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Modeling Land-Use/Land-Cover Dynamics Using Remote Sensing and GIS Techniques: The Case of Ambo Town

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Modeling Land-Use/Land-Cover Dynamics Using Remote Sensing and GIS Techniques: The Case of Ambo Town

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ABSTRACT

LULC changes are complex and tremendously dynamic. The purpose of this study was to monitor the land use and land cover dynamics of Ambo town and to model its future development under different scenarios using GIS & RS techniques. This research used GIS and remote sensing in mapping LULC cover dynamics in Ambo Town between 1990 and 2020 to distinguish and examine the dynamics that have taken in the Town between these portions of time. The data sets used were Landsat TM of 1990, Landsat ETM

2000, 2010, and Landsat 8 OLI 2020. The maximum likelihood algorism of supervised image classifications is used to generate land-use land-cover maps and assessment of their dynamics. The cellular Automata Markov (CA-Markov) modeling approach was used to forecast land-use change for 2030. Analysis of Landsat image data of Ambo Town from 1990 – 2020 showed there are significant LULC changes in the town. In 1990 forest, agricultural land, and built-up area covered 21.8 %, 60.19 %, and 13.73 % of the whole area, respectively. Bare land constituted less than 5% of the area. However, in 2000, after a decade, the agricultural land area was declined to–16.0 8% while built-up area, forest, and bare land were increased to 8.84 %, 3.69%, and 3.62% respectively. In 2010, after three decades, bare land and built-up area constituted 2.94 % and 22.55% of the area, respectively. Then again, agricultural and bare land areas were decreased by 14.71% and 10.83% from 33.33 % to 22.5 % and 26.47% to 11.7% respectively. With existing conditions, the simulated LULC map of the year 2030 indicates the same trends that forestland and built-up areas will increase by 2.99 %, and 4.04 %, respectively whereas agricultural land and bare land areas will be decreased by 3.76%, and 2.82. Therefore, the government has to provide different innovative policy reform strategies/scenarios to overcome the BAU scenario. Thus, the town administration has to devise a mechanism that reduces urban expansion.

Keywords: CA-Markov, GIS, Land cover, Land dynamic, Land use, Modeling, Remote sensing

1. Introduction

The land is a compound and dynamic scheme that consists of hydrology, topography, geology, soil and microclimate, and a community of plants and animals that are people activities and continually interacting under the influence of climate (Lu & Weng, 2007). Land-use is subject matter to the natural environment and involvement of human activities, thus considerate the driving factors at the back the land-use change (LUC) is crucial for the land-use planning and management of key land surface of the earth's ecosystems services and functions (Leemhuis *et.al*., 2017). Land- cover captured in the distribution of soil, water, vegetation, every applied on an undulation of the ground surface of the earth and other physical facial appearance (Li *et.al*.,2016). Land-use and land-cover (LULC) change has been regarded as an important factor influencing climate change and environmental conditions (Pickett *et.al*., 2017) and has a close relationship to population migration and economic conditions (Korantenge*t.al.,*2016). Proximate (or direct) causes of land-use change make up human activities or instant events that create from future land use and in a straight line affect land- cover (Lepers, 2014). Underlying causes are shaped by a complex of, political, social, economic, technological, cultural, demographic, and biophysical variables that comprise preliminary conditions in the human-environment relations and are structural (Lu and Weng, 2007). Remote sensing has become a major data source for mapping and monitoring LULC dynamics over time (Leemhuis *et.al*., 2017)because it can capture land surface information at the time when satellites pass through. Models of land-use and cover dynamics are powerful devices that can be used to understand and analyze the crucial linkage between socio-economic series of actions associated with agricultural activities, land development, and natural resource management strategies and the ways that these changes affect the structure and function of ecosystems. For that reason, satellite images can often be used to detect land-use dynamics through the ability to notice significant details of the biophysical characteristics of the land. They have implemented and user land-cover dynamic models that can simulate multiple land-use and land-cover dynamics types. As a result, Cellular Automata are collected of five fundamentals as described underneath (Tizora,2018): Cell Space: The cell breathing space is collected of an individual cell. The community within a Town: every cell has two very close to an additional in one-dimensional cellular automata, while in two-dimensional cellular automata model there are two conducts to describe it. This current research

aimed at an option the spatial evolution concept embedded in CA (Cellular Automata) and applies it to land-use and land-coverage dynamic in West Shoa Zone. In the study, present here, the aim is to explore the dynamic and future spatial patterns of land-use changes from 2020 to 2030 using the Dynamics of Land System (DLS) model under two scenarios: The BAU (Business-as-Usual) scenario was set for future land transitions based on historical and recent socioeconomic trends, e.g. Economic and population growth without any new sustainable environmental no change everything. The business as usual (BAU) scenario was intended mostly based on the supposition of a continuance of land-use and land- cover change rates of the history 30 years in the deliberate landscape (Kindu *et.al*., 2018). Generally, this research aimed to analyze and model the long term land-use and land-cover dynamic and future spatial patterns of land-use changes over 40 years(1990-2030) in West Showa Zone and Ambo town by integrating remote sensing, geographical information system (GIS), and Modeling tools and provided quantitative analysis of land-use and-cover dynamic information in the area.

2. **Materials and Methods**

2.1. Study area

Ambo Town (meaning mineral water in Afaan Oromo) is the capital city of the Oromiya Regional State of West Shoa. *Ambo town is located in Western Ethiopia and Western Oromia region in West Shoa Zone. It is located west of Addis Abeba at a 114 km distance. T*his *town* has a latitude of 8°58′N-8° 59′N and longitude 37°50′E -37°52′E(figure 1) and an elevation of 2106 meters. The area of the town is 10.2 sq km^2 (ten-point two square kilometers). A*mbo* is known for its mineral water, which is bottled outside of *town*; it is reportedly the most popular brand in

Ethiopia.

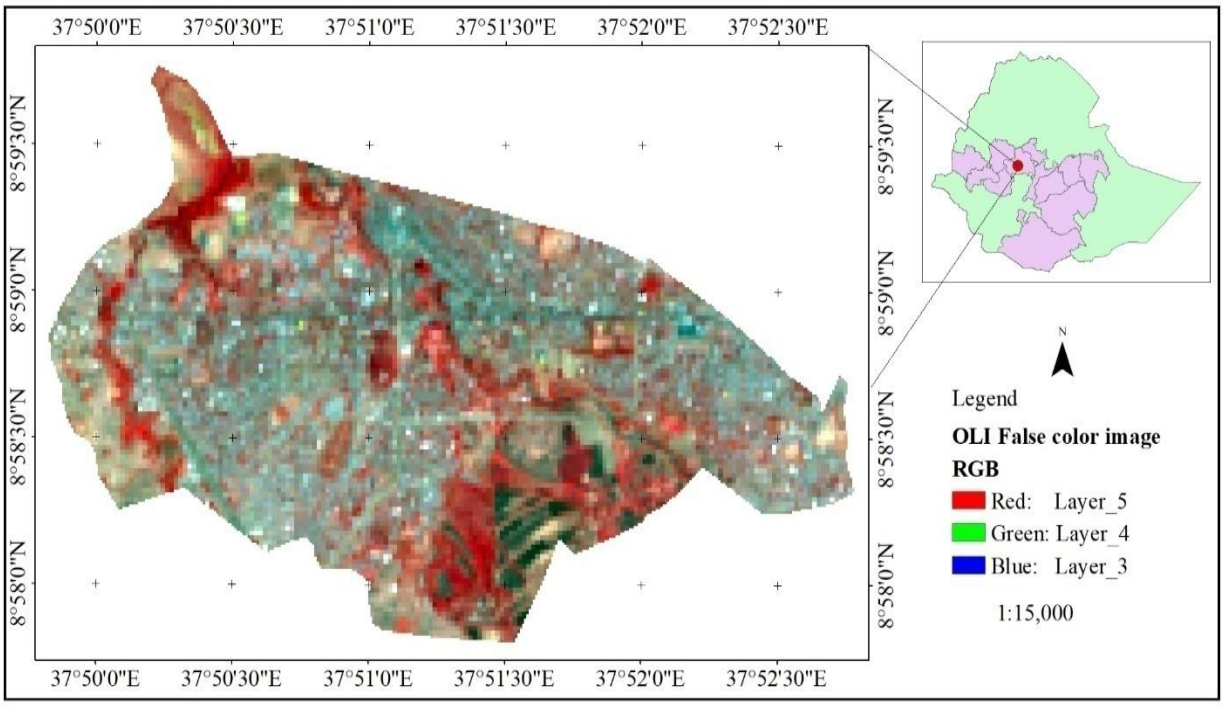


Figure 1: Location of the study area

Ambo Town falls within the climatic zone, which is characterized by a rainy season in the area is from May to September and the wettest month is July (233.7 mm). It is dry season, with erratic rain of less than 65 mm per month between October and April. Annual rainfall in the study area ranges from 775 mm to 1265.70mm yr^{-1} with a mean annual rainfall of 1044.6mm yr-1.

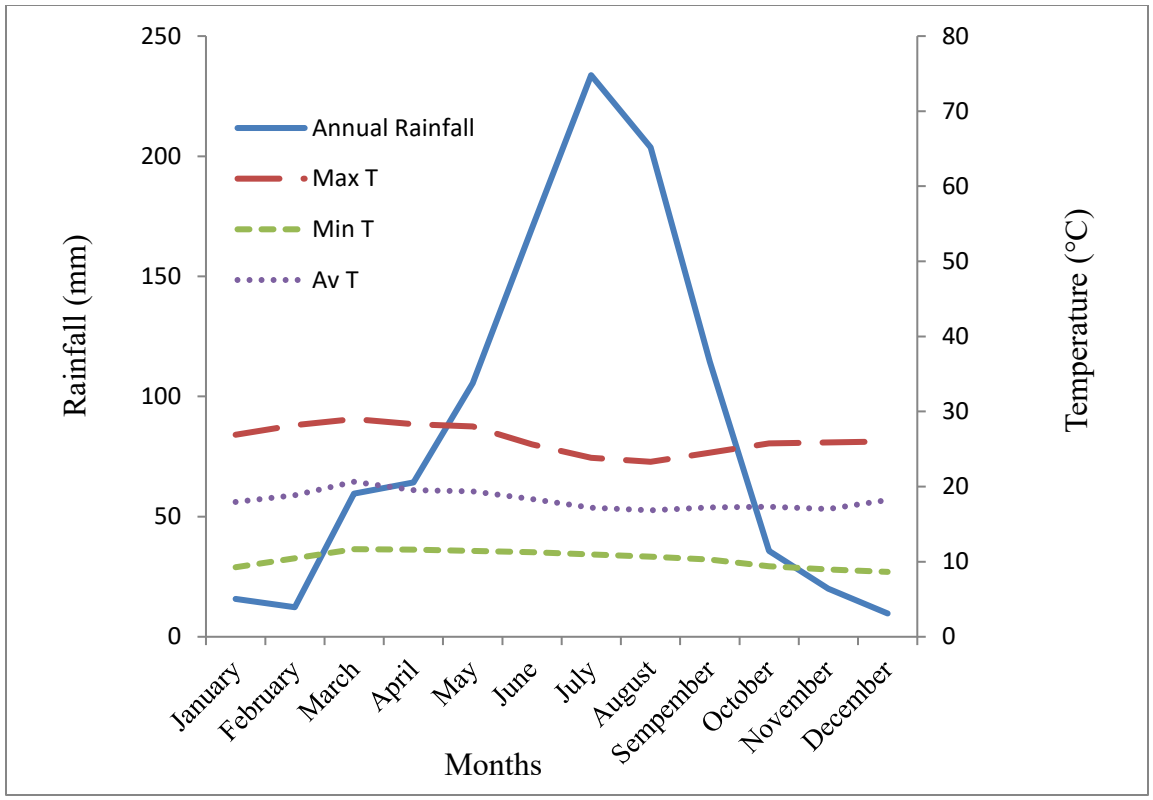


Figure 2: Monthly average rainfall and temperature of Ambo town

According to the population in the census, Ambo town was 47,261 in 1994; 67,604 in 2007 source from (CSA) and has grown to 94,049.9 in 2020 (estimated), showing that the population of the town has increased by around thirty doublings within the past 30 years (Ambo Town Communication office 2020).

2.2. Data Used

2.2.1. Satellite Imagery

Satellite images for 1990, 2000, 2010, and 2020 from Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) were acquired from the United States Geological Survey (USGS) website. The image downloaded as standard surface reflectance products at height applied within the atmospheric correction. There were then geometrically referenced to the World Global System 1984 (UTM zone 37 projection systems). The mere omission was the Landsat 5 TM image for 1990, 2000, and 2010 which demonstrated some geometric distortions and anomalies. In due to this case, geometric corrections were performed to enhancement 1990, 2000, and 2010 images applying the geo-referencing algorithm.

The reference years were determined based on the most important regimes and policy changes in the study site. The satellite images were also preferred based on three criteria: acquisition time, season, and data availability. All the images were acquired in January for dry season analysis. The image was deliberately selected from the same months and season to decline inconsistency in land cover due to seasonal changes.

2.2.2. Other Datasets

Other datasets required for this study were collected although both primary and secondary sources. Field data was collected with the use of Global Positioning Systems (GPS), selected key informants (natural resource management experts, and other responsible bodies) by using structured interviews. Ground–truth data were gathered on the field to be used for image classification and verification of the satellite imagery. Focus group discussions (FGDs) and key informants' interviews (KII) were used to provide qualitative information. Key informants were selected purposively from different social groups, who have detailed knowledge about the LULC dynamics of the study area (Angessa et.al., 2019). Three FGDs were conducted where two of them were represented with seven individuals, and eight individuals represented the third group and related published and unpublished materials. The overall processes allowed the investigator to better enhance and improve the images for classification and interpretation and the resulting sampling sizes for point data were 200 points with a maximum sample size of 50 samples per class and a total of 200 GPS data's were collected. From these 70 (35%) points were used for training and the rest 130 (65%) points to assess the accuracy of land use land cover classification.

2.3.1. Major Land-Use and Land-Cover Classes and Image classification

In the study area, there are four major land-use and land-cover classes; those are built-up area, forest land, bare land, and agricultural land (Table 1)

Table 1: Major land-use and land-cover class types of the study area

LULC Class	Description
Forest land	In a wider sense cover around Tentale and Huluka river in Ambo Town and include any kind of woody plant vegetation growing in and around human settlements
Built-up area	Urban areas with permanent residential, commercial land other facilities of varied patterns.
Bare land	Bare land represents areas with no dominant vegetation cover.
Agricultural land	Agricultural land is defined as the land area that is either arable, under permanent farms, or permanent pastures

Images from different periods are used for the classification of LULC dynamics in Ambo Town during (1990-2030) period. This multi-temporal raw satellite data were imported to Erdas Imagine 2015 image processing software. After this, land-use and-covers dynamic maps, and land-cover statistics were generated to compare the temporal dynamic of the study area for the past three decades using ERDAS 2015 software. The flow chart for the general methodology to classify LULC types is shown in Figure 2. Finally, land-cover maps of Ambo town were produced based on 1990 Landsat TM, Landsat (2000, 2010) ETM+, and (2020) OLI data using supervised. However, after supervised classification, some classes were combined and the final land-cover map of Ambo Town was sketched. The step-by-step approach (methodology) takes to achieve the stated objectives of this project are the following; the satellite image of the study area was classified using ERDAS Imagine2015. The existing analog boundary map was converted into digital format through digitizing using ArcGIS 10.5 application software.

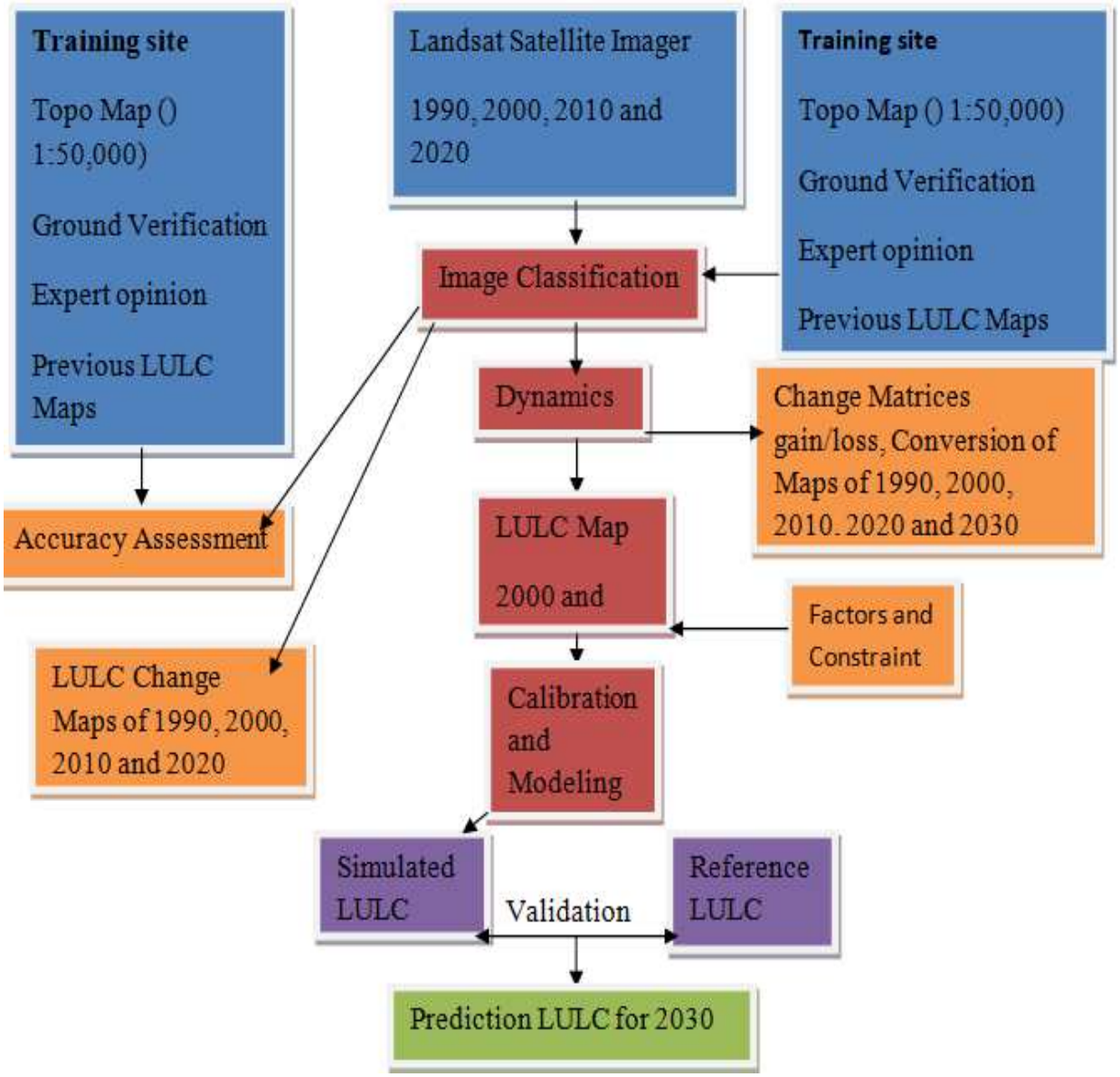


Figure 2: Flow chart of the image classification and general procedures of the study

The BAU scenario was designed mainly based on the assumption of a continuation of LULC conversion results of the past 30 years in the current study area (Kindu *et.al*., 2018). Thus, before the demand calculations for 2030 in the BAU(business as usual) scenario, the rate of change between 1990 and 2020 for each LULC type was determined using the following formula (Kindu *et.al*., 2018):

$$\boldsymbol{r}=(\frac{\mathbf{1}}{\boldsymbol{t_{1-t_2}}})*1n\,(\frac{\boldsymbol{A_2}}{\boldsymbol{A_1}}) \qquad (1)$$

Where r = rate of changes for each LULC type, A1 and A2 = extent of each LULC type at time t1 and t2, respectively.

$$A_n = A_O e^{rt} \quad (2)$$

Where A_n = the area estimates for each LULC type in year n, A0 = area of the base year, t = period that is the difference between year n and year 0; and r = average annual rate of change.

Calculated land use and land cover types of each land use by using in the simple formula were generated.

$$\text{LULC types} = \frac{\text{Rate of land use}}{\text{The total study area}} * 100 \quad (3)$$

A transition probability matrix was first developed using the Markov module in Idrisi for each land-use and land-cover class between 2000 and 2010 to use as an input for projecting land-use change for 2020 (Table 4).

Table 3: Transition probability matrix for the projection of 2020 land-use and land-cover

LULC Class type 2000/2010	Bare land	Agriculture land	Built-up area	Forest land
Bare land	**0.0296**	0	0.5143	0.0889
Agriculture land	0.2056	**0.5524**	0.2309	0.1338
Built-up area	0.0389	0.5143	**0.7198**	0.0731
Forest land	0	0.0334	0	**0.0825**

Model validation refers to comparing the simulated and reference maps. Sometimes the simulated maps can give ambiguous results. In that case, it is necessary to validate the projected/simulated map with the base/reference map(Eastman, J. R., 2009). For validating the output of the simulated LULC map in 2020, two maps were compared the reference LULC map of 2020 and the simulated LULC map of 2020. All of these Kappa values can be referred to Landis and Koch (1997), which explained the kappa value range. The value between 0.41-0.6 corresponds to a moderate agreement between the reference map and the simulated map. The total correctness value is 53.41%, which indicates that the moderate accuracy of the simulated LULC map in 2020 Validate.

The multi-resolution indicated the perfect location and medium quantity information between the reference map and the simulated map, which means that the historical LULCD process from 2000 to 2010 is accurate and reliable to predict LULC patterns in 2030. However, the validation of the simulated map is a challenge because there is no criterion to assess the performance of the different LULC dynamics models. Another problem is parameters to indicate the overall accuracy, parameters for comparing different modeling results, and the minimum accuracy standard (Muzein, 2006).

Kappa is a statistical measure of overall agreement between two maps (e.g. output of classified/simulated map and ground truth/reference map) or a matrix (Canada Centre for remote sensing, 2010).

The Kappa statistics (K) is defined according to the following equation(Fekadu, 2017) (Hagen, A., 2002).

$$K = \frac{P\ (A) - P\ (E)RL}{1 - P(E)RL} \quad (4)$$

It depends strictly on the spatial distribution of the categories on the map. It indicates how well the grid cells are located in the landscape(Araya, 2009).

$$P(A) = \sum_{n}^{m} = 1\, pnn \quad (5)$$

$$\text{P (E) RL} = \sum_{n}^{m} 1{=}1\ \text{Pn} * \text{Pm} \quad (6)$$

Where, P (max) = the maximum success rate P (E) RL = the fraction of expected agreement for the whole map, where RL stands for random location.

2.3.2 Land Surface Temperature (LST)

Land surface temperature is one of the main variables measured using thermal bands of different sensors such as Landsat-7 ETM+, band B6 for Landsat-8 TIRS band B10 used to calculate at-Satellite Brightness Temperature. Image pre-processing which comprises layer stacking, image enhancement, band combination, and false color combination were applied to the images. In addition, LST for each year was computed to observe the change of LST induced by LULC change.

The digital number (DN) values are then transformed to LST using a multiplication factor (0.00341802) and an additive number of 149 (Sayler & Zanter, 2023;Ahmed et al., 2024) (Equation 2).

$$LST = (DN * 0.00341802 + 149) - 273.15 \quad \text{Eq. 2}$$

Where**:** DN is a digital Number from the satellite image (raw pixel value), typically from Thermal Infrared (TIR) Band 10 (Landsat 8/9); 0.00341802 is a multiplication factor (also known as radiometric rescaling factor or gain), used to convert DN to Top of Atmosphere (TOA) radiance or scaled thermal values; 149 is empirical additive constant, used to adjust the result into a more accurate thermal range for LST, specifically calibrated for Band, and -273.15, is to convert Kelvin to Celsius (because LST is often reported in °C for environmental and agricultural analysis.

The output unit for the LST is in Kelvin, which is converted to Celsius by subtracting 273.15. Its accuracy is validated with an R^2 of 0.997 (very strong correlation with in-situ measurements) by Crawford et al. (2023) and an R^2 of 0.96 (very good) by Wachmann et al. (2024). To ensure consistency with the leaf area index (LAI) pixel size, the LST data were 30m pixel size and projected UTM zone 37N (used for spatial consistency in mapping).

2.3.2. Accuracy Assessment

The process of doing an accuracy assessment involved generating a set of points from the classified image and comparing the positions of points whose location was determined by the ground truth data and corresponding coordinates from the original maps (ERDAS, 2009). In this study, these sets of points were selected with random sampling. Random sampling was used to select a set of points. Training points used in image classification were not used for accuracy assessment. The reference points for 1990, 2000, and 2010 were collected from the corresponding key informant, FGDs, Topo map, and Google Earth; original Landsat images, previous reports and maps, and field observation for 2020.

The overall result of the current study for kappa coefficient, user accuracy, producer accuracy, and overall accuracy of 1990, 2000, 2010, and 2020 were presented in Table 4. Accordingly, the overall accuracy ranges from 85.5% (1990) to 90% (2020) which is at the acceptable range of accuracy assessment. Similarly, producer's and user's accuracy for almost all the classified images of the respective study years falls within the acceptable ranges, except for user accuracy for the year 2020, which is 83%. Kappa coefficient that associates the classified images to the reference data also showed a strong agreement (fall between 84% and 86%) for the study years.

2.3.3. Change detection analysis

Remotely sensed images are vital in land-use and land-cover change detection as it provides spatial and temporal information of the land-use, and cover condition of the Town. In this research thesis, 30-year time span (1990-2020) and four-period change detection (1990-2000, 2000-2010, 2010-2020, and 1990-2020) these periods were chosen based on the availability of

satellite images and other data in the town. This method is widely used and easy to understand (Fasika et al., 2019). The advantage of this method includes the detailed from-to information that can be extracted. Change detection and comparison were done for 1990 -2000, 2000 – 2010, 2010 -2020, and the fourth 1990-2020 to get from-to information of changes in LULC and especially to see the rate (trend) of the built-up area, agricultural land, forest, and bare land coverage of the study area. Change statistics would be computed by comparing the values of the area of one data set with the corresponding value of the second data set in each period. The value was presented in terms of hector and percentage. Quantification of the rate of change has been applied to generate information about the land use and land cover change of the study area.

3. Results

3.1. LULC Classification

A total classification scheme built-up area, agricultural land, bare land, and forest lands are the major LULC classes for the study area. Table 4 and figure 3 show the LULC of Ambo town in 1990, 2000, 2010, and 2020. In 1990, agricultural land was the dominant LULC covering 60.2% followed by forest land (21.9%); whereas, built-up area and bare lands covered 13.7%, and 4.2%, respectively. In the LULC classification of 2010, the built-up area became the dominant LULC class covering 34.3%, followed by forest land (33.3%), agricultural land (26.5%), and bare land (5.9%). In the LULC classification of 2020, a built-up area further increased to 56.9% followed by forest land, agricultural land, and bare lands, which constituted 22.5%, 11.8%, and 8.8%, respectively.

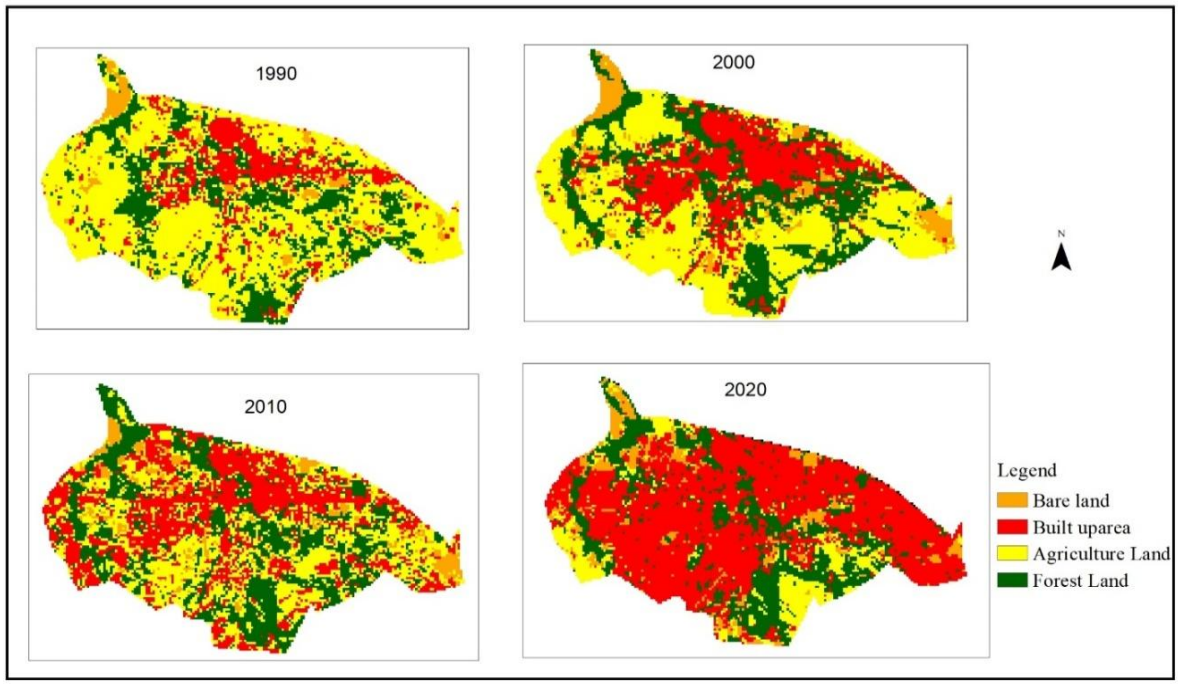


Figure 3: Land use/land cover change (LULC) map of the study area

Table 4: Summaries of the area of classified land use/land covers in the study area

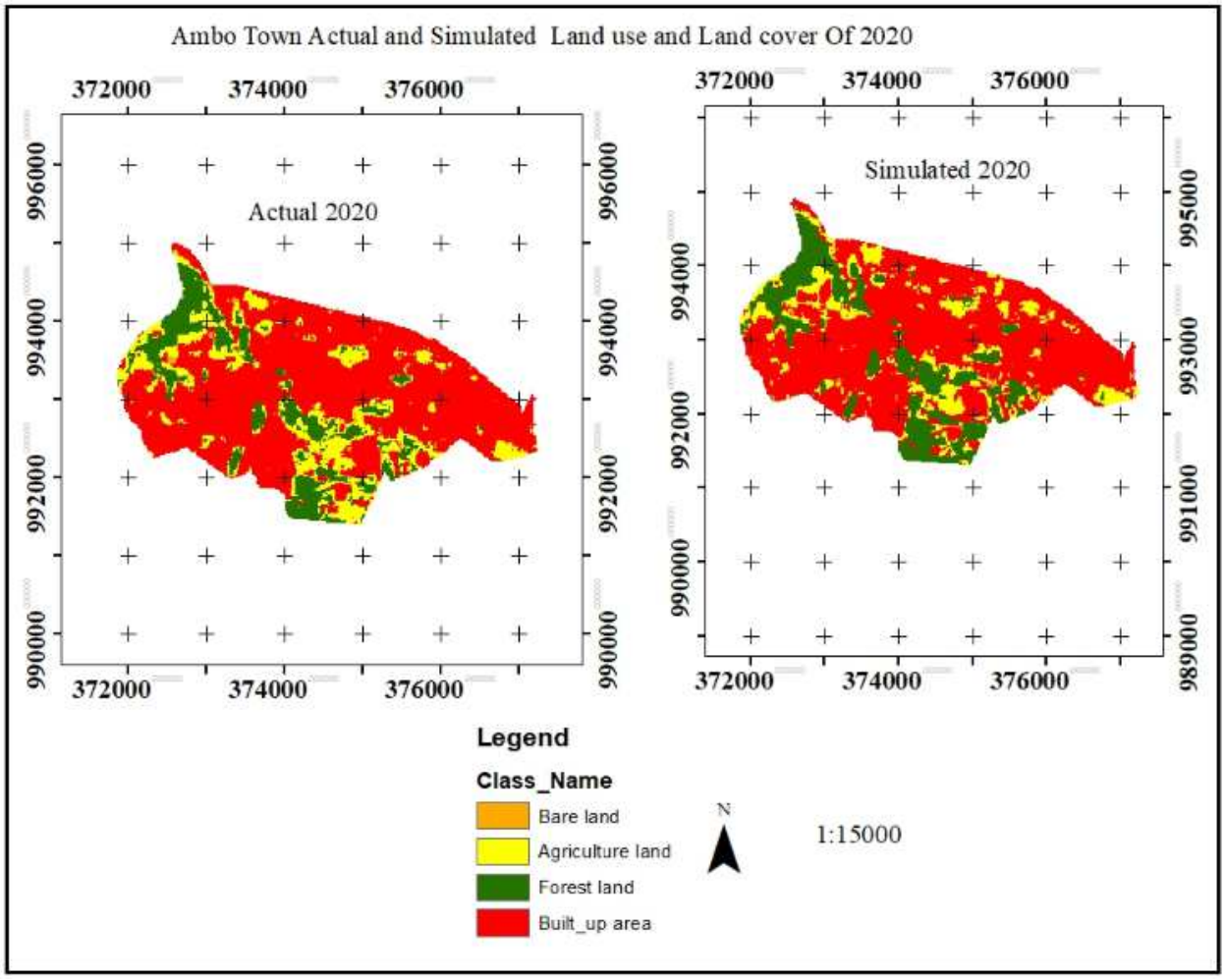
LULC type	1990		2000		2010		2020	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Bare land	43	4.22	80	7.84	60	5.88	90	8.82
Forest	223	21.86	260	25.49	340	33.33	230	22.54
Agriculture	614	60.19	450	44.11	270	26.47	120	11.76
Built-up area	14	13.73	230	22.54	350	34.31	580	56.86
Total	1020	100	1020	100	1020	100	1020	100

Modeling approaches were combined into Cellular Automata models. Cellular Automata models that were shortly were Cellular Automata (CA) and Markov, which was referred to as CA Markov.

These models were shortlisted based on a multitude of publications and literature, which suggests their wide applications in various topics in different regions and countries. Land change prediction in Land Change Modeler is an empirically driven process that moves in a stepwise

fashion from Change Analysis to Transition Potential Modeling from Transition potential to Change Prediction.

Markov model was selected for simulating the land-cover map of Ambo Town for the year 2020 for validation and predict the final land-use and land-cover map for 2030.



This was achieved by using GIS software to analyze LULC maps derived from remote sensing imagery. The LULC quantitative analysis results indicate that there were significant LULC changes between 1990 and 2020 characterized by a decline in Agriculture land. In contrast, urban/settlement classes exhibited increases. The LULC change results also show that there was an Ambo Town increase in built-up areas with about from 13.73 % to 56.86% increase with past three decades. However, analyses of individual district municipalities' LULC changes reveal that the increase in settlement areas was concentrated in the Ambo Town area. The increase in urban

areas was due to rising infrastructure demands generated by population growth and informal expansion.

In this study, the CA-MARKOV model was used to predict two scenarios-businesses as usual scenarios (BAU) and policy reform scenario-of the future LULC system in Ambo Town using historical maps from 1990 to 2020. The BAU scenario kept the development trend in the past decades, and there is still a relatively high speed of urban expansion. Based on this scenario, agricultural and bare land areas will be significantly decreased whereas built-up area, forest land, areas will be increased. The simulation results indicate that the agricultural land and bare land will decline and would have an extremely high level for a long time in Ambo Town. Under the BAU (business as usual) scenario, which assumed that the current socioeconomic development trends would continue, urbanization is projected to increase significantly in 2030. If this scenario persists, it will have a rigorous impact on the environment, soils, and the deterioration of climate. Therefore, the government should take the appropriate measures or policies at different stages to meet the real requirements of socio-economic development. Therefore, the baseline scenario is not suitable for future agricultural land control.

The policy reform scenario refers to when the government provides different innovative strategies to overcome the BAU scenario. Reform and innovation are key drivers of any town's remarkable economy. (PRS) will be designed implementation of spatial policies in which assumed that the policy reform (condominium buildings and apartment, reforestation, and plantation) would be leading to the competition of the remaining LULC types to obtain the demands for LULC types in 2030.

3.2. Classification Accuracy

The overall result of the current study for kappa coefficient, user accuracy, producer accuracy, and overall accuracy of 1990, 2000, 2010, and 2020 was presented in Table 3. Accordingly, the overall accuracy ranges from 85.5% (1990) to 90% (2020) which is at the acceptable range of accuracy assessment. Similarly, producer's and user's accuracy for almost all the classified images of the respective study years falls within the acceptable ranges, except for user accuracy for the year 2020, which is 83%. Kappa coefficient that associates the classified images to the reference data also showed a strong agreement (fall between 84% and 86%) for the study years.

Table 5 Summaries of the classification accuracies for 1990, 2000, 2010, and 2020

Year	Overall accuracy (%)	Producer Accuracy (%)	User Accuracy (%)	Kappa coefficient
1990	88.5	84	85.7	0.84
2000	88.5	94	88.6	0.84
2010	89	88	86.2	0.85
2020	90	94	83	0.86

3.3. Land Use /Land Cover (LULC) changes

The LULC change results also indicate that there have been Ambo Town increases in settlement area or built-up areas with about 8.82%, a 5% increase in bare land and forest. An assessment of the individual kebele in the Ambo town however provides a clearer picture of the actual LULC changes and shows that the increase in urban areas in the past 30 years is concentrated in the Awaro kebeles area and the adjacent Sanqale and Faris kebeles. Despite the 57.8% Ambo Town has experienced 250 hectares loss (-24.51%) in agriculture land to other LULC classes showed in table 6.

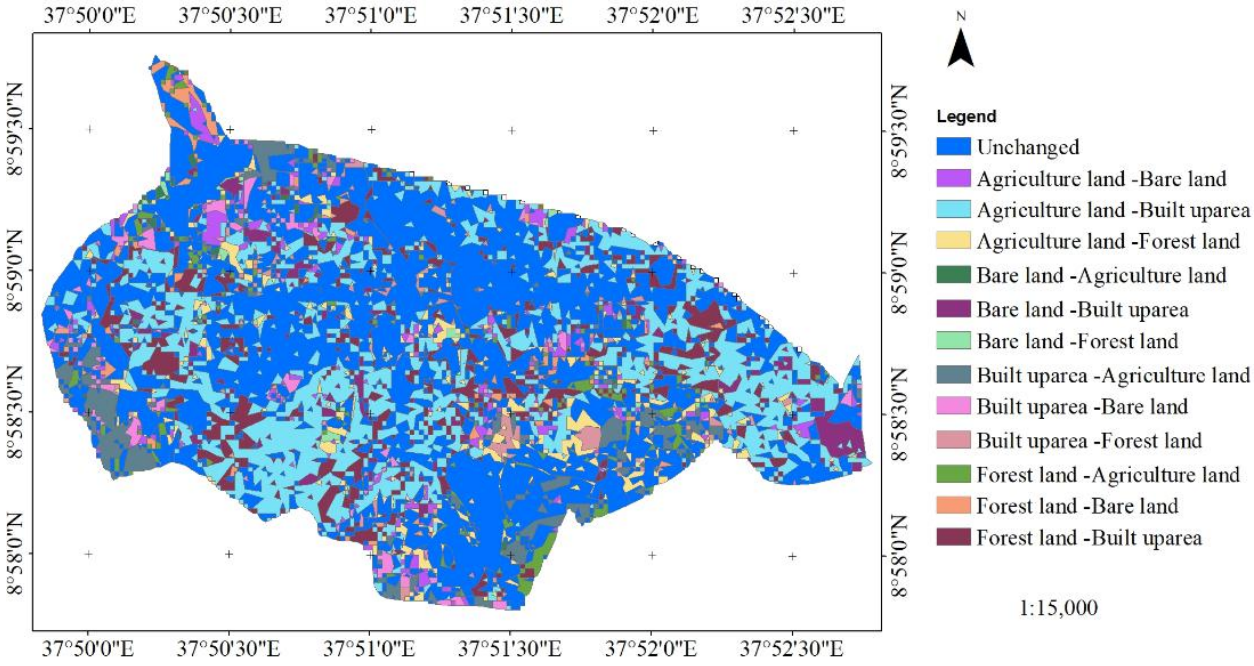
Table 6: Result of land use/land cover between different periods in hectare (ha) and percentage (%)

LULC Classes	1990-2000	2000-2010	2010-2020	1990-2020
Built up area (ha)	+90	+120	+230	+440
Built up area (%)	+8.81	+11.77	+22.55	+43.13
Agriculture land (ha)	-164	-180	-150	-494
Agriculture land (%)	-16.08	-17.64	-14.71	-48.43
Bare land(ha)	+37	-20	+30	+47
Bare land (%)	+3.62	-1.96	+2.94	+4.6
Forest land(ha)	+37	+80	-110	+7
Forest land (%)	+2.63	+7.84	-10.79	+1

3.4. Expansion of urban-up area

Ambo town the total built-up area calculated within the administrative boundary of Ambo Town was predictable at 140 ha, 230 ha, 350 ha, 580 ha, and 620 ha in 1990, 2000, 2010, 2020, and 2030, respectively. The in general change between the periods 1990-2000,2000-2010,2010-2020,2020-2030 and 2030-1990 were 8,82 %,11.76 %, 22.55 %,3.92% 47.1% respectively.

As shown from the map most land-use and land-cover of the study area were unchanged. However, areas that had been agricultural land in 2010 were highly changed to built-up areas in 2020. Moreover, areas located at the southwest of the area were highly changed. The built-up area has been changed to the bare, forest, and agriculture land was insignificant, these mean results show that 1.9 %, and 3.9 % respectively. The measurement of southwest and northeast is based on the position/direction of the Maps.



4. Discussion

The general monitor the land-use and land-cover dynamics of Ambo town and to model the spatial pattern of land use under different scenarios based on the result and the consequence of the past years. This was most likely caused by the expansion of built-up areas to migration from Guder, Goro sole, and Ginch town in 2000 and the high rate of population growth (Angessa et.al., 2019). The LULC classification result of 2000 indicated a decline in agricultural land by 16.1%, while results from the rest of the LULC types, built-up, forest, and bare land increased by

8.8%, 3.6%, and 3.6%, respectively. The LULC change results also indicate that there has been a provincial increase in urban or built-up areas with about 12% and a 1% increase in cultivation (Tizora, 2018).

According to (Ayele, 2017) also reported that the built-up area increased in Hawassa town at the same time as an agricultural land decreased during 1995-2017 and the change in the land use/ land cover in the study area was by increase attributed to the expansion of bare land (44.3%) and settlements (21.7%). Generally, there is a continuous land use/land cover change taking place for most parts of Hawassa Town in the last 21 years. The land cover change from 1995 to 2016 has been discussed in four periods. The LULC change assessment in Ghana for the period 1991–2016 also established a continuous increase in the settlement at the expense of open forest and closed forest lands (Ackom *et.al.,* 2020). The current finding agrees with the result of Lencho A, (2019) who concluded that built-up area increased by (44%) whereas agricultural lands decreased by (5%). The LULC change results also indicate that there have been Ambo Town increases in settlement area or built-up areas with about 8.82%, a 5% increase in bare land and forest. An assessment of the individual kebele in the Ambo town however provides a clearer picture of the actual LULC changes and shows that the increase in urban areas in the past 30 years is concentrated in the Awaro kebeles area and the adjacent Sanqale and Faris kebeles.

The increment in the built-up area may be connected to the natural population growth, and/or migration of the rural population particularly of the young generation in search of better livelihood and job opportunities, which intern may also lead to informal settlements. The increase in forest land may be explained by the fact that the government of Ethiopia gave great attention to tree plantation under the Climate Resilient Green Economy Strategy (CRGE); where the Ambo Town Municipality in collaboration with Ambo University undertake reforestation and tree plantation with the aim of urban greening, gave attention campaign of forest tree plantation after millium encourage, mainly along the roadside, that is evident still now. For, instance forest land is just like the cover in the study along the roadside in Ambo Town.

The increase in bare land was mainly attributed to road expansion, reservation for construction materials like red ash, Ambo granite, and fine aggregate gravels. The model in this study is the first one for the Ambo town and essential as it can be useful for LULC planners and agriculture land managers to identify the delicate environmental systems and take proper measures. The

accuracy of the model is tested by comparing the actual 2020 LULC map with its simulated matching part using the 1990 and 2000 LULC maps. If a reform scenario is applied, agricultural land and forest land areas will increase as the government might measure conserve and plant forests.

The government will encourage the vertical expansion of the town through the apartment and condominium buildings hence, the built-up area and bare land will decrease in the coming ten years. Finally, if this scenario is applied, the livelihood of the society will be enhanced as the changes might bring modernization and changes in the Mode of living through industrialization, commercialization, social benefits and services, and employment opportunities, which will be environmentally sustainable and economically profitable for the Ambo Town

5. Conclusions

Remotely sensed images are vital in land-use and land-cover change detection as it provides spatial and temporal information of the land-use and land-cover condition for rapidly developing towns including Ambo Town. The main objective of this study was to assess the dynamics of urban land-use and land-cover of Ambo Town using Landsat satellites of 1990, 2000, 2010, and 2020 and predictions for 2030. Image classification and change detection assessment was also made to evaluate the change transitions. The accuracy assessment of 1990, 2000, 2010 and 2020 were 88.5%, 88.5%, 89% and 90% respectively. At the same time, the kappa coefficient of 1990, 2000, 2010, and 2020 were 0.84, 0.84, 0.85, and 0.86 respectively. The results of this study revealed the existence of significant land-use and land-cover changes in the last 30 years particularly the expansion of built-up land area increased and the declining of agricultural lands. The land-use transition from 1990 to 2020 has shown a dramatic change in several LULC categories. Built-up area, bare land, and forest land increased by 580 ha (56.86%), 47 ha (4.9 %), and 7 ha (0.69 %). On the other hand, agriculture showed a reduction of- 494 ha (-48.94 %) and respectively. Accordingly, more land was converted to the built-up area. The result indicated that an increase in a built-up area and bare land coverage of the town resulted from population pressure. There are also conducive government policies for encouraging and increasing green areas including afforestation. CA Markov modeling approach was also used to predict a land-use change in the future. To use the model for short-and long-term forecasting, the predictive ability of the model was also assessed. Regardless of the factors that might have had an impact on the

simulation output, it was inferred that the current trend of expansion of the built-up area would continue in the future. The Ambo Town urban land-use and land-cover change (built-up area) more expanded in Ambo kora, Sanqele, and faris, and Awaro, Gosu, and Areda kebele with alarming rate since 1990 that cause many problems such as deteriorating environmental quality, loss of prime agricultural lands, displacement of farm communities, enclosing surrounding rural land to the urban territory, overexploitation of usual possessions. As urban land, use is expanding to agricultural land and forest, alternative land use is disproportionality affected, which has an impact on productivity and environmental services. Therefore, the town administration has to apply the policy reform scenario suggested by this study that tremendously reduces urban expansions.

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Reference

Ackom, E. K., Amaning, K., Samuel, A., & Odai, N. (2020). Monitoring land - use and land - cover changes due to extensive urbanization in the Odaw River Basin of Accra , Ghana , 1991 – 2030. *Modeling Earth Systems and Environment*, *0123456789*. https://doi.org/10.1007/s40808-020-00746-5

Angessa, A. T., Lemma, B., & Yeshitela, K. (2019). Land-use and land-cover dynamics and their drivers in the central highlands of Ethiopia with special reference to the Lake Wanchi watershed. *Geojournal*. https://doi.org/10.1007/s10708-019-10130-1

Araya, Y. (2009). *Urban Land Use Change Analysis and Modeling: A Case Study of Setúbal and Sesimbra, Portugal*. *September*, 72.

Ayele, A. (2017). Land Use and Land Cover Change Detection Analysis using Remote Sensing Techniques : The Case of Hawassa Town , Southern Ethiopia. *A Thesis Project, Hawassa*

University, Ethiopia.

ERDAS. (2009). *ERDAS Field Guide ™ - Tutorial*. *November*, 810.

Fasika, A., Motuma, T., & Gizaw, T. (2019). Land Use Land Cover Change Trend and Its Drivers in Somodo Watershed South Western, Ethiopia. *African Journal of Agricultural Research*, *14*(2), 102–117. https://doi.org/10.5897/ajar2018.13672

Fekadu, D. (2017). *Addis Ababa Institute of Technology Addis Ababa Institute of Technology*. *June*, 1–100.

Kindu, M., Schneider, T., Döllerer, M., Teketay, D., & Knoke, T. (2018). Scenario modelling of land use/land cover changes in Munessa-Shashemene landscape of the Ethiopian highlands. *Science of the Total Environment*, *622–623*, 534–546. https://doi.org/10.1016/j.scitotenv.2017.11.338

Koranteng, A., Zawila-Niedzwiecki, T., & Adu-poku, I. (2016). Remote Sensing Study of Land Use / Cover Change in West Africa. *Journal of Environment Protection and Sustainable Development*, *2*(3), 17–31. http://www.aiscience.org/journal/jepsd

Leemhuis, C., Thonfeld, F., Näschen, K., Steinbach, S., Muro, J., Strauch, A., López, A., Daconto, G., Games, I., & Diekkrüger, B. (2017). Sustainability in the food-water-ecosystem nexus: The role of land use and land cover change for water resources and ecosystems in the Kilombero Wetland, Tanzania. *Sustainability (Switzerland)*, *9*(9). https://doi.org/10.3390/su9091513

Lepers, E. (2014). *D YNAMICS OF L AND -U SE AND L AND -C OVER C HANGE IN T ROPICAL R EGIONS*. *June*. https://doi.org/10.1146/annurev.energy.28.050302.105459

Li, X., Wang, Y., Li, J., & Lei, B. (2016). Physical and socioeconomic driving forces of land-use and land-cover changes: A Case Study of Wuhan City, China. *Discrete Dynamics in Nature and Society*, *2016*(2014). https://doi.org/10.1155/2016/8061069

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, *28*(5), 823–870. https://doi.org/10.1080/01431160600746456

Muzein, B. S. (2006). *Remote Sensing & GIS for Land Cover / Land Use Change Detection and Analysis in the Semi-Natural Ecosystems and Agriculture Landscapes of the Central Ethiopian Rift Valley*. *November 2006*.

Pickett, S. T. A., Cadenasso, M. L., Rosi-Marshall, E. J., Belt, K. T., Groffman, P. M., Grove, J. M., Irwin, E. G., Kaushal, S. S., LaDeau, S. L., Nilon, C. H., Swan, C. M., & Warren, P. S. (2017). Dynamic heterogeneity: a framework to promote ecological integration and hypothesis generation in urban systems. *Urban Ecosystems*, *20*(1), 1–14. https://doi.org/10.1007/s11252-016-0574-9

SIraj, M. mmo, HZang, Ke., & 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.

Tizora, P. C. (2018). Modelling land use and land cover change in the western cape of province. *Dissertation Submitted to University of Pretoria, South Africa*, *February*.

Ackom, E. K., Amaning, K., Samuel, A., & Odai, N. (2020). Monitoring land - use and land - cover changes due to extensive urbanization in the Odaw River Basin of Accra , Ghana , 1991 – 2030. *Modeling Earth Systems and Environment*, *0123456789*. https://doi.org/10.1007/s40808-020-00746-5

Angessa, A. T., Lemma, B., & Yeshitela, K. (2019). Land-use and land-cover dynamics and their drivers in the central highlands of Ethiopia with special reference to the Lake Wanchi watershed. *Geojournal*. https://doi.org/10.1007/s10708-019-10130-1

Araya, Y. (2009). *Urban Land Use Change Analysis and Modeling: A Case Study of Setúbal and Sesimbra, Portugal*. *September*, 72.

Ayele, A. (2017). Land Use and Land Cover Change Detection Analysis using Remote Sensing Techniques : The Case of Hawassa Town , Southern Ethiopia. *A Thesis Project, Hawassa University, Ethiopia*.

ERDAS. (2009). *ERDAS Field Guide ™ - Tutorial*. *November*, 810.

Fasika, A., Motuma, T., & Gizaw, T. (2019). Land Use Land Cover Change Trend and Its

Drivers in Somodo Watershed South Western, Ethiopia. *African Journal of Agricultural Research*, *14*(2), 102–117. https://doi.org/10.5897/ajar2018.13672

Fekadu, D. (2017). *Addis Ababa Institute of Technology Addis Ababa Institute of Technology*. *June*, 1–100.

Kindu, M., Schneider, T., Döllerer, M., Teketay, D., & Knoke, T. (2018). Scenario modelling of land use/land cover changes in Munessa-Shashemene landscape of the Ethiopian highlands. *Science of the Total Environment*, *622–623*, 534–546. https://doi.org/10.1016/j.scitotenv.2017.11.338

Koranteng, A., Zawila-Niedzwiecki, T., & Adu-poku, I. (2016). Remote Sensing Study of Land Use / Cover Change in West Africa. *Journal of Environment Protection and Sustainable Development*, *2*(3), 17–31. http://www.aiscience.org/journal/jepsd

Leemhuis, C., Thonfeld, F., Näschen, K., Steinbach, S., Muro, J., Strauch, A., López, A., Daconto, G., Games, I., & Diekkrüger, B. (2017). Sustainability in the food-water-ecosystem nexus: The role of land use and land cover change for water resources and ecosystems in the Kilombero Wetland, Tanzania. *Sustainability (Switzerland)*, *9*(9). https://doi.org/10.3390/su9091513

Lepers, E. (2014). *D YNAMICS OF L AND -U SE AND L AND -C OVER C HANGE IN T ROPICAL R EGIONS*. *June*. https://doi.org/10.1146/annurev.energy.28.050302.105459

Li, X., Wang, Y., Li, J., & Lei, B. (2016). Physical and socioeconomic driving forces of land-use and land-cover changes: A Case Study of Wuhan City, China. *Discrete Dynamics in Nature and Society*, *2016*(2014). https://doi.org/10.1155/2016/8061069

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, *28*(5), 823–870. https://doi.org/10.1080/01431160600746456

Muzein, B. S. (2006). *Remote Sensing & GIS for Land Cover / Land Use Change Detection and Analysis in the Semi-Natural Ecosystems and Agriculture Landscapes of the Central Ethiopian Rift Valley*. *November 2006*.

Pickett, S. T. A., Cadenasso, M. L., Rosi-Marshall, E. J., Belt, K. T., Groffman, P. M., Grove, J. M., Irwin, E. G., Kaushal, S. S., LaDeau, S. L., Nilon, C. H., Swan, C. M., & Warren, P. S. (2017). Dynamic heterogeneity: a framework to promote ecological integration and hypothesis generation in urban systems. *Urban Ecosystems*, *20*(1), 1–14. https://doi.org/10.1007/s11252-016-0574-9

SIraj, M. mmo, HZang, Ke., & 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.

Tizora, P. C. (2018). Modelling land use and land cover change in the western cape of province. *Dissertation Submitted to University of Pretoria, South Africa*, *February*.