Progress, Challenges and Implications of Land Use/Land Cover Detection Methods in Ethiopia: A Review

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Abstract: *Remote sensed imageries are rich in geospatial data's pertinent for natural resources conservation. However, extracting accurate and reliable information was remained critical. This review is aimed to compile the progress, challenges and examine implications of land use/land cover detection methods executed in Ethiopia. In the diverse landscape of Ethiopia, existing satellite image classification techniques were operated. Most of the studies agreed that automatic techniques are crucial in detecting the spectral responses of features. However, it was limited under heterogeneous landscape. To retain its digital recognition, a successive hybrid of the automatic techniques were also executed then again doubted by its limitation on areas which have similar reflectance for different land covers. Other studies also applied on-screen-digitizing, which bears better accuracy but criticized as it was exhaustive, costly, and expert dependent on fine-resolution data. In order to reduce the limitations and incorporate their advantages, a hybrid of automatic and on-screen-digitizing has been effected. Even though this technique refined spectral confusion sourced from automatic operation with better accuracy, the drawback of on-screen-digitizing was followed. Indeed, if an error happen in data processing, it is obvious that decisions and modeling outputs could be doubtful. In so far, those studies showed virtuous progress in adopting the tools to Ethiopia. Nevertheless, the absence of well-organized, accessible, and up-to-date information catalog, the country was investing (in/directly) for those fragmented studies. Devising site-specific methodologies, providing accurate inputs for modeling and decision makers, organizing fragmented studies, and establishment of an accessible resource assessment database are recommended.*

Keywords: GIS, Hybrid Classification, land use/land cover, on-screen-digitizing, Remote Sensing, Supervised Classification

1. Introduction

All human kinds were directly or indirectly involved in the adaptation of landscape to fulfill the livelihood demands. This intrusion has transformed and disturbed the equilibrium condition of nature (Burka, 2008). The reason is that the land is the major natural resource that economic, social, infrastructure and other human activities are undertaken on (Fisseha *et al*., 2011). In order to convince decision makers and manage the extreme resource use, the global science agenda on environmental change becomes targeted in monitoring and providing information on unremittingly occurring land use/land cover change (LU/LCC) (Lambin *et al.*, 2001). As a tool to detect LU/LCC, ever since the launch of the first Land sat satellite (1972) and the old aged airborne platform products have been processed through remote sensing and geographic information system (GIS) to map the spatial characteristics of a landscape and its link among people (Giri, 2012).

Even though remote sensed imageries are rich in geographic data, the conversion of this raw data into meaningful form needs simple to complex geospatial processing (Balamurugan and Jayarraman, 2016). As it is compiled by Weng (2010), information extraction from those images needs the integration of remote sensing and GIS using (i) remote sensing as a tool for gathering data for use in GIS, (ii) GIS data as ancillary information to improve the products derived from remote sensing, and (iii) remote sensing and GIS together for modeling and analysis.

In either of using the semi/self-executing (automatic), manual or combination of them (hybrid) techniques of image classification, the information should be accurate and acceptable in line with existing landscape conditions (Meshesha *et al*., 2014; Abburu and Golla, 2015). Zhang *et al*. (2014) indicated that automated methods could provide satisfactory results when applied to homogeneous land covers like water bodies, built-ups, and sandy land. Similarly, recent studies reported inefficiency of this approach in extracting LU/LC information from heterogeneous landscape (Büttner, 2014; Meshesha *et al*., 2014; Wondrade *et al.,* 2014; Sahle *et al*., 2016; Mekonnen *et al*., 2016; Betru *et al*., 2019). Those authors recommended the use of either hybrid or manual approaches. The rationale is that the application of automatic classification is more limited in a larger area because of the massive parameter requirement to handle spectral confusion (Herold *et al.,* 2008). This is an implication that automated image classification should be classified based on some considerations (Herold *et al.,* 2008).

Spatial heterogeneity emanated from soil type, topography, farming practices and land use history makes the estimation of global degraded lands vary across larger spatial scales (Gibbs and Salmon, 2015). The African continental-scale land cover mapping through fuzzy (crisp) approach is employed on four different datasets. The result revealed that mapping of heterogeneous landscapes in the four products is not very successful. In the end, using smarter algorithms, better timing of image acquisition, and improved class definitions are options provided to overcome the challenge (Tchuenté *et al.,* 2011).

Ethiopia is characterized by enormous agro-ecosystems, which explained into diverse vegetation zones (Teketay *et al*., 2010). Despite great geographic diversity, there are areas where a growing population in conjunction with rising subsistence demand has contributed to the deterioration and depletion of natural resource base, which is further, indicated the greater heterogeneity of land use patterns (Meshesha *et al*., 2014).

The reviewed studies showed that starting from the 1957 aerial photograph (Deribew and Dalacho, 2019) to this date of high-resolution satellite imagery (Mekonnen *et al*., 2016), LU/LC assessments were done almost in all parts of Ethiopia. In the overall information extraction, good progress has been realized from simple to very complex digital methodologies (Ariti *et al*., 2015; Gidey *et al*., 2017; Gebremicael *et al*., 2018; Betru *et al*., 2019). However, none of the studies have suggested a specific methodology to a certain nature of the landscape. Moreover, some limitations are observed in their level of accuracy, which is sourced from landscape heterogeneity, imaging property, information extraction methodologies, and availability of ancillary data's. Due to the absence of well-organized and up-to-date national level geospatial database (i.e. LU/LC), Ethiopia have been costing (finance and human resources) to assess the land surface resources for different purposes from individuals thesis (Burka, 2008) to national/regional projects (WBISPP, 2004; Mekonnen *et al*., 2016; MoEFCC, 2016).

Even though LU/LCC studies have been done so far, regardless of the doubt on outputs accuracy, local natural resource managers and national policymakers are entirely dependent on the information generated from those investigations. Decisions made from that uncertain information could yield to further cost on the sustainable use and conservation of natural resources.

It is important to note that, no particular classification method is inherently superior to any others. Therefore, the overall intention of this review is (i) to compile the progress, (ii) to point out the challenges and situations where one classification method is liable to be more accurate than the other, and (iii) to examine the implications of LU/LCC studies done so far in the diverse landscape of Ethiopia. This may have a great role to be used as a baseline document of methods used to quantify LU/LCC in Ethiopia and may be used as an inspiration to develop a new methods/techniques based on the progress and challenges encountered so far in the country.

2. Definitions and Basic Concepts

2.1. Definitions

Application of remote sensing and GIS becomes the prominent tool in the scientific communities for land resource assessments. Consequently, phrases like land use, land cover, land use change, and land cover change are the common elements throughout assessing and monitoring environmental changes (Giri, 2012). Therefore, as of most studies did, it is important to define those phrases for common understanding.

Table 1. Summarized explanations of common phrases

Phrase	Description
Land cover	Land cover is the biophysical outlook of the Earth. E.g. A land covered by forests, scrubs, grass, agriculture, barren, ice and snow, urban, and water.
Land use	Land use is the function or the socioeconomic purpose of the land being used. E.g. Recreational or educational forest.
Land cover change (LCC)	LCC refers either the total conversion (forest to urban) or modification (forest degradation) of the land cover. Monitoring conversion is easier using remotely sensed data.
Land use change (LUC)	LUC is the change in the use or management of the land by the user. Sometimes, LUC may not be caused by LCC. E.g. a production forest can be declared to a recreational forest. However, LUC is likely to cause LCC.

Adapted from Giri (2012)

Despite the enactment of remote sensing technology, it is limited in defining the issue of land uses. Instead, it detects the overall reflectance of targeted land covers. That may be the reason for the use of LUC and LCC as supplemental. This is to mean LUC is possible only through ground observation or measurement but LCC uses records of the electromagnetic energy from remotely sensed imagery. Therefore, the synergy of techniques used to detect LUC and LCC objectify monitoring of environmental changes, LU/LCC (Giri, 2012).

2.2. Satellite image classification techniques

LU/LCC are sourced from satellite image processing with the aid of real ground knowledge, processing techniques, and use of the available ancillary data. This process is laid under the concept of satellite image classification which is a multidisciplinary procedure aimed to extract meaningful information from the raw data (Giri, 2012; Abburu and Golla, 2015).

According to Abburu and Golla (2015), satellite image classification process involves grouping the image pixel values into meaningful categories. It is broadly classified into three categories 1) automatic 2) manual and 3) hybrid.

In the manual approach, a human analyst attempting to classify features in an image uses the elements of visual interpretation to identify homogeneous groups of pixels, which represent land cover classes of interest. However, the automatic (digital) image classification produced a mosaic of spectrally homogeneous pixels, essentially a thematic map, of the original image (Giri, 2012).

The automatic approach can be self-executing (unsupervised) and user-driven (supervised). The former generates a cluster of pixels which needs to be further verified and labeled, while, the later needs supervision of the expert to train the software from the ground information (Abburu and Golla, 2015; Balamurugan and Jayarraman, 2016).

In the reviewed studies, various forms of hybrid classifications those combined automatic to manual techniques were identified. These are a combination of unsupervised and supervised (Teka *et al.*, 2018), unsupervised and manual (WBISPP, 2004), and supervised and manual approach (Betru *et al*., 2019). In general, for the sake of clarity, the previously mentioned hybrid approaches are grouped into successive and merged process based categories.

A cluster of spectral classes from the unsupervised classification is used as training sets to define land cover information classes for supervised classification. This is a kind of successive hybrid when the output of the primary procedure is used as an input for the next one (Gashaw and Fentahun, 2014; Teka *et al*., 2018), whereas, the other approach is a hybrid through merging technique. In this process, there is independent execution of supervised and on-screen-digitizing techniques. In the end, rule-based statement is used to merge those results for the final map (Sahle*et al*., 2016; Betru *et al*., 2019). This is achieved through automated methods to do initial classification and then further manual methods are used to refine classification and correct errors (Abburu and Golla, 2015).

Indeed, the extraction of information from image classification in remote sensing technology is dependent on the landscape heterogeneity and the data used which affects the selection and accuracy of image classification techniques. This is issue bothers an area on which the pattern and texture of the landscape cover change abruptly (Meshesha *et al*., 2014; Mekonnen *et al*., 2016). This is also a challenge in a country like Ethiopia where there is larger vegetation and landscape diversity is gifted. Therefore, the following section discusses the different LU/LC detection techniques used by various scholars in the Ethiopian landscape only.

3. LU/LC Detection Methods Used in Ethiopia

This section has summarized the different methodologies used in so far to assess the multi-temporal changes accounted in LU/LC patterns along the Ethiopian landscape. In Ethiopia, it is obviously known that most landscape heterogeneity is changed with altitudes including population density from lowland to highlands. As Burka (2008) narrated, the majority of the population of Ethiopia settled in the Ethiopian highlands, which facilitates the degradation of the environment and triggers LU/LCC faster than the lowland ecosystem. The population growth would lead to the need for new settlement areas and agricultural lands which have contributed to the deterioration of natural land covers (Meshesha *et al*., 2014). Therefore, the under-reviewed image classification techniques are also considered the texture of their area of investigation.

3.1. Unsupervised image classification

Table 2. Summary of unsupervised image classification techniques used in Ethiopia

Study area	Altitude range (m.a.s.l.)	Image/data used	Ancillary data/sand source	LU/LC and producer accuracy for the latest year (%)	Challenges/ corrections made	Source
West Shewa, Oromia	1200 – 1600	TM (1984), ETM+ (1999), and SPOT (2007)	Field observation	Shrub/grassland, Grassland, cultivated land, settlement, and a town. No accuracy report.	Individual settlements from the surrounding farm plots was not separated	Mulugeta and Weldesemait, 2011
Central Rift Valley	1572 – 2800	1973 (MSS), 1986 (TM), and 2000 and 2014 (ETM+)	Aerial photo, Google earth and field survey	Forest (96), woodland (93), grassland (88), cropland (96), water (91).	120 classes were generated and re-classed to five LU/LC types.	Ariti *et al*., 2015

Note: Producer's accuracy is computed by dividing correctly classified pixels to the total reference points of the specific LU/LC category. TM: Thematic Mapper; ETM+: Enhanced Thematic Mapper plus; MSS: Multispectral Scanner; SPOT: Satellite Pour I'Observation de la Terre.

Mostly unsupervised classification method is executed for an initial understanding of the area under study and further applied as a training cluster of pixels for other techniques (Section 3.4). However, in the above investigations (Table 2), it was used to cluster homogeneous pixels into a large number of classes and after ground information, reclassification provides the existing major LU/LC categories/classes (Mulugeta and Weldesemait, 2011; Ariti *et al*., 2015).

The prior intention of Mulugeta and Weldesemait (2011) was to map the effect of resettlement packages occurred in the area on the surrounding land use patterns. This study reveals an intensive inclusion of ground information resulted in a better detection of the existing LU/LC maps. The second study (Ariti *et al*., 2015) conducted at central rift valley (CRV), reveals an accuracy above the acceptable minimum threshold which is 85%. Confidentially, the study reasoned out that, the unsupervised techniques were recognized and clustered the spectral response patterns of the different LU/LC types of the area with the aid of efficient ancillary data's (Figure 1).

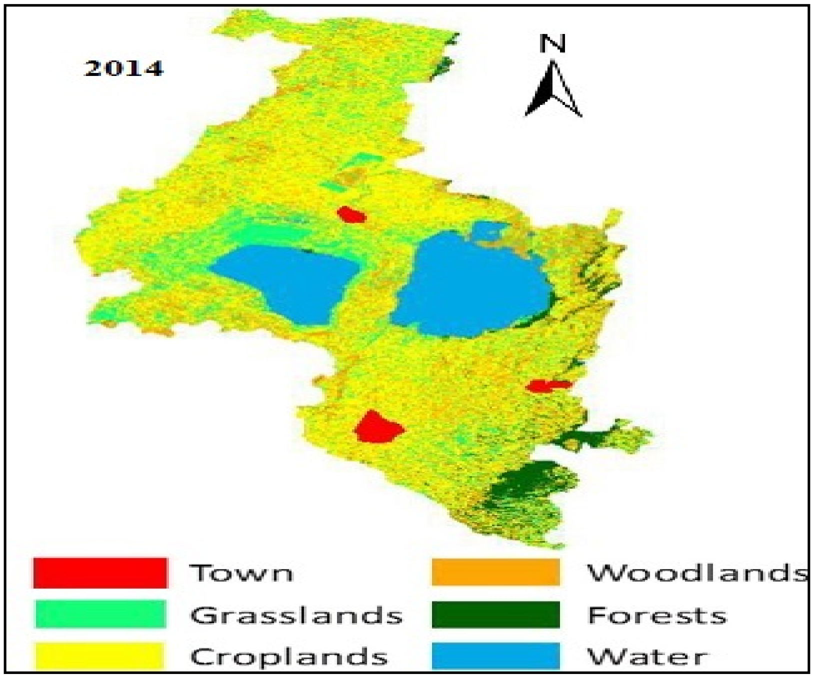

Figure 1. LU/LC maps of CRV for 2014 (Ariti et al., 2015)

3.2. Supervised image classification

Table 3. Summary of supervised image classification techniques used in Ethiopia

Study area	Altitude range (m.a.s.l.)	Image/data used	Ancillary data/s and source	LU/LC and producer accuracy for the latest year (%)	Challenges	Source
Borana rangelands, Southern Ethiopia	1000 – 1700	Aerial photographs (1967 and 1987), ETM+ (2002)	Topographic maps, aerial photographs, and field observation	Grass cover, woody vegetation cover, cultivated cover, bare land, settlement. No accuracy.	Bushes and shrubs and trees are merged in a class.	Haile *et al*., 2010
Kemekem district, Northwest Ethiopia	1900 – 2800	Panchromatic aerial photographs (1957 and 1980), ETM+ (2003)	Field survey and Topographic map	Dense forest, Cultivated and Settlement land, Woodland, Shrub land, Grassland, and Riverine vegetation. No accuracy.	Plantation vs. natural forest, rural dowelling vs. cultivated land were not separated	Molla *et al*., 2010
Northern Afar rangelands, Ethiopia	100 - 2500	MSS (1972), TM (1986), ETM+ (2007)	Field survey and Aerial photographs	Woodland (80.77), bush land (88.24), bushy grassland (78.26), grassland (100), scrubland (81.13), cultivated land (97.22) and bare land (100)	Cropping fields and settlements areas were merged together	Tsegaye *et al*., 2010
Gerado catchment, South Wollo Highlands, Ethiopia	2174 – 3032	Aerial photographs (1958 and 1980), and SPOT (2006)	Field survey and Topographic map	Cultivated and rural settlements, shrub land, woodland, bare land, grassland, urban built-up, and forest. No accuracy data	Cultivated areas and rural settlement land were not separated	Asmamaw *et al*., 2011
Borena district, South Wollo zone, Ethiopia	1000 – 4000	1972 (MSS), 1985 (TM), and 2003 (ETM+)	Field survey and Topographic map	Cropland, forest, Shrub land, grassland, bare land. No class accuracy. Overall accuracy = 86.11	Cropland vs. rural residents were not separated	Shiferaw and Singh, 2011
Semen mountains NP, Northwestern Ethiopia	1900 – 4430	1984 (TM) and 2003 (ETM+)	Field survey and DEM	Agriculture (96.3), mixed forest (100), pure forest (72.7), shrub/young trees (100), and grassland (84).	Shadow areas are left unclassified as one LU/LC category	Wondie *et al*., 2011
Midwest escarpment of Rift Valley	2000 – 2400	Aerial photographs (1972), TM (2004)	topographic map, slope map, field and household survey	Riverine trees, plantation trees, perennial croplands andsettlement, shrub/ grassland, annual crop land, and bare land. No class accuracy. Overall accuracy = 87%	Areas with enset and chat tree crops, rural settlements were detected together	Mengistu *et al*., 2012
Gish-Abay watershed, Northwestern highland, Ethiopia	2000 – 3100	Panchromatic aerial photographs (1957 and 1982), TM (2001)	Field survey	Forest and dense trees, riparian vegetation, shrub grassland, open grassland, cropland and rural settlement, and town. No accuracy	Rural settlements and surrounding farm plots couldn't separated	Bewket and Abebe, 2013

				report.		
Arsi-Negele Districts, Ethiopia	1500 – 3400	MSS (1973), TM (1986), ETM+ (2000), and Rapid Eye (2012)	DEM, Aerial photo, NDVI, Topo map, field survey, other administrative and infrastructure data.	Bare lands (90), grasslands (88.7), water (100), settlements (94.4), croplands (81.6), tree patches (96.9), plantation forests (96.4), natural forests (98.2), woodlands (97.9)	Image segmentation – classification – merging were done in turn to map LU/LC and avoid errors	Kindu *et al.*, 2013*
Koga catchment, Northwestern Ethiopia	1500 – 2400	Aerial photographs (1957), MSS (1979), TM (1986), ETM+ (1999), and ASTER (2010)	Field survey, elder's interview, topographic map and aerial photo	Woody vegetation, pasture, crop field, bare land, settlement, and water. No class accuracy. Overall accuracy = 99.48	Trees and shrubs $\geq$20% crown cover and taller than 2m were detected as woody vegetation	Yeshaneh *et al.*, 2013
Bantneka Watershed, Southern Ethiopia	1750 - 2200	TM (1986), ETM+ (2000), and SPOT (2006)	Field survey, interview and discussion, topographic map	Annual cereal crop land, mixed land, perennial crop land, woodland and settlement land. No accuracy report.	Coffee and Enset were not separated from large indigenous trees and perennial fruit trees.	Fentahun and Gashaw, 2014
Ameleke watershed, South Ethiopia	1200 – 2000	TM (1986), ETM+ (2000), and SPOT (2006)	Field survey, topographic map and elder's interview	Agroforestry, crop land, grass land, mixed cover, shrub land, and riverine forest. No class accuracy. Overall accuracy = 85.71	Some areas (1.16%) were unclassified. Resident areas weren't detected.	Worku *et al.*, 2014
Nech Sar National Park, South Ethiopia	1100 – 1650	TM and ETM+ (1985, 1995, 2005 and 2011) Sensors are not indicated separately.	Field survey, elder's interview, and NDVI	Forest (90), grassland (94), encroaching plants (92), wooded grassland (80), woodland (86), cultivated (85) and bush/shrubs (98)	------------	Fetene *et al.*, 2015
Libokemkem District, South Gondar, Ethiopia	------------	MSS (1973), TM (1985 and 1995), ETM+ (2003), and OLI (2015)	Field visits, interviews, Google Earth image, black and white aerial photograph, and raw images	Agricultural lands (92), wetlands (96.7) degraded land (88.9), settlements (88), bush/shrub lands (78.7), grasslands (76.3), and forest land (100).	------------	Demissie *et al.*, 2017
Mekelle City, northern Ethiopia	1930 – 2353	TM (1984, 1994, and 2004), and OLI (2014)	Topographic maps, aerial photographs, Google Earth, field observation	Agricultural land (91), Built-up (94), plantation (87), shrub land (85), water body (-).	Grazing lands and crop lands were combined together.	Fenta *et al.*, 2017
Raya, Northern Ethiopia	324 - 4129	TM (1984 and 1995), and OLI (2015)	Field survey	cropland (90), forestland (88.5), shrub/bush (95), built-up area (93.3), water bodies (100), grassland (84), barren land (85.5)	Sparse rural resident are ignored. Shrubs, bush lands and riverine trees are merged.	Gidey *et al.*, 2017

				and floodplain area (88)		
Gelana sub-watershed, Northern highlands of Ethiopia	1365 - 3328	Aerial photo (1964 and 1986) and OLI (2014)	DEM and Field survey	Forest (85.5), shrub land (81.5), cultivated and rural settlement land (80.8), grass land (84.8), bare land (86.7), urban built up (92.9), wetland (92)	Cultivated and rural settlement is merged. On-screen digitizing is was to detect LU/LC from aerial photo's	Miheretu and Yimer, 2017
Yezat Watershed, North Western Ethiopia	1485 – 3207	TM (2001), ETM (2010), and OLI (2015)	DEM, topographic map, NDVI and field survey	Crop land, grassland, woodland, shrub/bush land, and homesteads. Overall accuracy = 93.2.	---------------------	Tadesse *et al.,* 2017
Keleta watershed, Awash River basin, Ethiopia	1583 – 4199	TM (1985, 1998 and 2011)	topographic map, field survey	Degraded land (81.3), farm and settlement (85.7), forest (92.2), grasslands (84.8), shrubs (93.4)and water (92.9)	Merging of annuals and perennials crop lands and scattered rural settlements	Bekele *et al.,* 2018
Chilimo forest, Central Highlands of Ethiopia	2170 – 3054	MSS (1973), TM (1984 and 98), ETM+ (2008) and OLI (2015)	Field survey for 2015 map	Shrub land (80), Rural settlements (40), Bare land (80), Forest land (95.89) and Agricultural land (86.49)	Broader LU/LC categories were privileged the result	Siraj *et al*., 2018
North-eastern Addis Ababa, central highlands of Ethiopia.	2244 – 3240	Aerial photographs (1957), MSS (1975), TM (1995) and Sentinel-2 (2017)	DEM, topographic map, Google Earth, and Field survey	Water body (100), Agricultural land (98.3), Settlement (98.3), Forest (98.3), and Bare land (96.7)	Agricultural and grazing lands are together. To tackle LU/LC confusions:**	Deribew and Dalacho, 2019*

Note: most aerial photographs used as a time series data was interpreted using on-screen-digitizing technique. OLI = Operational Land Imager; DEM = Digital Elevation Model; NDVI = Normalized Difference Vegetation Index; *refers studies used Object Based Classification (OBC) through image segmentation which is considered as supervised classification by Abburu and Golla (2015). **effected indexes like bare-area index, built-up-area index, normalized vegetation index, and masking out settlements and agricultural lands were employed to refine confusions on supervised approach.

Most of the studies in the above Table (3) were limited in detecting rural residents from cultivated lands. Unlikely, cropland with grazing land (Fenta *et al*., 2017) and coffee with Enset and large indigenous trees and perennial fruit trees were not separated (Fentahun and Gashaw, 2014; Bekele *et al.,* 2018). Majority of the studies have used broader LU/LC categories which are assumed to be caused by the coarse image resolutions and confusion of reflectance. Indeed, object-based classification techniques revealed a positive return in detecting detail LU/LC categories in Arsi-Negele and north-eastern Addis Ababa areas (Figure 2) (Kindu *et al*., 2013; Deribew and Dalacho, 2019).

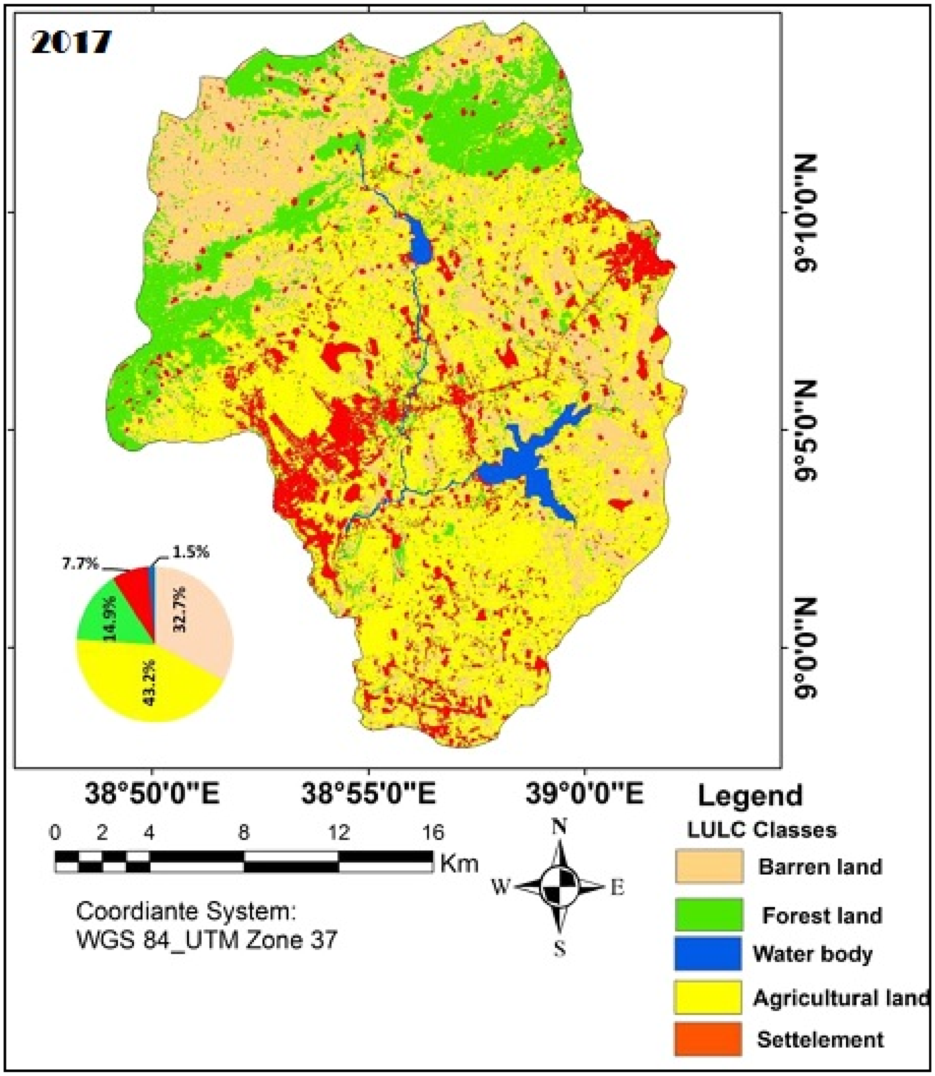

Figure 2. LU/LC map of North-eastern Addis Ababa for 2017 (Deribew and Dalacho, 2019)

3.3. Visual image interpretation

Table 4. Summary of visual image classification techniques used in Ethiopia

Study area	Altitude range (m.a.s.l.)	Image/data used	Ancillary data/s and source	LU/LC and producer accuracy for the latest year (%)	Challenges	Source
Ghibe valley, Southwestern Ethiopia	1400 - 1800	Aerial photographs (1957 and 1973), TM (1987 and 1993)	Topographic map, field survey, and elders interview	Smallholder cultivation, large holder cultivation, riverine forest, wooded grassland. No accuracy report	Larger LU/LC category leads absence of information for the smaller LU/LC classes.	Reid *et al.*,2000 Stereoscope + on-screen-digitizing
Dembecha area, Northwestern highlands of Ethiopia	1800 - 2800	Aerial photo (1957 and 1982), satellite image (1995)	Topographic map and field survey	Cultivated land, Natural forest, Plantations, Grassland, Temporary grassland, Bush land, Shrub land, Bare land, Grass- and bush land, Grass-, bush land and bare land, Small towns. No accuracy report	Cultivated land mixed with bushes and trees, and rural homesteads are categorized under Cultivated land	Zeleke and Hurni, 2001 on-screen-digitizing
Chemoga Watershed, Blue Nile Basin, Ethiopia	2420 - 4000	Panchromatic aerial photographs (1957 and 1982), SPOT (1998)	Topographic map, field survey, and discussion	Forest, woodlands, shrub lands, farmland and settlements, grassland and degraded land, Riverine trees, marshland, and pond. No accuracy report.	Dispersed rural settlements and cultivated land was not separated.	Bewket, 2002 on-screen-digitizing
Derekolli Catchment, South Wello Zone, Ethiopia	1600 - 1800	Aerial photographs (1957 and 1986), TM (2000)	Topographic map, field survey, and discussion	Shrub land, shrub-grassland, grassland, valley-rim vegetation, cropland, all-weather road, dry-weather road, and town. No accuracy.	Dispersed rural settlements were not detected.	Tegene, 2002 on-screen-digitizing
Begasheka Watershed, Tigray, Ethiopia	1739 - 1862	Field resource sketch – digitized into map – validated at field – corrected, accepted and analyzed.		Arable land, Forest land, and Grazing land.	It was based on local community knowledge about the area.	
Eastern Tigray, Ethiopia	2040 - 2840	Aerial photographs (1965 and 1994), TM (2000/5)	Topographic map, DEM, NDVI, field survey, and group discussions	Intensively cultivated land, Moderately cultivated land, Sparsely cultivated, Dense forest, and other 13 classes. No accuracy report.	Large number of LU/LC types supported by intensive ground survey was used to reduce confusions.	Alemayehu *et al.*, 2009 stereoscope + on-screen-digitizing
Central Rift Valley	Below 1800	MSS (1973), TM (1986), ETM+ (2000)	Topo. map, field survey	Cropland, cropland with trees, perennial crop, grassland, wet-	Annual rain-fed crop lands with sparsely	Garedew *et al.*, 2009

of Ethiopia				grassland, wooded-grassland, woodland, shrub land, and bare land.	stocked trees are merged together with settlements areas.	on-screen-digitizing
Northern Ethiopia	2146 - 2218	Aerial photograph (1964 and 1994), and field survey (2006)	Topographic map, field survey, and elder's interview	Forest land, cultivated land, plantation, area exclosure, woodland, shrub land, grazing land, water body, settlement.	----------------------	Gebresamuel *et al.*, 2010 On-screen-digitizing
Debre-Mewi watershed, Blue Nile Basin, Northwest Ethiopia	2200 - 2360	Panchromatic aerial photographs (1957 and 1982), TM (2008)	Topographic map, field survey, and focus group discussion	Natural forest, Shrub and bush land, Grazing land, Cultivated and settlement land, Eucalyptus plantation, and Rock outcrop. No accuracy report.	Map was generated based on field information and again validated with the local informant's	Fisseha *et al.*, 2011 stereoscope + on-screen-digitizing
Mandura district, Northwestern Ethiopia	1015 - 1480	Aerial photographs (1957 and 1982), and SPOT-5 (2006/07)	Topographic map, field survey, interview, and focus group discussion	Forests, woodlands, shrub lands, grassland with scattered trees, bare land, riverine trees, farmland, and settlement	Rural homesteads were included under farm land	Emiru and Taye, 2012 on-screen-digitizing
Bahir Dar, Ethiopia	average = 1801	Aerial photographs (1957, 1984and 1994)	Field survey and mapping	Built-up area, forest land, water bodies, agricultural land. No accuracy report. Overall accuracy = 87	----------------------	Haregeweyn *et al.*, 2012
Tigray province, northern Ethiopia	500 - 4000	Aerial photographs (1965 and 1994), and IKONOS and Quickbird (2007)	Field survey, interview, and group discussion	Arable land, Bare land, grass land, built-up area, shrub land, bush land, forest land, and water body. No accuracy report.	----------------------	Teka *et al.*, 2013 on-screen-digitizing
Eastern highland of Ethiopia	1980 - 2343	TM (1985, 1995, 2006, and 2011)	Topographic map, aerial photos, and field survey	Grassland (85), degraded land (86), marsh area (75), perennial cropland (93), plantation (89), residential (89), shrub land (85), water bodies (-), woodland (83), and temporal cropland (89)	Time taking, tedious, and vulnerable to errors.	Meshesha *et al.*, 2014 On-screen-digitizing
Eastern Tigray, Ethiopia	2300 - 3000	Aerial photographs (1965 and 1994),	Field survey and informant's	Arable land, bare land, grass land, built-up area, shrub land, bush land,	----------------------	Belay *et al.*, 2014 On-screen-

		IKONOS (2007)	interview	forest land, and water body. No class accuracy report.		digitizing
Hirmi watershed, Northern Ethiopia	1800 - 2500	Aerial photographs of 1964 and 1994, and SPOT-5 (2006)	Topographic map, key informant's interview, and group discussion	Forest, grassland, cultivated and rural settlement, town, shrub land and an artificial pond. No class accuracy report.	Rural settlement and cultivated land cover units were also grouped under the same category	Gebrelibanos and Assen, 2015 stereoscope + on-screen-digitizing
Amhara Region, Ethiopia	-------------	SPOT-5 image	Field survey, key informant's interview, and discussion	Forest types of the region: Woodlands, natural dense forest, plantation, open woodland, riverine forest	Time taking, needs experts' agreements. Intensive field work done to reduce errors.	Mekonnen *et al.*, 2016 on-screen-digitizing

Majority of studies that used visual image interpretation technique argued for the accuracy of the automatic image classification approach. For instance, Meshesha *et al*. (2014) has first employed automatic one and observed a significant level of errors occurred due to landscape heterogeneity then visual image interpretation was used to generate the LU/LC maps (Fihure 3). However, despite the higher accuracy level and simple software requirements of visual image interpretation, it needs large number of trained manpower, higher cost, exhaustive time, and fine resolution data for larger and heterogeneous areas (Büttner, 2014; Zhang *et al.,* 2014; Mekonnen *et al*., 2016; Sahle*et al*., 2016; Betru *et al*., 2019).

Almost all of the above studies have agreed on the performance of manual (on-screen-digitizing) method. In-depth, this approach is robust, effective and efficient methods. Efficiency and accuracy of this approach is depending on analyst knowledge and familiarity towards the field of study. The analyst needs to know aspects of the study area in addition to the spectral response of the image. Even though there were purposive class-categories are applied, the researcher's need to have appropriate support data and skill for accurate and reliable resource mapping (Meshesha *et al*., 2014; Mekonnen *et al*., 2016).

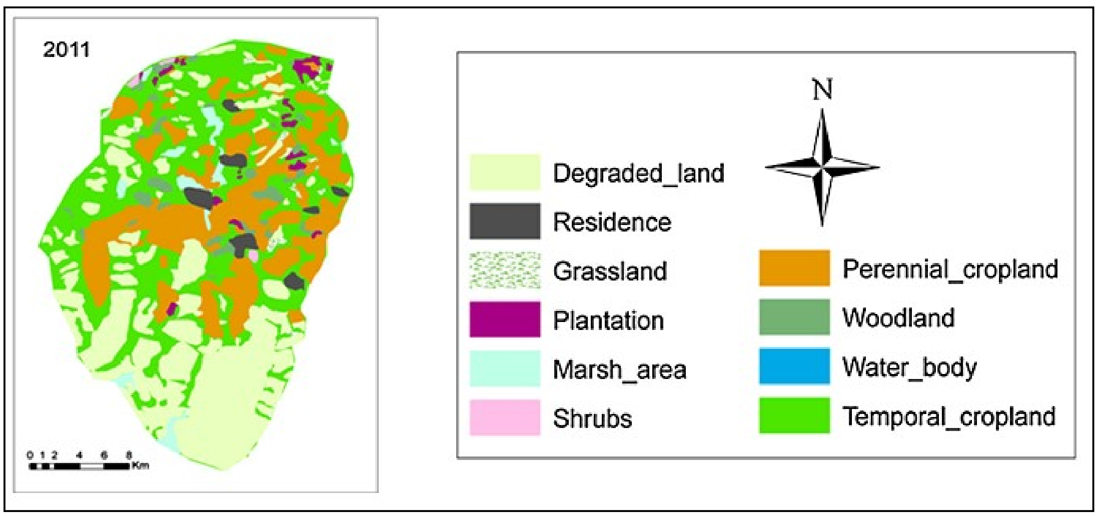

Figure 3. LU/LC map of eastern highland Ethiopia (Meshesha et al., 2014)

3.4. Hybrid image classification

Table 5. Summary of hybrid image classification techniques used in Ethiopia

Study area	Altitude range (m.a.s.l.)	Image/data used	Ancillary data/s and source	LU/LC and producer accuracy for the latest year (%)	Challenges/ corrections made	Source
Jedeb watershed, Upper Blue Nile, Ethiopia	2172 – 4001	Aerial photograph and MSS (1972), TM (1986 and 1994). TM and ASTER (2009)	Aerial photograph, SPOT image, and field survey	Grassland (97), afro alpine grassland (94), cultivated land (99), shrubs and bushes (86), woodland (80), plantation forest (88), ericaceous forest (75), marshland (97), and barren land (89).	Urban and marshlands land was digitized and masked out from the image to tackle signature confusion among marshland and grassland, urban land and barren land and cultivated land.	Teferi *et al*., 2013 *unsupervised± supervised*
East of Lake Tana, Ethiopia	1779 – 1846	TM (1985) and ETM+ (2011)	Topographical map, field observation, group discussion	Cultivated land, forest land, shrub land, grass land, water body and degraded land. No class accuracy. Overall accuracy = 80	Cultivated land mixed with some bushes, trees and the scattered rural settlements included within the cultivated fields.	Gashaw and Fentahun, 2014 *unsupervised± supervised*
Dera District, Ethiopia	1798 – 2118	TM (1985)and ETM+ (2011)	Field observations, NDVI, Toposheet	Forest land, shrub land, grass land, cultivated land, degraded land and water body. No class accuracy. Overall accuracy = 84	Cultivated land mixed with some bushes, trees and the scattered rural settlements included within the cultivated fields.	Gashaw *et al*., 2014 *unsupervised± supervised*
Lake Hawassa Watershed, Ethiopia	1571 - 2962	MSS (1973), TM+SPOT (1985), and TM (1995 and 2011)	Aerial photographs, and topographical maps, SPOT image, and field survey	Water (94.3), built-up (84.1), cropland (84.3), woody vegetation (81.4), forest (87.1), grassland (75), swamp (88.9), bare land (87.5), and scrub (86.8)	Scattered trees, Khat and Coffee are merged under woody vegetation. Images was segmented and clustered to identify the range of training areas for supervised classification.	Wondrade *et al*., 2014 *unsupervised (Segmentation) ± supervised*
North Western Lowlands, Ethiopia	500 - 1849	TM (1985, 1995, and 2010)	Topographic map, Google Earth, and Field survey	Wood land (86.5), shrub/bush land (85.3), Grass land (81.86), Agricultural land (90.45), Bare land and settlement (84.08), water body (100).	Patches of trees are compiled in to two categories (grass lands and shrub/bush land. Bare land and settlement were not separated.	Alemu *et al*., 2015 *unsupervised± supervised*

Infraz watershed, NW Ethiopia	1777 – 2110	MSS (1973), and TM (1986, 1995 and 2011)	Field survey, topographic map, SPOT image and Google Earth	Forest, agriculture and settlement areas, bush lands, grass lands and wetlands. No class accuracy. Kappa Statistics = 0.86	Agriculture and settlements were merged and swamps, ponds, riparian vegetation and marsh areas were also merged.	Sewnet, 2015 *Unsupervised ± supervised*
Batena watershed, Rift Valley Lakes, Southwestern Ethiopia	2063 – 2947	MSS (1973), TM (1984), ETM (1995), ETM (2003), and ETM (2008). *TM and ETM was pan-sharpened*	NDVI and field survey	Agricultural land, grazing land, scrub lands, mixed forest, and water body. No class accuracy. Overall all accuracy = 76% and Kappa statistics = 0.67	Scattered rural settlement were included under agricultural land.	Ayele *et al*., 2016 NDVI± unsupervised ± supervised
South Central Ethiopia	1600 - 3100	MSS (1972), TM (1984 and 1994), ETM+ (1999 and 2013), OLI (2013)	Aerial photo. And topo. maps, DEM, Landsat image composites, Google Earth, and field observation / group discussions	Agriculture (0.8), irrigation (1), greenhouse (1), grassland (0.55), forest / woodland (1), trees outside forest (0.89) lake / reservoir (1), swamp (1), bare land (1), and built-up (0.79).	Rule based corrections were made to refine classification errors by merging the outputs of the visual and supervised method.	Sahle *et al*., 2016 *Supervised + Visual (on-screen-digitizing)*
Tekeze-Atbara Basin, Ethiopia	930 - 3300	MSS (1972), TM (1989), ETM+ (2001), and OLI (2014)	Aerial photo, topographic map, Existing LU/LC map, DEM, field survey, and elder's interview	Grassland, agriculture, bushes and shrubs, wooded bushes, settlement, water body, bare land, forest land, and plantation forest. The overall accuracy = 84.3 and Kappa coeff. = 81.1%	ISODATA algorithm and several GTP has enabled detail LU/LC detection	Gebremicael *et al*., 2018 *Unsupervised ± supervised*
Borana rangelands, Southern Ethiopia	1000 – 1600	MSS (1973), TM (1986) and ETM+ (2003)	NDVI and field survey	Woodland, grassland, bare land, cultivated/built-up area. No class accuracy. Overall = 69.5	Crop lands and settlements areas were not separated.	Teka *et al*., 2018 *Unsupervised ± supervised*
Assosa Zone, Western Ethiopia	613-1641	MSS (1978), TM (1986, 1991 and 2010), ETM+ (1999) and OLI (2013 and 2016)	Field survey, key informant interview, focus group discussion, DEM, Google earth/ Engine, Landsat image composite	Forest (96.7), Agriculture (96.0), Shrub/grass (84.3), and Settlement (94.9). Over all = 93.57	Wrong classification (caused by spectral confusion) outputs in the supervised techniques was refined based on visually interpreted map.	Betru *et al*., 2019 *Supervised + Visual (on-screen digitizing)*

Note: Most aerial photographs used as a time series data was interpreted using on-screen-digitizing technique.
The hybrid forms successive (±), merged (+) were considered the way how the classification techniques used for final LU/LC map

As stated in the above Table (5), except Sahle *et al*. (2016) and Betru *et al*. (2019), all of the studies used the successive operation of unsupervised and supervised classifications. The combination of automatic techniques has a great role in detecting the spectral responses of features but commonly vulnerable to errors and limited where spectral confusions exist. The researchers' suggested that, in order to reduce classification errors, it is better to use a combinations approach than a reliance on a single technique. Unlikely, Sahle *et al*. (2016) and Betru *et al*. (2019) pointed out limitation on the automatic techniques. Instead, these studies recommended combining the digital system with the manual approach through merging technique to refine classification confusions and generate reliable LU/LC information.

4. Progress and Challenges in LU/LC Detection Methods

The growing necessity of land cover changes for a wide range of applications makes the global environmental changes assessment to rely on remote sensing data. These phenomena engaged many scholars in developing from simple to complex satellite image classification methods.

In the past two decades, from the earliest stereoscope and/or on-screen-digitizing (Reid *et al*., 2000) to the recently emerged hybrid of automatic and manual (Teferi *et al*., 2013; Sahle *et al*., 2016) as well as object-based classification (OBC) (Kindu *et al*., 2013) technique were executed and found to be a pioneers in Ethiopia. However, the majority of the studies were relied on supervised classification preceded to the visual interpretation which show change in LU/LC types in the country.

Indeed, visual interpretation has remained an exceptional technique for aerial photographs. Later, it is widely adopted for satellite imageries with the need of medium to high-resolution data. Nowadays, it is used independently (Mekonnen *et al*., 2016) also involved in the hybrid and OBC approaches (Betru *et al*., 2019; Deribew and Dalacho, 2019). In overall, the progress on information detection showed a great improvement in detail of resource assessment and reducing labor consumption through digital procedures. On the other hand, there is an increasing doubt on the efficiency of the techniques on different landscape conditions.

The first and the prominent challenge observed was the data quality (spatial-resolution) to magnify the spatial variability of the landscape features. In this regard, among the 50 reviewed studies, the majority has used medium resolution images from open-sourced Landsat generations.

However, some studies those effected manual technique has privileged the classification detail using high-resolution images from other sensors (Mulugeta and Weldesemait, 2011; Teka *et al*., 2013; Belay *et al*., 2014; Fentahun and Gashaw, 2014; Gebrelibanos and Assen, 2015; Mekonnen *et al*., 2016; Deribew and Dalacho, 2019). However, the central concern is the efficiency of the aforementioned techniques under similar data characteristics whereas in diverse landscape patterns.

Due to the spectral confusion between the reflectance of different land surface features, the supervised and unsupervised methods are in a doubt by their inefficiency to separate diverse composites of land surface features when applied separately (Wondrade *et al*., 2014). However, with exhaustive ancillary and reference data, supervised technique revealed promising results around south Gondar (Demissie *et al*., 2017). In meanwhile, to overcome the inherent limitation, the combination of them (hybrid) was employed from low-to-highland areas of the country (Teferi *et al*., 2013; Teka *et al*., 2018). This approach achieved better accuracy than using them alone. As far as the reflectance values are in focus, still misclassification of some land covers those have similar spectral reflectance was observed as a challenge.

In addition, visual interpretation (on-screen-digitizing) was also revealed as a better technique for heterogeneous land surface features through medium to high resolution satellite imagery. Nevertheless, it needs a large number of trained manpower, higher cost, and exhaustive time (Meshesha *et al*., 2014; Mekonnen *et al*., 2016). Complete execution of on-screen-digitizing losses the digital response values of surface features. As indicated in Sahle *et al*. (2016) and Betru *et al*. (2019), the combination of automatic techniques with manual mapping were another option to detect the spectral responses and the real outlook of surface features. Both of these studies recommended this approach to refine classification errors and generate reliable LU/LC information's.

The accuracy of LU/LC map largely depends on image classification methods and reference data is used. Most studies recommended that reference data be like an aerial photograph, topographic map, and other soft information are required in accordance with the characteristics of the landscape. To support the LU/LC mapping, Sydenstricker-Neto *et al*. (2004); Sahle *et al*. (2016) and Betru *et al*. (2019) acknowledged collection of reference points using participatory approach integrated with composite satellite imagery in the absence of historical aerial photographs.

5. Implications of LU/LC Detection Methods

Information is a primary impute to identify existing problems and its prioritization to set appropriate interventions. In Ethiopia, almost all of the existing LU/LC assessment methods are applied to extract information from remote sensing data by different researcher and organizations. Despite the reliability of the output, the absence of an up-to-date national database caused for routine and disintegrated investment for different purposes at different time.

For instance Woody Biomass Inventory and Strategic Planning Project (WBISPP, 2004); Ethiopia's forest reference level submission to the UNFCCC published by Ministry of Environment, Forest, and Climate Change (MoEFCC, 2016); and a report on causes of deforestation and forest degradation in Ethiopia (MoEF, 2015a) are the main countrywide projects engaged in forest and related resource assessments. A successive hybrid of unsupervised and visual interpretation, unsupervised classification, and supervised classification are the different techniques used by the projects, respectively. Similar to LU/LC map of Europe (Büttner, 2014) and China (Zhang *et al*., 2014), forest resource map of Amhara regional state of Ethiopia was quantified using only visual image interpretation with maximum accuracy (Mekonnen *et al*., 2016). Those projects were aimed to enrich the spatio-temporal resources database under a certain time for different purposes.

There are also numerous studies conducted and used LU/LC information as an input for further modeling purposes, for instance hydrological modeling (Gashaw *et al.,* 2018), soil erosion mapping (Gessesse *et al*., 2015), ecosystem service modeling (Tolessa *et al.,* 2017), wildlife and biodiversity monitoring (Mengesha *et al.,* 2014), climate change modeling (Reid et al., 2000), ecotourism potential area mapping (Nino *et al.,* 2017), its impact on forest resources and soil quality (Bessie *et al*., 2016; Teferi *et al*., 2016),watershed prioritization/land use planning, and etc. Those studies employed the most common types of image classification approaches.

Zhang *et al.* (2014) of China and Meshesha *et al*. (2014) of Eastern Ethiopia confirmed the validation of automatic classification methods which provide satisfactory results at smooth landscape patterns. Therefore, the independent application of digital classification methods makes difficult land cover identification in areas where larger biophysical heterogeneity and inconsistent variability of land cover patterns exists like in Ethiopia. Its accuracy may depend on the extent of fieldwork done and ancillary data's used. In order to generate reliable information, a consensus should be made on the mapping technique which aimed to set a landscape based methodologies.

According to the review of REDD+ report, the status of forest resource of Ethiopia is narrated at different periods in 1900 (40%), 1954 (16%), 1961 (8%), 1975 (4%), 1980 (3.6%), 1998 (2.7%), and 2015 (15%) (MoEF, 2015b). Forest cover increment in 2015 was due to the addition of dense woodlands, bamboo forest, natural and plantation forest as "Forest" cover. But according to the 2015 estimate of Global Forest Resources Assessment, Ethiopia's forest resource was accounted as 11.4% of its total land mass (FAO, 2015). This variation in forest cover estimation is mainly reliant on the working definitions and methods of detecting forest cover. This problem has a larger influence on the resources utilization and conservation planning and carbon credits of the country. This was the rationale for revision of national forest definition. According to this estimate, 15.5% of Ethiopia's landmass was covered by forest (MoEFCC, 2016).

6. Conclusion

Ethiopia is diverse in vegetation types/species and land use system along with a range of altitudes and population distribution. In Ethiopia, many scholars, and governmental and non-governmental organizations have undertaken land resources assessment tasks. Historical and recent scenarios of LU/LC studies were done in almost all parts of the country. All of the studies revealed a continued change in all LU/LC types.

Due to the lack of commonly accepted LU/LC detection approaches and database, the progress of detection techniques were observed from simple to more detail approaches and their accuracy level. Nevertheless, most of the existing findings have a doubt in the reliability of achieved accuracy level. Almost all of the studies have some sort of challenges in detecting the existing land resource features.

The inclusion of exhaustive ancillary data's and ground information is a common element for image interpretation. Integration of one or more image classification techniques revealed a better accuracy and detail of information than independent application. To this end, object-based classification and a hybrid of on-screen-digitizing and automated techniques are the recent and most promising approaches to handle spectral confusions and incorporate reflectance values with actual field outlooks (visual elements). Afterward, site-specific methodologies are prominently required to avoid over-/under-estimation and extract reliable land resources information.

Therefore, providing information on LU/LCC is vital to monitor resources over time. Gathering such information could be an input for further studies and contribute to policymakers with insights to make an informed decision over land use planning and enhancing farmer's livelihoods through proper support.

There should be an up-to-date national database which can organize and publicize available studies that have better level of methodological acceptance and reliable results. The national database is also expected to coin fragmented studies, undertake, and report timely resource assessment activities. This will help to reduce the cost and recourse of studies done by different scholars, for different purposes at different parts of Ethiopia. On the other hand, in-depth comparison of LU/LC detection techniques under different landscapes of the country will signify efficient site specific methodology. Therefore, to fill the gap, in-situ image processing is recommended for further investigation.

References

Abburu, S. and Golla, S.B. (2015). Satellite image classification methods and techniques: A review. *International journal of computer applications*. 119(8): 20-25.

Alemayehu, F., Taha, N., Nyssen, J., Girma, A., Zenebe, A., Behailu, M. and Poesen, J. (2009). The impacts of watershed management on land use and land cover dynamics in Eastern Tigray (Ethiopia). *Resources, Conservation and Recycling*. 53(4): 192-198.

Alemu, B., Garedew, E., Eshetu, Z. and Kassa, H. (2015). Land use and land cover changes and associated driving forces in north western lowlands of Ethiopia. *Int. Res. J. Agric. Sci. Soil Sci*. 5(1): 28-44.

Ariti, A.T., Vliet, J.V. and Verburg, P.H. (2015). Land-use and land-cover changes in the Central Rift Valley of Ethiopia: Assessment of perception and adaptation of stakeholders. *Applied Geography*. 65: 28-37.

Asmamaw, L.B., Mohammed, A.A. and Lulseged, T.D. (2011). Land use/cover dynamics and their effects in the Gerado catchment, northeastern Ethiopia, *International Journal of Environmental Studies*. 68(6): 883-900.

Ayele, G. T., Demessie, S. S., Mengistu, K. T., Tilahun, S. A., and Melesse, A. M. (2016). Multi temporal land use/land cover change detection for the Batena Watershed, Rift Valley Lakes Basin, Ethiopia. In A.M., Melesse, and W., Abtew (Ed), *Landscape Dynamics, Soils and Hydrological Processes in Varied Climates*, (pp. 51-72).Springer International Publishing, Switzerland.

Aynekulu, E., Wubneh, W., Birhane, E., and Begashaw, N. (2006). Monitoring and evaluating land use/land cover change using Participatory Geographic Information System (PGIS) tools: A case study of Begasheka Watershed, Tigray, Ethiopia. *The Electronic Journal of Information Systems in Developing Countries*. 25(1): 1-10.

Balamurugan, G., and Jayarraman, K.B. (2016). Classification of Land Cover in Satellite Image using Supervised and Unsupervised Techniques. *International Journal of Computer Applications* (0975-8887).135(5): 15-18.

Bekele, D., Alamirew, T., Kebede, A., Zeleke G. and Melesse, A.M. (2018). Land use and land cover dynamics in the Keleta watershed, Awash River basin, Ethiopia. *Environmental Hazards.* DOI: 10.1080/17477891.2018.1561407

Belay, K.T., Van Rompaey, A., Poesen, J., Van Bruyssel, S., Deckers, J. and Amare, K. (2014). Spatial analysis of land cover changes in eastern Tigray (Ethiopia) from 1965 to 2007: are there signs of a forest transition? *Land Degradation and Development.* DOI: 10.1002/ldr.2275

Bessie, S., Beyene, F., Hundie, B., Goshu, D., and Mulatu, Y. (2016). Land use/land cover change and its effects on bamboo forest in Benishangul-Gumuz region, Ethiopia. *International Journal of Sustainable Development and World Policy*. 5(1): 1–11.

Betru, T., Tolera, M., Sahle, K., and Kassa, H., 2019. Trends and drivers of land use/land cover change in Western Ethiopia. *Applied Geography*.104: 83-93.

Bewket, W. (2002). Land cover dynamics since the 1950s in Chemoga watershed, Blue Nile basin, Ethiopia. *Mountain Research and Development*. 22(3): 263-269.

Bewket, W., and Abebe, S. (2013) Land-use and land-cover change and its environmental implications in a tropical highland watershed, Ethiopia, *International Journal of Environmental Studies*. 70(1): 126-139.

Burka, A. (2008). *Land Use /Land Cover Dynamics in Prosopis juliflora invaded area of Metehara and the Surrounding Districts Using Remote Sensing and GIS Techniques (M.Sc. thesis).* Addis Ababa University, Ethiopia.

Büttner, G. (2014). CORINE land cover and land cover change products. In I., Manakos, and M. Braun (Ed). *Land Use and Land Cover Mapping in Europe: Practices and Trends* (55-74). Springer International Publishing, Switzerland.

Deribew, K.T. and Dalacho, D.W. (2019). Land use and forest cover dynamics in the North-eastern Addis Ababa, central highlands of Ethiopia. *Environmental Systems Research.* 8(8): 2-18.

Demissie, F., Yeshitila, K., Kindu, M., Schneider, T. (2017). Land use/Land cover changes and their causes in Libokemkem District of South Gondar, Ethiopia. *Remote Sensing Applications: Society and Environment*. 8: 224-230

Emiru, T.S., and Taye, A. (2012). Land use/cover dynamics in lowland Ethiopia since 1957: the case of Mandura district, Benshangul-Gumuz Regional State. *Journal of Biodiversity and Environmental Sciences*. 8: 36-49.

FAO (Food and Agriculture Organization) (2015). Global Forest Resources Assessment 2015. Food and Agriculture Organization of the United Nations. Rome, Italy.

Fenta, A., Yasuda, H., Haregeweyn, N., Belay, A.S., Hadush, Z., Gebremedhin, M.A., and Mekonnen, G. (2017). The dynamics of urban expansion and land use/land cover changes using remote sensing and spatial metrics: the case of Mekelle City of northern Ethiopia. *International Journal of Remote Sensing*. 38(14): 4107-4129.

Fentahun, T., and Gashaw, T. (2014). Evaluation of land use/land cover changes of Bantneka Watershed, Ethiopia. *Civil and Environmental Research*. 6(7): 90-93.

Fetene, A., Hilker, T., Yeshitela, K., Prasse, R., Cohen, W. and Yang, Z. (2015). Detecting Trends in Land use and Land cover Change of Nech Sar National Park, Ethiopia. *Environmental Management*. DOI 10.1007/s00267-015-0603-0.

Fisseha, G., Gebrekidan, H., Kibret, K., Yitaferu, B. and Bedadi, B. (2011). Analysis of land use/land cover changes in the Debre-Mewi watershed at the upper catchment of the Blue Nile Basin, North West Ethiopia. J. Biodivers. *Environ. Sci.* 1(6): 184-198.

Garedew, E., Sandewall, M., Söderberg, U. and Campbell, B.M. (2009). Land-use and land-cover dynamics in the central rift valley of Ethiopia. *Environmental management*. 44(4): 683-694.

Gashaw, T. and Fentahun, T. (2014). Evaluation of land use/land cover changes in east of Lake Tana, Ethiopia. *Journal of Environment and Earth Science.* 4(11): 49-53.

Gashaw, T., Bantider, A. and Mahari, A. (2014). Evaluations of land use/land cover changes and land degradation in Dera District, Ethiopia: GIS and remote sensing based analysis. *International Journal of Scientific Research in Environmental Sciences*. 2(6):199-207.

Gashaw, T., Tulu T., Argaw, M., and Worqlul, A.W. (2018). Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. *Science of the Total Environment*. 619-620: 1394-1408.

Gebrelibanos, T. and Assen, M. (2015). Land use/land cover dynamics and their driving forces in the Hirmi watershed and its adjacent agro-ecosystem, highlands of Northern Ethiopia. *Journal of Land Use Science.* 10(1): 81-94.

Gebremicael, T.G., Mohamed, Y.A., Van der Zaag, P. and Hagos, E.Y. (2018). Quantifying longitudinal land use change from land degradation to rehabilitation in the headwaters of Tekeze-Atbara Basin, Ethiopia. *Science of the Total Environment*. 622:1581-1589.

Gebresamuel, G., Singh, B.R. and Dick, Ø. (2010). Land-use changes and their impacts on soil degradation and surface runoff of two catchments of Northern Ethiopia. *Acta Agriculturae Scandinavica Section B–Soil and Plant Science.* 60(3): 211-226.

Gessesse, B., Bewket, W. Bräuning, A. (2015). Model-Based Characterization and Monitoring Of Runoff and Soil Erosion in Response to Land Use/Land Cover Changes in the Modjo Watershed, Ethiopia. *Land Degrad. Develop.* 26: 711–724.

Gibbs, H.K. and Salmon, J.M. (2015). Mapping the world's degraded lands. *Applied Geography*. 57: 12-21.

Gidey, E., Dikinya, O., Sebego, R., Segosebe, E., Zenebe, A. (2017). Modeling the Spatio-temporal dynamics and evolution of land use and land cover (1984-2015) using remote sensing and GIS in Raya, Northern Ethiopia. *Model. Earth Syst. Environ.* DOI 10.1007/s40808-017-0375-z

Giri, C.P. (2012). Remote Sensing of Land Use and Land Cover: Principles and Applications. CRC Press.

Haile, G., Assen, M. and Ebro, A. (2010). Land use/Cover dynamics and its implications since the 1960s in the Borana rangelands of Southern Ethiopia. *Livestock Research for Rural Development*. 22(7). http://lrrd.cipav.org.co/lrrd22/7/hail22132.htm. Received: June 20, 2018.

Haregeweyn, N., Fikadu, G., Tsunekawa, A., Tsubo, M. and Meshesha, D.T. (2012). The dynamics of urban expansion and its impacts on land use/land cover change and small-scale farmers living near the urban fringe: A case study of Bahir Dar, Ethiopia. *Landscape and urban planning.* 106(2):149-157.

Herold, M., Mayaux, P., Woodcock, C. E., Baccini, A., and Schmullius, C. (2008). Some challenges in global land cover mapping: An assessment of agreement and accuracy in existing 1 km datasets. *Remote Sensing of Environment*. 112: 2538–2556.

Kindu, M., Schneider, T., Teketay, D. and Knoke, T. (2013). Land use/land cover change analysis using object-based classification approach in Munessa-Shashemene landscape of the Ethiopian highlands. *Remote Sensing*. 5(5): 2411-2435.

Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., Folke, C., and George, P. (2001). The causes of land use and land-cover change: moving beyond the myths. *Global environmental change*. 11(4): 261 -269.

Mekonnen, M., Sewunet, T., Gebeyehu, M., Azene, B. and Melesse, A.M. (2016). GIS and remote sensing-based forest resource assessment, quantification, and mapping in Amhara Region, Ethiopia. In A.M. Melesse, and W. Abtew (Ed): *Landscape Dynamics, Soils and Hydrological Processes in Varied Climates* (Chapter 2, pp. 9-29). Springer International Publishing, Switzerland.

Mengesha, G., Mamo. Y., Sahle, K., Elphick, C., and Bekele, A. (2014). Effects of Land-use on Birds Diversity in and around Lake Zeway, Ethiopia. *Journal of Science and Development*. 2(2): 5-22.

Mengistu, D.A., Waktola, D.K. and Woldetsadik, M. (2012) Detection and analysis of land-use and land-cover changes in the Midwest escarpment of the Ethiopian Rift Valley. *Journal of Land Use Science.* 7(3): 239-260.

Meshesha, D.T., Tsunekawa, A., Tsubo, M., Ali, S.A. and Haregeweyn, N. (2014). Land-use change and its socio-environmental impact in Eastern Ethiopia's highland. *Regional environmental change*. 14(2): 757-768.

Miheretu, B.A. and Yimer, A.A. (2017). Land use/land cover changes and their environmental implications in the Gelana sub-watershed of Northern highlands of Ethiopia. *Environmental Systems Research*. 6(7). DOI 10.1186/s40068-017-0084-7

MoEF (Ministry of Environment and Forest) (2015a). Study of causes of deforestation and forest degradation in Ethiopia and the identification and prioritization of strategic options to address those. Mid-Term Report, REDD+ Secretariat, Addis Ababa, Ethiopia.

MoEF (Ministry of Environment and Forest) (2015b). Strategic Environmental and Social Assessment (SESA) For the Implementation of REDD+ in Ethiopia including Oromia Forested

Landscape Program (OFLP) Social Assessment (SA). REDD+ Secretariat and Oromia REDD+ Coordination Unit. Addis Ababa, Ethiopia.

MoEFCC (Ministry of Environment, Forest and Climate Change) (2016). Ethiopia's forest reference level submission to the UNFCCC. Addis Ababa, Ethiopia. redd.unfccc.int/files/ 2016_submission_frel_ethiopia.pdf Retrieved: May 20, 2018

Molla, E., Gebrekidan, H., Mamo, T. and Assen, M. (2010). Patterns of Land Use/Cover Dynamics in the Mountain Landscape of Tara Gedam and Adjacent Agro-Ecosystem, Northwest Ethiopia. *Ethiop. J. Sci*. 33(2): 75-88.

Mulugeta, M., and Weldesemait, B. (2011). The Impact of Resettlement Schemes on Land-Use/Land-Cover Changes in Ethiopia: A Case Study from Nonno Resettlement Sites, Central Ethiopia. *Journal of Sustainable Development in Africa*. 13 (2): 269-293.

Nino, K., Mamo, Y., Mengesha, G., Sahle, K.K. (2017). GIS based ecotourism potential assessment in Munessa Shashemene Concession Forest and its surrounding, Ethiopia. *Applied Geography*. 82: 48-58.

Reid R.S., Kruska, R.L., Muthui, N.M., Taye, A., Wotton, S., Wilson, C.J., and Mulatu, W. (2000). Land-use and land-cover dynamics in response to changes in climatic, biological and socio-political forces: the case of southwestern Ethiopia. *Landscape Ecology*.15: 339–355.

Sahle, K., Marohn, C., and Cadisch, G. (2016). Assessment of land use and land cover change in South Central Ethiopia during four decades based on integrated analysis of multi temporal images and geospatial vector data. *Remote Sensing Applications: Society and Environment*. 3: 1-19.

Sewnet, A. (2015). Land use/cover change at Infraz watershed by using GIS and remote sensing techniques, north-western Ethiopia. *International Journal of River Basin Management*. 1-10. DOI: 10.1080/15715124.2015.1095199.

Shiferaw, A., and Singh, K.L. (2011). Evaluating the Land Use and Land Cover Dynamics in Borena Woreda South Wollo Highlands, Ethiopia. *EJBE*. 2(1): 69-104.

Siraj, M., Zhang, K. and Moges, K. (2018). Retrospective Analysis of Land Use Land Cover Dynamics Using GIS and Remote sensing in Central Highlands of Ethiopia. *Journal of Landscape Ecology*. 11(2): 31-52.

Sydenstricker-Neto, J., Parmenter, A.W., and DeGloris S.D. (2004). Participatory Reference Data Collection Methods for Accuracy Assessment of Land-Cover Change Maps. In R.S. Lunetta and J.G. Lyon (Ed), *Remote sensing and GIS accuracy assessment*, (Chapter 6, pp. 75-90). CRC press. US.

Tchuenté, K.T.K., Roujean, J. and De Jong, S.M. (2011). Comparison and relative quality assessment of the GLC2000, GLOBCOVER, MODIS and ECOCLIMAP land cover data sets at the African continental scale. *International Journal of Applied Earth Observation and Geoinformation*. 13: 207-219.

Tadesse, L., Suryabhagavan, K.V., Sridhar, G. and Legesse, G. (2017). Landuse and landcover changes and Soil erosion in Yezat Watershed, North Western Ethiopia. *International Soil and Water Conservation Research*. http://dx.doi.org/10.1016/j. iswcr.2017.05.004

Teferi, E., Bewket, W., Uhlenbrook, S. and Wenninger, J. (2013). Understanding recent land use and land cover dynamics in the source region of the Upper Blue Nile, Ethiopia: Spatially explicit statistical modeling of systematic transitions. *Agriculture, eco-systems and environment*. 165: 98-117.

Teferi, E., Bewket, W., and Simane, B. (2016). Effects of land use and land cover on selected soil quality indicators in the headwater area of the Blue Nile basin of Ethiopia. *Environmental Monitoring and Assessment*.188:83: 1-12. doi: 10.1007/s10661-015-5086-1

Tegene, B. (2002). Land-cover/land-use changes in the derekolli catchment of the South Wello Zone of Amhara Region, Ethiopia. *Eastern Africa Social Science Research Review*. 18(1): 1-20.

Teka, H., Madakadze, C.I., Botai, J.O., Hassen, A., Angassa, A. and Mesfin, Y. (2018). Evaluation of land use land cover changes using remote sensing Landsat images and pastoralists perceptions on range cover changes in Borana rangelands, Southern Ethiopia. *International Journal of Biodiversity and Conservation*. 10(1): 1-11.

Teka, K., Van Rompaey, A. and Poesen, J. (2013). Assessing the role of policies on land use change and agricultural development since

1960s in northern Ethiopia. *Land Use Policy*. 30(1): 944-951.

Teketay, D., Lemenih, M., Bekele, T., Yemshaw, Y., Feleke, S., Tadesse, W., Moges, Y., Hunde, T. and Nigussie, D. (2010). Forest Resources and Challenges of Sustainable Forest Management and Conservation in Ethiopia. In: F. Bongers and T. Tennigkeit (Ed). *Degraded forests in Eastern Africa: Management and Restoration* (pp. 19-64).

Tolessa, T., Senbeta, F., and Kidane, M. (2017). The impact of land use/land cover change on ecosystem services in the central highlands of Ethiopia. *Ecosystem Services*. 23: 47-54.

Tsegaye, D., Moe, S.R., Vedeld, P. and Aynekulu, E. (2010). Land-use/cover dynamics in Northern Afar rangelands, Ethiopia. *Agriculture, Ecosystems and Environment*. 139: 174-180.

WBISPP (Woody Biomass Inventory and Strategic Planning Project) (2004). WBISSP - PHASE 2: Terminal Report. Ministry of Agriculture, Addis Ababa, Ethiopia.

Weng, Q. (2010). Remote Sensing and GIS Integration: Theories, Methods, and Applications. McGraw-Hill Inc.

Wondie, M., Schneider, W., Melesse, A.M. and Teketay, D. (2011). Spatial and Temporal Land Cover Changes in the Simen Mountains National Park, a World Heritage Site in Northwestern Ethiopia. *Remote Sens*. 3: 752-766.

Wondrade, N., Dick, Ø.B. and Tveite, H. (2014). GIS based mapping of land cover changes utilizing multi-temporal remotely sensed image data in Lake Hawassa Watershed, Ethiopia. *Environmental monitoring and assessment.* 186(3): 1765-1780.

Worku, G., Bantider, A. and Temesgen, H. (2014). Land use and land cover change in Ameleke Watershed, South Ethiopia. *Journal of Natural Sciences Research*. 4(14): 42-47.

Yeshaneh, E., Wagner, W., Exner-Kittridge, M., Legesse, D., and Bloschl, G. (2013). Identifying Land Use/Cover Dynamics in the Koga Catchment, Ethiopia, from Multi-Scale Data, and Implications for Environmental Change. ISPRS *International Journal of Geo-Information*. 2: 302-323.

Zeleke, G. and Hurni, H. (2001). Implications of land use and land cover dynamics for mountain resource degradation in the Northwestern Ethiopian highlands. *Mountain research and development.* 21(2): 184-191.

Zhang, Z., Wang, X., Zhao, X., Liu, B., Yi L., Zuo, L., Wen, Q., Liu, F., Xu, J., and Hu, S. (2014). A 2010 update of National Land Use/Cover Database of China at 1:100000 scale using medium spatial resolution satellite images. *Remote Sensing of Environment*.149*:* 142-154.