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Rate of Land use land cover Changes of Setema District Jimma Zone South west, Ethiopia

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***Abstract*—**LULCC is the result of the long-time process of natural and anthropogenic activities that have been practiced on the land. The study intended to carry out the rate of land use /land cover changes, trends, and their magnitude over the last 30 years (1988-2018). The study has initiated loss of biodiversity (used for food, fuelwood, construction medicine, etc.) and wetland expansion to agricultural land. The study has used QGIS software 2.18.3. SCP plug-in extension 5.4.2 and MOULUSCE plug-in extended version.3 for image detection, classification, and Simulation. The LULCC classification result revealed that at the base period of 1988 Land sat imagery, forest land (56.22%), grassland (15.7%), Agricultural land(23.13%), Bare land(0.03%), wetland (2.18), and Settlement land(1. 58%) were identified with their respective percentage. On the contrary in the recent period of 2018 land sat imagery forest land, grassland, wetland were decreased to (39.71%), (6.53%), (0.87%),(23.13%) respectively. The maps of 1998 and 2008 were used to simulate the LULC for 2018 using MOLUSCE available in QGIS software. The predicted result was compared with the classified LULC map of 2018 to validate the model. Finally, based on this, the prediction of future LULC for the years 2028 was performed. The outcomes of this study show that there would be decreasing in forestland; grassland and increasing in agricultural land and settlement area.

***Keywords*—** *Cellular Automata, Geographic Information system, Land use/land cover change, Modules for Land Use Change Evaluation, Quantum Geographical Information system, Semi-automatic Classification Plug-in.*

I. INTRODUCTION

The land use and land cover system (LULC) is an important part of the earth's surface, and LULC changes (LULCC) have significant impacts on human society, climate, biodiversity, hydrological cycles, biogeochemical processes [7,18,36]. Land use/land cover (LULC) information is seriously utilized for mapping environmental conditions and monitoring changes such as deforestation, land degradation, drought, or urbanization [8]. LULCC are being mostly influenced by government policies for economic development that promotes the expansion and promotion of agricultural production as well as infrastructure and urban growth [22].LULCC represents one of the key drivers of global environmental change. LULCC processes and anthropogenic drivers are still implemented in Dynamic Global Vegetation Models (DGVMs) and Earth System Models (ESMs), which assess processes and impacts of global environmental change such as the reports of the Intergovernmental Panel on Climate Change (IPCC) [26]. Knowledge about lands and land cover has become increasingly important as the nation plans to overcome the problems of disorganized, which is not controlled, affect the environment, damage farm and destruction of wetland. Land use data is essential for analyzing ecological processes and problems. Understand whether you want to improve your living conditions and standards, or update them in time. One of the prime prerequisites for better use of land is information on existing land use patterns and changes in land use through time [4]. The land is a mother for every living and non-living entity on the earth. LULCC is the result of a long-term process of natural and man-made activities on the earth. There are various natural events that alter the LULC such as weather, flooding, climate fluctuation, and fire and ecosystem dynamics [2]. In Ethiopia, deforestation of forest land and changed to agriculture is one of the major processes of LULC change. Though LULC change in Ethiopia a major problem on agricultural development; the country develop the strategy of Growth and Transformation Plan (GTP) developed by the Ministry of Finance and Economic Development (MoFED) and the 2011 Climate Resilient Green Economy strategy (CRGE)[23].

II. RELATED WORKS

Remote sensing data integrated with geographic information systems (GIS) and statistical analysis is an effective tool to identify, analyze and understand LULCC patterns [10, 21, 29, 34]. Many studies have proved to achieve good spatial modeling and prediction of the future LULCC through several models such as logistic regression, Cellular Automata, and agent-based [5,16,19,30,31,36]. Therefore, this study focuses on applying remote sensing data and GIS techniques integrated with the variables and LULCC model to analyze the LULCC patterns and the driving forces in the Setema district over 30 years from 1988-2018 in order to predict LULCC in 2028.

III.MATERIALS AND METHODS

Study area

The study area of Setema district is one of the Jimma zones located in the southwestern part and has 21 kebeles. Setema is bordered on the south by Gera, on the west by Sigmo, on the north by the Illubabor zone, and on the southeast by Gomma. The administrative center of the district is Gatira.The geographical location of the district is lying at 7°58'51"N and 36°12'36"E Southwest of Addis Ababa and Jimma at a distance of 450 km and 100 km respectively. The altitude of Setema district ranges from 2,250-3,010M a.s.l which the highest points are in the Damu Siga Mountain [14].

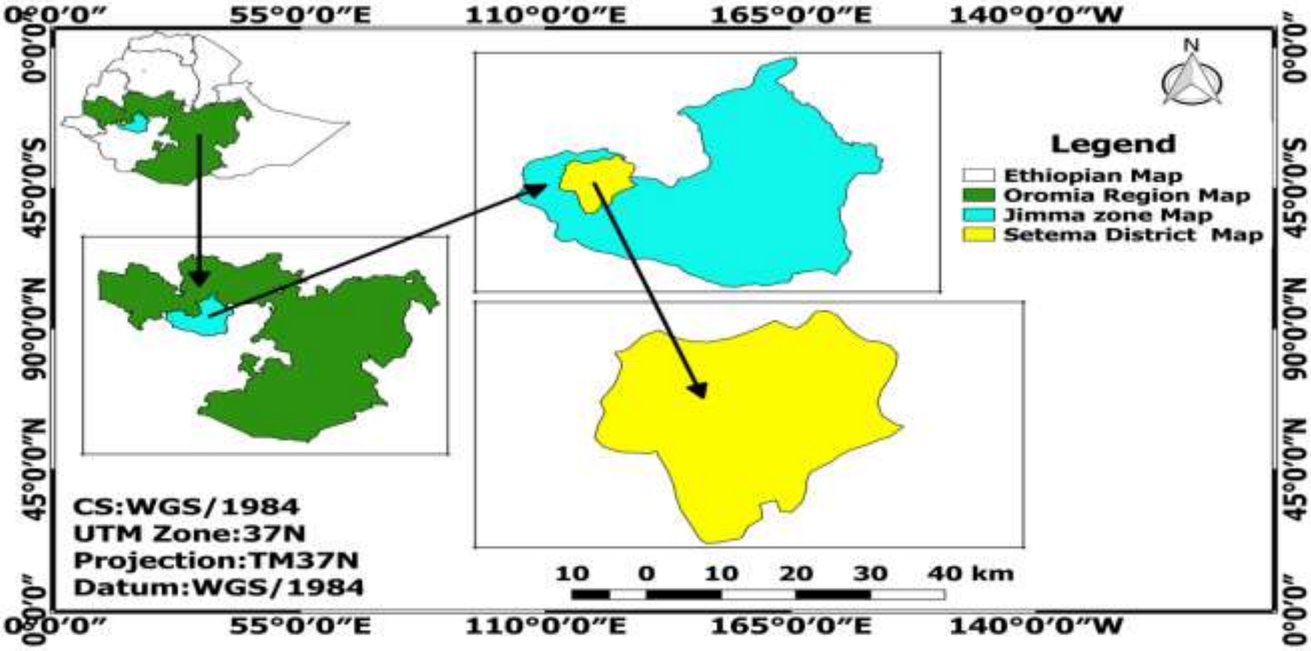

Figure: 3.1. Map of Study area

Methods of data collection

Secondary data of (remote sensing satellite image and Google earth data) were used to accomplish the objectives of the study area. Remote-sensing data were collected at different spatial and temporal scales. For this study, satellite imageries of land sat 5, the land sat 7 and land sat 8 were downloaded from the United States Geological Survey (USGS). In addition to satellite imageries, Google earth was used to extract information where the location is inaccessible to take sample point, to take the information for previously downloaded information whereas for overlaying of sample point collected from the study area which was first converted to CSV and KML by showing and moving time slider of Google Field data of land use classes were identified such as forestland, agricultural land, grassland, wetland, bare land, bushland, and settlement/build-up to assess the existing land use and land cover types and other environmental conditions in the study area. According to the rule of thumb, the minimum number of sampling units that should be collected is 50 sampling points for each land cover class, and although if land use land cover class area exceeds 500 km^2 and more than 12 land cover classes, the minimum number of sampling units that should be collected should be between 75 and 100 [9]. Consequently, because of the land use, the land cover of the study area is less than 12 classes 30,30,30,15,20,21 and 30 sampling points were collected for each forest land, agricultural land, grassland, wetland bare land, bushland, and settlement /build-up respectively depending on the size of land use land class by using Garmin GPS 72H and by using high resolution of Google Earth, for classification and accuracy assessment.

Method of Data analysis

Data analysis for GIS and Remote Sensing

Before the actual image classification process, image pre-processing was performed using QGIS image analysis software to remove and correct some geometric distortions, calibrate the data radiometrically, and eliminate the noise present in the data [27].

Therefore the downloaded image from earth explorer was preprocessed (stripe error were corrected for each band of land sat 7, stacked/merged of bands, clipped/subsetting to study area, and enhanced) whereas image enhancement was carried out to improve the appearance of the imagery to assists in image analysis, classification, and visual interpretation by making the downloaded image 432 red, green and blue (RGB) and 543 (RGB) false-color composite for Land Sat5 and land sat7 and Land Sat8 respectively [6] using linear contrast stretch/contrast enhancement with the help of QGIS software version 2.18.3 by using open/free QGIS software version 2.18.3.

Supervised classification usually requires a priori knowledge about the region/area, where ground truth data are collected for each land-use class [17]. In supervised classification, an analyst uses previously acquired knowledge of an area, or prior knowledge, to locate specific areas, or training sites, which represent homogeneous samples of known land use land cover types such as cropland, grassland, salt-affected and waterlogged, etc., [24]. Therefore to accomplish the objectives of classification supervised classification (Semi-automatic classification) was used MLC algorithm to classify the downloaded clipped image of the study area by using a three-band combination of red, green, and blue of (4, 3, and 2) false composite color for Land Sat5, land sat7 and three-band combination of red, green and blue (5, 4, 3) false composite color for land Sat8 respectively. The objective of the classification is to classify false composite color satellite image into Macro classes (Built-up, vegetation, water body, and soil) and micro classes (forest land class, grassland class, agricultural land class, bushland class, Settlement/build-up class, bare land class, and wetland class) by selecting region/area of interest (AOI) based on ground truth point/field data, reflection characteristics of the image, high resolution (Google Earth,) in which training point/ region/area of interest were gathered from a satellite image of 1988,1998,2008 and 2018 by using free software QGIS 2.18.3 version with semi-automatic classification plug-in(SCP).

Methods of LULCC Prediction

Prediction of LULCC of 2028

For LULC simulation the LULCC classification of 1998, 2008, proximity to the river, proximity to the road, and population density of 2000, 2005 and 2010 and 2015 were used to simulate LULC for 2018 whereas, 2008 LULC classification, 2018 LULC classification, proximity to the river, proximity to the road population density of 2010 and 2015 were used to simulate LULC for 2028 (See figure 3.2 and 3.3).It is important to estimate the predictive ability and reliability of the model. Therefore, simulated LULC in 2018 was conducted from the transitional potential of the LULC map for time t1 (1998) and for time t2 (2008) to predict LULC for time t3 (2018). Then the result was validated between the simulated LULC in 2018 and the reference map in 2018 (classified LULC map of 2018). Therefore, the validated result achieved an acceptable accuracy, and then 2028 LULCC would be simulated and conducted. The simulated LULCC of 2018 and 2028 were carried out in the QGIS MOLUSCE extension plug-in.

Proximate to R and road sources

The proximate to water sources and proximate to the road were digitized using an open street map and Google satellite which is used for livestock and for a population living in the study area and connecting kebele to kebele in the study area respectively. Then digitized river and road were rasterized using 30m*30 m cell size resolution and its distance was calculated by Euclidean distance using Grass tools (See figure 3.2)

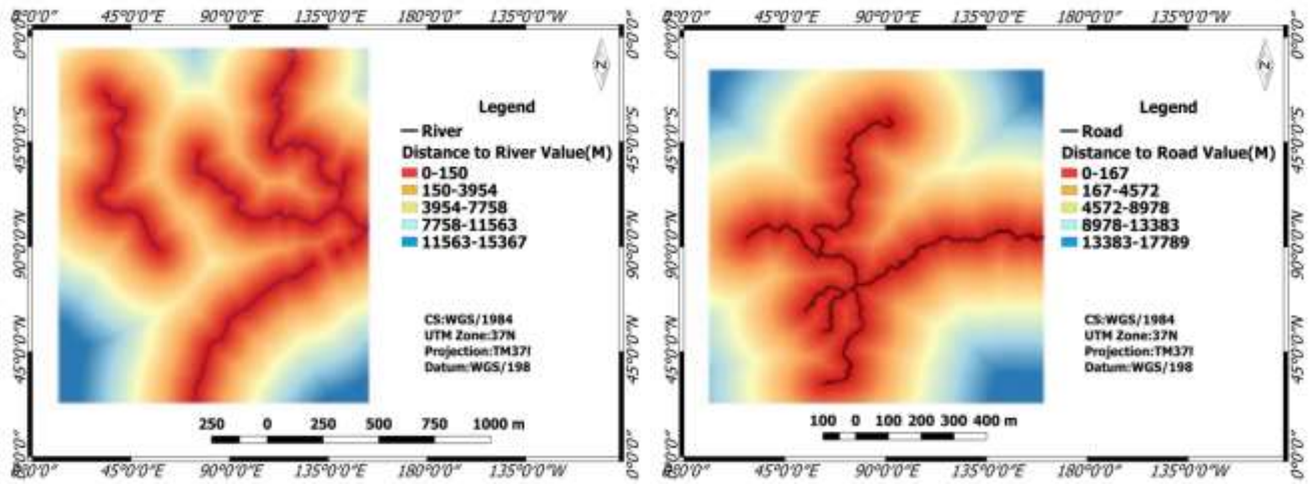

Figure 3.2.Distance to road and distance to river map (left and right)

Population density data

The population density is an important variable for LULCC analysis [34]. Therefore, the population density data was downloaded from Socioeconomic Data and Application Center (SEDAC) site using Gridded population of world Version

4(GPWv4) for Global UN- Adjust Population Density in the years of 2000, 2005, 2010, and 2015 with a cell size 1x1 km resolution [28] were re-projected to WGS 84 UTM zone (EPSG: 32637) using QGIS 2.18 software. Then the population density data was clipped and resized to 30x30m pixel size resolution and resized population density data were classified using QGIS 2.18 to estimate number the population density of the study area per square kilometer. Therefore the minimum and maximum population density per square kilometer for the period 2000,2005,2010,2015 were showed in (See figure 3.3) which red color shows minimum population density per square kilometer and blue color shows maximum population density per square kilometer.

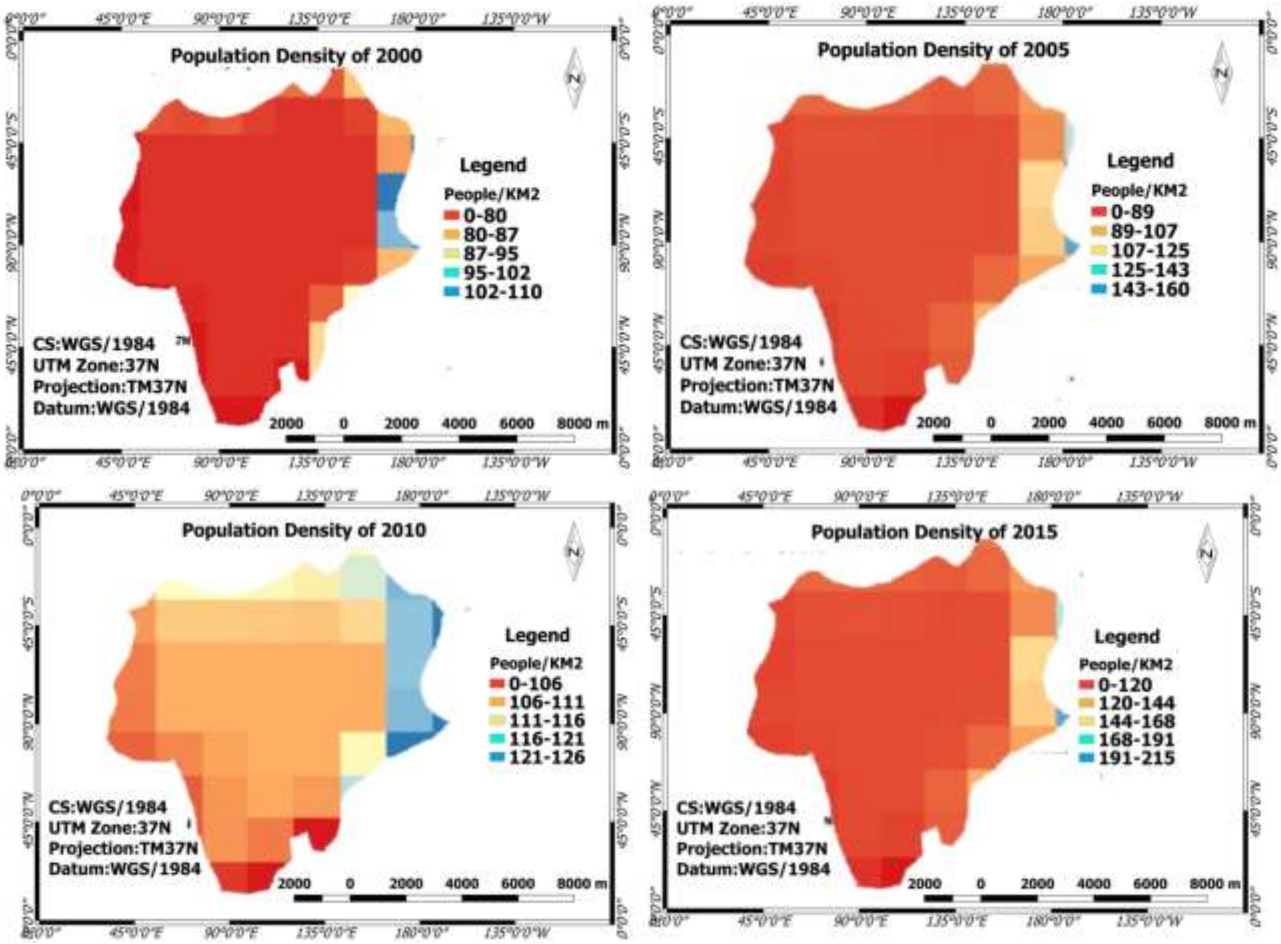

Figure 3.3.Population density map of 2000, 2005, 2010 and 2015

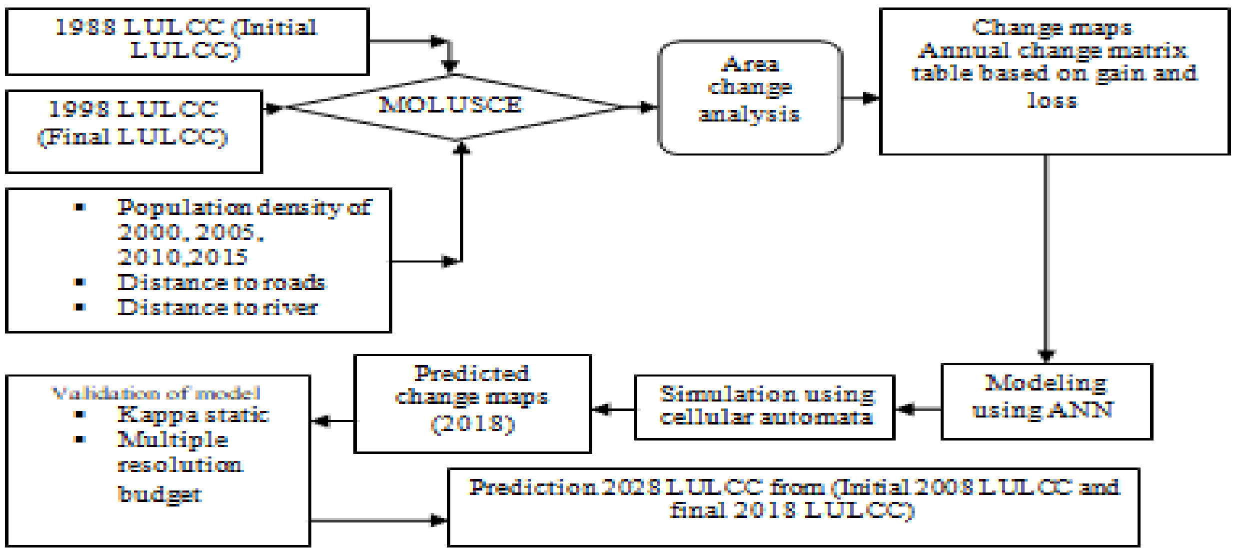

Figure 3.4: Methodological flow chart for future land use land cover prediction

IV.RESULTS AND DISCUSSION

Analyzing the trend, magnitude, and rate of LULCC of the study area (1988-2018)

Four LULC maps were produced for the years 1988, 1998, 2008, and 2018 and seven LULCC were identified and classified: forestland (FL), grassland (GL), agricultural land(AL), settlements(SL), bushland(BL), wetland cover(WL) and bare land cover(BL) (Fig. 4.1).

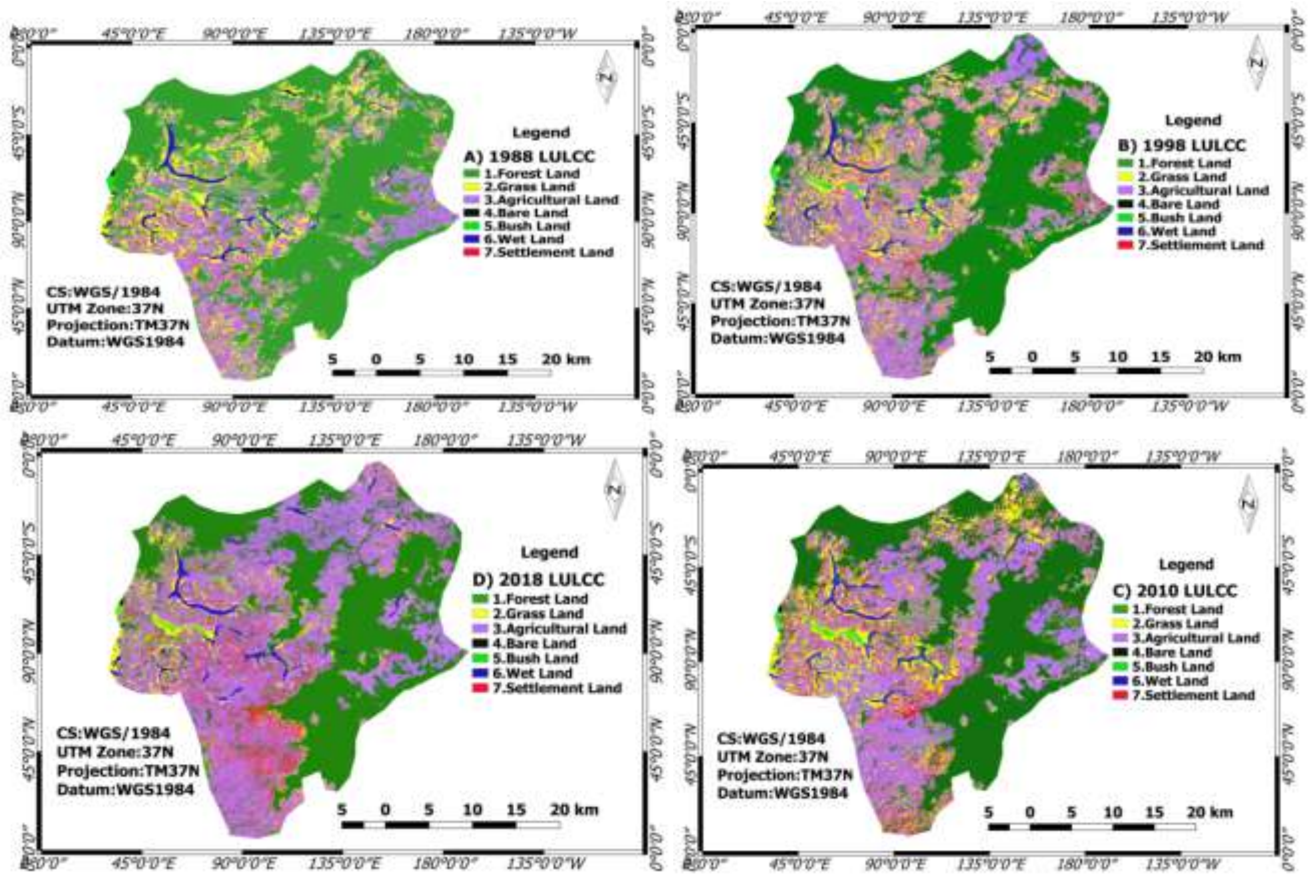

Fig 4.1 Spatial distribution LULCC of Setema district (1988- 2018).

Generally, over thirty years (1988-2018), the gross changes in hectares (loss and gain) and percentage change in the study area varied from one LULC class to another whereas the transition matrix was also varied from period to period which is computed by using Modules for Land Use Change Evaluation (MOLUSCE) Plug-in extension version 3 (Figure. 4.2 and 4.3).

In the study area at the base year (1988) from the total area of 110458 hectares the area was covered by dense forest 62104.4 ha-1 (56.22%) followed by grassland 17416 ha-1 (15.77%) and wetland 2409.48 ha-1 (2.18%); the other LULC of bare land, agricultural land, settlement land, bushland together accounted for 28,528.72 (25.82%); however, in the recent year (2018) forest cover 43867 ha-1 (39.71%) were declining in alarming rate followed by grassland cover 7208 ha-1 (6.53%) and wetland 2335.23 ha-1 (2.11%) (Table.4.1).

The analysis of land use and land cover change during the period of 1988–1998 and 2008-2018 showed that there was a significant decrease in the forest, with a consequence of an increase in agricultural land and settlement land (Table 4.2).
Between 1988-2018 periods there were increasing in agricultural land, settlement area, and bare land from (23.13%) to (43.89%), from (1.58%) to (6.85%) respectively (Table 4.1). During the same period, agricultural land and settlement land were changed from (23.13%) to (43.89%), from (1.58%)ha-1 to (6.85%).

In the period between 1998-2008 (Table 4.1) the total area of forest land cover, grassland cover was decreased from 51415.9 ha-1 to 46259.9 ha-1 from 17298.1 ha-1 to 15899.5 ha-1 respectively with magnitude area and percentage change of -5156 ha-1(-4.66%),-1399 ha-1(-1.26%,) respectively (Table 4.2). The annual decreasing rate of forest land cover and grassland cover change between 1998-2008 was (-0.466%), (-0.126%) respectively per year in the study area (Table 4.3). Similarly, during the period between 1998-2008 (Table 4.1) agricultural land cover, Settlement land cover, and bare land were increased from 34718.0 ha-1 to 38853.3, from 3442.23 ha-1 to 5928.62ha-1 and from 39.06 ha-1 to 42.48ha-1 in which the magnitude trend of 413.53ha-1 (0.373%), 248ha-1 (0.225%) and 0.342 ha-1 (0.0%) respectively with annual increase per year (Table 4.3).

Table (4.1) in the time period from 2008 to 2018 the change of land use the land cover of the study showed that there is an increase in area coverage/proportion of agriculture land cover, Settlement/build-up, and bare land cover from 38853.3 ha-1 (35.17%) to 48480.5 ha-1 (43.89%), from 5923.62 ha-1(5.37%) to 7562.79 ha-1(6.85%) and 42.48 ha-1to 44.82 ha-1respectively.During this period there is also decline of forest land cover, grassland cover, bushland cover and wetland cover (Table 4.1) changed from 46259.9 ha-1 (41.88%) to 43867 ha-1 (39.71%),from 15899.5 ha-1 (14.39%) to 7208 ha-1 (6.53%), from 1075.05 ha-1 (0.97%) to 959.40 ha-1 (0.87%) and from 2398.59 ha-1 (2.17%) to 2335.23 ha-1 (2.11%) with the area change and percentage change of -2392 ha-1(-1.30%),-8691 ha-1(-4.74%),-115 ha-1(-0.06%) and-63.36 ha-1(-0.03%) respectively (Table 4.3).Between 2008 and 2018 the annual decreasing rate of forest land cover, grassland cover, bush land cover and wetland cover were -239.2ha-1(-0.216%),-869.1ha-1(-0.786%),-11.5ha-1(-0.01%)and-6.336ha-1(-0.0053%) respectively; whereas annual increasing rate of agricultural land cover, and settlement cover were 962.72 ha-1 (0.875%), 163.91 ha-1(0.1480%), 204.88 ha-1 (0.111%) and 0.292 ha-1 (0.0%) respectively per year.(Table 4.3). The expansion of wetland and bush land between 1988-1998 and 1988-2008 were insignificant (Table 4.3.) which were absent.
Generally, forest land is the major LULC of the area in the 1988 period in relation to the total coverage area of the land whereas; agricultural land is the major LULC of the area in the 2018 period in relation to total area coverage of LULCC.

Table 4.1: Categories and patterns of Land Use/Land Cover of study area.

Land use Land cover Classes	1988		1998		2008		2018	
	ha^{-1}	(%)	ha^{-1}	%	ha^{-1}	%	ha^{-1}	%
FL	62104.4	56.22	51415.9	46.55	46259.9	41.88	43867	39.71
GL	17416	15.77	17298.1	15.66	15899.5	14.39	7208	6.53
AL	25553.5	23.13	34718	31.43	38853.3	35.17	48480.5	43.89
BL	37.98	0.03	39.06	0.04	42.48	0.04	44.82	0.04
BUL	1196.91	1.08	1138.14	1.03	1075.05	0.97	959.4	0.87
WL	2409.48	2.18	2406.15	2.18	2398.59	2.17	2335.23	2.11
SE	1740.33	1.58	3442.23	3.12	5928.62	5.37	7562.79	6.85
Total	110458	100.	110458	100.	110458	100	110458	100.

Note: FL= Forest land, GL=Grass land, AL=Agricultural Land, BL=Bare Land, BUL=, Bush land, WL=Wetland, SL=Settlement land

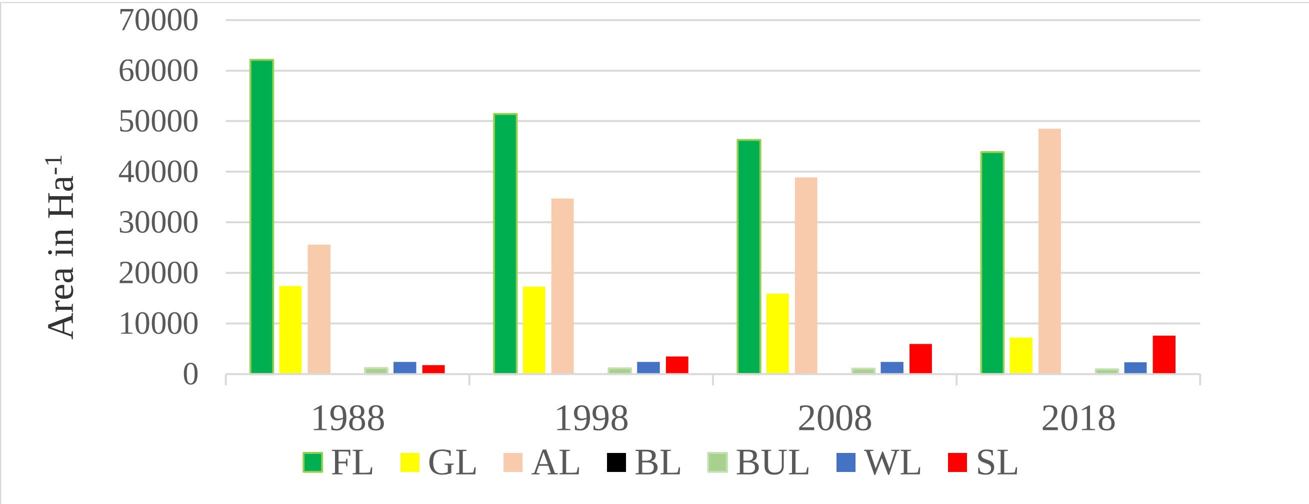

Figure.4.2 Chart of Land use land cover classification map of 1988, 1998, 2008 and 2018.

Table 4.2:Trend and Magnitude of Land Use /Land Cover change in 1988-1998, 1998-2008, 2008-2018, 1988-2018

Land Cover classes	1988-1998		1998-2008		2008-2018.		1988-2018	
	Δ Area(ha)	Δ %	Δ Area(ha)	Δ %	Δ Area(ha)	Δ %	Net Δ Area(ha)	Net Δ %
FL	-10688.4	-9.96	-5156	-4.66	-2392	-2.16	-18237.06	-16.5
GL	-117.9	-0.1	-1399	-1.26	-8691	-7.86	-10207.53	-9.2
AL	9164.52	8.1	4135.3	3.73	9627.2	8.75	22927.05	20.78
BL	1.08	0	3.42	0	2.34	0	0.020716	0.0062
BUL	-58.77	-0.05	-63.09	-0.04	-115	-0.1	-237.51	-0.21
WL	-3.33	0	-7.56	0	-63.36	-0.05	-74.25	-0.077
SL	1701.9	1.54	2481	2.25	1639.1	1.48	5822.46	5.28

Note: FL= Forest land, GL=Grass land, AL=Agricultural Land, BL=Bare Land, BUL=, Bush land, WL=Wetland, SL=Settlement land

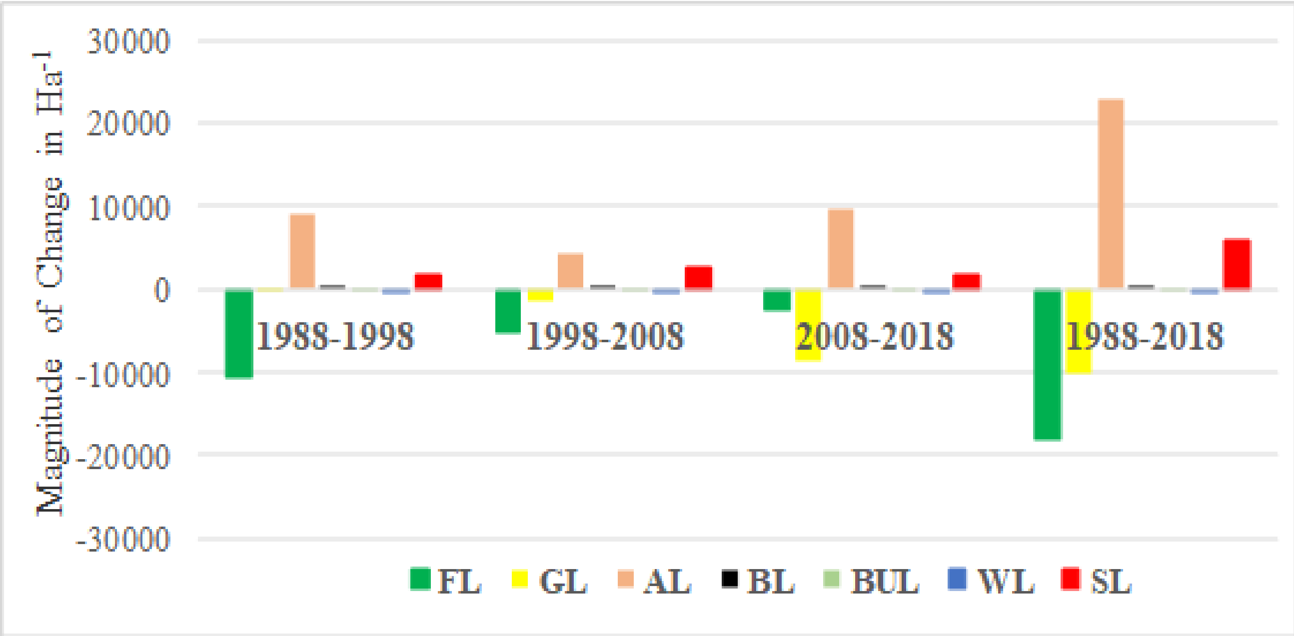

Figure 4.3. Changes of LULC classes between 1988-1998, 1998-2008, 2008-2018, 1988-2018

Table 4.3: Rate of Land Use/ Land Cover Change in 1988-1998, 1998-2008, 2008-2018, 1988-2018

Land Cover classes	1988-1998		1998-2008		2008-2018.		1988-2018	
	Δ Area(ha)/ year	Δ in%/ year.	Δ Area(ha)/ year	Δ in %/ year	Δ Area(ha)/year	Δ in %/ year	Δ Area(ha)/ year	Δ in %/ year.
FL	-1068.84	-0.996	-515.6	-0.466	-239.2	-0.216	-1823.706	-1.65
GL	-11.79	-0.01	-139.9	-0.126	-869.1	-0.786	-1020.753	-0.92
AL	916.452	0.81	413.53	0.373	962.72	0.875	2292.705	2.078
BL	0.108	0	0.342	0	0.234	0	0.00207	0.00062
BUL	-5.877	-0.005	-6.309	-0.004	-11.5	-0.01	-23.751	-0.021
WL	-0.333	0	-0.756	0	-6.336	-0.005	-74.25	-0.0077
SL	170.19	0.154	248.1	0.225	163.91	0.148	582.246	0.528

The overall accuracy of the classified image 1988, 1998, 2008 and 2018 were 82.6%, 85.5%, 87.6%, and 91.06% respectively with kappa coefficient of 0.796, 0.829,0854 and 0.984 which is attained kappa coefficient perfect (0.81-1.00) [9]. (Table 4.4-6) The reason why the producer's accuracy and user's accuracy were computed because the overall accuracy of the map does not always represent the accuracy of the individual class. For instance, in (Table 4.4) the higher users accuracy of agricultural land (87.5%) and lower producer accuracy (66.4%) implies that there the gain of agricultural land in map classification and gain in reference data whereas, the higher producers accuracy of forest land (93.8%) and the lower user's accuracy (89.2%) implies that the more forest loss in map classification and lost in reference data.(Table 4.8-10) shows the conversion matrix of land use land cover in which pixels change from one of LULC type to another (from the period of 1988-1998, 1998-2008, and 2008-2018.

Table 4.4. Confusion matrix for LULC of 1988

LULC Classes		Ground truth reference							Total	UA (%)
		FL	GL	AL	BL	BUL	WL	SL		
Classified image	FL	**107**	3	2	0	8	0	0	120	89.2
	GL	0	**113**	4	0	0	0	3	120	94.2
	AL	0	8	**105**	0	0	0	7	120	87.5
	BL	0	0	10	**65**	0	0	5	80	81.3
	BUL	7	3	2	0	**75**	0	0	85	88.2
	WL	0	3	2	0	0	**55**	0	60	92
	SL	0	7	35	11	4	0	**63**	120	52.5
Total		114	137	158	76	87	55	78	705	
PA (%)		93.8	82.4	66.4	85.5	86.	100	80.7		
OA (%)	82.6 %									
Kˆ (%)	79.60%									

Table .4.5.Confusion matrix for LULC of 1998

LULC Classes		Ground truth reference							Total	UA (%)
		FL	GL	AL	BL	BUL	WL	SL		
Classified image	FL	105	2	1	0	9	0	3	120	87.5
	GL	2	**114**	0	0	0	1	3	120	95.0
	AL	0	7	**104**	3	1	2	3	120	86.6
	BL	0	0	7	**68**	0	0	5	80	85.0
	BUL	6	3	2	0	**74**	0	0	85	87.0
	WL	3	0	0	0	6	**51**	0	60	85.0
	SL	0	3	17	13	0	0	**87**	120	72.5
Total		116	129	131	84	90	54	101	705	
PA		90.5	88.3	79.3	76.9	82.2	94.4	86.1		
OA	85.5 %									
Kˆ	82.9%									

Table. 4.6 Confusion matrix for LULC of 2008

LULC Classes		Ground truth reference							Total	UA (%))
		FL	GL	AL	BL	BUL	WL	SL		
Classified image	FL	**97**	6	3	0	9	0	5	120	80.8
	GL	2	**104**	4	0	0	3	7	120	86.6
	AL	0	2	**108**	4	0	0	6	120	90.0
	BL	0	2	6	**69**	0	0	3	80	86.2
	BUL	5	1	3	0	**76**	0	0	85	89.4
	WL	2	0	0	0	1	**57**	0	60	95.0
	SL	0	3	4	5	1	0	**107**	120	89.1
Total		104	120	128	78	87	60	128	705	
PA (%)		93.2	86.6	84.3	88.4	87.3	95.0	83.5		
OA (%)	87.65%									
Kˆ (%)	85.47%									

Table.4.7. Confusion matrix for LULC of 2018

LULC Classes		Ground truth reference							Total	UA (%)
		FL	GL	AL	BL	BUL	WL	SL		
Classified image	FL	**112**	2	2	1	3	0	0	120	93.3
	GL	0	**115**	0	0	2	3	0	120	95.8
	AL	0	2	**105**	3	3	0	7	120	87.5
	BL	0	2	3	**71**	0	0	4	80	88.7
	BUL	4	1	0	3	**77**	0	0	85	90.5
	WL	2	5	0	0	0	**53**	0	60	88.3
	SL	0	3	3	5	0	0	**109**	120	90.8
Total		118	130	113	83	85	56	120	705	
PA (%)		94.9	88.4	92.9	85.5	90.5	94.6	90.8		
OA (%)	91.06%									
Kˆ (%)	89.4%									

PA=producer accuracy, A=over all accuracy, Kˆ =Kappa coefficient, A=User accuracy, FL= Forest land, GL=Grass land, AL=Agricultural Land, BL=Bare Land, BUL=, Bush land, WL=Wetland, SL=Settlement land

Table.4.8: LULC conversion matrix of LULCC 1988-1998

LULCC	FL	GL	AL	BL	BUL	WL	SE
FL	**0.765251**	0.015057	0.197164	0.000020	0.003110	0.002311	0.017086
GL	0.018138	**0.506129**	0.422078	0.000181	0.010366	0.008454	0.024654
AL	0.011697	0.024874	**0.894119**	0.000004	0.010619	0.004593	0.054095
BL	0.030806	0.049763	0.009479	**0.736967**	0.144550	0.002370	0.000000
BUL	0.029858	0.023103	0.271593	0.005489	**0.603560**	0.002033	0.064363
WL	0.035896	0.075713	0.060772	0.000000	0.017182	**0.801098**	0.009338
SE	0.000998	0.014925	0.003479	0.000000	0.003239	0.009981	**0.967378**

Table.4.9: LULC conversion matrix of LULCC between 1998 – 2008

LULCC	FL	GL	AL	BL	BUL	WL	SE
FL	**0.783881**	0.043938	0.140351	0.000053	0.004362	0.003093	0.024322
GL	0.070977	**0.651270**	0.238809	0.000239	0.007128	0.009797	0.021737
AL	0.009122	0.002561	**0.922487**	0.000075	0.006092	0.003699	0.055844
BL	0.004608	0.057419	0.006912	**0.857327**	0.069124	0.004608	0.000000
BUL	0.043037	0.025336	0.055180	0.003163	**0.851039**	0.004605	0.017640
WL	0.018676	0.065468	0.099633	0.000000	0.009650	**0.790077**	0.016458
SE	0.000963	0.013162	0.007260	0.000183	0.006458	0.004236	**0.967555**

Table.4.10: LULC conversion matrix of 2008-2018

LULCC	FL	GL	AL	BL	BUL	WL	SE
FL	**0.807021**	0.024951	0.139465	0.000006	0.005817	0.003811	0.018928
GL	0.016663	**0.321147**	0.593869	0.000102	0.003379	0.003089	0.061751
AL	0.001167	0.057544	**0.918464**	0.000009	0.002252	0.003336	0.017228
BL	0.018136	0.069915	0.014407	**0.863220**	0.023136	0.004831	0.006356
BUL	0.054793	0.086898	0.106266	0.006949	**0.705638**	0.005634	0.033822
WL	0.001087	0.057071	0.209636	0.003865	0.009041	**0.694554**	0.004559
SE	0.004866	0.015332	0.006557	0.000030	0.003464	0.007597	**0.982154**

Note: FL= Forest land, GL=Grass land, AL=Agricultural Land, BL=Bare Land, BUL=, Bush land, WL=Wetland, SL=Settlement land

LULCC prediction using Cellular automata

Cellular automata are a simple way of modeling type which allow detailed mathematical analysis to estimates the taken time in transition that can generate complex spatial patterns from the simple set of rules and predicts LULCC in the future [32]. (Figure 4.4) shows modeling of land use cover of the study area by using Cellular Automata modeling which was used distance to road rasterized input data, population density map of 2000,2005, and 2015, classified satellite image map of 1998 and 2008. Therefore the simulation of the training artificial neural networks (ANN) with the help of Multi-Layer Perceptron (MLP) was used. At the end of the training artificial neural networks process, the minimum validation error was calculated as 0.01172 and the validation kappa value was 0.81150.

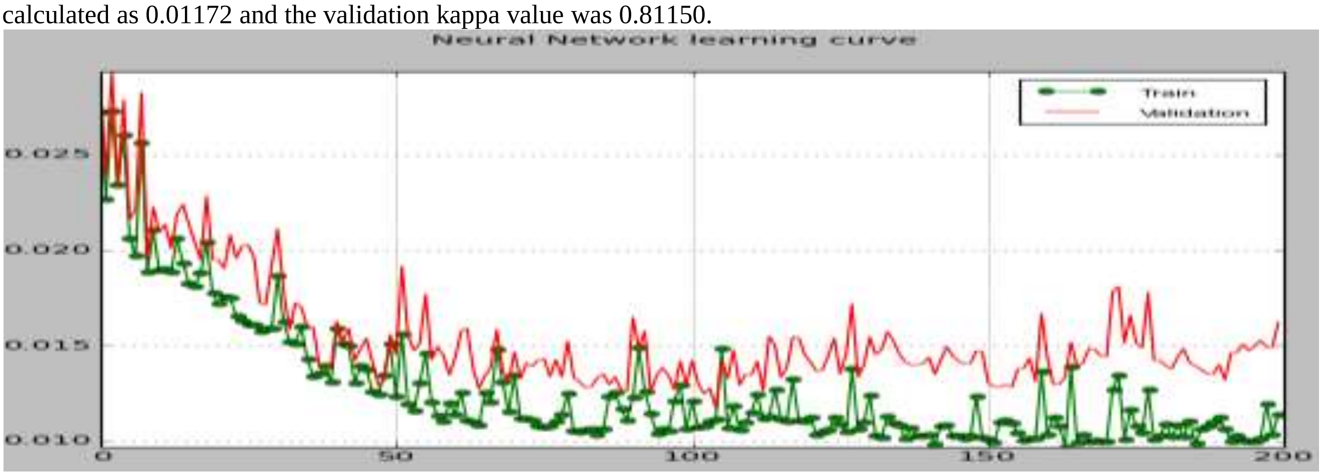

Figure 4.4. Neural Network learning curve

Prediction of 2018 LULCC

Table (4.11) shows the 2018 LULCC which was simulated from the initial period (1998) and final period (2008) for calculation of accuracy and kappa statics which is used for prediction of LULCC for the year of 2028 by using MOLUSCE plug-in extension [12].Then simulated map of 2018 and classified map 2018 which was used as reference was compared for validation and for the prediction of 2028.

Table 4.11. Changed areas in hectare and in percent between the references LULC map 2018 and the simulated LULC map 2018

LULCC Classes	Reference/Classified LULCC in 2018		Predicted/Simulated LULCC in 2018	
	ha^{-1}	%	ha^{-1}	%
Forest land	43867.4	39.71	43866.4	39.71
Grass land	7208.55	6.53	7207.55	6.53
Agricultural land	48480.6	43.89	48484.6	43.89
Degraded land	44.82	0.04	43	0.04
Bush land	959.40	0.87	959.2	0.87
Wetland	2335.23	2.11	2335.13	2.11
Settlement land	7562.79	6.85	7561.79	6.85

Validation of Model

For the validation of the model overall kappa and multiple resolution budget and were used to check, compare and validate simulated image (2018) from 1998 and 2008 by using actual land use pattern/ classified image (2018) as reference map and simulated map of 2018 [20] whereas, image correlation coefficient (r) between two images was also calculated by MOLUSCE extension plug-in to determine the similarities between the two images. According to [11] suggests for the absolute value of correlation: 0.00-0.19 "very weak".20-0.39 "weak 0.40-0.59 "moderate"0.60-0.79 "strong"0.80-1.0 "very strong" Therefore the results of the correlation coefficient gave a value of 0.808 which indicate very strong correlation of classified map of 2018 and simulated map of 2018, which indicates a good positive relationship between the two images and acceptable for the prediction of 2018 maps as shown in (Table.4.12.).The multiple resolutions are the accuracy in location and in the quantity of the reference map and the simulated map that corresponds to the agreement and disagreement component between two maps [25].

According to [25], the most important plot is "perfect location, medium quantity inform" where the plot is almost 1 means the perfect location and medium quantity information are almost 100% between both maps (reference map and simulated map) in which the perfect location is a grid cell level information of the reference map that has a perfect location in the simulated map and medium quantity is the reference map that has the same quantity as the simulated map which is considered as a good agreement. Therefore for this study, because the total value (overall correctness) is 79.1%,(Table 4.13) which indicates that the Substantial agreement of the simulated LULC map in 2018 with comparison map of 2018 and Multi-resolution budget accuracy result of the 2018 reference map and 2018 comparison map are shows good agreement and perfect location, medium quantity inform" then, the prediction of 2028 LULCC was acceptable (Figure.4.5).

Table .4.12. Image correlation matrix.

	2018 classified reference map	2018 Simulated map
2018 Classified reference map	1	0.808
2018 Simulated map	0.808	1

Table 4.13. Kappa and correctness of the simulated LULC map in 2018

Simulated LULC map in 2018	
Correctness	79.1%
Kappa (overall)	0.708
Kappa (histogram)	0.934
Kappa (location)	0.758

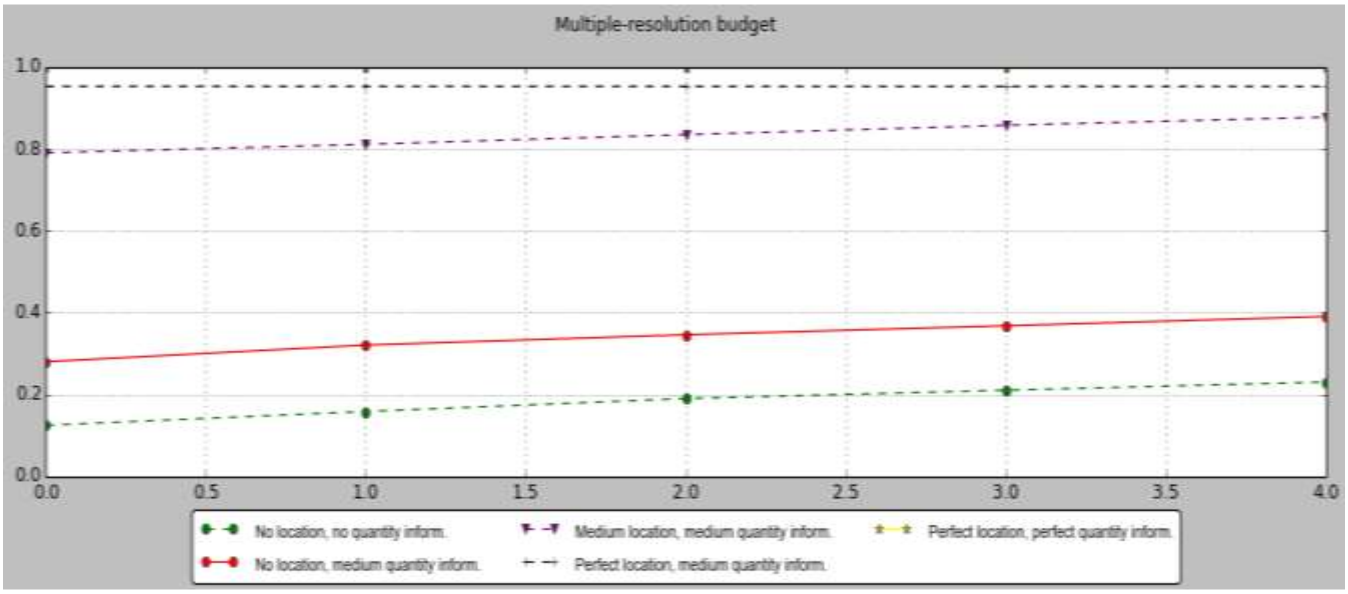

Figure 4.5: Multi-resolution included 4 plots of simulated LULC in 2018

Prediction of future LULC for the year 2028

After the change detection of LULC classes and validation were checked by overall correctness, correlation of the image checked (2018 classified and simulated), and Multiple resolution budget in which overall correctness and Multiple resolutions budget the study was aimed for prediction of the next ten future land use land cover changes for the year of 2028 from the initial period (2010) and final period (2018). Then future predicted land use classification map of 2028 was compared with the actual classification map of the year 2018 (Figure 4.6 and Table 4.14).

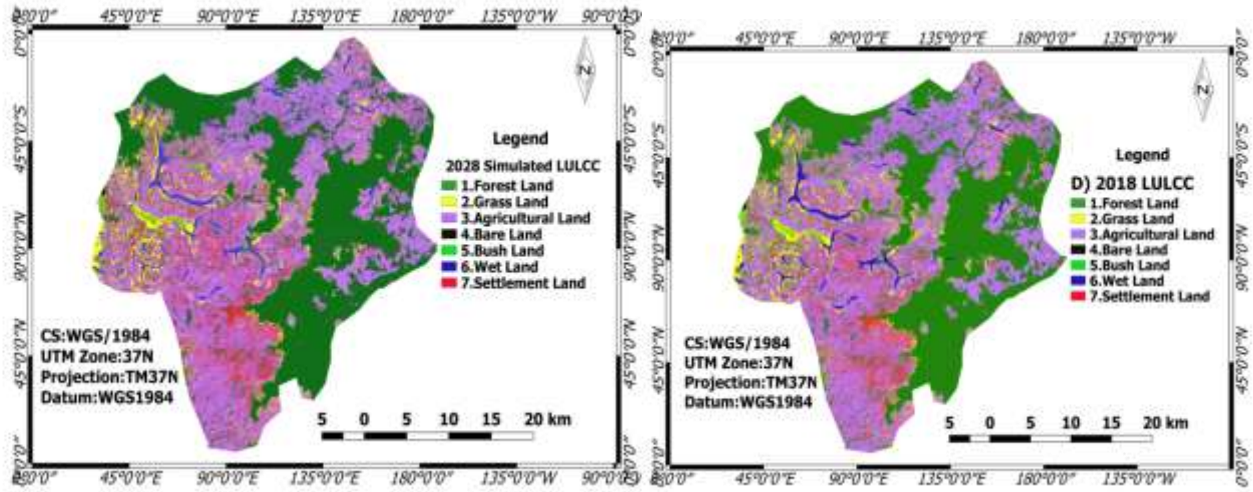

Figure 4.6. Land use land cover map in 2018 and simulated land use land cover in 2028 (Left and Right)

From the Table (4.14) the result of simulated LULCC of 2028 shows there were decreasing forest land, grass land, bush land, and wet land from 43867.35ha^{-1} (39.71%) to 43516.17 ha^{-1}(39.39%), from 7208.55 ha^{-1} (6.53%) to 4335.75ha^{-1}(3.92%),from 959.40 ha^{-1} (0.87%) to 673.92 ha^{-1} (0.6%) from 2335.23 ha^{-1}(2.11%) to1592.46 ha^{-1}(1.4%) with area decreasing changed-351.18 ha^{-1}(-0.32%), -2872.80 ha^{-1} (-2.61%),-285.48 ha^{-1}(-0.27%) and-742.77 ha^{-1}(-0.71%) respectively, whereas agricultural land, bare land and settlement land were increased from 48480.57 ha^{-1} (43.89%),51406.43ha^{-1} (46.5%),from 44.82 ha^{-1}(0.04%) to 60.39 ha^{-1} (0.05%), from 7562.79 ha^{-1}(6.85%) to8873.24 ha^{-1} (8.03%) with area change increasing 2925.86ha^{-1} (2.57%),15.57 ha^{-1} (0.01%) and 1310.45 ha^{-1} (1.18%) respectively .

Table 4.14: LULC Changed areas in Ha^{-1} and % between LULC in 2018 and 2028

LULCC Classes	LULCC in 2018		Predicted LULCC in 2028		Change in LULCC	
	Δ ha^{-1}	Δ %	Δ ha^{-1}	Δ %	Δ ha^{-1}	Δ %
Forest land	43867.35	39.71	43516.17	39.39	-351.18	-0.32
Grass land	7208.55	6.53	4335.75	3.92	-2872.80	-2.61
Agricultural land	48480.57	43.89	51406.43	46.5	2925.86	2.57
Bare land	44.82	0.04	60.39	0.05	15.57	0.01
Bush land	959.40	0.87	673.92	0.6	-285.48	-0.27
Wet land	2335.23	2.11	1592.46	1.4	-742.77	-0.71
Settlement Land	7562.79	6.85	8873.24	8.03	1310.45	1.18

V.CONCLUSION

Based on information of satellites classified image integrated with GIS, field observation and ground control point the study was conducted to identify LULCC, to analyse rate of land use land cover change for 30 years (1988-2018) as well as prediction of LULCC for the year 2028 LULCC by using spatial variables, remotes sensing satellite classified map with the help of QGIS software 2.18.3 and MOLUSCE extension plug-in of version 3.Therefore based on downloaded satellite image classification, forest land cover, grassland cover, bush land cover and wetland cover were decreased from 62104.4ha-1 (33.8%) to 43867 ha-1 (23.9%),from 17416.0 ha-1 (9.4%) to7208 ha-1 (3.93%),from 1196.91 ha-1 (0.6%) to 959.40 ha-1 (0.52%) 2409.48 ha-1 (1.31%) to 2335.23 ha-1 (1.27%) respectively over 30 years(1988-2018)whereas agricultural land, settlement land and bare land were increased from 25553.5 ha-1 (13.9%) to 48480.5 ha-1 (26.4 %) ,from 1740.33 ha-1(0.94 %) to 7562.79 ha-1(4.12%) and from 37.98 ha-1 (0.02%) to 44.82ha (0.02%) respectively.

From the finding, the result showed the prediction of 2028 LULCC were carried out by using MOLUSCE extension plug-in with integrating of QGIS in which forest land, grassland, bushland, and wetland will decrease to 43516.17 ha-1(39.39%),4335.75 ha-1(3.92%),673.92ha-1(0.6%), and 1592.46ha-1(1.4%) respectively compared to LULCC classified map of 2018 whereas agricultural land, Settlement land, and bare land will be increased to 51406.43ha-1(56.5%),8873.24ha-1(8.03%), and 60.39 ha-1(0.05%) respectively. Therefore, the use of QGIS and remote sensing data to investigate LU/LC class patterns and to simulate the next period of LULCC in the study area suggests a quicker, cost-free, and cost-effective technique with the advantage of covering a large area.

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