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# Prediction of Land Use Change in Katsina-Ala through a Geospatial Approach

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**Abstract**

The objective of this study was to quantify land use and land cover (LULC) changes and predict future urban growth in Katsina-Ala. Three Landsat satellite images TM, ETM+ and OLI for 1987, 2007 and 2017 respectively were classified using maximum likelihood classifier in Idrisi Selva to detect the land cover changes and a classification accuracy of 87.18%, 89.32% and 91.6 for 1987, 2007 and 2017 maps was achieved . The result of the classification revealed that between 1987 and 2017, urban area increased by 80.38ha (102.17%) at the rate of 3.41%, farmland increased by 88453ha (133.56%) at the rate of 4.45% per year, forest declined by -4219ha (-5.92%) at the rate of -0.2% and grassland declined by 53656ha (-44.54%) at the rate of -1.48%. The study found that evidence likelihood and the distance from rivers. urban areas and elevation were the most important factors shaping urban growth in Katsina-Ala. Thereafter, a Multilayer Perceptron Markov (MLP-Markov) model was used to model transition potentials of various LULC types to predict future changes in 2030. The model had a reliability of

85.8% after validation. The results of the prediction show that urban area will increase from 5.92% to 6.35% with forest declining from 10.8% to 9.46%. It reveals that Katsina-Ala will grow at the rate of 0.46%. Analysis of the prediction revealed that the rate of urban growth will continue and would certainly threaten forest areas in the area. Katsina-Ala stands the risk of extreme deforestation if appropriate measures are not taken.

**Keywords:** Katsina-Ala, Land use and land cover, Urban growth, Landsat satellite, Maximum likelihood classifier, Idrisi Selva, Evidence likelihood, Multilayer Perceptron Markov.

## 1.1 Introduction

Land use refers to the way in which, and the purposes for which, humans employ the land and its resources. Land cover refers to the habitat or vegetation type present, such as forest and agriculture area. Land use and land cover (LULC) change also known as land change is a term for the human modification of Earth's terrestrial surface. Land use and cover change (LUCC) is one of the central themes of the global change research. Rapid world population growth accompanied by economic activities causing urban growth and acceleration of urbanization processes has led to rapid LULC changes (Yirsaw, *et al*, 2017; Yuan, *et al*, 2015). Land use and land cover change has been identified as an important driver of environmental change on all spatial and temporal scales (Mishra, *et al*, 2014), as well as emerging as a key environmental issue and on a regional scale is one of the major research endeavors in global change studies. These changes encompass the greatest environmental concerns of human populations today, including climate change, biodiversity loss and the pollution of water, soils and air. LULC change studies have resulted in diverse impacts including the extensive modification of Earth's ecosystems. The impact of human activities is becoming more and more visible in the natural environment. One of the most important and obvious areas of concern of these activities is LULC change. The key activity in the LULC change projects is to simulate the syntheses of knowledge of LULC change processes, and in particular to advance understanding of the causes of land cover change. But the most important issue is understanding the causes of LULC change. Factors that operate at the global level seem to be the main determinants of land cover change, as they amplify or attenuate local factors (Lambin et al., 2001) Understanding of how land cover change occur is very critical given that these anthropogenic processes can have broad impact on the environment (Tayyebi et al., 2010). Still, there is a need of developing regional models for case studies to understand LULC change patterns. And this is the reason for this research to be undertaken. What is often unsaid, the lack of land cover datasets is a huge problem, as they are an essential basis for any LULC change analysis.

Nowadays there are plenty of models and approaches in LUCC modelling. In the past decade researches revealed that many factors are responsible for changes in LUCC patterns (Ahmed & Bramley, 2015). Among these factors there are biophysical, economic, social, cultural, political or institutional ones. It is impossible to use all of these approaches and to take into account every factor, but often more complex and interdisciplinary models can have more predicting power. Monitoring and mediating the negative consequences of LULC while sustaining the production of essential resources has therefore become a major priority of researchers and policymakers around the world. There is no doubt that the modelling of LULC change and environmental changes are the subject of increasing importance. A broad range of models has been developed for this discipline. There are two fundamental steps in every study of land change, i.e. detecting change in the landscape and describing that change to some set of causal factors. The last step is crucial for the research quality. A better understanding of

LULC patterns will assist planners to properly evaluate complex causes and responses in order to better project future trends of human activities and LULC change. In this research, it is much needed to estimate the land use changes over the time and predict the future scenario of Katsina-Ala. For this study, analysis is performed by a remote sensing based Land Change Modeler (LCM) method. Based on past trend from 1987-2007 of land use changes, the future land use prediction map of Katsina-Ala area for the year 2030 has been generated.

This work presents changes in land cover between 1987and 2017 as well as modelling outputs for the study area. This study is aimed at prediction of land use change in Katsina-Ala through a geospatial approach so as to achieve these specific objectives:

i. Map the types and extent of LULC classes in Katsina-Ala area of Benue State.
ii. Analyse the trend and rate of LULC changes between 1987 and 2017.
iii. Identify the drivers and their contributions to urban growth in the area.
iv. Predict the pattern of urban growth in Katsina-Ala area for 2030

## 2.0 Material and Methods

### 2.1 Study Area

Katsina-Ala, created in 1976 is situated within the lower River Benue valley in Central Nigeria. Its lies between longitude 9° 15′ and 9° 56′ East and Latitude 6° 55′ and 7° 36′ North as shown in Figure 1. Benue has a population of, 225,471 (2006 census) and occupies a landmass of 2688.64 square kilometres. (Etim, 2007 and BNSG, 2017). Katsina-Ala is the location of one of the oldest schools in Nigeria, Government College Katsina-Ala , founded in 1914.

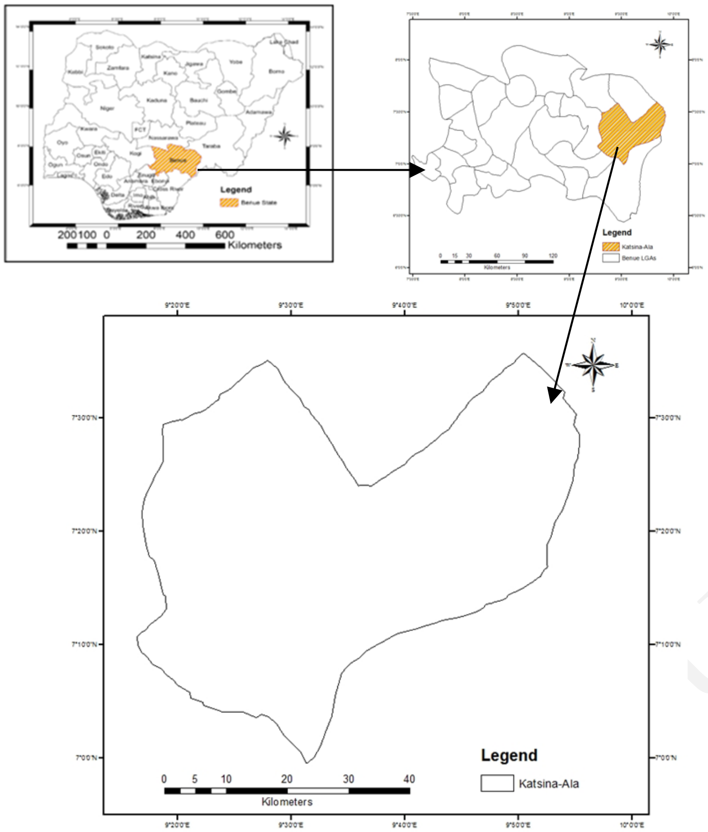


Figure 1: Study Area

The drainage system of the area is influenced by factors such as relief, climate, rock structure and human activities in the area. The major drainage feature in the area is the River Katsina-Alan which is the major tributary of the River Benue. It takes its source from the Cameroonian Mountains. The river is used for transportation purposes, as well as for tourism, fishing and irrigated farming (BNSG, 2017). These waters are utilised for a wide range of purposes such as irrigation, fishing, source of potable pipe-borne water, industrial uses, domestic uses, drinking water for livestock and recreational purposes (Uchua, 2011).

The climate of Katsina-Ala has two different seasons, the rainy (wet) season and the dry season (Abah, 2014).The wet season commences in the month of April and lasts till October having a break in August, while the dry season starts from November and ends in March. The yearly rainfall is between 15cm and 18cm. Temperatures varies between

$23^0$C-$38^0$C for most of the year.. According to the classification by Thornthwaite, 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. This has brought about twoe distinct rainfall periods in the area: the wet period and the dry period. The harmattan winds usually brings a cooling effect particularly from November to February and it is linked with seasonal dust haze coming from the prevailing dry NE trade winds from the Sahara Desert (BNSG, 2017).

The vegetation of the area is mainly the Guinea savannah with trees and grasses mixed together having average height. The guinea savannah has isolated riparian forests along the river banks, 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 in some places 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 others, have to a large extent, impacted on the original forests. The original forest vegetation is now reduced to secondary forest and savannah vegetation. The grasses grow very tall and are coarse when matured. There are pockets of scattered trees that are of economic importance and they include mango, shea butter, locust bean, African iron, Isoberlinia, cashew, *Danielliaoliveri*, *Gmelina arborea*, oil palm, etc. These trees produce products that serve as raw material for some small-scale industries.

Katsina-Ala is mostly rural, where settlements are dispersed in small homesteads with a population density of about 180 persons per $km^2$ who are mostly farmers. Katsina-Ala is administrative headquarters of Katsina-Ala LGA (BNSG, 2017).

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 Katsina-Ala valley. Katsina-Ala is part of the Sankara chiefdom noted for the production of yam and other agricultural crops such as cassava, rice, soya beans, millet, potatoes, guinea corn, groundnuts, maize and benniseed. and is regarded by many as the 'Food Basket of Benue'. (Benue State Government, 2017).

**2.2 Data Requirement and Collection**

The data for this research was derived from primary and secondary sources. The primary data consist of first-hand information and comprises personal observation, taking of pictures; and taking of location of points using handheld Global Positioning System (GPS). The GPS was also used for ground truthing during image classification. The secondary data consists of Satellite Remote Sensing imageries, Digital Elevation Model (DEM), Population data, Road network, Rail network, and drainage network characteristics.

The Satellite imageries used included Landsat TM (1987); Landsat ETM+ (2007); and Operational Land Imager (OLI) (2017). The Landsat imagery dataset were downloaded from the United States Geological Surveys (USGS) using the *Earthexplorer* platform, 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 reflection of most features are easily comparable across the different images. In addition, high resolution Google earth images were used to aid in classification.

The Digital Elevation Model (DEM) data used were the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) DEM for the year 2014, (Table 1). The data is a raster data format, having spatial resolution of 30 meters and a scene coverage of $1^{o}$ x $1^{o}$ (approximately 111 km x 111 km).

Table 1: Specifications of Satellite Imageries

| 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 |
| ASTER GDEM* | - | Radiometer | 1 | - | 2011 | 30m |

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

The data were downloaded using the *Earthexplorer* online platform from United States Geological Surveys (USGS).A subset of the area covering the study area was done. The DEM was used for the determination of slope and elevations of points which affect the cost of construction. Higher slopes and marshy areas attract higher cost of construction as opposed to plain and gentle slopes.

Other ancillary data used include:

*Population data*- were sourced from the National Population Commission. The population of the 23 local government areas was mapped to produce the population density of the state from which the area was clipped.

*Transportation network*- Major roads and rail network were mapped from Google Earth in order to have an up-to-date database of the transportation network in the state.

*Drainage network characteristics*- The major water bodies in the state (rivers and lakes) were mapped from Google Earth to ensure higher accuracy.

The tools used for carrying out the research were;

i. ArcGIS 10.2 used for pre-processing of images and vector data.
ii. ERDAS Imagine 2014, used for classification and accuracy assessment of classification
iii. Idrisi Selva, used for change detection and modelling.
iv. Google Earth Image, used for delineation and updating of transportation and drainage maps. It was also used in preparing point data files for modelling.
v. Global Positioning System-This was used for classification and data validation

**2.3 Mapping the types and extent of LULC cover classes in Katsina-Ala**

This objective was achieved by examining Landsat TM of 1987, Landsat ETM+ of 2007 and Landsat OLI of 2017 images acquired and their subsequent classification. In order to map the types and extent of LULC classes, the data were subjected to these processing and analytical procedures as shown in Figure 2:

*i) Data Pre-processing* The Landsat images were pre-processed, so that inherent errors and formatting that are required for further direct processing of the data will be done. The downloaded Landsat images were in separate bands and need to be layer stacked.

This is a process whereby different bands of an image are joined together to form a single multispectral image. These individual bands were then stacked sequentially from 1 to 7 using ERDAS Imagine 2014. Specifically, the three (3) satellite imageries, Landsat TM (1987); Landsat ETM+ (2007); and Landsat OLI (2017) were corrected radiometrically through haze removal operations, so that radiometric errors added to data, due to atmospheric scattering were corrected, using the ERDAS Imagine 2014 image processing software.

Radiometric correction refers to the elimination of distortions in the degree of electromagnetic energy registered by each detector. Focal analysis module in ERDAS 2014 was used in removing scan lines on images especially the 2007 Landsat image. Geometric correction refers to the process of co-registration of the satellite images, so that the images could overlap in the best possible way. This function was achieved in IDRISI through the RESAMPLE module. This is very essential due to the fact that some of the essential methods are based on the comparison of the two images from different time periods, e.g. supervised classification Although most of Landsat images have been already georeferenced, images with a lot of cloud cover could have low geometric accuracy, and therefore required to be geo-referenced.

The Digital Elevation Model (DEM) data were used to produce elevation and slope characteristics of the area.

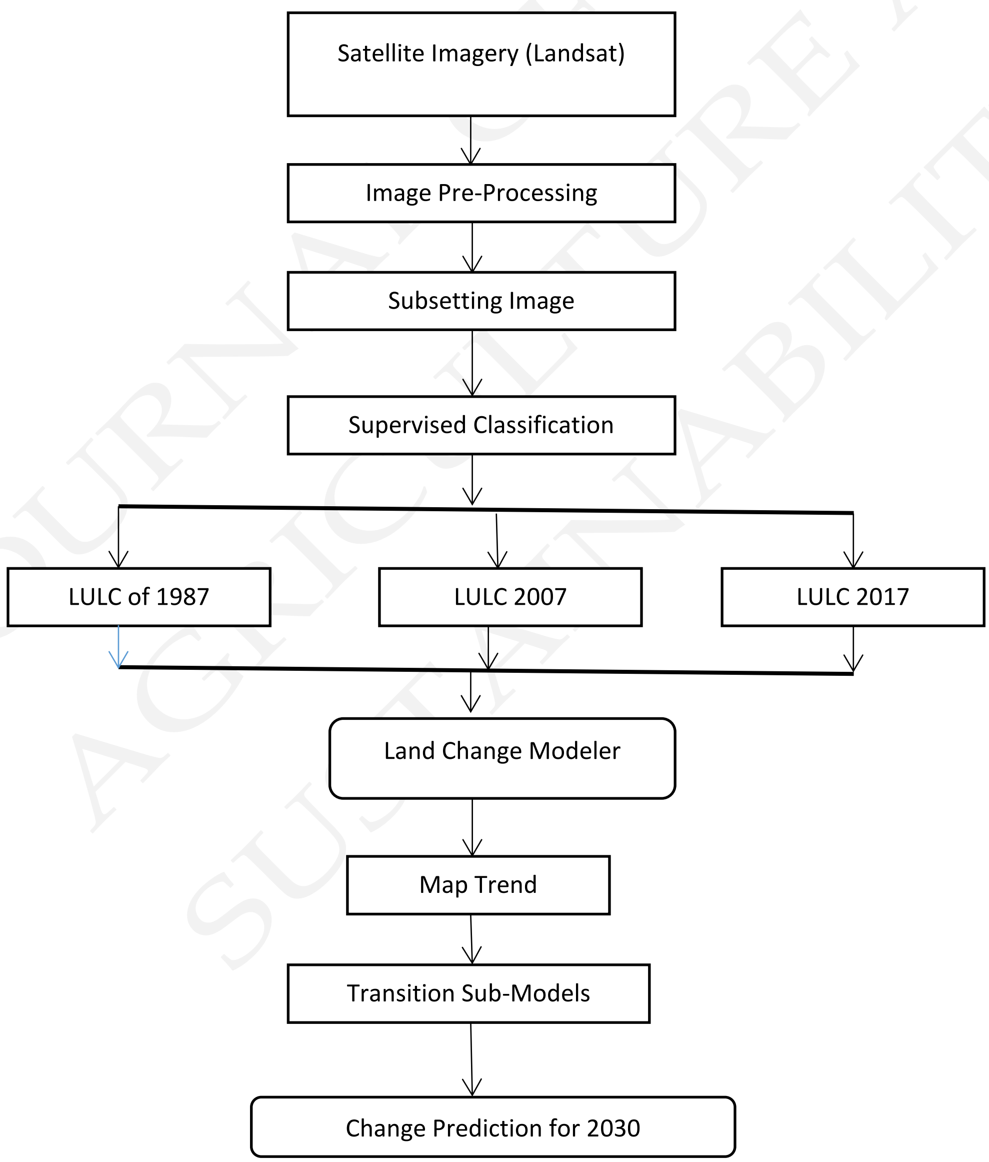


Figure 2: Flowchart of the Research Methodology

*ii) Image rectification*

This operation was carried out through clipping of the study area from the scenes. The shapefile of Katsina-Ala was used to subset from the larger scenes. This was done through the use of the subset method in ERDAS 2014 and the desired shapefile of Katsina-Ala was used as the Area of Interest (AOI). The choice of this method was based on its simplicity of use and its higher accuracy.

*iii) Image enhancement:*

Image enhancement is concerned with the alteration of images to make them more suited to the capabilities of human vision. Irrespective of the extent of digital intervention, visual interpretation plays a very strong role in all aspects of remote sensing (Eastman, 2012). In order to improve visual quality and outlook of an image for easy interpretation, image enhancement is necessary. It increases the contrast among different features thereby enhancing easy identification of features and subsequent classification. After the enhancement process, band combination operations were performed to select the different bands which will enable the classification of a given earth surface feature. The major reason for colour composite is to highlight certain brightness values that are associated with certain surface features. 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 boundaries.

*iv) Image classification:*

A per-pixel image classification method for ground cover analysis was used through a 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). It is a process of using samples whose identity is known to categorize samples whose identity is unknown. A Maximum Likelihood algorithm of supervised classification was adopted because of the author's familiarity with the terrain. This method was chosen because it is easier to accomplish and more so, the large volume of images to be interpreted could not warrant the use of visual on-screen interpretations. The visual method depends largely on the skill and familiarity of the interpreter and is therefore prone to much error if the interpreter is not well experienced. The identification of training sites used was based on spontaneous recognition and logical inference both of which are products of visual interpretation. Spontaneous recognition refers to the capability of the interpreter to recognize objects at a glance such as agricultural plots. In logical inference, the interpreter draws conclusion on the basis of ground control points, his professional knowledge and field experience over the years(Congedo and Munafò, 2012).

The Maximum Likelihood is one of the most commonly used supervised classifiers, which uses the Gaussian threshold stored in each class signature to assign every pixel a class (Huang *et al.*, 2009). Maximum Likelihood classification assumes that the probability distributions for the classes follow the normal distribution model(Richards and Jia, 2006). The discriminant function, as described by Richards and Jia, (2006), is:

$$g_i(x) = \ln p(\omega_i) - ½ \ln |\Sigma_i| - ½ (x - m_i)^t \Sigma_i^{-1} (x - m_i) \qquad (1)$$

where: $\omega_i$ = class (where i = 1, . . . M and M is the total number of classes)

x = pixel vector in n-dimension where n is the number of bands

$p(\omega_i)$ = probability that the correct class is $\omega_i$ occurs in the image and is assumed the same for all classes

$|\Sigma_i|$ = determinant of the covariance matrix of the data in class $\omega_i$

$\Sigma_i^{-1}$ = inverse of the covariance matrix and $m_i$ = mean vector

The Maximum Likelihood method was used, because it is one of the best classification methods which assigns pixels to the class with the largest probability to determine class membership 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 of Katsina-Ala, 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)

$C_a = T_a(t_2) - T_a(t_1)$; *(2)*

$C_e = C_a / T_a(t_1)$; *(3)*

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

*v) Fieldwork and Ground-truthing*

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 were 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 they 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 and land cover 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.

Table 2: Classification scheme adopted.

| S/N | Class | Description |
|---|---|---|
| 1 | River/ water bodies | Open water features including lakes, rivers, streams, ponds and reservoirs. |
| 2 | Built-up/Urban Areas | 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 consisting 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)

*vi) Sampling Technique*

The sampling technique adopted in selecting control points for accuracy assessment was the stratified random sampling. There are two primary purposes to implement stratification in the accuracy assessment: 1) when the strata are of interest for reporting results and 2) when there is the need 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.

*vii) Accuracy Assessment*

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 as used by Friehat*et al, (*2015) to assess the accuracy of the classification.

Accuracy assessments of the classified maps (1987, 2007 and 2017) were done using the error matrix (ERRMAT in Idrisi Selva). 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 (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 the 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 (Pedro, 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.

$$k = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)} \qquad (4)$$

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).

A simpler method of determining Kappa in an error matrix with number of rows and columns is given by Siddhartho (2013):

K = (NA - B) / (N2 - B) *(5)*

Where, N = total number of observations included in the error matrix

A = the sum of correct classifications contained in the diagonal elements

B = the sum of the products of row total and column total for each LULC type in the error matrix

Simply put:

$$\check{K} = \frac{\text{Observed Accuracy} - \text{Chance Agreement}}{1 - \text{Chance Agreement}} \qquad (6)$$

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 Katsina-Ala, 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).

2.4 Analysis of the trend of land use and land cover changes from 1987- 2017

The methodology for achieving this objective was through the use of Change Analysis Tab in IDRISI. Here, the focus was on the spatial trend of change panel to directly detect the actual spatial pattern of each major land conversion that has taken place in Katsina-Ala from 1987-2007, 2007-2017 and1987-2017. The principle under which this panel works is the polynomial order in which the spatial pattern and trend of land use and land cover between two periods is generalized. According to Eastman (2012), the spatial trend of change panel in LCM is to follow a similar pattern on Trend Surface Analysis (TSA) as in the TREND module in IDRISI. It calculates trend surface polynomial equations up to the 9$^{th}$ order for spatial data sets, and then interpolates the surfaces based on those equations. The generic equation for the polynomials fitted by TREND as given by(Saifullah, Barus, & Rustiadi, 2017) is:

$$Z = \sum_{i=0}^{k} \sum_{j=0}^{i} b_{ij} X^{i-j} y^{j} \qquad (7)$$

Where k = is the maximum order to be fitted;

*b* = coefficient of the polynomial equation;

both *i*and *j* are iteration variables associated with *k*, in which *i = 0,…k* and *j = 0,…i*. (Saifullah et al., 2017)

### 2.4.1 Establishing the rate of rural-urban land conversion in Katsina-Ala

This section is also part of objective two of the study. After a successful classification, the LULC classes for 1987, 2007 and 2017 were compared to determine the extent of change. The extent of change was divided by the time interval between the initial and the later date to arrive at the rate of rural- urban conversion. This operation is represented by the following equation as given by Yesserie (2009):

$$C_r = C_e/(t_2 - t_1); \qquad (8)$$

Where $C_e$ = Change extent

$t_1$ and $t_2$ = the starting and ending times respectively of the LULC studies conducted

## 3.0 Results and Discussion

### 3.1 Classification of Land use and land cover for 1976, 2007 and 2017

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.

### 3.1.2 Extent of land use and land cover types in Katsina-Ala

An analysis of the classification of land use and land cover classes revealed that urban area has been on a steady increase from 7867ha (2.93%) in 1987 to 10381ha (3.86%) in 2007 and rising sharply to 15905ha (5.92%) in 2017. This huge increase in urban area may be due to migration from rural areas to urban areas in search of job opportunities and better standard of living which has increased demand for urban residential settlements. Forest land on the other hand has been on the decline during the same period from71200ha (26.40%) to 66401ha and then decreasing sharply to 29026ha (10.8%) in the three periods.

The decrease in forest land is due to the pressure from farming activities and increase in settlements as evidenced by their increase in the same period under review. Farmland too has been increasing from 66226ha (24.63%) to 106926ha (39.77%) and sharply to 154679ha (57.58) in 2017. Bare surface and water body each accounted for less than 1% of the land cover and showed no significant changes. This can be seen in Table 3 and Figures 3, 4, 5.

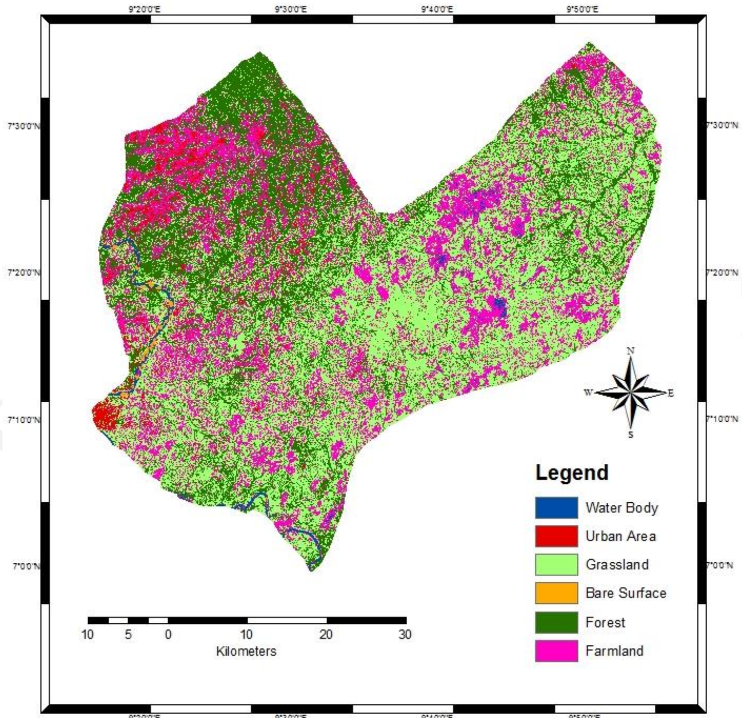


Figure 3: Land use and Land cover map of Katsina-Ala for 1987

Source: Author's fieldwork, 2018

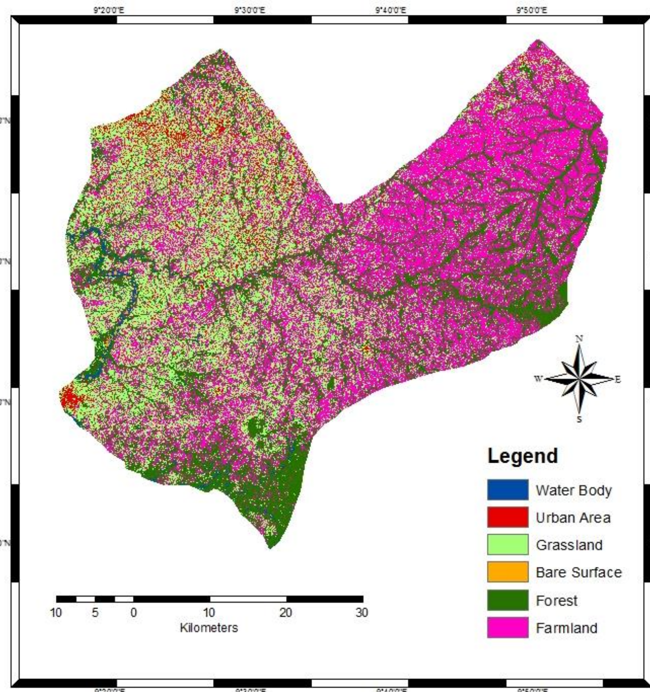


Figure 4: Land use and Land cover map of Katsina-Ala for 2007

Source: Author’s fieldwork, 2018

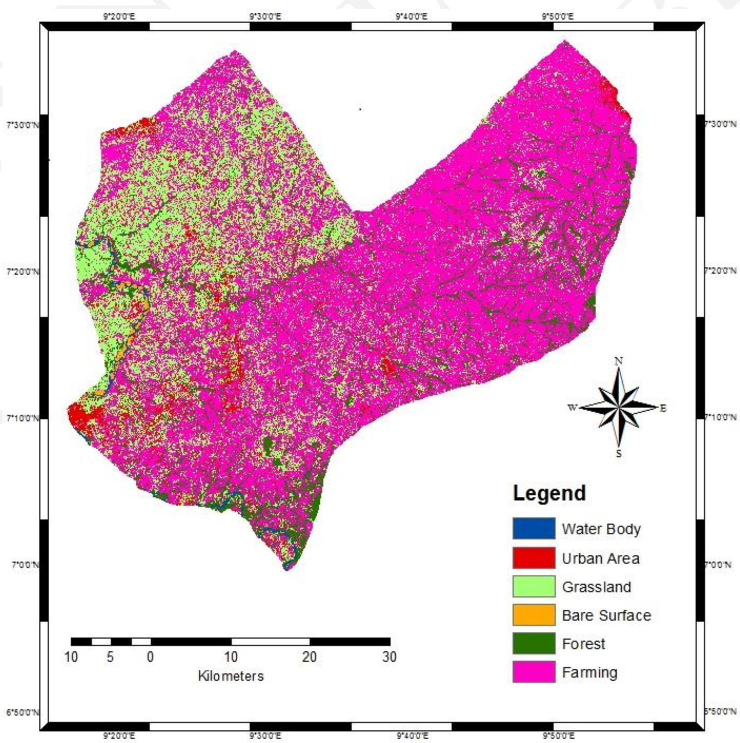


Figure 5: Land use and Land cover map of Katsina-Ala for 2017

Source: Author’s fieldwork, 2018

Table 3: Area Statistics of LULC in Katsina-Ala (1987, 2007 and 2017)

| | 1987 | | 2007 | | 2017 | |
|---|---|---|---|---|---|---|
| Land cover Class | Area (Ha) | Area (%) | Area (Ha) | Area (%) | Area (Ha) | Area (%) |
| Water Body | 2402 | 0.89 | 3256 | 1.21 | 1323 | 0.49 |
| Urban Area | 7867 | 2.93 | 10381 | 3.86 | 15905 | 5.92 |
| Grassland | 120480 | 44.81 | 81295 | 30.24 | 66824 | 24.87 |
| Bare Surface | 673 | 0.25 | 605 | 0.22 | 896 | 0.34 |
| Forest | 71216 | 26.49 | 66401 | 24.70 | 29026 | 10.80 |
| Farmland | 66226 | 24.63 | 106926 | 39.77 | 154679 | 57.58 |
| Total Area | 268864 | 100 | 268864 | 100 | 268864 | 100 |

Source: Author's fieldwork, 2018

**3.1.3: Accuracy Assessment of Classified Maps**

It is difficult to attain a 100% accuracy in any classification and as such there exist some standards to which each classification must attain for it to be acceptable. The accuracy of satellite image classification could be controlled by the resolution of images used and lack of fine details as well as the impact of unavoidable generalization and therefore, errors are always expected. This is why, to ensure prudent utilization of the produced LULC maps and their associated statistical results, the errors and accuracy of the analysed outputs should be quantitatively evaluated. .

**3.1.4: Assessment of classification accuracy of LULC in Katsina-Ala**

The result of classification accuracy for 1987, 2007 and 2017 for Katsina-Ala showed an overall accuracy of 87.18%, 89.32% and 91.6% respectively (see Table 4). Based on the scale of assessment, the overall accuracy was considered a good one and, therefore, usable for change detection analysis. The user's accuracy for the different classes ranged between 73.08% and 96.61% and the producer's accuracy ranged between 81.82 % and 95.16%. The results of overall kappa for the three periods 1987, 2007 and 2017 revealed Kappa statistics of 0.84, 0.87 and 0.90 respectively.

Table 4: Accuracy assessment result of LULC classification in Katsina-Ala

| LULC Class | 1987 classification Producer's Accuracy (%) | 1987 classification User's Accuracy (%) | 2007 classification Producer's Accuracy (%) | 2007 classification User's Accuracy (%) | 2017 classification Producer's Accuracy (%) | 2017 classification User's Accuracy (%) |
|---|---|---|---|---|---|---|
| Water Body | 81.82 | 75 | 83.33 | 95.24 | 87.5 | 95.45 |
| Urban Area | 86.11 | 88.57 | 90.62 | 87.88 | 91.67 | 94.29 |
| Grassland | 87.93 | 91.07 | 90.48 | 96.61 | 91.23 | 96.3 |
| Bare Surface | 86.36 | 73.08 | 86.96 | 76.92 | 88.89 | 80 |
| Forest | 90 | 92.31 | 89.13 | 87.23 | 90.57 | 94.12 |
| Farmland | 87.5 | 90.74 | 91.21 | 87.5 | 95.16 | 86.76 |
| **Overall Accuracy** | **87.18%** | | **89.32%** | | **91.6%** | |
| **Overall Kappa** | **0.84** | | **0.87** | | **0.90** | |

Source: Author's fieldwork, 2018

The Kappa coefficient for the three periods showed that the kappa agreement was virtually in perfect agreement implying that it can be used.

**3.1.5: Trend and rate of change in LULC in Katsina-Ala (1987, 2007 and 2017)**

Land use and land cover trend in Katsina-Ala is presented in Table 5 and Figure 6. The trend reveals that urban area continued to expand throughout the period. In the first period, it increased by 2514ha (31.96%) at the rate of 1.6%. By the second period, it increased by 5524ha (53.21%) at the rate of 5.32%. The overall trend shows that urban area increased by 80.38ha (102.17%) at the rate of 3.41%.This indicates that the urban area in

Katsina-Ala is not expanding at a very fast rate as other towns. This results collaborates with that of Hashem and Balakrishnan, 2015 in the modelling of urban growth in Greater Doha, Qatar. As with other areas, forest in Katsina-Ala has been on the decline over the years. In the first period, -4815ha (-6.76%) was lost at the rate of -0.34% per year while 37375ha (-56.29%) was lost in the second period at the rate of -5.63% per year.

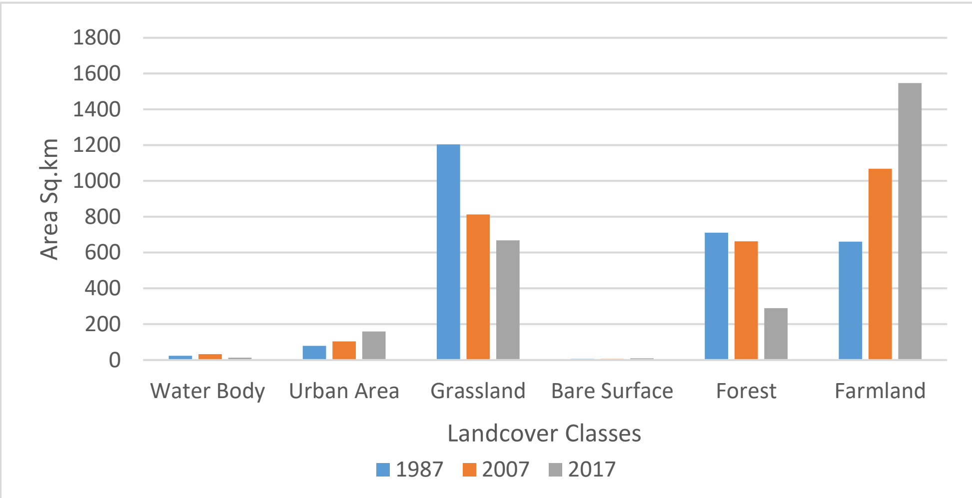


Figure 6: Trend of Land cover changes in Katsina-Ala (1987-2017)

Source: Author's fieldwork, 2018

The overall trend shows that forest declined by -4219ha (-5.92%) at the rate of -0.2%. The decline in forest area was mostly due to expansion in farmlands. Farmland has been on the increase over the entire period. It increased by 407ha (61.46%) at the rate of 3.07% during the first period and 47753ha (44.66%) at 4.47% rate per year during the second period. The trend over the entire period shows an increase of 88453ha (133.56%) at the rate of 4.45% per year. The rate of expansion of farmland is very high in this region owing to the fact that the inhabitants are largely agrarian and the area forms one of the core areas agricultural base in Benue State. As farmland increases, grassland decreases. In the first period, grassland lost -39185ha (-32.52%) at the rate of -1.63% increasing to -14471ha (-17.8%) at the rate of -1.78% in the second period. The overall trend shows that 53656ha

(-44.54%) was lost at the rate of -1.48%. This massive loss was largely due to expansion of agricultural land.

Table 5: Annual Rate of change for Katsina-Ala (1987, 2007 and 2017)

| LULC Class | 1987-2007 Area(ha) Change | Percentage of Change | 2007-2017 Area (km) Change | Percentage of Change | 1987-2017 Area (ha) Change | Percentage of Change | ANNUAL RATE OF CHANGE 1987-2007 (%) | 2007-2017 (%) | 1987-2017 (%) |
|---|---|---|---|---|---|---|---|---|---|
| Water Body | 854 | 35.55 | -1933 | -59.37 | -1079 | -44.92 | 1.78 | -5.94 | -1.5 |
| Urban Area | 2514 | 31.96 | 5524 | 53.21 | 8038 | 102.17 | 1.6 | 5.32 | 3.41 |
| Grassland | -39185 | -32.52 | -14471 | -17.8 | -53656 | -44.54 | -1.63 | -1.78 | -1.48 |
| Bare Surface | -68 | -10.1 | 291 | 48.1 | 223 | 33.14 | -0.51 | 4.81 | 1.1 |
| Forest | -4815 | -6.76 | -37375 | -56.29 | -4219 | -5.92 | -0.34 | -5.63 | -0.2 |
| Farmland | 40700 | 61.46 | 47753 | 44.66 | 88453 | 133.56 | 3.07 | 4.47 | 4.45 |

Source: Author's fieldwork, 2018

**3.2: Land change analysis using Land Change Modeler (LCM)**

The land cover transition in Katsina-Ala (Figure 7a, b and c) show that all the land cover classes underwent changes. Farmland and urban area maintained a positive change throughout the period. Grassland was positive only during the first period but was negative in the second and overall periods. Forest land declined throughout the period but was highest in the first period. Urban area gained more from bare surface in the first period but was overtaken by grassland in the other periods. Farmland and forest were the other major contributors. Farmland, grassland and forest were responsible for declining forest in the area. From the analysis of the pattern, trend and rate of land use and land cover transition in Benue State and the selected urban areas, it is clear that these land cover classes are not static in nature. Urban areas are continually on the increase in size by taking up lands previously occupied by farmland, grassland and forest. Forest land had been lost due to human activities such as farming and urban settlement. In other areas, the forests were cleared giving way for takeover by grassland. This is clearly evident in the contribution to net change in urban areas and forest.

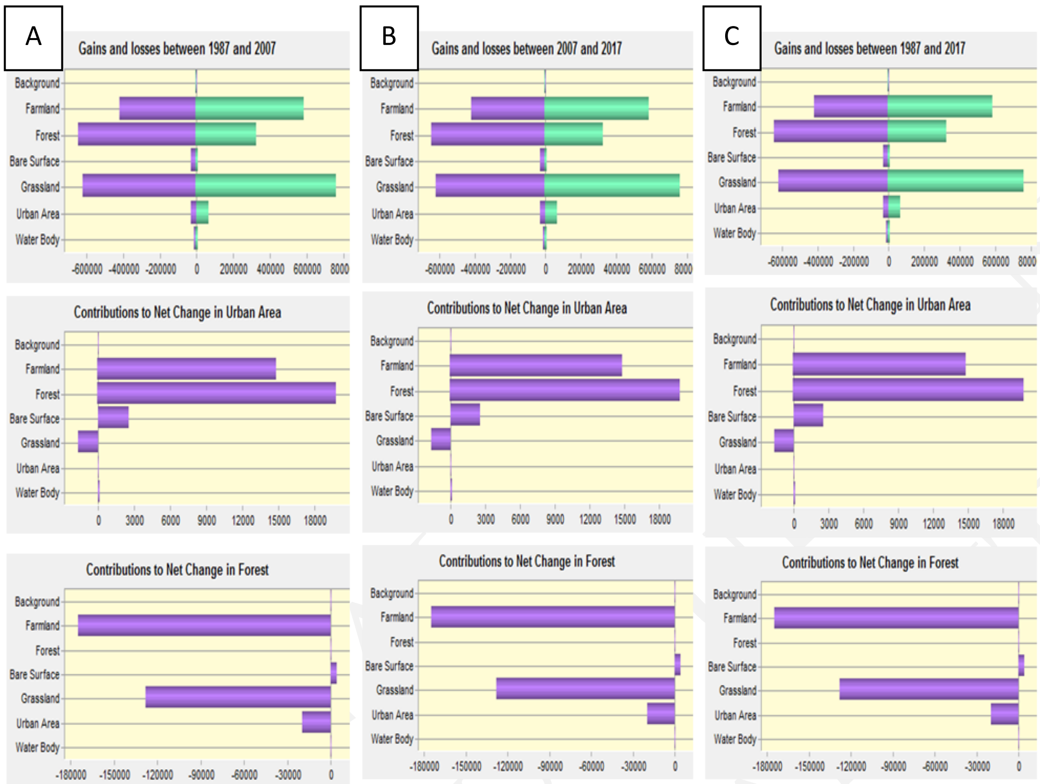


Figure 7: Gains/losses of LULC classes, contribution to net change in Urban area and Forest (ha) in Katsina-Ala from (a):1987 – 2007, (b): 2007 -2017 and (c): 1987- 2017.

Source: Author's fieldwork, 2018

**3.3: Identification of driving factors and their contribution to urban growth**

In order to test the potential power of the drivers (explanatory variables), the LCM's Test and election of site and driver variable module was used. These set of explanatory variables were chosen based on preliminary investigations as well as reviews from relevant academic literatures. Table 6 shows the Cramer's V coefficient for each of the explanatory variables, As can be seen from the table, all the variables namely, likelihood of transition, distance from urban areas, roads, rivers, railways, digital elevation model (DEM), slope and population density selected for transition development were greater than 0.15, some of them were higher than 0.4 which indicates the selected variables have association with the changes and were used in the process as was shown by Wang and Maduako (2018). It is also evident that likelihood of transition, DEM and population density have values higher that 0.4, meaning that these three variables are strongly associated with transition and therefore kept in the sub-model structure. Also, the LCM MLP model results reveal that likelihood of transition, distance from urban areas and railways were most important drivers in shaping urban growth as revealed by the influence order.

Table 6: Cramer's V Test values for explanatory variables in Katsina-Ala

| Variable | Cramer's V |
|---|---|
| Likelihood | 0.4048 |
| Dist_Urban | 0.3623 |
| Dist_Roads | 0.2418 |
| Dist_Rivers | 0.2563 |
| DEM | 0.4375 |
| Slope | 0.3846 |
| Pop density | 0.4140 |

Source: Author's fieldwork, 2018

### 3.3.1: Sensitivity Analysis

Upon completion of the entire process, MLP outputs a number of statistics that provide information regarding the power of the explanatory driver variables as well as the models accuracy in predicting class transitions and persistence. One important aspect of the statistics generated is termed "Forcing Independent Variables to be Constant". After the system has trained on all of the explanatory variables, the system tests for the relative power of explanatory variables by selectively holding the inputs from selected variables constant. Holding the input values for a selected variable constant effectively removes the variability associated with that variable. Using the modified model, the MLP procedure repeats the skill test using the validation data. The difference in skill thus provides information on the power of that variable. This process is repeated for all the driver variables to determine their influence on the skill measure and accuracy of the model.

Three different sensitivity analyses were run. In the first section, a single variable is held constant. This is repeated for all variables. Table 7 shows the sensitivity of holding one variable constant. In the second sensitivity, all variables are held constant (at their mean values) except one.

Table 7: Forcing a Single Independent Variable to be Constant in Katsina-Ala

| **Model** | **Acc(%)** | **SM** | **IO** |
|---|---|---|---|
| With all variables | 71.43 | 0.6571 | N/A |
| Var. 1 constant | 68.91 | 0.6269 | 4 |
| Var. 2 constant | 72.69 | 0.6723 | 7* |
| Var. 3 constant | 64.71 | 0.5765 | 2 |
| Var. 4 constant | 65.97 | 0.5916 | 3 |
| Var. 5 constant | 72.27 | 0.6672 | 6 |
| Var. 6 constant | 70.17 | 0.6420 | 5 |
| Var. 7 constant | 29.41 | 0.1529 | 1** |

Key: Acc= Accuracy, SM= Skill measure, IO= Influence order, ** = Most Influential, * = Least Influential

Source: Author's fieldwork, 2018

The final test in section 3 is entitled Backwards Stepwise Constant Forcing. Starting with the model developed with all variables, it then holds constant every variable in turn to determine which one has the least effect on model skill. Step 1 thus shows the skill after holding constant the variable that has the lowest negative effect on the skill. If a variable is held constant and the skill does not decrease much, then it suggests that that variable has little value and can be removed (See Table 7).

It then tests every possible pair of variables that include that determined in step 1 to figure out which pair, when held constant, have the least effect on the skill. It continues in this manner progressively holding another variable constant until only one variable is left. The backward stepwise analysis is very useful for model development. The backward stepwise MLP result was used in assessing the best model combination of independent variables based on percentage accuracy and skill measure by consecutively eliminating the weakest independent variable one by one.

The results of the backwards stepwise constant forcing in Table 7 shows that the

Table 8: The Result of MLP with backwards stepwise constant forcing in Katsina-Ala

| Model | Variables included | Accuracy (%) | Skill measure |
|---|---|---|---|
| With all variables | All variables | 71.43 | 0.6571 |
| Step 1: var.[2] constant | [1,3,4,5,6,7] | 72.69 | 0.6723 |
| Step 2: var.[2,5] constant | [1,3,4,6,7] | 72.69 | 0.6723 |
| Step 3: var.[2,5,6] constant | [1,3,4,7] | 71.43 | 0.6571 |
| Step 4: var.[2,5,6,3] constant | [1,4,7] | 65.97 | 0.5916 |
| Step 5: var.[2,5,6,3,1] constant | [4,7] | 60.92 | 0.5311 |
| Step 6: var.[2,5,6,3,1,4] constant | [7] | 57.14 | 0.4857 |

Source: Author's fieldwork, 2018

exclusion of variable 2 and 5 (distance from roads and slope) yielded the best combination of variables with an accuracy of 72.69% and a 0.6723 skill measure compared with the 71.43% accuracy and a 0.6571skill measure obtained from the inclusion of all the variables. These best combinations were then used to project sensitivity of urban built-up area expansion.

Table 9 presents list of all independent variables used in the modelling process with their corresponding numbers. Distance from urban area was assigned number 1, distance from roads, number 2, through to the last variable distance from railways with number 8.

Table 9: List of independent variables used in LULC change prediction in Katsina-Ala

| Variable Code | Name of Variable |
|---|---|
| Independent variable 1 | Distance from urban area in 1987 |
| Independent variable 2 | Distance from roads |
| Independent variable 3 | Distance from rivers |
| Independent variable 4 | Digital elevation model |
| Independent variable 5 | Slope |
| Independent variable 6 | Population density |
| Independent variable 7 | Evidence likelihood of transition |
| Independent variable 8 | Distance from railways |

Source: Author's fieldwork, 2018

### 3.3.2: Transition Potential Modelling using MLP

After selecting the predictor variables, all the transitions were then modeled in one transition sub-model called urban area, as they had the same driving forces, with the aim of producing the transition maps.

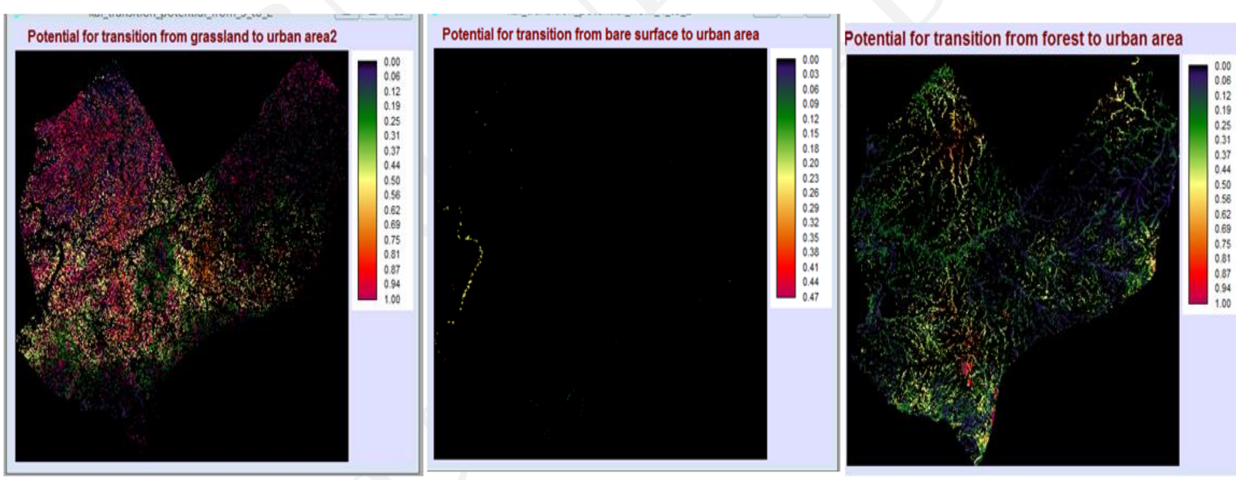


Figure 8: Transition potential maps for Katsina-Ala

Source: Author's fieldwork, 2018

As earlier stated, MLP was used in modelling the transitions and it generated transition potential maps for each of the evaluated transition sub-models. The results of the MLP transition modelling is presented in Figures 8 and reveals the transitions from grassland, bare surface and forest to urban area. These transition potential maps generated from MLP modelling were then used in Markov Chain model for determining the amount of change to be expected for each transition and for predicting of future scenarios.

At this stage, the model was ready to predict urban growth scenarios for 2017 based on the changes that occurred between 1987 and 2007, and the location of the possible future changes simulated from the transition potential maps. The simulated land cover maps were then generated from the transition model. This was named the KAL model.

**3.3.3: Model Predictions and Validations**

Results from Markov chain model predictions are based on a transition probability matrix of land use and land cover changes from 1987 to 2007 and changes in the past. This formed the basis for projection to 2017. Figures 9 showed the actual and predicted land cover maps of Katsina-Ala for the year 2017 which showed noticeable differences. This had been expected as the historical change processes from 1987 to 2007 cannot be the same as from 2007 to 2017 in Markov chain analysis. Again, the driving variables are bound to vary during the period thereby affecting the prediction results It shows that urban areas were underestimated while forest area was slightly overestimated. On the whole, these models were able to correctly predict future scenario to some degree. In contrast to the hard prediction, in the soft prediction map most of the areas that had actual change in 2017 are considered to be vulnerable. In order to assess the extent to which these models were able to predict future land use and land cover through soft prediction, the Relative Operating Characteristic (ROC) in Idrisi Selva was used.

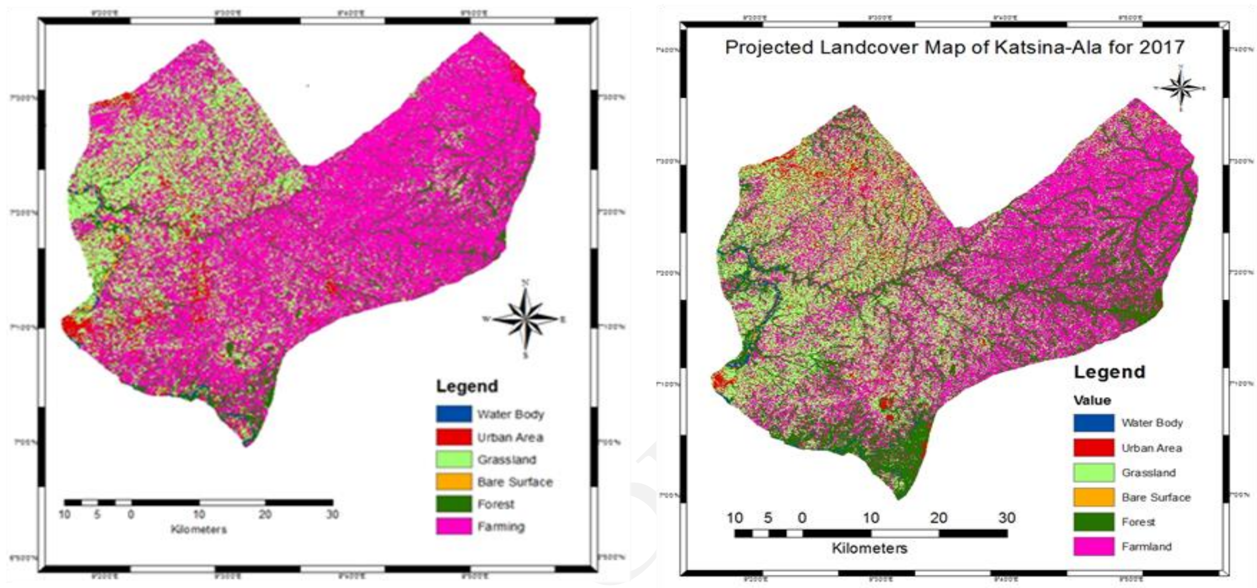


Figure 9: Land cover maps of Katsina-Ala for 2017 (Actual, left and predicted, right)

Source: Author's fieldwork, 2018

The ROC statistic reveals how well a continuous surface predicts the locations given a distribution of a Boolean variable. In this case the soft prediction was used as the continuous surface to evaluate against the real change between 2007 and 2017. The result of the ROC statistic reveal that the Area Under the Curve (AUC) value of was 0.858, which indicate strong value, indicating the soft prediction were very good . Spatial modelling and simulation are not about creating models that can perfectly predict future states. It is and will always be impossible. But efforts should be made to bring us as close to this state as possible. In this context a created model can be considered a successful modelling tool.

**3.4: Modelling and prediction of the pattern of urban growth for 2030**

After model validation, both hard and soft predictions were performed for the year 2030 so as to map possible transitions from other land use and land cover categories to urban area. The prediction was restricted to short-term as they are more accurate than long term predictions (Alba, 2011; Araya, 2009). Figure 10 shows the predicted land cover maps in

2030 complemented by Table 10. The resulting 2030 prediction indicate that there will be significant changes in the future

Table 10: Projected land cover statistics for in Katsina-Ala for year 2030

| Land cover | Area (Ha) | Area (%) |
|---|---|---|
| Water Body | 3247 | 1.21 |
| Urban Area | 17083 | 6.35 |
| Grass land | 115669 | 43.02 |
| Bare Surface | 605 | 0.23 |
| Forest | 25431 | 9.46 |
| Farm land | 106829 | 39.73 |
| **Total** | **268864** | **100** |

Source: Author's fieldwork, 2018

Based on the predicted results for 2030 grassland will dominate the land cover classes in the area accounting for 43.02% of the area followed by farmland (39.73%), forest (9.46%), urban area (6.35%), water body(1.21%) and bare surfaces (0.23%). The trend shows that grassland, urban area and water body will increase by 18.15%, 0.43% and 0.73% respectively as depicted in Figure 9 and Table 11. This agrees with the works of Jande et al, ( 2019) in their study on urban growth assessment and its impact on deforestation in Makurdi metropolis , Nigeria. Urban area is predicted to cover the south western, north western parts of the area and grassland will cover the south east and the west. Farmland, forest and bare surface will decrease during the period by 18.21%, 1.34% and 0.11%. The trend in farmland transition between 2017 and 2030 is similar to that of Otukpo area where farmlands are decreasing with time.

Table 11: Changed areas between LULC in 2017 and 2030 for Katsina-Ala

| Land cover | LULC in 2017 | | LULC in 2030 | | Change | |
|---|---|---|---|---|---|---|
| **Classes** | **Area (Ha)** | **Area (%)** | **Area (Ha)** | **Area (%)** | **Area (Ha)** | **Rate %** |
| Water Body | 1323 | 0.49 | 3247 | 1.21 | 1924 | +0.72 |
| Urban Area | 15905 | 5.92 | 17083 | 6.35 | 1178 | +0.43 |
| Grassland | 66824 | 24.87 | 115669 | 43.02 | 48845 | +18.15 |
| Bare Surface | 896 | 0.34 | 605 | 0.23 | -291 | -0.11 |
| Forest | 29026 | 10.80 | 25431 | 9.46 | -3595 | -1.34 |
| Farmland | 154679 | 57.58 | 106829 | 39.73 | -47850 | -18.21 |
| Total | 268864 | 100 | 268864 | 100 | | |

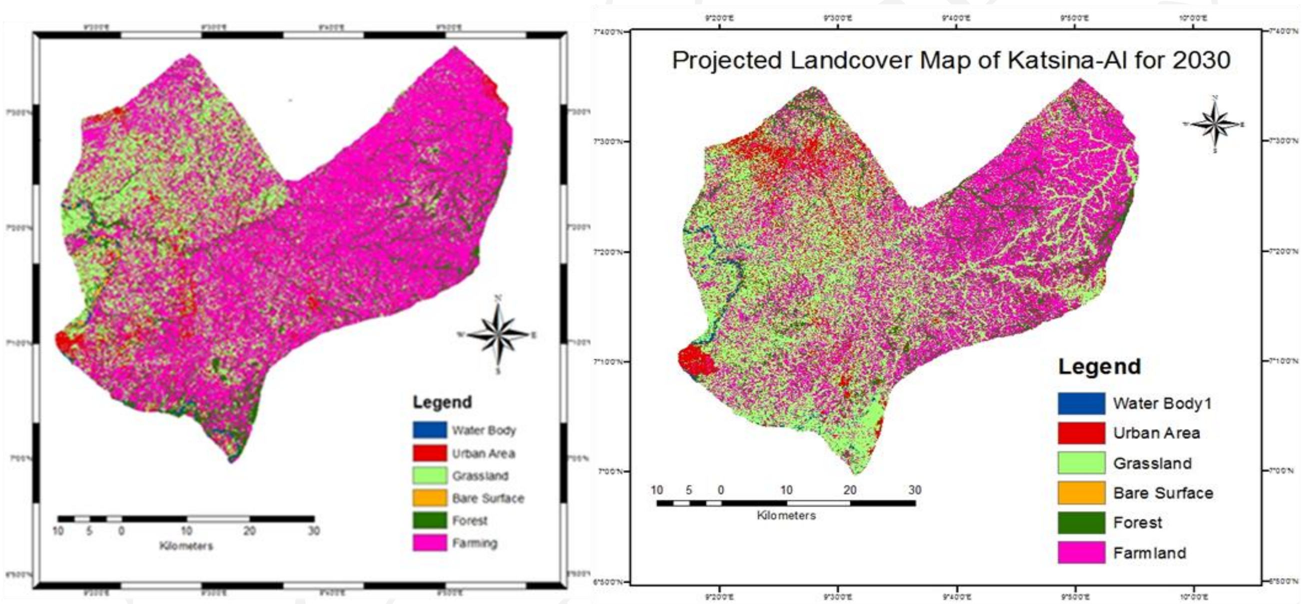


Figure 10: Land cover maps of Katsina-Ala (2017 left, and 2030 projected, right)

Source: Author's fieldwork, 2018

### 3.4.1: Soft Prediction

The soft prediction output is made up of maps that show the probability of change for a given set of transitions. The soft output represents a continuous mapping of vulnerability to change for selected set of transitions. This prediction identified the extent to which the land area has the susceptibility to be altered. The soft prediction output detected the areas with varying degrees of vulnerability instead of identifying what and how much of land cover categories would be changed. From the modelled output for Katsina-Ala, the north west has higher degree of vulnerability of transition to other land cover categories

**3.4.2: Impact of Urban Growth on Deforestation**

The impact of urban growth on forest loss (deforestation) was assessed after the 2030 projection. A closer look at the contributions to net change in forest and urban area between 1987 and the projected 2030 reveals the salient details (See Figure 11).

The urban area is the third largest contributor to deforestation with forest losing over 4052ha of land to urban expansion during the period. Forests are ranked second in contribution to urban expansion, second only to farmlands.

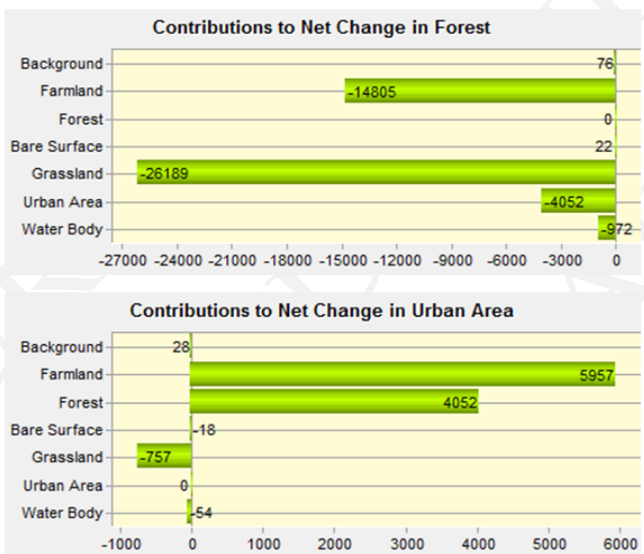


Figure 11: Contributions to net change in forest and urban area from 1987-2030 in Katsina-Ala

Source: Author's fieldwork, 2018

**3.5: Conclusion**

This study has mapped and evaluated land use and land cover changes in Katsina-Ala so as to predict future patterns using a geospatial approach. The study predicted that by the year 2030 grassland will dominate the land cover classes in the area accounting for 43.02%

of the area followed by farmland (39.73%), forest (9.46%), urban area (6.35%), water body(1.21%) and bare surfaces (0.23%). The trend shows that grassland, urban area and water body will increase by 18.15%, 0.43% and 0.73% respectively. These predicted changes was attributed to increase in population and infrastructural developments to meet this population growth. Going by this development, it is obvious that the forest area of Katsina-Ala will be adversely affected because of increase in deforestation and urban area. Agricultural expansion is also affected by urban expansion as areas previously under cultivation are converted to urban areas. This has the effect of reducing areas under cultivation especially at the peri-urban fringes where there exist barriers to prevent further expansion of these agricultural areas. This has a tendency of reducing farm output if intensive practices are not adopted. Where there are no barriers, there is the tendency for cultivated areas to expand further to accommodate the loss to urban areas thereby causing more deforestation.

Based on the nature and rate of change of various land use and land cover types identified in the study area especially from 1987 to 2017 and the modelled results for 2030, the following recommendations are made:

- As a result of the increasing urban expansion at the cost of farmland and the likelihood of its continuation in the future, food insecurity and environmental disequilibrium are most likely. Developing and implementing proper urban plans for sustainable land use is highly recommended.
- Government should evolve a policy that will prioritise the provision of infrastructural facilities and social amenities to area where development is predicted to occur.
- Public enlightenment on the practice of community and urban forestry, afforestation and the need to desist from deforestation should be encouraged.
- Most importantly, the planning and decision-making authorities must integrate new technologies, such as remote sensing and GIS into their decision making

processes. Using remote sensing data and information to understand the dynamics of the urban environment may contribute to better urban policy and management.

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