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ASSESSMENT OF BAISSA FOREST DISTURBANCE IN TARABA STATE, NIGERIA FROM 1984 TO 2014

Danladi Dauda Shatalis;[1*]Benjamin Ezekiel Bwadi;[2] Ebeiyamba Okon;[1] Olaniran Aluko[1] & Godwin E. Akpan[1]

[1]African Regional Centre for Space Science & Technology Education in English (ARCSSTEE), Obafemi Awolowo University, Ile-Ife (OAU), Osun State, Nigeria.
2 Department of Geography Taraba State University, P.M.B 1167, Jalingo
*** E-mail of the corresponding author: ddshatalis@gmail.com**

Abstract

This study analyzed the rate and the extent of Baissa forest disturbance in Taraba state, Nigeria. The intention was to assess disturbance in the forest from 1984 - 2014 and to predict the future state of the forest using Markov Model. The secondary data used were; Landsat TM 1984, ETM^{+} 1999 and LDCM 2014. The cadastral map and GPS coordinates of the study area were used as ancillary data and analyzed. The Image overlay and change detection methods were employed so that comparison was made for the three images. The observed changes were deduced in hectares to examine, measure, identify and presented the results that helps to understand the rate and extent of the forest disturbance in the reserve. Classification and other statistical methods employed revealed several canopy or forest lost in most part of the reserve by 23.6 %. Disturbed forest decreased from 6001 hectares in 1984 to 734 hectares in 1999 and increased to 5423 hectares in 2014. Agricultural land increased from 2469 hectares 1984 to 8869 hectares in 1999 then decreased to 8717 hectares in 2014 respectively. Built-up area increased by 35% from 1984 to 1999 and decreased to 33.2% from 1999 to 2014, Water body decreased by 6.3% from 1984 to 1999 and slightly increased to 2.9% from 1999 to 2014. By the projection analysis, using Markov Model, Dense Forest will decrease from 4766 hectares from 2014 to 3136hectares in 2029. Generally, the research revealed changes in the level of forest Disturbance from 1984 to 2014, which could be traced to illegal logging, agricultural and hunting activities. This therefore, proves the importance of Remote Sensing and GIS in addressing forest disturbance in Baissa forest in Taraba state, Nigeria.

Keywords: *Baissa forest, forest disturbance, Normalised Difference Vegetation Index (NDVI)*

Introduction

Forest disturbance is a change process within the forest, which negatively affects the characteristics of the forest (Dowsett, 1989). The combination of various forest characteristics (forest quality) can be expressed as the structure or function, which determines the capacity to supply forest products and services (IPCC, 2003). Forest disturbance occurs when there is loss in terms of any of the goods and services that they provide (wood, food, habitat, water, carbon storage) and other protective socio-economic and cultural values (Guariguata, 2009).

According to FAO (2002) disturbance of forest may be as a result of natural occurrences or human induced activities, which vary in terms of the extent, severity, quality, origin and frequency. The natural induced process can be through fire, storm, drought, pest and disease among others, and the human induced activities could be unsustainable logging, excessive fuel wood collection, shifting cultivation, unsustainable hunting, overgrazing just to mention but few.

Forest disturbance occurs often and with great effects, sometimes resulting in the removal of large amounts of biomass particularly in developing countries. It is estimated that as much as eight hundred and fifty (850) million hectares of forests and forest lands are disturbed (ITTO, 2002). Yet it is difficult to quantify the scale of the problem since at national and sub-national levels forest disturbance is perceived differently by the various stakeholders who have different objectives. Disturbance forces can have profound immediate effects on ecosystems and could greatly alter the natural community. As result of the impacts on populations, these effects can continue for an extended period of time (Mas, 1999).

The conditions under which natural disturbances occur are influenced mainly by climate, weather, and location (Hurt, 2003). Fire disturbances will only occur in areas where there is low precipitation, some form of ignition (typically lightning), and enough flammable biomass to allow spread. Conditions often occur as part of a cycle and disturbances may be periodic. Other disturbances, such as those caused by humans, invasive species and impact events, can occur anywhere and are not necessarily cyclic (Pateaude, *et al.,* 2005). Extinction vortices may result in multiple disturbances or a greater frequency of a single disturbance.

Baissa forest disturbance (Davis, *et al*., 1994) is caused mostly by human activities such as logging, excessive fuel wood collection, shifting cultivation, unsustainable hunting, overgrazing just to mention but few which affect the economy of the state. In view of this set-back, Policy makers and forest managers need information on forest disturbance. They need to be able to monitor changes happening in forests. They need to know where forest disturbance is taking place, what causes it and how serious the impacts are in order to prioritize the allocation of scarce human and financial resources to the prevention of disturbance. Knowing the pattern of disturbance could assist the restoration and rehabilitation of disturbed forests (Simula, 2009). The Government of Taraba state introduced laws and policies that bind the illegal activities in Baissa forest reserve to protect and to preserve the forests. Trespassers if arrested are prosecuted. In spite of these laws, forests continue to be disturbed. The failure of this management policy could be attributed to; the negligent in supervision, inadequate training of the insufficient personnel and lack of motivation on the part of forestry officials. Other ill effects of the management policy are; Government pressure on revenue generation without regard for biodiversity conservation, active collusion of forestry officers, politicians' interest, village chiefs and merchant loggers in illegal logging and ultimately forest destruction. Forest destruction has been linked with economic decline of forest communities and global climate change hence it must be halted (FAO, 2009).

Materials and Methods

The Study Area

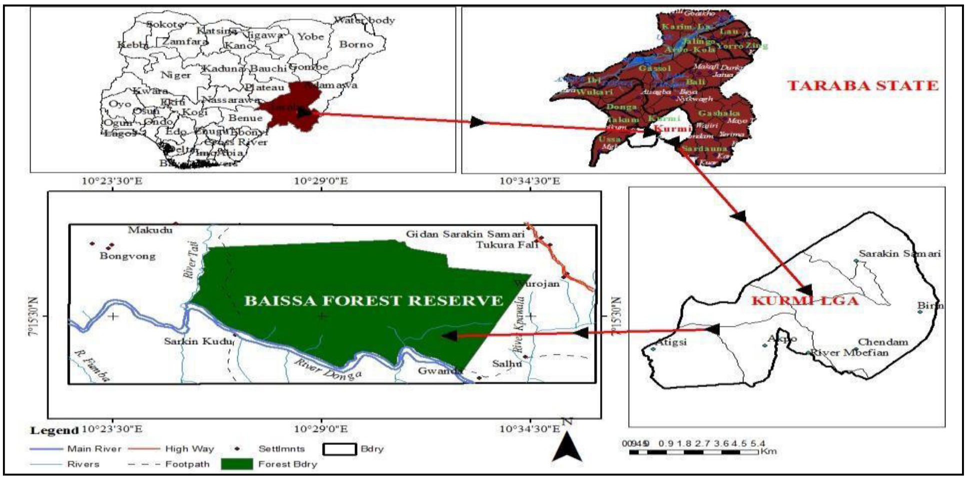

Figure 1: Maps showing the location of the study area.

Baissa Forest is located in Baissa area in Kurmi local government area of Taraba State, Nigeria. The forest was gazette early 1970 by former Gongola State government for protection and conservation of biodiversity. Baissa has an area of 4,353 km² and a population density of 91,531(Census 2006). Baissa Forest is a lowland forest, lying 230 m above sea level between, latitudes 7° 14" & 7^0 199" North, and longitude 10° 22" &10^0 36" East. Chapman, (2000) Stated that the Reserve covers an area of 113 km^2, including about 66 km^2 of high forest in the early 1970s. Singh, (1989) examined the mean annual rainfall recorded over a period of 7 year, was 1,870 mm. For half the year (April through October) the monthly mean was in excess of 100 mm, and October was the wettest month, with 310 mm ((Bawden & Tuley, 1966).

In this study, multi-temporal satellite images that were used include Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper plus (ETM+) and Landsat Operational Land Imager (OLI). Landsat TM, ETM+ and OLI were extracted for December 1984 December, 1999 and December, 2014 respectively with path and row of 186 and 055 respectively. All sensors have spatial resolution of 30m. Radiometric corrections were applied to the images. In addition, The Enhanced satellite Thematic Mapper plus (ETM^+) image of December 1999 and Operational Land Imager (OLI) image of December 2014 were obtained from the United States Geological Survey (USGS) website.

Image Processing

The images were pre-processed to correct them for spectral variation resulting from sensor differences before the study area was extracted from each dataset. False colour composite (FCC) was created using near-infrared, red and green Bands (432,432 & 654) for each of the images respectively. The selection of Band combination was done to enhance our ability to clearly distinguish vegetation types from non-vegetated land use the pattern of en change was determined using the post classification comparison method proposed by Peterson (2009) The co-ordinates of Kurmi local government area was obtained using Global Positioning System (GPS) to ground truth the study area (Baissa forest) so that the training pixels is sub-set for classification.

Land Use Land Cover (LULC) Classification

A supervised classification of the satellite imagery was used to produce Land Use Land Cover (LULC) classes. Maximum Likelihood Classification technique was used in classifying the satellite images. This is the most widely adopted classification algorithm (Manandhar, 2009). The images of the study area were taken through three stages to generate land cover classes of the study area. These include: (1) feature extraction; (2) selection of training data (signatures); and (3) selection of suitable classification approaches. The following six Land Use and Land Cover (LULC) classes were identified and mapped: Dense Forest, Disturbed Forest, Agricultural land, Bare Soil, Built-up area, and water body. After the classification, sample points were obtained from the field for accuracy assessment. These samples points were used for classification Accuracy Assessment which will be discussed here after. The image classification was guided by reconnaissance information gathered from the study area. The results of the classification were presented in a Table showing area covered by the particular classes in hectares m^2 for the selected environmental years. Also classified images of the selected years were produced and finally a reclassification image showing dense forest and disturbed forest areas of Baissa forest.

Post-Classification Comparison

Of many methods (i.e., Image overlay, change vector analysis, principal component analysis, image rationing) that are available for change detection in forest cover (Devi, 2012), post classification comparison and Image overlay were used in this research. In this technique, images of different dates were classified and labeled individually. Using supervised classification, the classified Images were then compared and the disturbed areas extracted were determined using Idrisi. Post-classification comparison was used to detect dense forest from disturbed forest area, and changes in general Land Use.

Normalized Difference Vegetation Index (NDVI)

Several vegetation indices have been developed of which, NDVI is the most commonly used (Bicheron, 2008). It is used to distinguish healthy vegetation from Unhealthy or non-vegetated areas (Mannandhar, 2009; Njoku, 2006). Using red and near-infrared reflectance values, this was integrated in the post-classification analysis to discriminate between areas covered by forest (green) and disturbed forest area or bare soil. Theoretically, NDVI threshold value ranges from -1 to +1. Measured value range from -0.35 (water) through zero (soil) to +0.6 (dense green vegetation). Based on grey scale this corresponds to a pixel digital number. It can be concluded that the more positive the NDVI, the greener vegetation there is within a pixel. Immarzeel *et al.* (1997) recorded that the use of NDVI is based on the red band and near-infrared band of Landsat imageries and this was given as (Equations 1) for Landsat imageries.

$$NDVI = \frac{NIR - R}{NIR + R} \text{------------------ (1)}$$

Where; NIR is the spectral reflectance measurements acquired in the near-infrared region (band), R is the spectral reflectance measurements acquired in the red region (band). In the case of Landsat image. The 1984, 1999, and 2014 satellite images were reclassified based on the NDVI threshold values and the results were presented in Figures 2, 4, 6 and in **Table** 3 respectively.

Classification Accuracy Assessment Using Confusion Matrixes)

The overall accuracy of each of the Land use Land cover maps was generated from the confusion matrix derived from data obtained from the Land Use Land Cover maps extracted from the image analysis. The accuracy assessment is the simplest and most often used statistical measure of classification accuracy of remote sensing data. It is computed by dividing the total correctly classified pixels by the total number of pixels in the confusion matrix (Congalton, 1991)

Markov Cellular Analyses (Mca)

A Markova process is simply one in which the future state of a system can be modeled purely on the basis of the immediately preceding state. Markov Chain analysis describes Land Use change from one period to another and uses this as the basis to project future changes. This is accomplished by developing a transition probability matrix of Land Use change from time one to time two, which will be the basis for projecting to a later time period to another and use this as the basis to project future changes. In this research, landuse data for Baissa forest from two different time periods, 1999 and 2014, are used to project land use change into the future for the year 2029, using MARKOV Model. What was predicted was the change to occur in the next 15-year period. The Markov model was used to predict this change based purely on the state of Land Use in 1999 and on Land Use change in the preceding 15 years between 1999 and 2014. To achieve this, a Run CROSSTAB with LANDUSE 99 as the first image and LANDUSE 2014 as the second image.

The output was specified for both the image and the **Table**. The output image was called CROSS9914.Using the resulting image, the changes of any particular Land Use to any other land use can be identified (**Table** 3).

Table 1: Materials

Data	Source	Date of Acquisition	Spatial Resolution
Landsat-MSS.	USGS.	25 December, 1984.	30m
Landsat-TM.	USGS.	26 December, 1999.	30m
Landsat-LDCM.	USGS.	27 December, 2014	30m
Ancillary data: Field data &Maps.	Baissa forest and TSMLS.		
Software.	ArcGIS-10.3 and IDRISI.		

Results and Discussions

In this Section, the results of the supervised LULC classifications using Landsat images are presented and discussed. The classification accuracy, the Image overlay and spatial extent of LULC after classification are also discussed. The supervised classification of the images yielded three land cover maps of the study area (as shown in Figures 3 and 6). As already mentioned, the following six (6) LULC classes were distinguished after classification; dense forest, disturbed forest, agricultural land, bare soil, built-up area and water body.

Table 2: Land Use/ Land Covers type from 1984, 1999 & 2014.

Land use/land cover type.	Description
Dense forest	Areas with virgin forest that has not been disturbed by any activity.
Disturbed forest	Areas which were known as virgin forest before but now have been disturbed by some activities and only some dotted trees left.
Agricultural land	Areas that are being cultivated and left fallowed.
Bare soil	Empty soil surfaces.
Built-up area	Areas that are populated with residents, bare lands and as well as roads.
Water body	Areas that are covered with water.
Built-up area	Areas that are populated with residents, bare lands and as well as roads.
Water body	Areas that are covered with water.

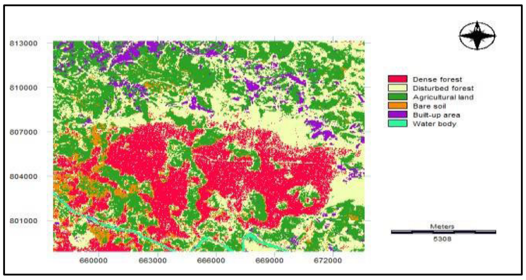

Figure 2: Classification Image of 1984

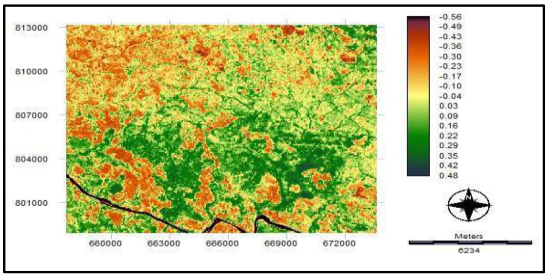

Figure 3: NDVI of 1984

LULC Map from 1999 Landsat ETM$^+$ Image

The supervised classification procedures applied to the 1999 image yielded land cover map as can be seen in Figure 4. The Dense Forest occupying second to the largest area coverage of the LULC classes having 5836.0 hectares which represents 26% (Table 5). This is concentrated around the Donga River with a few around North Western part of the area. Disturbed Forest covers an area of 734.0 hectares (3.2%) and it is mainly occurred around the Northern, Western, Southern, Eastern corners and also along the fringes of the river. The decrease of the disturbed forest was as a result of additional recruitment of forest guards to protect the reserve when the local government headquarters was sited at Baissa in 1996.

Agricultural land could be mainly found along river courses and northern areas with an area of 8869.0 hectares (39%). Bare soil covered an area of 5486.0 hectares (24%) which was centered at the Eastern portions of the map Built-up occupies an area of 1505.7 hectares (0.7%) and mainly concentrated at the Northern, Eastern and small patches around the western parts of the map. Water body covers an area of 176.0 hectares (0.8%) which is mainly lying around the southern part of the map (Figure 5). Also, the statistical information of the LULC is shown in Figure 7 below.

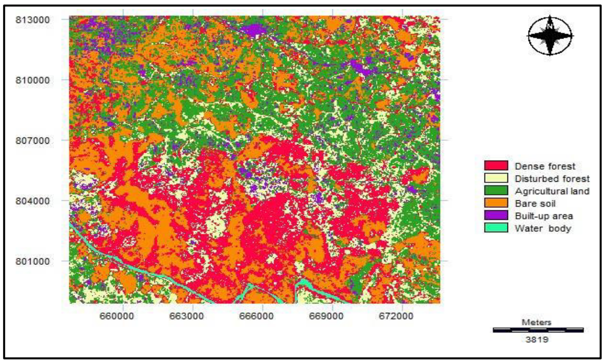

Figure **4 NDVI Images of 1999.**

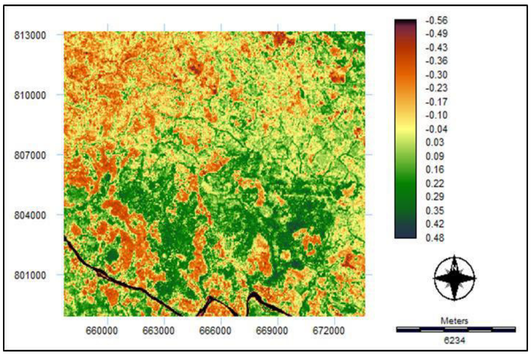

Figure **5 NDVI Images of 1999.**

Landsat LDCM (2014) was classified and the result yielded Land cover map displayed in Figure 6. It is evident from the classification results that, the area of Dense Forest is 4766.0 hectares (22%) was found concentrated around the Donga River with a few around the North Western part of the area. Disturbed Forest covers an area of 5423.0 hectares, (25%) and mainly around the North Western, Southern, small patches around the North and along the fringes of the River Donga. Agricultural activities were found in patches around the forest and mostly centered on the northern part of the map. It was occupied the largest area of 8717.0 hectares (40%). Bare soil covers 2515.0 hectares (12%) and was found almost every part of the North in the map. Built-up occupies 1005.0 hectares (05%) of the total area covered. This was concentrated at the Northern, Eastern and small patches around the western part of the map. Water body, having 182.0 hectares (0.8%) was found concentrated within the southern. DsF covers 27% while Agricultural land (AL) occupies 11% and bare soil (BS) 27% respectively (**Table 4**. and Figure 7).

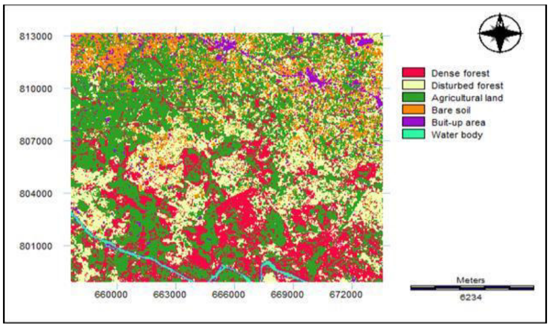

Figure **6: Classified of Image 2014**

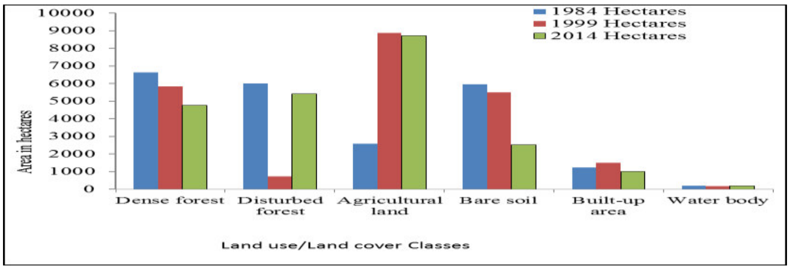

Figure 7 Graph Shows Image of 1984, 1999 and 2014. LULC classes.

Image Overlay of 1984/1999 and 1999/2014

Images overlay of 1984/1999 and 1999/2014 were made and changes that occurred were examined and noted (**Figure** 9, **Figure** 10 and **Table** 4) below. From 1984 to 1999 and 1999 to 2014 LULC map, DF decreased by 23% and 26%. DsF decreased by 21% and by1.8% from 1984 to 1999 and 1999 to 2014 respectively. AL and BU decreased by 12%, 8.2% and increased to 1.7%and 13.8% respectively (**Table** 4) bare soil increased by 1.2% and decreased by 0.9% from 1984 to 1999 and 1999 to 2014 respectively. Water body reduced by 33% and increased by 24% from 1984 to 19999 to 2014 respectively (**Table 4**). The statistical representation of the LULC classes for the past three decades indicated in **Figure** 8 above and **Table** 4 below.

From the 1984&99 Image overlay, Water body (WB), DF, DsF assumed higher position in the area coverage, Agriculture and Bare soil experienced positive change while dense forest, disturbed forest, built-up and water body experienced negative change. The results of 1984/14 Image overlay is indicated the changes as shown in Figure 4. The Image overlay was to observe the rate and extent of the occurrence in forest disturbance of Baissa forest assessment.

Generally, it is noted that the land areas of DF, DsF and BS have decreased with increase of land areas for buildup and Agricultural activities. Factors, which could influence this trend, are the population expansion, rapid urbanization, and uncontrolled grazing (specially the low canopy forest areas.

The exceptional reduction and increased of built-up and water body in 1999/2014 could be as a result of the terrorists' operation in the area between 1999 and 2014 and the release of Lado Dam in Cameroon-by-Cameroon Government in October, 2013. But these are not investigated. Further analysis of these factors is needed to better explain the impact of these factors on forest disturbance

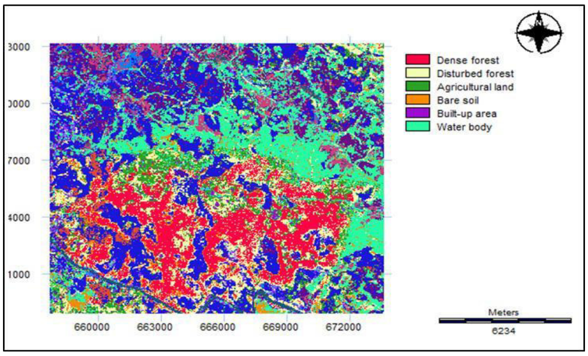

Fig. 9: Overlay classified Image of 1984 & 1999

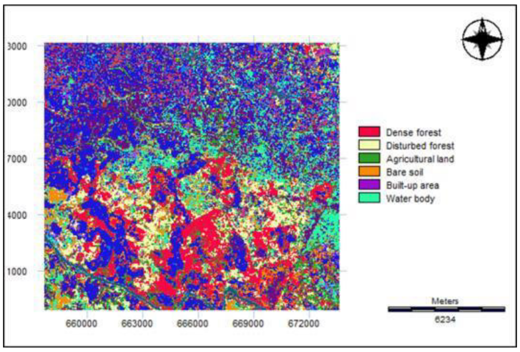

Fig. 10: Overlay classified Image of 1999 & 2014

Table 3: Change detection and Image overlay

Rate of change detection for Image overlay (hec)				
LULC	1984/99	Change detection (%)	1999/14	Change detection (%)
Dense forest	30400	23.6	29900	26.3
Disturbed forest	27900	21.7	19900	1.8
Agricultural land	15800	12.3	19600	1.7
Bare soil	10500	8.2	15700	13.8
Built-up area	1400	1.2	1000	0.9
Water body	42800	33.2	27800	24.4
Total	128800		113900	

Accuracy Assessment of LULC Classes

As previously mentioned, accuracy assessment of the classified image is an important step in image classification. The quality of a thematic map from a satellite image is determined by its accuracy. A classification accuracy assessment was performed on the 1984 Landsat TM image, 1999 landsat Etm^{+} and LDCM 2014. The results were obtained having an error matrix, accuracy totals and a kappa statistic (as in Table 4 & 5). An overall classification accuracy of 94%, 78% and 89% were obtained from the classification carried out for 1984, 1999 and 2014 Images respectively. Kappa coefficient (overall kappa statistics) of 0.6, 0.7 and 0.5 were achieved in respect of the order of the classification in above. Only Built-up area and water body have producer's accuracy of 78%. Bare soil and Agricultural land have producer's accuracy of 99% and 98 each with bare soil having the highest, 99%. All the remaining LULC classes were having their accuracies above 80%. The user's accuracies of all the LULC types were above 80% with Agricultural land having the highest accuracy of 96% in 2014 Image classification. The trend analysis of the Baissa forest disturbance in Taraba state -Nigeria reveals a change in size of the six LULC Classes over the 30 years period of the study (**Table** 5).

	1984 classified Acc.		*1999 classified Acc*		*2014 classified Acc*	
Category	***KIA_1***	***KIA_2***	***KIA_1***	***KIA_2***	***KIA_1***	***KIA_2***
Dense forest	***0.5946***	***0.9434***	***0.6941***	***0.725***	***0.9512***	***0.6072***
Disturbed forest	***0.4738***	***-0.1122***	***0.7936***	***0.3271***	***0.562***	***0.9654***
Agriculture	***-0.1454***	***-0.2136***	***0.5617***	***0.8062***	***-0.017***	***-0.0189***
Bare soil	***0.92159***	***0.2146***	***0.7494***	***0.8462***	***0.7173***	***0.3084***
Built-up area	***0.78629***	***0.5397***	***0.7261***	***0.3016.***	***0.4462***	***0.5887***
Water body	***0.893***	***0.9081***	***0.9901***	***0.9338***	***0.9865***	***0.8584***
Overall"	***0.6***		***0.7***		***0.5***	

Table 4: Kappa Index of Agreement (KIA)

	Dense forest(hect)	**Disturbed forest(hect)**	**Agricultural land(hect)**	**Bare soil(hect)**	**Built-up area(hect)**	**Water body(hect)**
Dense forest	3136	3414	2395	756	287	3
Disturbed forest	2009	3825	2814	984	365	3

Markov Model for Prediction

To maintain ecological sustainability, there is need to project the course of change into future, assess the implications of the change for biodiversity and evaluating planning interventions. In view of that, Markova process was used in this study and the results indicated that, Areas covered by Dense Forest and Bare soil shall decrease from 4766.0 hectares to 3135.0hectares and from 2510.0 hectares to 1550.0 hectares respectively in the next fifteen years (2029), if all factors that will cause the changes remain the same as in the immediately preceding state

Conclusion

The relationship between the forest covers and its associated LULC classes were investigated and various thematic maps were developed. The main LULC types identified in the catchment area are; dense forest, Disturbed Forest, Agricultural land, Bare soil, Built-up area and Water body. It was observed that vegetation has changed remarkably from the period 1984-2014. The decrease in vegetation has been as a result of anthropogenic activities in the study area but these were not investigated. Therefore, further analysis of these factors is needed to better explain the impact of these factors on forest cover change. Also, by taken more factors such as rainfall, soil moisture etc. into consideration, the study could reach a higher accuracy for forest Disturbance and change detection, performing multi sensor data classification using neural networks by combination of ancillary data (i.e. elevation and aspect) with the Landsat image data would improve the classification result and produce higher accuracy than the use of Landsat image data only

Recommendations

When multi-temporal satellite data and multi layers ground truth data are available, it may be possible and useful to do further studies about change detection analysis to detect forest disturbance, built-up expansion and other LULC changes within the catchment. Future studies are recommended to assess and investigate the factors responsible for forest disturbance despite the recruitment of multiple forest guards. This study is here by recommended to Taraba state government to endeavors to use the available modern technology to assess and to protect Baissa forest and other forests within the State for sustainable development.

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