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ASSESSMENT OF LAND USE AND LAND COVER CHANGE USING GIS AND REMOTE SENSING TECHNIQUES IN KATSINA-ALA LOCAL GOVERNMENT AREA OF BENUE STATE, NIGERIA

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ABSTRACT

The aim of this study was to gain a quantitative understanding of land use and land cover changes in Katsina-Ala Local Government Area of Benue State over the period 1990-2020. Landsat TM (1990); Landsat ETM+ (2000, 2010); and Operational Land Imager (OLI) (2020) were used. The Landsat imagery dataset was sourced from the Earth explorer platform from United States Geological Surveys (USGS). Changes in land cover were measured using time series of remotely sensed data (Landsat TM, ETM and OLI). This study adopted the Error Matrix approach in ArcGIS to assess the accuracy of the classification. Result shows that 43.25% of farm land cover was gained during the period 1990 to 2020 with an annual rate of change of 1.44%. Forest land cover was lost by -53.19% between 1990 and 2020 with an annual rate of change of -1.77%, built up area has increased by 9.20% with an annual rate of change of 0.31%.

Key Words: Land use; Land cover change; Change detection; Katsina-Ala LGA

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INTRODUCTION

Land is one of the most important natural resource on earth which also serves as a platform for life and developmental activities. The term land use refers to human activities or economic functions associated with a specific piece of land. Land cover on the other hand relates the type of feature present on the surface of the earth (Lillesand *et al.*,2014). Land use and land cover data are essential for planners, decision makers and those concerned with land resources management (Gete and Hurni, 2001).

Human activities have continued to significantly shape the surface of the earth and the existence of man. It has affected the environment in its natural setting thereby greatly leading to a noticeable pattern in the land use and land cover time (Cheruto *et al.*,2016). Land use land cover is not static and, in many instances, is a response to population growth, socio-economic changes, ecological and demographic situation in a given area. Land use land cover change has become one of the major concerns of researchers and decision makers around the world today. Land use land cover change has been identified as one of the main driving forces of global environmental change and is vital to the environmentally sustainable development (Cheruto *et al.*,2016)

For ensuring planned development and monitoring the land utilization pattern, preparation of land use and land cover map is necessary. Remote sensing and GIS have the capability to capture and process recurring coverage, which is required for change detection studies. Remote Sensing research focusing on image classification has attracted the attention of many researchers and a number of researches have been conducted using different classification algorithms.

Change detection involves applying multitemporal Remote Sensing information to analyze the historical effects of an occurrence quantitatively and therefore helps in determining the changes associated with land cover and land use properties with reference to the multi-temporal datasets (Ahmad, 2012; Seif and Mokarram, 2012; Zoran, 2006). The basic premise in using satellite images for change detection is that changes in land cover result in changes in radiance values that can be remotely sensed. Techniques to perform change detection with satellite imagery have become numerous as a result of increasing versatility in manipulating digital data and increasing computing power. A wide variety of digital change detection techniques have been developed over the last two decades (Butt, et al., 2015). Although, series of works have been done in a conventional system to produce some information on the land use land cover in Nigeria, studies that adopted Remote Sensing and GIS are rare with and around Katsina-Ala basin. Therefore, the application of GIS using remotely sensed data to analyze land use land cover of Katsina-Ala Local Government Area would definitely enhance the available resources for sustainable development.

Katsina-Ala as one of the local governments created when the state was created in 1976. It has witnessed remarkable population growth over the years leading to increasing pressure on the available static land. The main aim of this study is to gain a quantitative understanding of land use and land cover changes in Katsina-Ala Local Government Area of Benue State over the period 1990- 2020.

MATERIALS AND METHOD Study Area

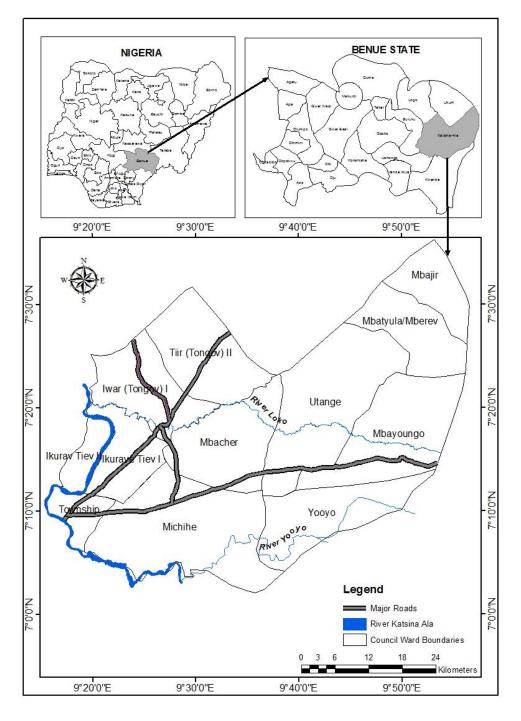
Katsina-Ala Local Government is one of 23 Local Government Councils in Benue state and has an area of about 2,613 km². It lies geographically, between latitude 7° 5′ 0″ N to 7° 30′ 0″ N of the equator and longitude 9° 15′ 0″ E to 9° 55′ 0″ E, of the Greenwich meridian. The Local Government has a projected population of 341,038 by the year 2020 (Projected from NPC, 2006). Population density per square kilometer is higher in the South than in the North. Politically the local government comprises twelve (12) Districts; it is located in the north-eastern part of the state and shares boundaries with Taraba State in the North-East, (Figures 1).

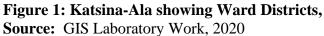
The study area falls within the Koppen's Aw (wet and dry) climatic classification system.

Like in most part of Nigeria, the area is biseasonal – the hot dry season with a short spell of harmathan when the Saharan monsoons change direction (November through March), and the wet season (April - October). Temperatures are mostly high throughout the year with average range between $23^{\circ}C - 28^{\circ}C$ with the peak of 38°C. The mean annual rainfall is about (900-1000) mm. The area lies between the transition zone of the rain forest and savannah vegetation, while the northern portion consists of typical grassland savannah vegetation, the south-east is of semi-deciduous forest vegetation (Enokela et al., 2013). The inhabitants of the Local Government are predominantly the Tiv people who speak Tiv language which is of Bantu origin. There are few settlements of Etulo people in the local government especially along the banks of River Katsina-Ala.

The Hausas also account for greater percentage of the township district population. Katsina-Ala Local Government Area is predominantly an agrarian society. Socio-economic activities in the local government revolve around agricultural produce. Greater percentage of the population engage in Agricultural practice while others engaged in non-farming activities including artisans, trading etc., Major items of trade include Yams, Rice, Soya beans, Cassava flour, Groundnut and Maize. The local government has one tertiary institution, the College of Education Katsina-Ala and numerous primary and secondary schools, a General hospital, one commercial bank, the First Bank of Nigeria Plc, five major commercial hubs, the Katsina-Ala township, Abaji, Gbor and Amaafu. Tor-Donga, Industrial activities in the local government is still at the early stage as a state-owned yam floor manufacturing factory is yet to commenced production.

The settlement pattern in the area and indeed, in the whole of Tiv land is isolated scattered pattern with a few pockets of clustered settlement mostly in urban places. The predominant isolated settlement is influence by quest for farmlands as Tiv people often reside amidst their farmlands. The clustered settlement pattern is largely influenced by availability of basic amenities.





Data Collection

Two types of data were collected and used for the purpose of this research; remote sensing data and topographic map. Satellite data comprising of four-years multi-temporal imageries: Landsat TM (1990); Landsat ETM+ (2000, 2010); and Operational Land Imager (OLI) (2020) were used. The Landsat imagery dataset was sourced from the Earth explorer platform from United States Geological Surveys (USGS). A topographic map of the local government was used as a guiding map for extraction of study area satellite images for processing. 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 four data sets were acquired from January to March in order to reduce the effects of clouds that are prevalent during the rainy season. Ancillary data included the ground truth data for the LU/LC classes. The ground truth data was in the form of reference points collected using Geographical Positioning System (GPS), high resolution Google earth images were also used to aid in classification and overall accuracy assessment of the classification results.

Table 1: Satellite data used									
S/No	Data type	Date	Resolution	Source					
1	Landsat TM imagery	January, 1990	30m	USSG Earth Explorer					
2	Landsat ETM imagery	March, 2000	30m	USSG Earth Explorer					
5	Landsat ETM imagery	November, 2010	30m	USSG Earth Explorer					
7	Landsat 8 OLI imagery	November, 2020	30m	USSG Earth Explorer					

Table 2: Land cover types used in the Classification of satellite derived land cover types

Code	Land Cover	Description
1	Forest	High density of trees with little or no undergrowth. Dominated by tropical trees
		such as Kyaya senegalensis, Magnifera indica, Daniella olivera, Isoberlina doka and parkia biglobosa
2	Farmland and	Environment dominated by grasses and herbaceous plants typically, spear grass
	Pasture	and elephant grass (<i>Andropogan gayanun</i>) often used for grazing livestock. It is used here collectively to also include agricultural land or mixed farming area that describes land that constantly shifts between farm and fallow land. Typically, the vegetation cover has been removed or modified and replaced by other types of vegetation cover of anthropogenic origin
3	Water body	Areas persistently covered by water typically lakes, dams and rivers
4	Bare Land	Land of limited ability to support biotic life and in which less than one-third of the area has vegetation cover. These areas typically have less than 4%
5	Built-up Area	vegetation cover such as exposed river sand land in-fillings sites, excavation sites, open space and bare soils.This comprise of urban and rural built-up including homestead area such as residential, commercial, industrial areas, villages, roads network, pavement and man-made structures.

Image pre-processing and classification

Pre-processing of satellite images before detection of changes is a very vital procedure and has a unique aim of building a more direct association between the biophysical phenomena on the ground and the acquired data (Coppin, Jonckheere, Nackaerts, Muys & Lambin 2004). Data were preprocessed in ERDAS imagine for band combination and sub-setting of the image on the basis of Area of Interest (AOI). The main objective of image classification is to place all pixels in an image into land use land cover classes in order to draw out useful thematic information (Boakye et al., 2008). Image classification was done in order to assign different spectral signatures from the LANDSAT datasets to different land use land cover. This was done on the basis of reflectance characteristics of the different land use land cover types. Different color composites were used to improve visualization of different objects on the imagery. Infrared color composite NIR (4), SWIR (5) and Red (3) was applied in the identification of varied levels of vegetation growth and in separating different shades of vegetation. Other color composites such as Short Wave Infra-red (7), Near Infrared (4) and Red (2) combination which are sensitive to variations in moisture content were applied in identifying the built-up areas and bare soils. This was supplemented by a number of field visits and use of goggle earth software that made it possible to establish the main land use land cover types. For each of the predetermined land use land cover type, training samples were selected by delineating polygons around representative sites. Spectral signatures for the respective land use land cover types derived from the satellite imagery were recorded by using the pixels enclosed by these polygons. A satisfactory spectral signature is the one ensuring that there is 'minimal confusion' among the land covers to be mapped (Gao and Liu, 2010) Maximum Likelihood classifier algorithm with decision rule was used for supervised classification by taking 100 training sites for five major land use land cover classes. The Maximum Likelihood Classification is the most widely used per-pixel method by taking into account spectral information of land cover classes (Qian, Zhou and Hou 2007). The delineated land use land cover classes were; built up areas, water bodies, farmlands, bare-lands and forest as described in Table 2.

Accuracy assessment

This study adopted the Error Matrix approach (ERRMAT in ArcGIS) 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. The number of samples correctly classified for a given column is divided by the total for that column. 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; Jande et al., 2019). On the other, the Kappa index measures the agreement between classification map and reference data (Congalton and Green, 1999). All accuracy parameters have index values between 0 and 1, where 0 symbolizes poor and symbolizes classification 1 strong accuracy/agreement.

The Kappa statistics formula developed by Cohen Kappa in 1960 and modified by Jenness and Wynne in 2007 was adopted for calculating Kappa statistic. It has the advantage of correcting for chance agreements between the observed and predicted values (Jande *et al.*, 2019).

Kappa Formula

$$K = \frac{N\rho - \delta}{N^2 - \delta} \qquad equation \dots .1$$

Where N is the Total number of Points, ρ is the sum of correctly mapped points, δ is the sum of the products between row and column for each class. Kappa value changes from -1 to +1 and the interpretation of the values can be determined according to these values:

Table 3: Kappa Index of agreement

Interpretation of Kappa Statistic					
Карра	Agreement				
< 0.20	Poor				
0.21-0.40	Fair				
0.41-0.60	Moderate				
0.61-0.80	Good				
0.81-100	Very Good				

(Borana and Yadav, 2017).

RESULTS

Classification Accuracy Assessment

The classification accuracy for the four periods of 1990, 2000, 2010 and 2020 for Katsina-Ala Local Government Area showed an overall accuracy of 83%, 87%, 86% and 84% respectively (see Table 4). This was also considered an acceptable overall accuracy for the subsequent analysis and change detection. The user's accuracy of different classes from 74% and 100% and producer's accuracy ranged between 64% and 94%. The overall Kappa index agreement was also calculated for each classified map to determine the accuracy of the results. The land use land cover distribution of extent for Katsina-Ala Local Government Area for the four Periods is shown in Table 3 and Figures 2.

The results of the four periods 1990, 2000, 2010 and 2020 showed Kappa statistics of 0.79, 0.84, 0.83 and 0.80 respectively. The Kappa coefficient for the four periods ranges from good agreement to very good agreement on the kappa scale, an indication that it can be used. see Table 5

200

LULC Type	1990 Classification Accuracy		2000 Classification Accuracy		2010 Classification Accuracy		2020 Classification Accuracy	
	Producer (%)	User(%)	Producer (%)	User (%)	Producer (%)	User (%)	Producer (%)	User (%)
Water Bodies	100	100	94	80	100	95	83	75
Built up Area	75	88	70	80	89	85	85	85
Farm land and Pasture	50	71	100	100	85	55	94	80
Bare land	95	86	81	85	100	95	100	90
Forest	95	86	95	90	67	100	67	90
Overall Accuracy	83%		87%		86%		84%	
Over all Kappa Index Agreement	0.79)	0.84	1	0.86	i	0.80	

	1990		2000		2010		2020	
LULC Type	Area in (Km ²)	Area (%)	Area in (Km²)	Area (%)	Area in (Km²)	Area (%)	Area in (Km²)	Area (%)
Farm land and pasture	811.88	31.03	1740.52	66.52	2064.03	78.88	1943.64	74.28
Forest	1674.89	64.01	730.29	27.91	348.54	13.32	283.03	10.82
Built up areas	56.89	2.17	67.44	2.58	117.17	4.48	297.69	11.38
Bare land	57.78	2.21	60.71	2.32	68.43	2.62	70.39	2.69
Water Bodies	15.12	0.58	17.57	0.67	18.41	0.70	21.80	0.83
Total	2616.56	100	2616.53	100	2616.58	100	2616.55	100

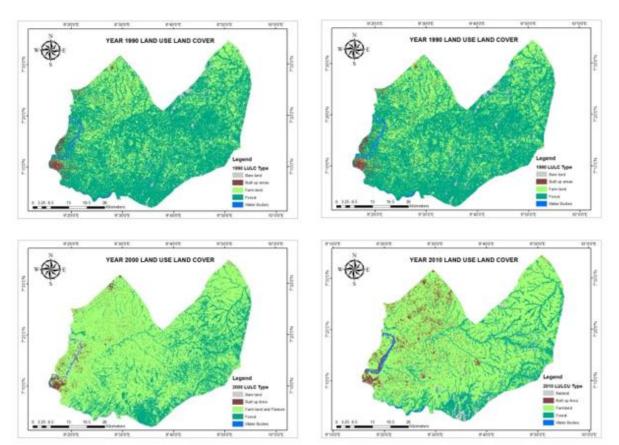


Figure 1: Land use and Land Cover of Katsina-Ala LGA in 1990 – 2020

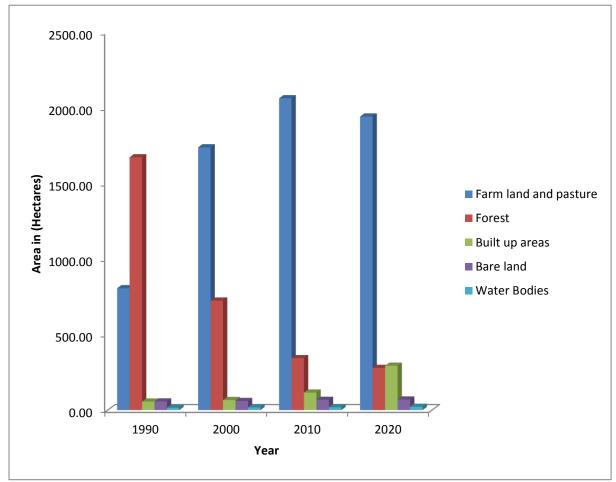


Figure 2: Changes in land use/land cover in Katsina-Ala LGA 1990-2020

	1990-2000		2000-2010		2010-2020		1990-2020		
LULC Type	Area in (Km2)	Area (%)							
Farm land and pasture	928.64	35.49	323.51	12.36	-120.39	-4.60	1131.76	43.25	
Forest	-944.60	-36.10	-381.76	-14.59	-65.50	-2.50	-1391.86	-53.19	
Built up areas	10.55	0.40	49.74	1.90	180.51	6.90	240.80	9.20	
Bare land	2.93	0.11	7.72	0.29	1.96	0.07	12.61	0.48	
Water Bodies	2.45	0.09	0.84	0.03	3.39	0.13	6.69	0.26	

Table 7: Annual rate of Land use land cover change in Katsina-Ala Local Government fror	n
1990 – 2020	

	1990-2000		2000-2010		2010-2020		1990-2020	
LULC Type	Area in (Km2)	Area (%)	Area in (Km2)	Area (%)	Area in (Km2)	Area (%)	Area in (Km2)	Area (%)
Farm land and pasture	92.86	3.55	32.35	1.24	-12.04	-0.46	37.73	1.44
Forest	-94.46	-3.61	-38.18	-1.46	-6.55	-0.25	-46.40	-1.77
Built up areas	1.05	0.04	4.97	0.19	18.05	0.69	8.03	0.31
Bare land	0.29	0.01	0.77	0.03	0.20	0.01	0.42	0.02
Water Bodies	0.25	0.01	0.08	0.00	0.34	0.01	0.22	0.01

DISCUSSION

The result of the land use/land cover change was analyzed using object-oriented approach which was based on a supervised and Gauss maximum likelihood classification method.

Farmlands and Pasture:

Results from the classification reveals that Farmland and Pasture land cover increased from 811.88 km² (31.03%) in 1990 to 1740.52 km² (66.52%) in 2000 and rose up to 2064.03 km² (78.88%) in 2010 but decline to 1943.64 km^2 (74.28%). This trend can be attributed to conversion of forest land to farmlands through deforestation and clearing of land for farming activities. The decline from 2010 to 2020 can be attributed to expansion of urban and rural settlement as can be seen from Figures 1 and table 4. Forest land. Result from the analysis shows that Forest land cover has decline over the period 1990 to 2020 in Katsina-Ala LGA. Forest cover decline from 1674.89km2 (64.01%) in 1990 to 730.29km2 (27.91%) in year 2000, 348.54km² (13.32%) in 2010 and 283.03km² (10.82%) in 2020. This can be attributed to increase farming activities and deforestation.

Built up Areas

From the statistical analysis of this research the built-up areas formerly occupied a proportion of 56.89km^2 (2.17%) in 1990 and increased to 67.44km^2 (2.58) %, 117.17km2 (4.48%) and 297.69km² (11.38%) in 2000, 2010 and 2020 respectively as shown in table 5. This is a clear indication of increase in population and infrastructure development in the areas.

Bare land

Bare land recorded slight but steady positive change over the year under study. Bare surface proportions were 57.78km² (2.21%) in 1990 increased to 60.71km² 2.32.74% in 2000, 68.43km² (2.62%) and 70.39km² (2.69%) in 2020. This can be attributed to human activities, which includes, over grazing, indiscriminate bush burning; it was also observed that sandbars at river Katsina-Ala contributed to the bare land cover.

Water Bodies

In a similar way, water bodies land cover class recorded slight variation. Water bodies land cover of the area increased from 15.12km² (0.58%) in 1990 to 17.57km² 0.67% in 2000,

18.41² (0.70%) in 2010 and 21.80km² (0.83%) in 2020. It was also observed that river Katsina-Ala contributed to the water body land cover as shown in table 5

Land use land cover Change Trend in Katsina-Ala Local Government between (1990-2020) The trend in land use and land cover changes in Katsina-Ala Local Government Area (Table 5 and Figure 5) shows that Farmland increased during the period 1990-2000 at 928.64km² (35.49%) being the first period with an annual rate of change of 92.86km² (3.55%), 323.51km² (12.36%) in second period 2000-2010 with an annual rate of change of 32.35km² (1.24%), and decline to -120.39km² (-4.60%) in the third period 2010-2020 with an annual rate of change of 12.4km² (0.46%). The overall trend indicates that 1131.76km² (43.25%) was gained between 1990 to 2020 respectively with an annual rate of change of 37.73km² (1.44%.) The increase in farmland for the two periods could be due to indiscriminate clearance of forest cover for extensive cultivation and other anthropogenic activities. The decline observed during the third period i.e 2010-2020 could be due to growth of human settlement especially in urban areas.

Forest land cover on the other hand has declined throughout the three decades periods. during the 1990-2000 period the forest cover decline stood at -944.60km² (-36.10%) with an annual rate of change of 94.46km² (3.61%), and further decline to -381.76km² (14.59%) with an annual rate of change of -38.18km² (-1.46%), and -65.50km² (-2.50%) with an annual rate of change of -6.55km² (0.25%) within the period 2000-2010 and 2010-2020 respectively. The overall trend indicates that -1391.86km² (-53.19%) was lost between 1990 to 2020 with an annual rate of change of -46.40km² (-1.77%.) The decreases in Forest land cover for the periods and area could be due to deforestation emanating from logging, extensive agriculture and other anthropogenic activities.

Built up area increased by $10.55 \text{km}^2 (0.40\%)$ in the first period at an annual rate of change of $1.05 \text{km}^2 (0.04\%)$ while in the second period the change was 49.74 km² (1.90%) at the annual rate of change of 4.97km² (0.19%) and $180.51 \text{km}^2 (6.90\%)$ at the annual rate of change of $180.51 \text{km}^2 (0.69\%)$ in the third period indicating a drastic increase in rate of change in the second and third periods which signifies a continuous rise in the rate of urban expansion between 2000 to 2020. The overall trend (1990-2000) revealed that built up area has increased up to 240.80km² (9.20%) with an annual rate of change as high as 8.03km² 0.31% higher than the rate in the first period, see (Table 6 & 7).

CONCLUSION

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 Katsina-Ala LGA, which is critical in sustainable environmental management. Result of classification clearly shows constant positive increase in built up area, and farm land but a decline in forest land cover.

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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.

Furthermore, the developed spatial map can serve as an efficient technical vehicle for spatial analysis and spatial modeling functions, to gain insights into a sustainable development. It is expected to be useful for formulating meaningful plans and policies so as to achieve a balanced and sustainable development in Katsina-Ala Local Government Area. It is concluded that satellite imagery can be very effective and fast in change detection of land use and land cover changes.

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