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Land use land cover change detection using Remote sensing and GIS technique: A case study of Addis Ababa, Ethiopia

Reta Birhanu Endale [1], Seid Ali Mohammed[2]
[1]*Assosa University, College of Engineering, Department of surveying Engineering, Ethiopia*
[2]*Assosa University, College of Engineering, Department of surveying Engineering, Ethiopia*
Corresponding email: Retabirhanubr12@gmail.com

ABSTRACT

Land use and land cover change is a modification of the earth surface by humans, due to an interaction between natural and anthropogenic processes. Land use land cover change provides important input for making decision regarding environmental management and planning the future. The objective of this research is assess the LULC changes in a fast growing city Addis Ababa by using satellite image of the years 2000, 2010, and 2023 in the study area using remote sensing and GIS techniques. Satellite images of the year 2000, 2010, and 2023 were downloaded from the USGS Earth Explorer online portal (path: 168, row: 54). To do this change detection supervised classification method has been employed. Supervised classification is important for grouping the different class of LULC sensed from the satellite imageries. The Land use land cover change in the respective years were obtained as the difference of the values of different years of the same category while percentage change is obtained by dividing it with the total area and multiplying by hundred. This calculation gives information on the trend of transformation of land use land cover over the time. The result indicates that during 2000 to 2010, the areal coverage of vegetation, bare land, and Agriculture land were decreased by 175.4 ha, 13,174.7 and 1,776.7 ha, respectively. In addition to that, Built-up area and water body land use land cover are increased in area coverage by 13,613.8 ha and 1,512.9 ha, respectively. Preceding period (2000–2023) Built-up showed an area increment of 12,919.4 hectare and vegetation, bare land, water body and agriculture land showed a decrease in area of 3,519.7, 5,839.3 ha, 175.7ha, and 3,387.5 respectively.

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INTRODUCTION

Land use land cover changes are considered as the major cause of environmental transformations, impacting human livelihoods, ecosystems, and biodiversity. Understanding the patterns and causes of these changes is vital for sustainable land management, urban planning, and natural resource conservation (Turner et al. 1994). The conversion of forests to urban areas, the expansion of agricultural land, and changes in water bodies are just a few examples of how land cover evolves over time. These shifts are often influenced by factors such as population growth, economic development, climate change, and policy decisions (Lambin & Geist, 2006).

To monitor and analyze LULC dynamics, traditional ground-based surveys are often limited in terms of spatial coverage and time frequency. In contrast, RS and GIS techniques plays an important role for mapping and analyzing LULC changes at various scales, providing both temporal and spatial insights (Jensen, 2005). Remote sensing, with its ability to capture vast and diverse land surfaces through satellite images and aerial photograph, enables change detection over time with a high degree of accuracy (Coppin et al. 2004). GIS aids for processing, analysis, and visualization of spatial data, enhancing the understanding of spatial relationships and trends (Long et al. 2013).

Recent advancements in satellite technology, such as high-resolution imagery and improved data processing algorithms, have significantly increased the accuracy and efficiency of LULC change detection (Singh, 1989). Through techniques like supervised and unsupervised classification, change detection, and time series analysis, these methods allow for a detailed assessment of LULC dynamics over time (Xie et al. 2008). In addition to facilitating and monitoring at local and regional scales Integration of remote sensing and geographic information system (GIS) also contributes to global initiatives, such as sustainable development goals (SDGs), by providing reliable data for decision-making and policy formulation (United Nations, 2015).

Several methods have been developed for analyzing LULC changes using remote sensing and GIS. Image post-classification comparison, image differencing, and change vector analysis are common techniques for detecting LULC change (Cihlar et al. 2004). These techniques often rely on classification algorithms, such as supervised or unsupervised classification, to identify different land cover types in an image (Jensen, 2005).

OBJECTIVE

The main objective of this study is to explore LULC changes GIS and remote sensing in detecting, with a focus on methodologies, case studies, and future directions. Through the integration of these techniques, we seek to highlight the potential for more effective monitoring and management of land resources, contributing to better environmental stewardship and informed decision-making.

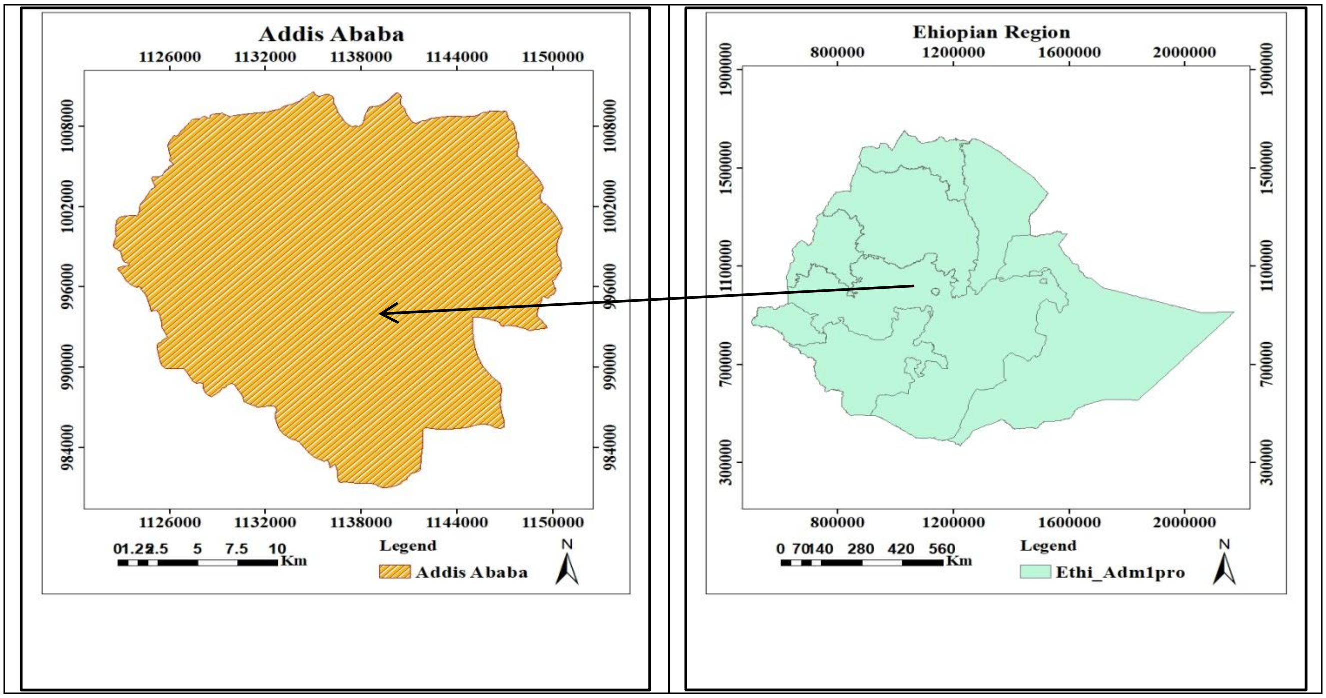
MATERIALS AND METHODS

Study Area

Addis Ababa is the capital city of Ethiopia with a geographic location of 485000m East and 1005000m North. The city is located in the central highlands of Ethiopia covering an area extent of about 527km^2 with an elevation of 2600m above sea level, which makes Addis Ababa the highest capital city in Africa. The administration of the city is divided in to ten sub-cities, namely, Bole, Yeka, Cherkos, Gullele, Kolfe Keraniyo, Arada, Lidata, Akaki-Kaliti, Nefas-Silk Lafto and Addis Ketema and 99 kebeles)

The city was federally-chartered city in accordance with Government Charter Proclamation No. 87/1997 in the Ethiopian Constitution Called the city as the political capital of Africa due to its historical, diplomatic, and political significance for the continent, Addis Ababa serves as the headquarters of major international organizations, such as the African Union and the United Nations Economic Commission for Africa.

The city located a few kilometres west of the East African Rift, which splits Ethiopia into two, between the Nubian Plate and the Somali plate. The city is surrounded by the Special Zone of Oromia, and is populated by people from different regions of Ethiopia. It is home to Addis Ababa University.



Methodology

The research employs Geographic Information Systems (GIS) and remote sensing techniques for analyzing, and monitoring land use and land cover (LULC) changes over time. The methodology is structured as: data acquisition, pre-processing, supervised classification, LULC change detection, and accuracy assessment. Each step is designed to enhance the reliability and accuracy of detecting LULC change using remote sensing and GIS tools.

Data Acquisition and Pre-processing

In this study Landsat images of year 2000, 2010, and 2023 downloaded from the USGS Earth Explorer was used, as these sources provide consistent, multi-temporal datasets suitable for long-term monitoring (Roy et al. 2016). The images were selected for different time periods to enable the detection of changes in land cover over time.

For the recent years, three periods of Landsat_5 TM (2000), TM (2010) and Landsat_9 (2023) freely available Landsat images were used. The satellite images were downloaded from earth Explorer (http://earthexplorer.usgs.gov) for free website which were selected based on ;(i) availability of the data, (ii) cloud cover percentage was 0 to 0.1 percent cloud cover, and (iii) association with years of major actions in the study area. The major satellite images used in the analysis are shown in Table 1 below.

To identify the actual LULC available in the study area field data collection was made. Field investigation was carried out to collect the representative ground coordinate points from each of the currently identified land use types. The GCPs were used for generation of signatures for supervised classification.

Table 1 satellite images data

Images	Sensor	Path/Row	Cloud cover (%)	Resolution	Acquisition time
Landsat-5	TM	168/54	0	30m	2000
Landsat-5	TM	168/54	1.00	30m	2010
Landsat-9	OLI	168/54	0.05	30m	2023

Pre-processing of Data

Pre-processing is a critical step to prepare the raw remote sensing data for analysis. The following preprocessing has been made to the satellite images:

To align the images from different dates spatially, geometric correction is applied to remove any distortions caused by sensor angles, earth curvature, or topography (Chavez, 1996). In addition to this calibration is was done to ensure that the radiometric values (such as pixel brightness) are consistent across multiple images, which helps reduce discrepancies caused by sensor differences (Lillesand et al., 2014).

Image Classification

The next step is to classify the satellite images into distinct land cover categories. This process was achieved through by supervised classification techniques of Maximum Likelihood Classifier (MLC).
Supervised Classification involves selecting training samples from known land cover types, which are used to train a classification algorithm. Popular classifiers include Maximum Likelihood Classifier (MLC), Support Vector Machines (SVM), and Random Forest (RF) classifiers (Foody, 2002). These classifiers can then assign each pixel in the image to one of the predefined LULC classes.

Change detection

Land use change detection is the process of identifying areas where LULC has changed between two or more time points. This can be accomplished through the method of Post-classification Comparison. This method involves classifying each image individually and then comparing the final classifications from different time periods (Coppin et al. 2004). This approach helps to account for shifts in land cover categories and allows for more precise tracking of LULC dynamics over time.

Accuracy Assessment

Accuracy assessment is essential to evaluate the correctness of image classification results and the effectiveness of land use change detection. The accuracy assessment is done by comparing the classified satellite image with reference coordinate data collected from field surveys or high-resolution imagery (Congalton, 1991). Confusion Matrix was developed for comparing the classified satellite image with ground truth coordinate data, providing measures of accuracy like overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient (Congalton & Green, 2009).

RESULTS AND DISCUSSION

Result

Accuracy assessment of 2000 to 2023 images

The Land sat TM Image of 2000 supervised classification results shows user's accuracy in this study the maximum class accuracy was 92%, which was water body where correctly classified and the minimum was bare land class with an accuracy of 83.6 % as presented in table 3 below. Kappa coefficient value of 0.83 is obtained for this classification which implies that the classification process was avoiding 83% of the errors that a completely random classification would generate.

Table 2 classification accuracy assessment for image 2000

	Ground Truth							
Classified Pixel	LULC types	Built-up	Vegetation	Agriculture	Water body	Bare Land	Grand total	Users accuracy
	Built-up	42	2	3	1	2	50	84.0
	Vegetation	3	56	4	0	2	65	86.2
	Agriculture	2	1	51	1	3	58	87.9
	Water body	0	1	0	46	3	50	92.0
	Bare Land	2	1	5	2	51	61	83.6
	Grand total	49	61	63	50	61	284	
	Producers accuracy	85.7	91.8	80.9	92.0	83.6		
Overall Accuracy = 86.61 Kappa coefficient = 0.83								

The land sat ETM+ Image of 2010 supervised classification with an overall accuracy of 86.6 % was achieved with a Kappa coefficient of 0.83. This value implies moderate agreement with good accuracy, and is often multiplied by 100 to give a percentage measure of classification accuracy. According to the table 4 therefore, the Kappa coefficient value of 0.83 is obtained from the supervised classification which represents a probable 83 % better accuracy. The user's accuracy in this study the maximum class accuracy was 88.3%, which was water body where correctly classified and the minimum was bare land class with an accuracy of 77.4.

Table 3 classification accuracy assessment for image 2010

	Ground Truth							
Classified	LULC types	Built-up	Vegetation	Agriculture	Water body	Bare Land	Grand total	Users accuracy
	Built-up	51	5	2	3	2	63	80.9
	Vegetation	3	49	3	1	4	60	81.7
	Agriculture	2	2	62	0	6	72	86.1
	Water body	3	0	1	53	2	59	89.8
	Bare Land	2	0	7	3	48	60	80.0
	Grand total	61	56	75	60	62	314	
	Producers accuracy	83.6	87.5	82.7	88.3	77.4		
Overall Accuracy = 83.8 Kappa coefficient = 0.83								

The Land sat-9 images 2023 supervised classification results of user's accuracy in this study showed that in 2023 the maximum class accuracy was 89.8 %, which was water body where correctly classified and the minimum was bare land class with an accuracy of 80.0 % as presented in table 5 below. In 2023, the class accuracies range from 80.0 % to 89.8 %. For this supervised classification it is obtained overall accuracy value of 86.0% which is acceptable for further analysis, and change detection and kappa coefficient of 0.82 which shows 82% of errors are removed from the classification indicating a good agreement between the reference data and the remotely sensed classification (SHAO, WU 2008).

Table 4 classification accuracy assessment for image 2023

	Ground Truth							
	LULC types	Built-up	Vegetation	Agriculture	Water body	Bare Land	Grand total	Users accuracy
Classified Pixel	Built-up	61	3	3	1	2	70	87.1
	Vegetation	5	56	2	2	3	68	82.4
	Agriculture	3	2	47	2	3	57	82.5
	Water body	0	2	0	49	1	52	94.2
	Bare Land	3	5	2	1	64	75	85.3
	Grand total	72	68	54	55	73	322	
	Producers accuracy	84.7	82.4	87.0	89.1	87.7		
Overall Accuracy = 86.0 Kappa coefficient = 0.82								

3.1.2 Land use pattern of Addis Ababa for 2000, 2010 and 2023

Figure 2 below shows the LULC map of Land use land cover classes over the study period of 2000, 2010 and 2023 and figure 3 indicates the land use change for the respective years. Supplementary Tables 6 contains the area distribution of each land use land cover classes in hectares, and percentages. In addition to this table 3, table 4 and table show result of accuracy assessment for supervised image classification along with the overall accuracy, and kappa coefficient for the year 2000, 2010 and 2023 respectively.

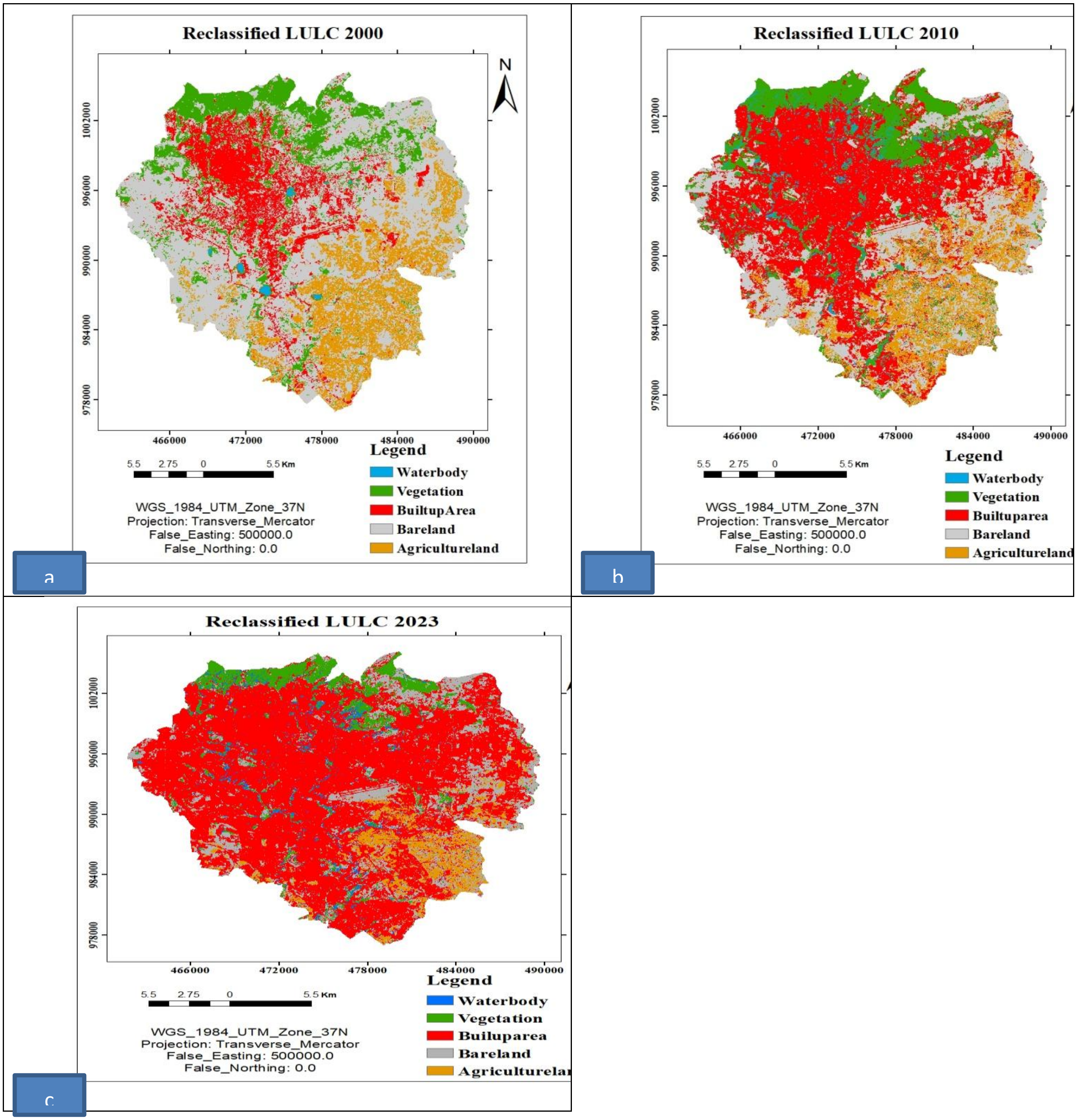


Figure 1 Land use land cover of a) 2000, b) 2010 and c) 2023

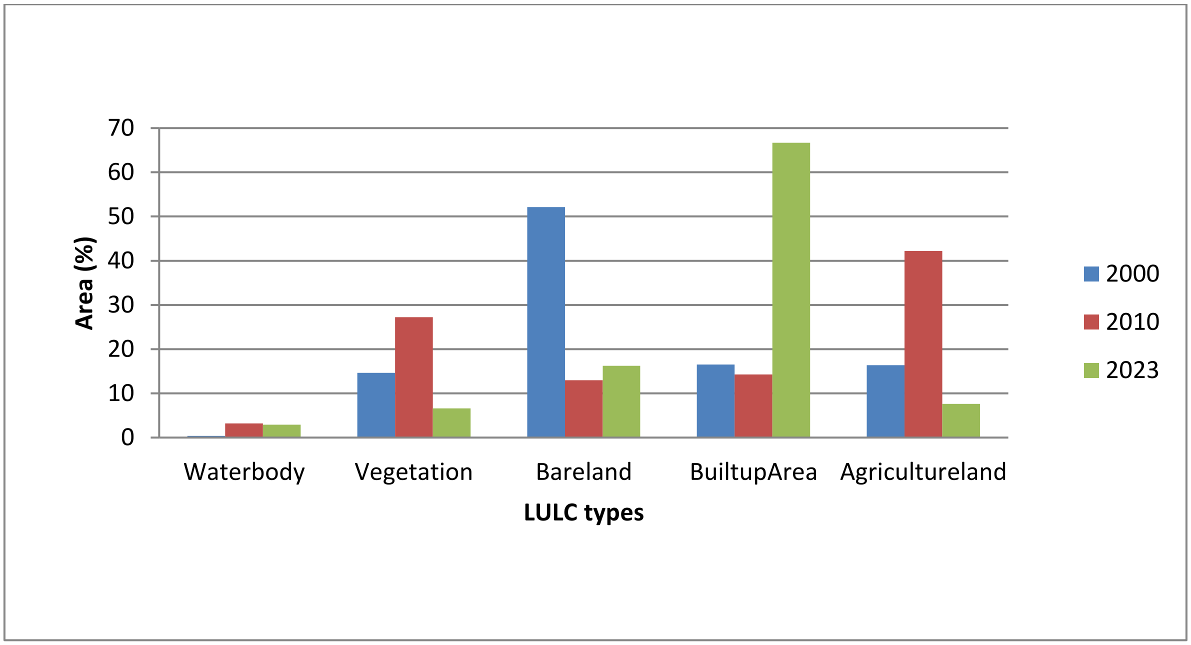


Figure 2 Land use land cover area coverage

Land use Land Cover change detection from 2000 to 2023

In order to analyze the land cover changes in the study area, the following table 6 showing the area in hectares and percentage changes between the periods 2000–2010, 2010-2023 and 2000-2023 was quantified for each LULC types. The change in LULC of the respective three periods was obtained as the difference of the values of different times of the same category while percentage change was calculated by dividing it with the total area and multiplying by hundred. This provided the information on the trend of conversion in terms of time. Finally, the areal coverage, annual rate of change, change rate and relative change were tabulated for each of the identified LULC types. The annual change rates were calculated using Eq. (1) (Dinka 2012; Etter et al. 2006):

The land use trend analysis made for the periods of 2000 to 2023 E.C indicates that Addis Ababa was subjected to considerable land use land cover changes. The temporal change of LULC in Addis Ababa over the period of 2000–2023 is presented in Table 6. The table indicates the LULC dynamics for two different periods 2000-2010, 2010-2023, and 2000-2023.

Table 5 area coverage of land use land cover class over the three period

LULC Class	**Area**			**Net change**					
	2000	**2010**	**2023**	**2000-2010**		**2010-2023**		**2000-2023**	
	(ha)	**(ha)**	**(ha)**	**(ha)**	**(%)**	**(ha)**	**(%)**	**(ha)**	**(%)**
Built-up Area	8724.3	22338.1	35257.5	13,613.8	25.74	12,919.4	24.43	26,527.2	50.17
Vegetation	7743.2	7567.8	4048.1	-175.4	-0.33	-3,519.7	-6.66	-3695.1	-6.99
Agriculture land	8648.8	6872.1	3487.7	-1,776.7	-3.36	-3,387.5	-6.4	-5,161.1	-9.76

Bare land	27585.1	14410.4	8571.1	-13,174.7	-24.9	-5,839.3	-11.04	-19,014.0	-35.94
Water body	189.5	1702.4	1526.6	1,512.9	2.86	-175.7	-0.33	1,337.1	2.53

Discussion

LULC change for 2000 to 2010

During this period, the areal coverage of vegetation, bare land, and Agriculture land were decreased by 175.4 ha, 13,174.7 and 1,776.7 ha, respectively. On the other hand, Built-up area and water body have increased by an aerial coverage of 13,613.8 ha and 1,512.9 ha, respectively. These increment and decrement of LULC cover were made due to the conversion of different land use into the above mentioned classes. As evident from Figure 2, built-up area shows a significant increase in area during this period at the expense of all the other LULC types.

The early stage of this study period was considered as the time of intensive government intervention for building condominium houses, and other activities like formal settlement and informal settlement causes a huge amount of area increment in Built—up area and decrements in vegetation and Agriculture land.

LULC change for 2010 to 2023

Conversely to the preceding period (2000–2023), only Built-up showed an area increment of 12,919.4 hectare with expense of other land use land cover types. In addition to this between these years decrement was observed in farmland which is about (9.8%). On the other hand vegetation, bare land, water body and agriculture land showed a decrease in area of 3,519.7, 5,839.3 ha, 175.7ha, and 3,387.5 respectively. See Table 6 above.
Generally major land use land cover changes were observed for the last 24 years or 2000-2023. Especially built-up area and water body showed significant change during this time with an area increment of 26,527.2 hectares and 1,337.1 hectares respectively. Table 6 transition matrix shows that built-up area was 8724.3 ha (16.5%) in 2000 and it increased to 35257.5 ha (66.7%) in 2023, and water body increased from 189.5 ha (0.4%) in 2000 to 1526.6 ha (2.9%). In contrast from all other land use land cover types bare lands showed a large amount in decrement from 27585.1 ha (52.1%) in 2000 to 8571.1ha (16.2) in 2023.

Urbanization has mainly exerted strong pressure on existing land use and the most affected is agricultural land which is transformed to built-up areas in every high rate (Basudeb et, al. 2011). In the study area this type of transformation is the main cause of land use land cover change and expansion of urban areas to the periphery areas. As shown in the above table 6 the largest share of land use land cover change between 2000 and 2023 in the project area was bare land which covers more than 16.2 percent next to built-up areas which covers about 66.7 percent of an area. There is increment of built up area and water bodies, in the city due to expansion of this land use land cover types towards farm land areas and other types of land covers. In contrast other land use land cover showed a decrement between the year 2000_2023 were vegetation (3695.1 ha), Agriculture land (5,161.1 ha), and bare land (19,014.0 ha) of the total area.

Conclusion and recommendation

Conclusion

This research is carried out in Addis Ababa Ethiopia, which is one of the emerging and rapidly growing city. From this reach it is possible to conclude that Built-up area is the primary land use in the studied region. A significant change in Land use land cover was observed in the study area since urbanization is associated with built up areas consequently with deforestation. Between 2000 and 2023, there was high expansion of construction activity, which led to a rise in the area covered by built-up areas, which increased by 50.17% (26,527.2 hectare). Bare land is the second land use in the study area showing a higher change which is decreased by 35.94% (19,014.0 hectares) as a result of the conversion barren land to built-up area. The area under the fourth category of land, i.e., the water body has increased by 2.53% (1,337.1 hectares). The build-up area observed significant changes mostly as a result of the expansion of the Addis Ababa city area and the growth of various industries over the previous 23 years.

Policy maker and stakeholder need to be conscious about the rapid development and changes in the land use pattern in Addis Ababa city. It has been observed that rapid urbanization and industrial activities in the study area are the driving factors to trigger the Land use land cover changes in the study area during the last two decades.

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