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ASSESSMENT OF LAND USE AND LAND COVER CHANGES AND URBAN EXPANSION USING REMOTE SENSING AND GIS IN GBOKO, BENUE STATE, NIGERIA

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ABSTRACT

There has been a rapid growth of urban areas across the globe since 1950s with the majority of world population living in urban areas rather than rural areas, in search of better job opportunities and higher quality of services. This trend of transition from rural to urban is expected to continue to rise and government in developing countries are likely going to face more challenges in different sectors, necessitating the need of understanding the spatial pattern of the growth for effective urban planning. The objectives of this study were to map and determine the nature, extent and rate of land use and land cover changes, to analyze the spatio-temporal land use and land cover change patterns and assess urban expansion in Gboko Local Government Area of Benue State, Nigeria. The emphasis was on determining the extent and rate of urban expansion in the area. The study focused on a period of 30 years; from 1987 to 2017. Satellite imageries used included Landsat TM (1987); Landsat ETM+ (2007); and Operational Land Imager (OLI) (2017). The Landsat imagery dataset was sourced from the Earthexplorer platform from United States Geological Surveys (USGS), Global Land Cover Facility (GLCF) and GloVis. The three images of 1987, 2007 and 2017 were classified using maximum likelihood classifier in Idrisi Selva to detect the land cover changes. The study resulted in an overall classification accuracy of 80.77% ,85.84% and 86.24% for 1987, 2007 and 2017 respectively. The result of the classification revealed that between 1987 and 2017, urban area increased from 3232ha (1.68%) in 1987 to 8542ha (4.45%) in 2007 and rose up to 16614ha (8.65%) in 2017. Forest land on the other hand declined from 52108ha (27.13%) to 46523ha (24.23%) down to 16723ha (8.71%) in the same period. Grassland was the dominant land cover occupying 69074ha (35.97%) in 1987 increasing to 79874ha (41.59%) and 129715ha (67.54%) in 2007 and 2017 respectively. The overall trend (1987-2017) revealed that urban area has increased up to 13382ha (9.01%) at an annual rate as high as 2.7% higher than the rate in the first period. Forest declined throughout the period with a loss of 5585ha(12.57%) in the first period at the annual rate of -2.51% and 29800ha (25.7%) in the second period at the annual rate of -2.57%. The overall trend shows that forest lost 35385ha (23.82%) at the rate of -7.15%. Farmland also decreased during the period losing 16006ha (36.03%) in the first period at an annual rate of -7.21% and 22317ha (19.25%) in the second with an annual rate of change of -1.93%. This high rate is an indication that in no distant future the area may be completely devoid of forest vegetation. From the result, it is evident that the rate of urban growth will continue and would certainly threaten forest areas in Gboko LGA. Finally, this study provides a guide to planners for successive urban planning in exploring the rate and pattern of urban growth in Gboko LGA.

KEY WORDS: Urban growth; LULC change; Landsat TM; Landsat ETM+; and Operational Land Imager (OLI), spatio-temporal, maximum likelihood classifier, Idrisi Selva , Gboko.

INTRODUCTION

Human activities have continued to significantly shape the surface of the earth and the existence of man on the surface of the Earth and his activities on it has affected the environment in its natural setting greatly thereby leading to a noticeable pattern in the land use and land cover (LULC) dynamics over time. Increase in human population will hence have a greater influence on the surface of the earth. Over the years, it has been observed that urban areas are the most areas prone to changes on the surface of the Earth. Urban growth exert a lot of influence on the immediate ecosystem despite their regional economic importance(Yuan *et al*, 2005). In most cases, urban growth is experienced towards the boundary between urban and rural areas where the density of settlements is less. Over the past few years, there has been a lot of growth in urban areas the world over, and population increase is one of the key reasons responsible for this. By 2015, the population of the world reached 7.3 billion and out of this, 16% lives in Africa according to the United Nations (UN) (UN, 2015).

By the 21st century, urban population had reached landmark point with half of the world's population living in urban centres (Jiao, 2015). Due to rapid upsurge in the population of urban areas, policymakers, and planners are faced with the problem of resources planning and redistribution to deal the envisaged hitches that may crop up in the future in trying to achieve sustainability in the growth of urban cities. Nigeria's population growth is not very different from the global picture. Today, Nigeria's population is projected to be more than 170 million and there is the general desire for urban migration which will increase the burden on the available resources. The continued increase in population in urban areas has led to modification in the land use and land cover at the urban fringes. This is because; the urban population has to be supported by an increase in food production and urban infrastructure and this is usually achieved through an increase in urban housing and the expansion of area under cultivation.

Nigeria has been witnessing a rapid change of her residents from the hinterland to urban cities. This increased rate of urbanisation has undoubtedly stimulated numerous problems. (Ojo, *et al* , 2017) identified some of the problems facing urban areas and their inhabitants in Nigeria to include poverty, unemployment, spreading destitution and expansion of slums, growing insecurity and increasing crime wave, poor housing, services and amenities.

Gboko as the traditional home of the Tiv has witnessed tremendous growth over the years. This has given rise to a steady upsurge in urban population especially of the town. The key problem of the research is the astronomical expansion and growth of the town. This infers that the growth of the town will have a great effect on the landscape on the outskirts of the town by changing them. As a result, there is need for special care and constant evaluation of our decision-making to monitor and plan the growth of the area. With the increasing importance of urban area of Gboko town in driving changes in the environment, there is burning desire to know how the urban area of Gboko has evolved, and how to plan for the expansion in the future.

It is against this background that this research assessed land use and land cover changes and urban expansion using Remote Sensing and GIS in Gboko, Benue State, Nigeria. This will have the potential to assist communities in their decision-making processes on land use. Certainly, increase in population may give rise to the expansion of urban areas which causes alteration in LULC in many urban cities (Hashem and Balakrishnan, 2015; Mundhe and Jaybhaye, 2014; Opatoyinbo, et al, 2015; Triantakonstantis and Mountrakis, 2012). The rate of such change is apparent in less developed countries where the percentage of population increase is high like Nigeria, Benue State and Gboko LGA in particular. The need to monitor the growth of these urban areas and be able to predict future scenarios for proper planning is, therefore, very pertinent (Adewumi, 2013; Ohwo and Abotutu, 2015). These processes of urban growth are not static but dynamic with time with its attendant products. Information on the rate of urban expansion, effects of these activities and their trend is however lacking or scarce. This research was aimed at filling this gap. This study aimed at Assessing Land Use and Land Cover Changes and Urban Expansion using Remote Sensing and GIS in Gboko, Benue State, Nigeria.

MATERIALS AND METHODS

Study Area

Gboko is located between Latitude 7° 0′ and 7° 40′ North of the Equator and Longitude 8° 35′ and 9° 15′ East of the Greenwich Meridian. It is bounded by Tarka LGA to the north, Buruku to the east, Ushongo to the south and Gwer East and Vandeikya to the west. Gboko is a fastest-growing towns in the Benue State, Nigeria. The name Gboko also refers to a Local Government in Benue State. The population for the town is over 500,000, mostly Tiv people. It is the traditional capital of the Tiv tribe and it has the official residence of the Tor-Tiv, who is the paramount traditional ruler of the Tiv people. The size of the study area is approximately 1920.48km^2.The relief of the area consist of hills prominent among which is the Mkar Hills and valleys with gently undulating plains. The area lies in the tropical climatic zone and it has two seasons: rainy season which starts from April to November and the dry season which starts from November to March. The rains are mostly convectional with isolated orographic type around Mkar hills. The yearly rainfall is between 15cm and 18cm. Temperatures varies between 23 ^{o}C-38 ^{o}C for most of the year. According to the classification by Thornthwaite,(1948) the area is represented as*B3* (Humid climate with seasonal distribution of moisture). The mean monthly values of rainfall in the area range from 0.77cm to 22.75cm. The vegetation consist mainly of Guinea savannah made up of trees and grasses mixed together having average height. The natural vegetation consists of woodland and tall grass. The guinea savannah has isolated forests, patches of woodland, scrubs and shrubs in addition to tall grasses (Abah, 2014). Halima and Edoja, (2016) and Hula, (2014)observed that the vegetation of the area was hitherto covered by forest but due to uncontrolled and continuous clearing of the vegetation for agricultural activities together with other anthropogenic activities such as burning of the bushes, grazing and hunting among other have to a large extent impacted on the original forests. The original forest vegetation is now reduced to secondary forest and savannah vegetation. There are pockets of scattered trees that are of economic benefits and include mango, shea butter, locust bean, African iron, Isoberlinia, cashew, *Daniella oliveri*, *Gmelina arborea*, oil palm, etc. These trees produce products that serve as raw material for some small-scale industries. The area has a population of 361325 according to the 2006 Population Census. It has one of the highest population densities in the state with over 300 persons/km^2. The people of the area are mainly farmers. Over 80% of the total population is dependent on farming for their living taking advantage of the rich alluvial soils of the Benue valley and the foothills of Mkar. The area is blessed with great agricultural products such as yam, cassava, rice, soya beans, millet, potatoes, guinea corn, groundnuts, maize and benniseed. Gboko produces over 40% of the state's soya beans yield, (Benue State Government 2017).

Satellite imageries used included Landsat TM (1987); Landsat ETM+ (2007); and Operational Land Imager (OLI) (2017). The Landsat imagery dataset was sourced from the *Earthexplorer* platform from United States Geological Surveys (USGS), Global Land Cover Facility (GLCF) and GloVis. Changes in land cover were measured using time series of remotely sensed data (Landsat TM, ETM and OLI). Table 1 gives a summary of the image characteristics for the dataset used. Dry season images of the three data sets were acquired from January to March in order to reduce the effects of clouds that are prevalent during the rainy season. Because the images are from the same season and comparable climatic conditions, it enhanced the classification as the spectral reflections of most features are easily comparable across the different images. In addition, high resolution Google earth images were used to aid in classification.

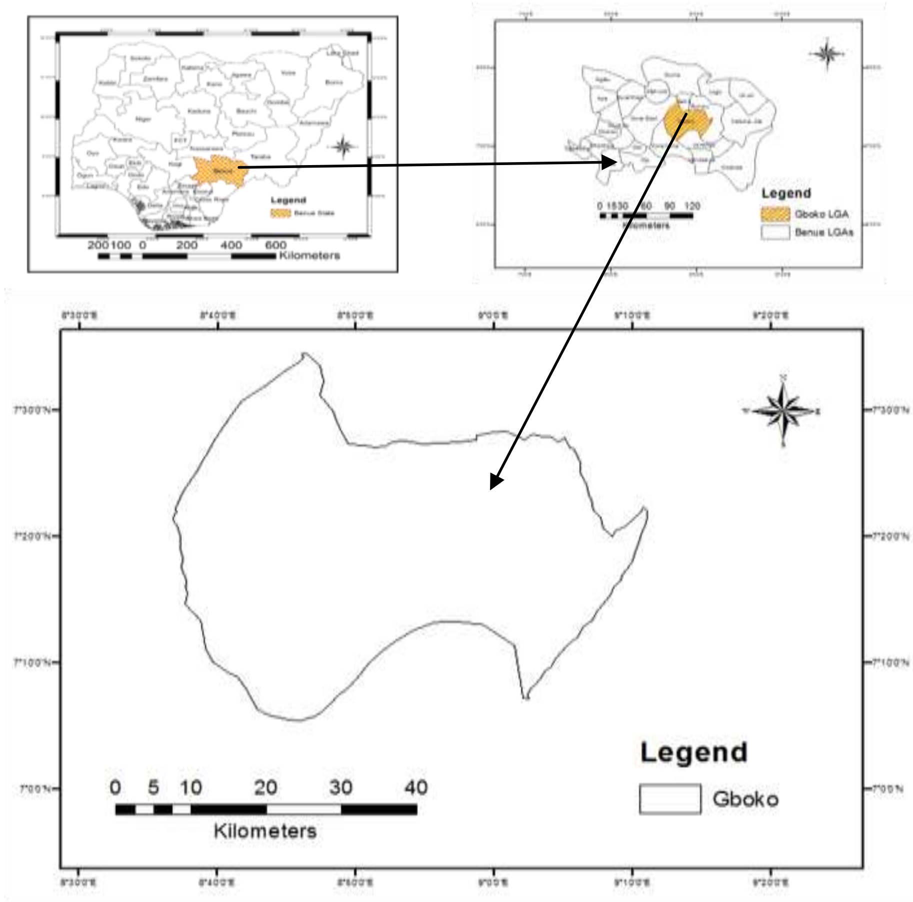

Figure 1 Study Area

The tools used for carrying out the research were; ArcGIS 10.2 used for pre-processing of images and vector data; ERDAS Imagine 2014, used for classification, accuracy assessment of classification; Idrisi Selva, used for change detection; Google Earth Image, used for delineation and ground truthing and Global Positioning System-used for classification and data validation. Mapping the types and extent of land use and land cover classes in Gboko was achieved through the examination of Landsat TM of 1987, Landsat ETM+ of 2007 and Landsat OLI of 2017 images acquired and their subsequent classification.

Table 1: Specifications of Satellite Imageries Used

Satellite	Path/Row	Sensor	No of Bands	Bands used	Date Acquired	Spatial Resolution
Landsat	188/54,55 187/55,56	TM	7	NIR, R, G (4,3,2)	29/01/1987	30m
Landsat	188/54,55 187/55,56	ETM+	8	NIR, R, G (4,3,2)	21/12/2007	30m
Landsat	188/54,55 187/55,56	OLI	11	NIR, R, G (5,4,3)	16/02/2017	30m

TM= Thematic Mapper, ETM+= Enhanced Thematic Mapper Plus, OLI = Operational Land Imager:

Source: Modified from(Northrop, 2015)* http://www.gisat.ez/content/en/products/digital-elevation-model/aster-gdem

In order to map the types and extent of LULC classes in the area, the data were subjected to some processing and analytical procedures which include data pre-processing, image rectification, image enhancement, Image classification. These procedures involved correction of Landsat images through haze removal, cloud removal, mosaicking of images scenes and clipping the images using the shapefile of Gboko LGA. The shapefile of Gboko LGA was used to clip from the larger scenes that were earlier mosaicked. The technique used was the subset method in ERDAS 2014 where the desired shapefile of Gboko was used as the Area of Interest (AOI). The choice of this method was based on its simplicity of use and its higher accuracy. This is because the mosaicked area is larger than the Area of interest (AOI) and it helps in defining precisely the study area.

Image enhancement was done to increases the contrast among different features thereby enhancing easy identification of features and subsequent classification. A band combination of 4,3,2 (for RGB) was used for the Landsat TM and ETM images and 5,4,3 for OLI images as this produced superior results. It is suitable for urban application and delineating land, water and vegetation boundary. Image classification was done using supervised classification algorithm which is a procedure for categorizing spectrally similar areas on an image by identifying “training” sites of known targets and then generalizing those spectral signatures to other areas of targets that are unknown *(*Mather and Koch, 2011). A Maximum Likelihood algorithm of supervised classification was adopted because it is one of the best classification methods which assigns pixels to the class with the largest probability to determine class ownership of a particular pixel. In choosing training sites, colour composite images formed by the combination of three individual monochrome images, which highlight certain surfaces, and help photo-interpretation were viewed; each band is assigned to a given colour: Red, Green and Blue (RGB)(NASA, 2011). A Supervised classification of Landsat image data for the three periods (1987, 2007 and 2017) was performed using the Maximum Likelihood Classifier to identify and map land use and land cover classes. In order to ascertain the areal extent and rate of change in the LULC in Gboko, the following variables were computed.

Total area (T_a), Changed area (C_a), Change extent (C_e) and Annual rate of change (C_r) .These variables can be described by the following formula as given by: (Yesserie, 2009).

$C_a = T_a(t_2) - T_a(t_1)$; …………**(1)**

$C_e = C_a / T_a(t_1)$; ……………..**(2)**

Where t_1 and t_2 are the beginning and ending time of the land use and land cover studies conducted.

Fieldwork was done so as to collect geographical data to map land cover and for accuracy assessment of the land cover classification. Ground-truth data was also collected on spatial features from the study area, such as spatial location, land cover and land use, road network with the aid of a GPS. Ground truthing enabled the collection of inference data and to increase ones’ knowledge of land cover conditions. It also enables familiarity of features as the appear on the satellite image on the computer screen, for verification and validation of the interpreted results. The process of identifying and transferring ground points onto the screen was done using the GPS. Each LULC class was physically identified in the field and the position of the area recorded using GPS which was later transferred to the image whereby it was easier to identify the appearance of such land uses on the screen. Inaccessible areas were complimented with the use of Google earth images. In summary, both visual interpretation and digital image classification methods were employed in data interpretation.

A stratified random sampling technique was adopted in selecting control points for accuracy assessment so as to improve the precision of the accuracy and area estimates (Olofsson*et al*., 2014). It avails one the opportunity of selecting control points within the different land use and land cover classes (strata) to be used for accuracy assessment. Each of the land use and land cover classes had control points proportional to the size of the area covered.

The accuracy of satellite image classification could be inhibited by the resolution of images used and dearth of fine details as well as unavoidable generalization impact and therefore, errors are always expected. This is why, to ensure wise utilization of the produced LULC maps and their associated statistical results, the errors and accuracy of the analysed outputs should be quantitatively explained (Siddhartho, 2013).

Accuracy assessment is a process whereby the final product of classification is compared with ground truth or reliable sources so as to assess the extent of agreement or disagreement. This study adopted the Error Matrix approach (ERRMAT in Idrisi Selva) to assess the accuracy of the classification. The error matrix assesses accuracy using four parameters which include overall accuracy, user's accuracy, producer's accuracy and the Kappa Index of agreement (KIA). The overall accuracy specifies the total pixels correctly classified and is derived by dividing the total number of pixels correctly classified by the total number of pixels in the error matrix. The producer's accuracy defines the probability of a reference pixel being correctly classified; it represents the error of omission.

Table 2: Classification scheme

S/No	Class	Description
1	River/ water bodies	Open water features including lakes, rivers, streams, ponds and reservoirs.
2	Built-up/Urban Area	Urban and rural built-up including homestead area such as residential, commercial, industrial areas, villages, settlements, road network, pavements, and man-made structures.
3	Grassland	Areas dominated by grasses including vegetated sandbars and grazing areas/
4	Bare surface	Fallow land, earth and exposed river sand land in-fillings, construction sites, excavation sites, open space and bare soils.
5	Forest	Trees, natural vegetation, mixed forest, gardens, parks and playgrounds, grassland, vegetated lands.
6	Farmlands	Areas consist of cultivated lands used for the production of annual crops, perennial woody crops. agricultural lands, and crop fields.

Source: Modified from Anderson *et al*.(1976)

The number of samples correctly classified for a given column is divided by the total for that column (Pedro, 2015). The user's accuracy on the other hand defines the probability that a pixel classified on a map actually represents that category on the ground. User's accuracy represents to error of commission. This can be calculated by dividing the number of samples correctly classified for a given row by the total of the row (Sarmento, 2015). On the other, the Kappa index measures the agreement between classification map and reference data (Congalton and Green, 2008). All accuracy parameters have index values between 0 and 1, where 0 symbolizes poor and 1 strong classification accuracy/agreement.

The Kappa statistics formula developed by Cohen Kappa in 1960 and modified by Jenness and Wynne (2007) was adopted for calculating Kappa statistic. It has the advantage of correcting for chance agreements between the observed and predicted values.

$$k = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)} \qquad \ldots\ldots\ldots\ldots \textbf{(3)}$$

Where :*i* is the class number

N is the total number of classified pixels that are being compared to ground truth

mi,i is the number of pixels belonging to the ground truth class i,that have also been classified with a class i (that is values found along the diagonal of the confusion matrix)

Ci is the total number of classified pixels belonging to class *i*

Gi is the total number of ground truth pixels belonging to *i*

Kappa value changes from -1 to +1 and the interpretation of the values can be determined according to these values:

< 0: Less than chance agreement
0.01–0.20: Slight agreement
0.21– 0.40: Fair agreement
0.41–0.60: Moderate agreement
0.61–0.80: Substantial agreement
0.81–0.99: Almost perfect agreement. (Borana and Yadav, 2017).

Under ideal conditions, the accuracy of the classification ought to be assessed by overlaying an already existing LULC map. Due to absence of already existing LULC classification for Gboko LGA, handheld Garmin GPS receiver was used to take coordinates of selected LULC as ground control points from the field complimented with Google Earth images. The points of these reference data were determined through stratified random sampling by identifying and locating the land use classes of interest in the field and their GPS points and coordinates taken at ±3m accuracy and recorded as was used by Appiah, (2016).

RESULTS AND DISCUSSION

The results of classification for the land use land cover changes in 1987, 2007 and 2017 are presented using tables, charts and figures for illustration and interpretation of all LULC classes in the three periods. The results are discussed immediately as they are presented for the area. The classification reveals that there was a steady increase in urban area from 3232ha (1.68%) in 1987 to 8542ha (4.45%) in 2007 and rising up to 16614ha (8.65%) in 2017. The growth of the urban area has been directed towards the northeast area of the map as can be seen from Figures 3 and 4. Forest land on the other hand declined from 52108ha (27.13%) to 46523ha (24.23%) down to 16723ha (8.71%) in the same period. Grassland was the dominant land cover occupying 69074ha (35.97%) in 1987 increasing to 79874ha (41.59%) and 129715ha (67.54%) in 2007 and 2017 respectively as shown in Table 3. Water body and Bare surface experienced slight variations during the same period. The classification accuracy for the three periods of 1987, 2007 and 2017for Gboko showed an overall accuracy of 80.77%, 85.84% and 86.24% respectively (see Table 4). This was also considered a decent overall accuracy for the subsequent analysis and change detection. The user's accuracy of different classes ranged between74.07% and100% and producer's accuracy ranged between 64 % and 94.44%. The overall Kappa index was also calculated for each classified map to determine the accuracy of the results.

The LULC distribution of extent for Gboko for the 3 Periods is shown in Table 3 and Figures 2, 3 and 4. The results of the three periods 1987, 2007 and 2017revealed Kappa statistics of 0.76, 0.83 and 0.83 respectively. The Kappa coefficient for the three periods ranges from substantial agreement to almost perfect agreement on the kappa scale, an indication that it can be used.

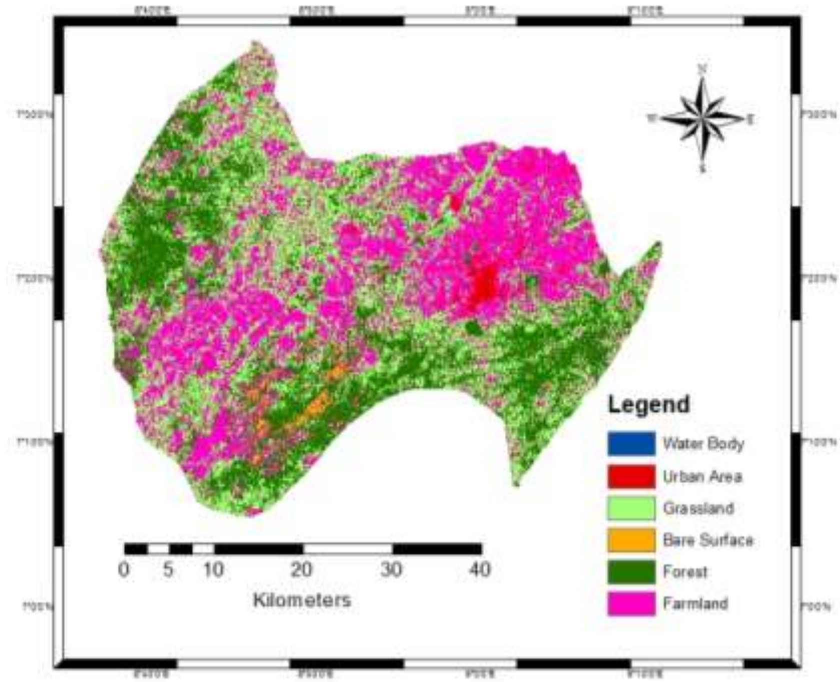

Figure 2: Land use and Land cover map of Gboko for 1987

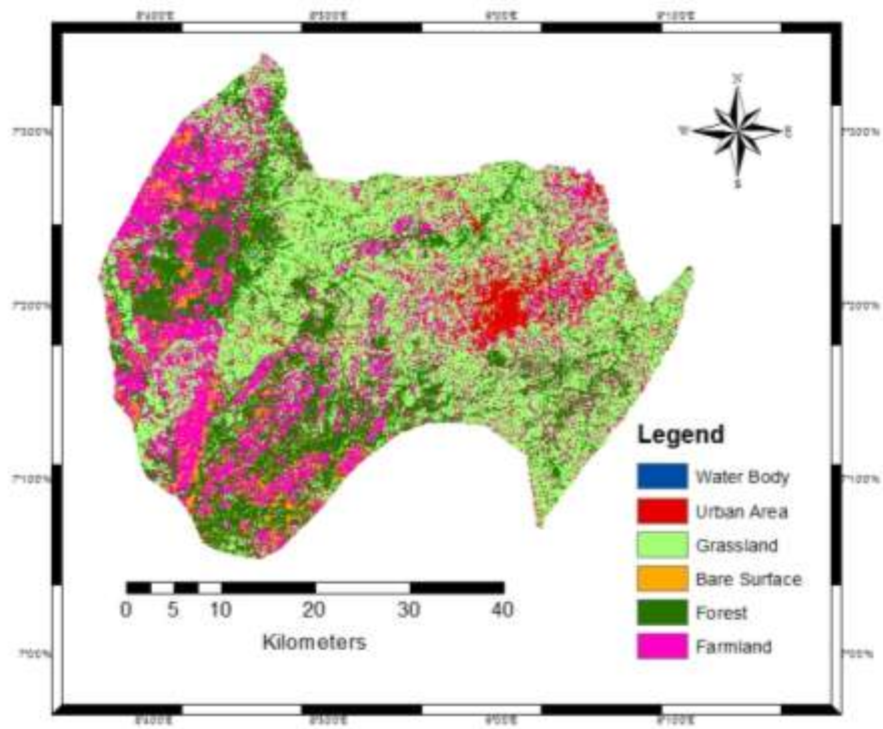

Figure 3: Land use and Land cover map of Gboko for 2007

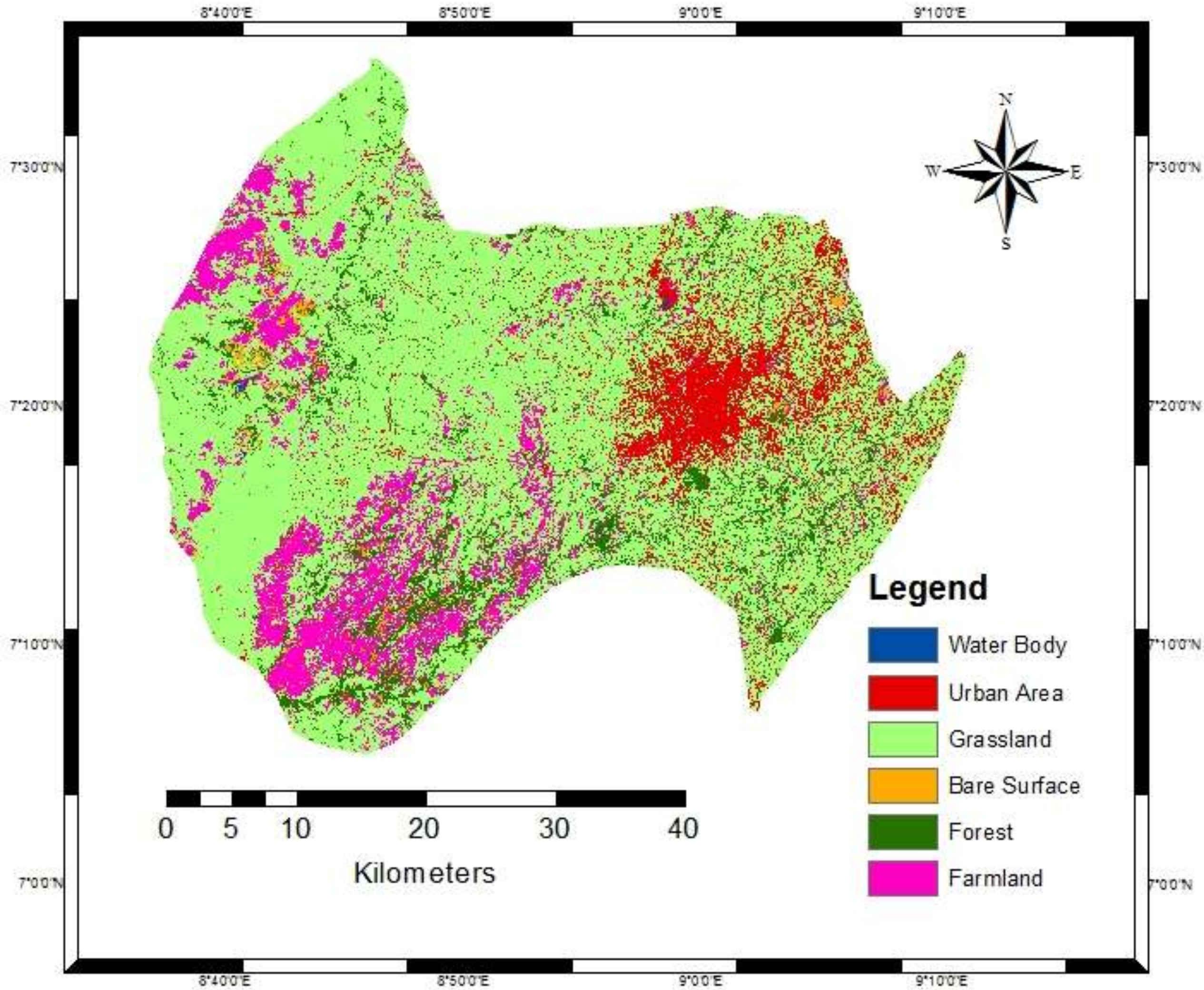

Figure 4: Land use and Land cover map of Gboko for 2017

Table 1: Area Statistics of LULC in Gboko (1987, 2007 and 2017)

	1987		**2007**		**2017**	
land cover Class	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**
Water Body	840	0.44	220	0.11	277	0.15
Urban Area	3232	1.68	8542	4.45	16614	8.65
Grassland	69074	35.97	79874	41.59	129715	67.54
Bare Surface	2252	1.17	8353	4.35	2500	1.30
Forest	52108	27.13	46523	24.23	16723	8.71
Farmland	64542	33.61	48536	25.27	26219	13.65
Total Area	**192048**	**100**	**192048**	**100**	**192048**	**100**

Table 4: Accuracy assessment result of LULC classification in Gboko

LULC Class	1987 classification Producer's Accuracy (%)	User's Accuracy (%)	2007 classification Producer's Accuracy (%)	User's Accuracy (%)	2017 classification Producer's Accuracy (%)	User's Accuracy (%)
Water Body	80.95	89.47	80	84.21	94.44	77.27
Urban Area	86.49	91.43	88.89	100	74.19	85.19
Grassland	80.56	76.32	82.98	81.25	86.89	82.81
Bare Surface	64	84.21	71.43	83.33	86.36	82.61
Forest	82.93	79.07	91.67	86.84	82.05	100
Farmland	83.33	74.07	90	80.36	93.62	88
Overall Accuracy	**80.77%**		**85.84%**		**86.24%**	
Overall Kappa	**0.76**		**0.83**		**0.83**	

The trend in land use and land cover changes in Gboko (Table 5 and Figure 5) shows that urban area increased by 5310ha (11.95%) in the first period at an annual rate of change of 2.39% while in the second period the change was 8072ha (6.96%) and the annual rate of change of 0.7%. Even though, there was an increase, the rate reduced greatly to 0.7% which signifies a slowdown in the rate of urban expansion between 2007 to 2017. The overall trend (1987-2017) revealed that urban area has increased up to 13382ha (9.01%) with an annual rate of change as high as 2.7% higher than the rate in the first period. Forest land in Gboko has been on the decline throughout the period with a loss of 5585ha(12.57%) in the first period having an annual rate of change of -2.51% and 29800ha (25.7%) in the second period with an annual rate of change of -2.57%. The overall trend shows that forest lost 35385ha (23.82%) with an annual rate of change of -7.15%.

This high rate is an indication that in no distant future the area may be completely devoid of forest vegetation. Farmland also decreased during the period losing 16006ha (36.03%) in the first period with an annual rate of change of -7.21% and 22317ha (19.25%) in the second with an annual rate of change of -1.93%. The overall trend indicates that 38323ha (25.8%) was lost between 1987 and 2017 with an annual rate of change of -7.74%. The decline in farmland could be due to involvement of the aged and absence of the youth who have migrated to the cities. Grassland increased throughout the period, 10800ha (24.31%) by the first period with a 4.86%change rate.

By the second period, it increased to 49841ha (42.99%) even though the annual rate of change decreased to 4.3%. The overall trend shows that it increased by 60641ha (40.82%) at an annual rate of change as high as 12.25%. This might be due to clearance of forested areas for agriculture and later abandoning it for grassland to take over. Water body and bare surface recorded minimal changes. The trend of land use and land cover changes in which urban area continue to increase at the expense of other classes and the decline in forest area and farmland agrees with the results of Addae and Oppelt, (2019) in Greater Accra Metropolitan Area (GAMA), Ghana.

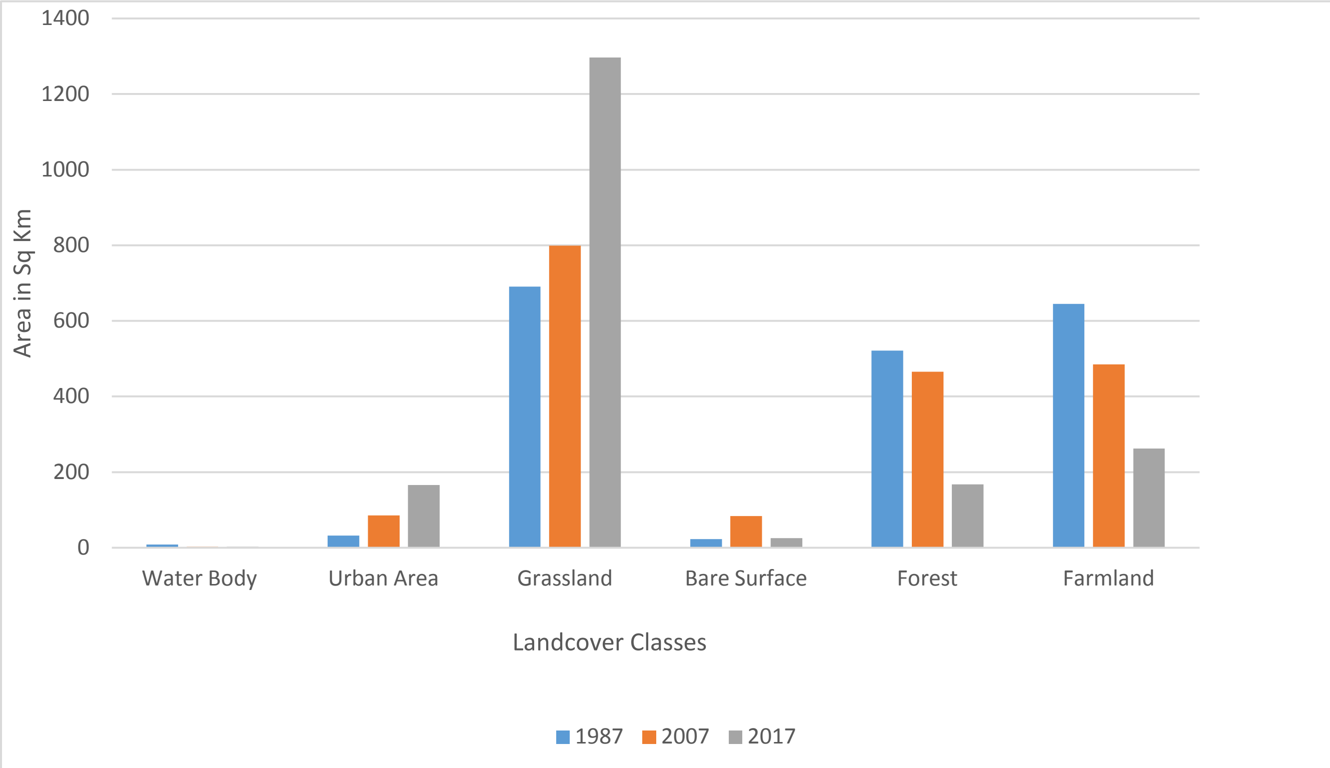

Figure 5: Trend of Land cover changes in Gboko (1987-2017)

Table 5: Annual Rate of change for Gboko (1987, 2007 and 2017)

LULC Class	1987-2007 Area(ha) Change	Percentage of Change	2007-2017 Area (ha) Change	Percentage of Change	1987-2017 Area (ha) Change	Percentage of Change	Annual Rate of Change		
							1987-2007 (%)	2007-2017 (%)	1987-2017 (%)
Water Body	-620	-73.81	57	25.91	563	67.02	-3.69	2.59	2.23
Urban Area	5310	164.29	8072	94.5	13382	414.05	8.21	9.45	13.8
Grassland	10800	15.64	49841	62.4	60641	87.79	0.78	6.24	2.93
Bare Surface	6101	270.91	-5853	-70.07	248	11.01	13.54	-7.01	0.37
Forest	-5585	-10.72	-29800	-64.05	-35385	-67.91	-0.54	-6.41	-2.26
Farmland	-16006	-24.8	-22317	-45.98	-38323	-59.38	-1.24	-4.6	-1.98

Gboko, the traditional headquarters of the Tiv people show marked trend in land cover transitions. All the classes experienced transitions but farmland had the highest positive transition followed by urban area. Grassland had the highest negative transition closely followed by forest land (Figure 6a). Farmland, grassland and forest were the major contributors to urban area expansion. Farmland, grassland and urban area were responsible for the decline in the forest land. In a similar vein, land cover transition pattern in the second period had a lot of resemblance to that of the first period. as can be seen in Figure in (6b). The period between 1987-2017 saw grassland having the dominant positive transition closely followed by urban area. Farmland and forest witnessed a negative transition (Figure 6c). Again, farmland, grassland and forest were the major contributors to urban growth while grassland, farmland, bare surface and urban area accounted for the decline in forest land.

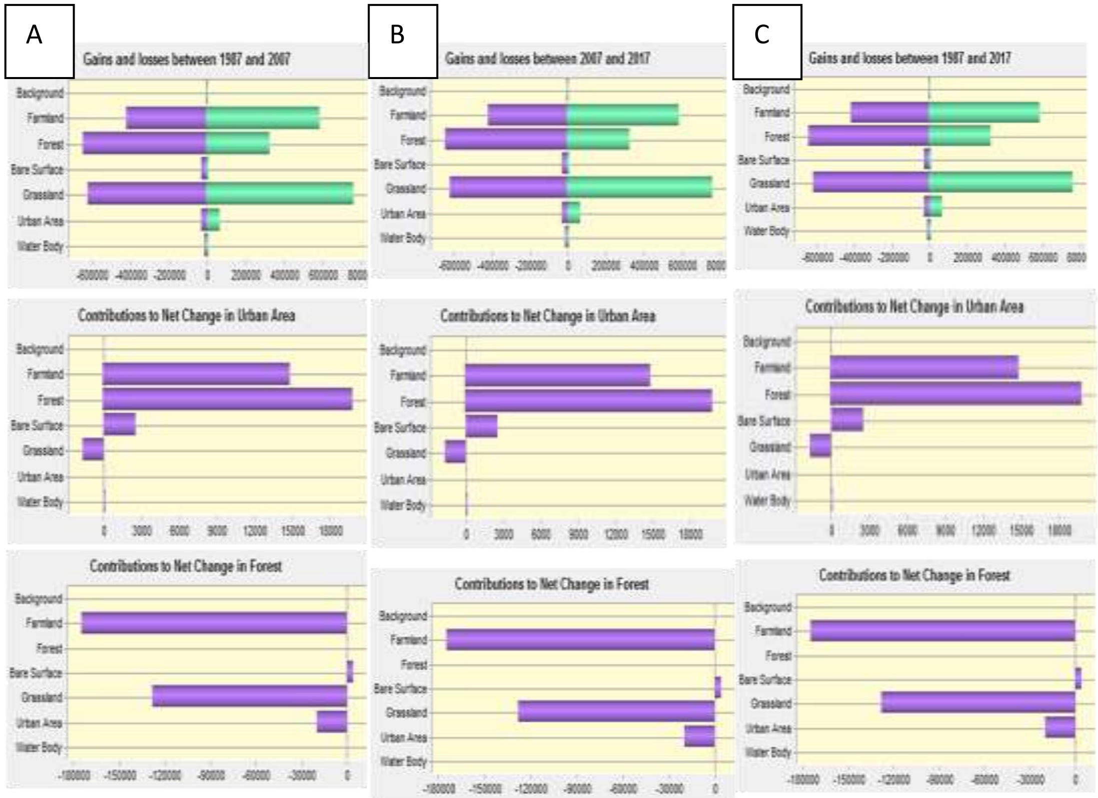

Figure 6: Gains/losses of LULC categories, contribution to net change in Urban area and Forest (ha) in Gboko from (A):1987 – 2007, (B): 2007 -2017 and (C): 1987- 2017.

The gain and losses graphs in Gboko (Figure 6a, b and c) show that grassland witnessed the major positive transition followed by urban area. Farmland had a negative transition in the first and second but was positive in the overall trend while forest declined throughout during the period. Contributors to urban expansion came mainly from farmland, grassland and forest during the first two periods but bare surface took over leadership in the overall trend. This was followed by farmland, forest and grassland.

.CONCLUSION

Land use and land cover change information over time is necessary not only for planning of urban areas, but also to improve the management of the use of earth resources. This study has established the value of using satellite remote sensing and GIS technique in producing accurate land use and land cover maps and change statistics for Gboko LGA, which is critical in monitoring urban expansion effectively over a time. The change detection results of the study area reveal that there was a steady increase in urban area from 3232ha (1.68%) in 1987 to 8542ha (4.45%) in 2007 and rising up to 16614ha (8.65%) in 2017. This increase in urban extent can be attributed to the increase in population due to large rural- urban migration The growth of the urban area has been directed towards the northeast area of the area. Forest land on the other hand declined from 52108ha (27.13%) to 46523ha (24.23%) down to 16723ha (8.71%) in the same period. The overall trend (1987-2017) show that urban area increased by 13382ha representing 414.05% at an annual rate of 13.5%. Forest and farmland declined to the tune of 35385ha and 38323 ha representing -67.91% and -59.38% respectively. In this study, the accuracy of the maps proved satisfactory; it confirms that the image processing procedures were effective in producing land use and land cover maps from Landsat images. It is therefore, highly recommended that city planners and decision makers can employ remote sensing and GIS techniques for effectively monitoring urbanization trends.

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