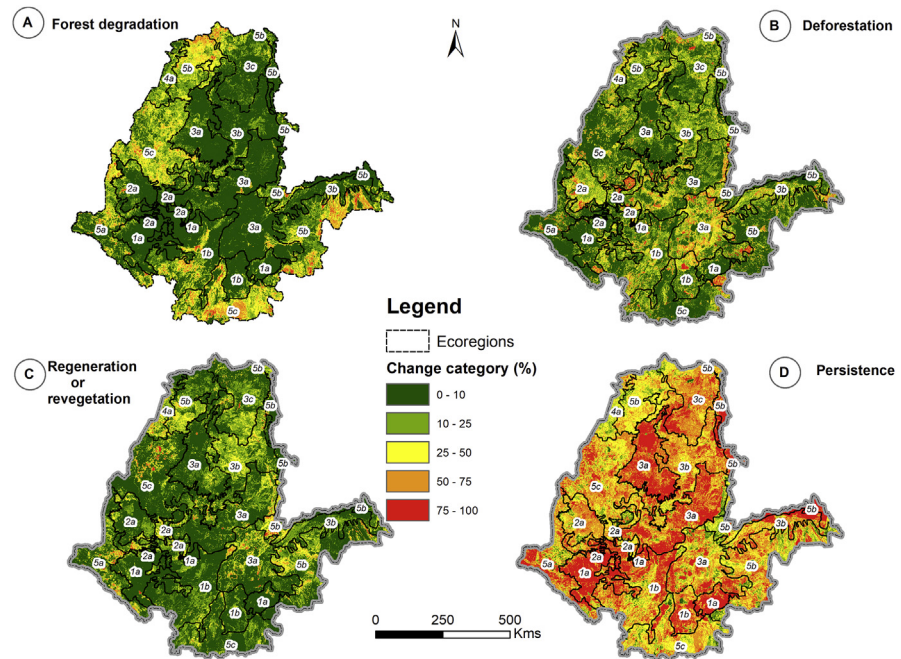


Fig. 10. Maps of the four main types of landscape transformation. The amount of change was obtained by calculating the total number of changed pixels out of maximum possible number of pixels in each respective window.

According to our results (Table 9), forest degradation and deforestation occurring in Ethiopia's Upper and Lower Kolla belts are relatively dense where human settlements are relatively recent. Most of the transitions measured in these AEB fall in change categories 3, 4, and 5, and are prominent examples of cropland expansion. This implies that deforestation and forest degradation are occurring more intensively in the lower and upper Kolla AEB than in the Dega and Woyna Dega AEB. The density of change in the Lower Dega and Upper Woyna Dega AEB is relatively minimal and these areas also appear stable (Fig. 8 and Table 9). Nevertheless, the conversion of remnant semi-natural landscapes (e.g. grassland, woodland, shrubland/bushland) to areas of crop cultivation still represents a crucial change occurring in these areas, albeit only over a relatively small proportion of land. On the other hand, high percentages of landscape "persistence" (revealed in change categories 3, 4, and 5) were found in Dega, Wurch, and Upper Woyna Dega, meaning landscapes in these AEBs are relatively stable.

4. Discussion

The present study was conducted based on the need for better data on land change processes in Ethiopia. Hitherto available land change data have been derived from relatively few studies with results that are sometimes incomplete, difficult to translate into policy, or not consistent enough to enable generalization or reasonable

Table 9. The amount of change summarized in each type of landscape transformation process occurring at different altitudinal ranges (traditional Agro-Ecological Belts, or AEB).

| Type of landscape transformation | Change category | Lower Kolla | Upper Kolla | Lower Woyna Dega | Upper Woyna Dega | Lower Dega | Higher Dega | Wurch | Average for the RAA |
|--|-----------------|-------------|-------------|------------------|------------------|------------|-------------|-------|---------------------|
| Forest degradation (FD) | 1 (<10%) | 41.2 | 41.5 | 51.5 | 52.4 | 60.6 | 73.4 | 91.3 | 58.8 |
| | 2 (10–25%) | 31.7 | 31.5 | 28.1 | 29.6 | 23.5 | 17.1 | 6.1 | 23.9 |
| | 3 (25–50%) | 22.8 | 20.2 | 16.1 | 14.8 | 12.7 | 8.1 | 1.9 | 13.8 |
| | 4 (50–75%) | 4.1 | 5.8 | 3.7 | 2.6 | 2.6 | 1.0 | 0.6 | 2.9 |
| | 5 (>75%) | 0.2 | 1.1 | 0.7 | 0.6 | 0.6 | 0.4 | 0.1 | 0.5 |
| Deforestation (DF) | 1 (<10%) | 24.9 | 31.8 | 69.4 | 80.5 | 89.0 | 89.5 | 95.5 | 68.7 |
| | 2 (10–25%) | 41.7 | 30.9 | 18.8 | 14.7 | 8.8 | 8.7 | 3.4 | 18.1 |
| | 3 (25–50%) | 28.0 | 28.5 | 9.9 | 4.2 | 1.8 | 1.5 | 0.8 | 10.7 |
| | 4 (50–75%) | 5.2 | 8.1 | 1.8 | 0.5 | 0.3 | 0.2 | 0.2 | 2.3 |
| | 5 (>75%) | 0.3 | 0.7 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 |
| Persistence (P) | 1 (<10%) | 0.5 | 1.6 | 1.6 | 1.3 | 1.1 | 1.7 | 0.9 | 1.2 |
| | 2 (10–25%) | 7.6 | 8.7 | 5.1 | 3.4 | 2.9 | 4.5 | 2.4 | 4.9 |
| | 3 (25–50%) | 40.8 | 43.4 | 24.5 | 17.7 | 18.2 | 18.4 | 8.1 | 24.4 |
| | 4 (50–75%) | 34.3 | 33.0 | 38.5 | 39.3 | 37.8 | 37.8 | 19.6 | 34.3 |
| | 5 (>75%) | 16.9 | 13.3 | 30.2 | 38.3 | 40.1 | 37.5 | 69.1 | 35.1 |
| Regeneration (RG) or Revegetation (RV) | 1 (<10%) | 53.1 | 60.5 | 58.6 | 61.9 | 60.8 | 54.3 | 63.3 | 58.9 |
| | 2 (10–25%) | 28.6 | 26.6 | 30.3 | 28.0 | 28.6 | 27.2 | 21.0 | 27.2 |
| | 3 (25–50%) | 15.6 | 11.0 | 9.8 | 9.0 | 9.3 | 13.9 | 11.2 | 11.4 |
| | 4 (50–75%) | 2.4 | 1.5 | 1.1 | 0.9 | 1.0 | 3.5 | 3.5 | 2.0 |
| | 5 (>75%) | 0.2 | 0.4 | 0.2 | 0.2 | 0.2 | 1.0 | 1.0 | 0.5 |

predictions. For instance, several previous studies were conducted solely at the local scale, such that they cannot describe land change process over the wider Ethiopian landscape (Heinimann, 2006; Wøien, 1995). One consequence of this is that the results of different studies sometimes appear to contradict one another. For instance, on the one hand, Nyssen et al. (2004a) argued that the northern parts of Ethiopia's RAA (sub-ecoregions 3a, 3b, and 3c) were largely deforested several hundred years ago or more (prior to the 1800s). This general assessment is supported by other researchers (McCann, 1997, 1990; Nyssen et al., 2009), including several (Bantider, 2007; Bewket, 2002) who argue that the Ethiopian highlands (overlapping with the RAA) are now in a state of regeneration and restoration. On the other hand, other researchers argue that the Ethiopian highlands are still undergoing massive transformation (Teferi et al., 2013; Zeleke and Hurni, 2001). These seemingly inconsistent viewpoints may be due to the limited geographic extent of study sites as well as the unrepresentativeness or unsuitability of areas/temporal scales selected for analysis (Crummey, 2009; Muluneh and Arnalds, 2010; Wøien, 1995). Wøien (1995) noted that land change processes in Ethiopia, especially deforestation, are typically generalized from local-level case study results that do not capture the wider complex land change processes occurring in the country. As a result, there is a risk of planning and implementing land-management strategies based on misleading data, thus hampering sustainable development efforts in the region (Sandewall et al., 2001). To address some of the relevant gaps and inconsistencies, the present study sought to provide more comprehensive, accurate information on LULC change across Ethiopia's RAA.

To properly identify the nature of land change processes over Ethiopia's RAA, the present study provided both pixel-level and neighbourhood-level change information. For regional- and national-level land change depiction and characterization, Kassawmar et al. (2018) recommend use of the neighbourhood approach — especially for large and complex areas. Application of the neighbourhood approach to our dynamic study area (i.e. varying in type, size, density of change) required multi-scale analysis. To implement a multi-scale approach, we subdivided the study area into different ecoregions and distinguished the optimal window size for each sub-ecoregion. This facilitated conversion of our pixel-level detected changes to neighbourhood-level changes, illustrating wider patterns of change at the national/regional scale. The changes occurring throughout the country are very diverse in nature, as was further confirmed based on expert knowledge and field visits. As depicted in our pixel-level change map, changes taking place across Ethiopia's RAA vary in their type, size, and density. In woodland-dominated areas (e.g. sub-ecoregions 1a, 4a, and 5a–c), where deforestation and forest degradation were important change processes, most of the changed pixels indicated similar transitions and occurred in large clusters. By contrast, in intensive crop-cultivation areas (e.g. sub-ecoregions 3a–c), comparably few pixels changed (i.e. changes occurred in

small clusters), but those that did point to different transition types (Table 7). This confirms that for better visualization of the change over the larger RAA, we need to translate changes to the neighbourhood level and select the appropriate window size. According to our neighbourhood-level change estimates, a smaller amount of landscape transformation occurred in the agroforestry- and forest-dominated ecoregion (1a), in which about 65% of the area appeared stable, making it a cold spot of change. This could be related to institutional factors, since the area has been officially designated as “pristine”, i.e. home to intact natural forest. Nevertheless, encroachments by coffee growers have caused considerable forest degradation even in these protected areas. This sort of “concealed” land change phenomenon is typically imperceptible to remote-sensing technology, as long as forest cover is not completely cleared. The amount and types of changes identified in sub-ecoregions 3a–c vary greatly. By contrast, ecoregions 1a, 2a, and 5a are considered high-potential areas for crop production and encompass disturbed forest landscape.

Due to its favourable agro-ecological setting, ecoregion 3 has been subject to very intensive agricultural practices. Previous local-level land change studies suggest that land degradation in sub-ecoregions 3b and 3c is the most severe in the RAA (Crummey, 2009; Munro et al., 2008; Jan Nyssen et al., 2004; Pankhurst, 1957). In these ecoregions, the natural landscape has been greatly transformed – more recently in the case of 3a (Zelege and Hurni, 2001). However, the present study assessment revealed that these areas were relatively stable over the assessment period (1986–2016). Nevertheless, agricultural expansion, intensification, and growth of human-settlement-driven afforestation remain important land change phenomena occurring on remnant natural landscapes in sub-ecoregion 3a, though these small-scale transitions are difficult to distinguish using 30 m-by-30 m satellite images (Bewket, 2002). Evidence suggests that these sub-ecoregions may have been even more degraded and less vegetated from the early 1900s to the late 1980s, when compared with the current situation (Crummey, 2009; Munro et al., 2008; J Nyssen et al., 2004b; Pankhurst, 1957), due to early human settlements and age-old traditional ploughing (Hurni, 2005; McCann, 1997, 1990; Jan Nyssen et al., 2004; Pankhurst, 1957). In the past, these ecoregions suffered extreme degradation of vegetation and soils, successive droughts, and famines (after 1960). As a result, they received greater attention from land rehabilitation programmes beginning in 1990 (Mengistu et al., 2005; Taddese, 2001). More recently, reverse (i.e. regeneration) processes are occurring in the region, mainly related to ongoing area closures (Mengistu et al., 2005), conversion of croplands to artificial plantations, rehabilitation of degraded areas (Alemayehu et al., 2009; Crummey, 2009), homestead developments linked to settlement expansions (Nyssen et al., 2009), and the slowdown of cropland expansion (Crummey, 2009; Wøien, 1995). Over the last three decades, more large-scale ecological restoration and land rehabilitation activities have been implemented in this part of Ethiopia than anywhere else (Nyssen et al., 2009).

Nevertheless, deforestation and forest degradation continue to occur in the least-accessible remnant vegetated landscapes. Study findings from [Amsalu et al. \(2007\)](#) point to ongoing reduction of vegetated landscapes and a small increase in cultivated areas in sub-ecoregion 3b. Further, [Gebresamuel et al. \(2010\)](#) found evidence of significant vegetation decline and cropland expansion in sub-ecoregion 3c.

Our assessment of pixel-based changes ([Table 7](#)) indicates that conversions from grassland to cropland predominate in ecoregion 3a. Remnant grasslands located in the floodplains of sub-ecoregion 3a have been targets of recent land conversions. On the other hand, slight improvements in vegetation cover were also detected in some parts of sub-ecoregions 3a–c. This is most likely linked to a population-based increase in vegetation around homesteads and smallholder eucalyptus plantations ([Bewket, 2002](#)). Similarly, in sub-ecoregion 3b, processes of reverse transformation or persistence (overall stability) are more common than an active forward (degrading) land change processes. In sub-ecoregion 3c, 56% of the area was moderately transformed during the study period, with regeneration processes accounting for 10–25% of the changes ([Table 5](#)). In the eastern part of sub-ecoregion 3c especially, recent major efforts towards land rehabilitation and afforestation are still difficult to capture with remote sensing (such as in the present study) in comparison with ground-level observations. This could be because rehabilitation of degraded lands – e.g. by means of area closures – is a long process, particularly in low-potential areas where soils are highly depleted ([Mengistu et al., 2005](#)). Moreover, many of the plantations implemented on degraded communal areas of sub-ecoregion 3a–3c have failed due to “tragedy of the commons” resource use ([Muluneh and Arnalds, 2010](#)). Though private-level afforestation practices have been implemented on many smallholder plots, they remain quite fragmented and have not been extensive enough to produce noticeable landscape change, or cannot be captured by remote-sensing data from medium- or high-resolution satellite sensors (e.g. Landsat TM). Furthermore, such phenomena are spatially limited to certain high-potential areas, settlement zones, or nearby (10 km buffer) main roads.

A considerable amount of transformation was measured in the agro-pastoralist areas. Among others, sub-ecoregion 4a – renowned for sesame production in the country – displayed substantial transformation over the assessment period. Year after year, the extent of sesame production increased through clearing of woody vegetation landscape. Among the agro-pastoralist sub-ecoregions, the degree of transformation was highest in sub-ecoregion 4a, followed by 5b, 5c, and 5a. Most of the land changes in ecoregion 5 were modifications of vegetated landscape, such as transformation from woodland to shrub or bushland (dense woodland to open woodland). Many changes are very recent, and a significant portion of these areas was recently granted to foreign investors for large-scale agricultural projects that are not yet fully operational. Some regeneration of vegetation observed in sub-ecoregions 5b and 5c may be attributed to rotational slash-and-burn type cultivation practiced by (illegal)

smallholders who have migrated here from highland areas (Dessalegn, 2003). The combined effects of land shortages in intensively cultivated sub-ecoregions (3a–c), biofuel energy needs, land concessions, and large-scale land investments have gradually pushed land-change processes into sub-ecoregions 1a, 2a, and 5a as well as the lower elevations of the study area, i.e. sub-ecoregions 4a, 5b, and 5c featuring lower population densities and less cultivation (Hurni, 2005). According to the AEB-based assessment result, the majority of the changes measured are observed in the Kolla and lower Woyna Dega AEB. This implies that recent deforestation- and forest-degradation processes were more intensive in the lower and upper Kolla AEB compared with Dega and Woyna Dega, making these regions – i.e. Kolla and lower Woyna Dega AEB – hotspots of landscape transformation. At the same time, conversion of remnant, semi-natural landscapes (e.g. grassland, woodlands, and shrub/bushlands) to croplands are still important changes occurring in Dega and Woyna Dega AEB, but they cover a relatively small proportion of the landscape.

The findings of the present assessment indicate hotspots of deforestation- and forest-degradation-driven landscape transformation in Ethiopia's RAA. Deforestation and forest-degradation hotspots comprise approximately 4% and 5% of the study area, respectively (Table 9). The majority of these processes are occurring in the low-lying part of Ethiopia's RAA (Fig. 10). Regarding processes of regeneration, only about 10% of the RAA is subject to such reverse transformation. On balance, the RAA is undergoing more forward-direction landscape transformations and/or remaining stable, whereas reverse-direction transformations are relatively insignificant. Overall, observed landscape transformations point to clear dividing lines stretching across the RAA. The dividing lines indicate highland–lowland, north–south, and east–west orientations for interpreting various land-change phenomena. High levels of deforestation and forest degradation were observed in the western (lowlands) of the RAA. Here, the density of these types of transformation gets higher as one moves from south to north. By contrast, a small eastern portion of the RAA (intensively cultivated highland) appears to be transforming in reverse (e.g. trending towards regeneration). Otherwise, the larger part remains stable.

Various factors underlie the remotely observed change processes and require further investigation, especially at the local level. However, agro-ecological-based assessment of change points to two important factors: the history of spatial patterns of human settlement, and trends in agricultural practices (linked to highland–lowland contexts). These two factors are determined by intricate political, socio-cultural, and, to some extent, natural biophysical processes. The highly populated highlands and the low-population density lowlands examined in our study represent historical frontiers of human–nature interactions, as evidenced by farming systems (intensively cultivated and agro-pastoralist systems); landscape characteristics (human-dominated and natural-/semi-natural landscape); degradation levels (highly

degraded and less-exploited areas). The more recent landscape stability observed in the High Dega/Lower Dega AEB is partly due to the history of human settlement and ancient traditional agricultural practices that transformed the landscape long ago and ran out of room to expand. Today, there are signs of spillover effects of land-resource stress, with pressures found in the highlands being transferred to the lowlands. Population increases have triggered land shortages in the highland areas of the RAA (sub-ecoregions 3b and 3c), forcing people to migrate and settle (sometimes illegally) in low-lying areas (5a), where they have converted the land for settlements and cultivation. Notably, unlike in the highland areas, reversing undesirable changes in the lowlands will be highly challenging or impractical due to difficult climatic conditions (Muluneh and Arnalds, 2010).

The presented approach may be implemented to characterize land change over complex and large areas using LULC time-series maps produced from high-/medium-resolution satellite images. This addresses many of the limitations of high-/medium-resolution satellite images (e.g. salt-and-pepper effect, error pixel contamination effect on classified LULC maps). However, generalization as a principle of cancelling out errors and wider presentation of patterns of change may not be an advantage for coarse-resolution images. Thus, the applicability of the presented approach is limited for change detection and characterization based on coarse-resolution images. Moreover, the presented approach and results apply to long-term change detection for only two time periods – a key limitation. Making the approach applicable for more than two time periods – such as 1986–1996, 1996–2006, and 2006–2016 – is a key area for further research.

5. Conclusions

The approach presented in this paper is useful for identification and understanding of patterns of change hitherto underexplored by local-scale and pixel-based assessments. In terms of land change, the results of this study show that the majority (about 40%) of Ethiopia's highland RAA remains stable. The central and (smaller) eastern parts of the RAA – intensively cultivated highland – appear to be transforming in reverse, that is, regenerating. By contrast, deforestation and forest degradation are prominent in the lowlands, appearing dense in the western (mainly lowland) part of the RAA. These types of transformation become denser as one moves from south to north in the western part. Understanding the drivers, extent, and impact of such changes is paramount. Spillover effects of land-resource stresses are evident, with pressures from the highlands being transferred to the lowlands due to migration of landless people, who have been transforming vegetated lowland landscapes to settlements and croplands. The slight improvement in vegetation cover, detected in the northern and central highlands, is likely linked to

population-driven improvement in vegetation around homesteads and smallholder eucalyptus plantations. Such information can help to make land change assessments more consistent, interpretable, and useful for policymakers and other general audiences. Based on the maps generated in the present study, we conclude that change maps produced at varying scales (selected based on the nature of change) are capable of identifying finer- and coarser-scale patterns of change, even for data that alone typically escapes analysis of fine-scale patterns of change. Thus, the corresponding outputs can provide planners and decision-makers with a synoptic view of land change processes, supporting policy formulation of sustainable land-resource management as well as rehabilitation activities at national and transnational scales. The results of the present study can also be used to select case study areas for closer examination and verification at the local scale. We recommend that similar studies be undertaken using even higher-resolution spatial data, comparing the results with spatially explicit overlapping data on economic development, human populations, and institutional dynamics.

Declarations

Author contribution statement

Tibebu Kassawmar: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Gete Zeleke: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Amare Bantider, Gizaw Desta Gessesse, Lemlem Abraha: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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