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NORMALIZED DIFFERENCE VEGETATION INDEX ANALYSIS FOR LAND COVER TYPES IN SOUTHERN PART OF GOMBE, NIGERIA

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ABSTRACT

Woody vegetation is an integral component of savannas. Anthropogenic factors mainly alter woody vegetation. While land covers embrace the quantity and type of surface vegetation, water and earth materials, land use can be in form of grazing, agriculture, urban/rural development, logging among others. These activities mostly result in deforestation, particularly when there is over-exploitation. This paper analyzed the land cover types in southern part of Gombe using Normalized Difference Vegetation Index (NDVI) between 1986 and 2017. The trend was studied using Landsat imageries acquired in 1986, 1996, 2006 and 2017; these were subjected to image processing using maximum likelihood classification scheme in ArcGIS 10.3 environment. Differences in the values obtained from the four sets of imageries were converted to percentages. Over the study period, the NDVI reduced from -0.24 to +0.69 in 1984 to-1 to +0.15 in 2017, implying reduction in greenness of the vegetal cover over the years. The result further showed that the vegetal cover during the period from 1986-2017 showed negative patterns of woody cover. Analysis of the NDVI indicates obvious decline in the woody species except for grasslands that increase considerably over the years. This study further affirmed the contribution of remote sensing and GIS in monitoring and proper utilization of vegetation resources for sustainable development and forest resources management.

Key words: Woody Vegetation, Savanna, NDVI, Deforestation, Vegetal Cover

1. Introduction

Savanna vegetation is characterized by the co-occurrence of trees, shrubs and herbaceous species with a distinguishing feature being their contrasting phenologies. The proportions of woody and herbaceous species vary widely, forming forests, grasslands and shrub lands (Murphy and Bowman, 2012). Woody vegetation is an important component of savannas (Chidumayo and Gumbo, 2010); it is essential not only at the local scale, where it provides resources for rural communities ranging from forage to timber, but also at the global scale, where it contributes key ecosystem functions affecting biodiversity, carbon and water cycling, surface energy balance and climate (Alkama and Cescatti, 2016). Vegetation cover helps to regulate the flow of biogeochemical cycles, its contribution in energy balance is important to the economy, it is the primary source of oxygen in the atmosphere and enables aerobic metabolism. Vegetation has contributed significantly to the control of soil erosion which is a serious threat to ecosystem functioning in many parts of the world (Bucala, 2014).

Throughout sub-Saharan Africa, the need for arable land and forest products; such as charcoal, is driving widespread deforestation and forest degradation (Baccini et al., 2012). Simultaneously, a contrasting land degradation process is also widely reported; namely, the thickening of the woody layer and associated loss of herbaceous vegetation (i.e. shrub encroachment), which is of vital economic importance for rural communities relying on cattle (Liu et al., 2015).Both processes involve changes in woody vegetation cover and are often associated with pervasive land degradation and desertification (Bond et al., 2010).

Adekunle and Ige (2006) noted that the rate of deforestation in Nigeria is increasing due to the rapid growth in human population to be fed, accommodation in expanding settlements, as well as engaging in commercialization of agriculture. Deforestation is noted as the most important cause of biodiversity loss in Nigeria. It has been reported by Usman and Adefalu (2010) that about four fifths of Nigeria was once savanna, but much of this land has been converted to agriculture or grazing lands. This by implication means that many species have been destroyed while many have also been endangered or threatened to extinction.

Satellite remote sensing offers a convenient tool to study trends in woody cover, due to its synoptic coverage and cost-effectiveness. Several vegetal cover available at the spatial resolution of Landsat is widely used to monitor processes such as deforestation (Broich et al., 2014; Hansen et al., 2016). Thus, satellite-derived indicators of vegetation dynamics are fundamental to identifying environmental change processes such as land degradation. These indicators are often derived from spectral vegetation indices of satellite imagery, which are related to the photosynthetic potential of vegetation canopies. For example, a time-series of Normalized Difference Vegetation Index (NDVI) effectively captures variation in photosynthetic activity, whether it results from phenological cycles or anthropogenic disturbances such as deforestation (Kuenzer et al., 2015). Bonham (2013) stated that the creation of vegetation indexes, calculated from the combination of spectral bands is an excellent remote sensing technique.

Normalized Difference Vegetation Index (NDVI) is one of the most widely used indexes which conveys spectral information of red and near infrared bands of the visible spectrum and generates a variable that predicts quantity, quality, and development of vegetation (Devries et al., 2015). To calculate this index, one can rely on existing decade's long data from satellite sensor, which highlights the potential of Landsat time series (Zheng, et al 2015). The LANDSAT series provides free access to an extensive gallery of relevant temporal and spatial resolution images, widely used and validated in scientific research in remote sensing. Therefore, it was considered as a promising tool for studying the vegetation of southern part of Gombe.

2. Materials and Methods

2.1 Study Area

The study area is located in Southern Gombe latitude 9°40′ -11^{0}30’ N and longitude 9^{0}20’ -12°20′E. The study sites include Balanga, Billiri, Kaltungo, and Shongom Local Government Area (LGA) covering a total land area of 4,166km^2 (figure 1). The climate of this study area is described as tropical continental climate of the AW type and is characterized by distinct wet (April –

October) and dry (November – March) seasons governed by the movement of Inter-tropical Discontinuity (ITD). Vegetation in the study area is diverse as it reflects the pattern of the climate and physiography of the area. The area is a typical Sudan savanna characterized by high shrubs with scattered trees, shrubs and species of grasses which grow up to 0.9 -1.5meter. Within the built-up area, the natural vegetation is being replaced by man-made plantation and made up of mainly exotic trees. While around the fringes of settlements, patches of natural vegetation are still thriving though it is highly impacted by human activities.

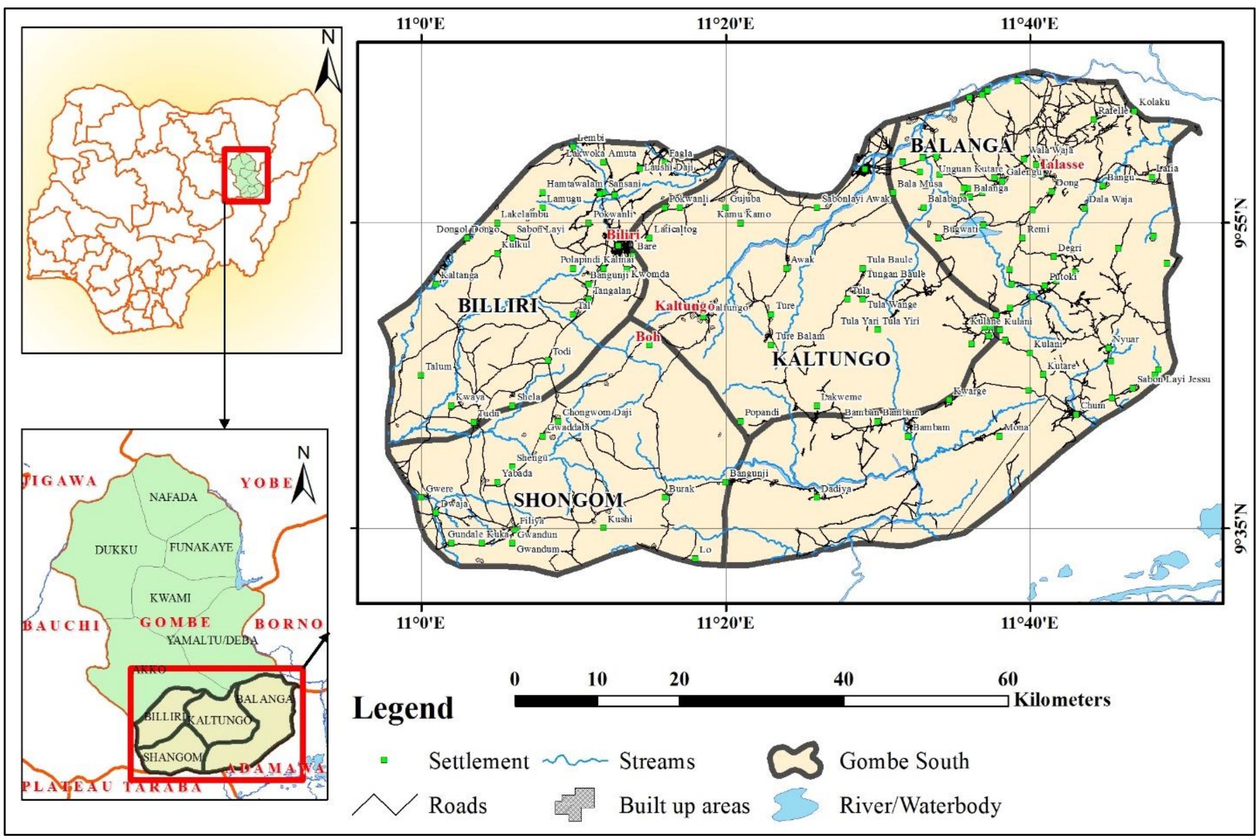


Figure 1: Study Area
Source: Modified from Ministry of land and survey, Gombe State

2.2 Methods

2.2.1 Land Cover / Land Use Analysis

Analysis of satellite images for land cover was done to ascertain the spatial extent of vegetation change. LandSat images have been utilized in this research due to availability of data as far back as 1986. Images of similar season (November) were used in order to minimize seasonal variation or changes. The processing of images was carried out using ArcGIS 10.3 software. The classification was carried out based on spectral characteristics. Supervised classification was done by training data sets, classification and output. Training samples were taken for each Land Use/ Land Cover (LULC) type to be classified in the image. In order to acquire accurate representation of the cover classes, training samples were repeatedly selected, assessed and carefully analyzed. Classification was done by using maximum likelihood classifier (Lillesand and Kiefer, 2004).

2.2.2 NDVI Classification

Vegetation index of four decades was generated using the infra-red and thermal band of respective imageries in ArcGIS environment. The NDVI is one of the most effective method for measuring changes in vegetation cover classification. It is a model that makes use of the differential information arising from distinctive spectral reflectance properties of healthy vegetation in the red (R) and Near Infra-Red (NIR) portion of the electromagnetic (EM) spectrum. The study area experiences only two main distinctive seasons in a year (rainy season and dry season). The choice of the dry season images made it possible for the NDVI results to depict visually distinction between unvegetated areas and other vegetation types in the study area.

NDVI is calculated as a ratio of Red and the NIR bands of a sensor system.

$$NDVI = NIR - RED/NIR + RED \quad \text{---} \ (1)$$

The NDVI values range from -1 to +1 (Lillesand and Kiefer, 2004). The classification scheme in Table 1 was used to classify and analyze the images. The range of values used in Table 1 was obtained from the NDVI imageries used for this study.

Table 1: NDVI Classification Scheme Adopted

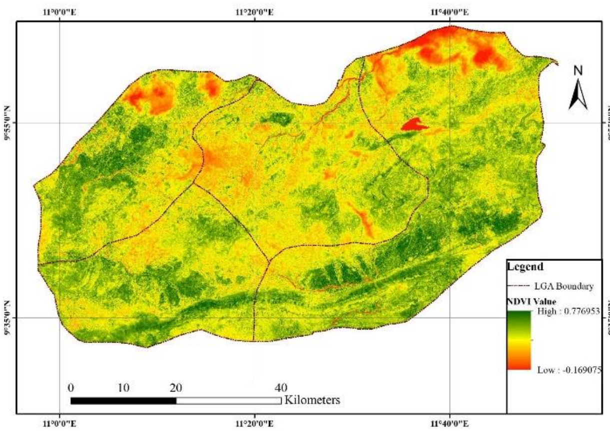
S/n	Class type	Range of value	Interpretation
1	Low density (non vegetated areas)	-0.17 – -0.52	These are basically the water bodies, built-up areas, rock outcrops.
2	Moderate density(non vegetated areas)	-0.53 – 0.11	Bare surfaces and settlements
3	High density(vegetated areas)	0.12 – 0.79	Areas that are vegetated, with both thick or light forest, shrubs and grasses

Source: Author's Laboratory Analysis, 2017

3. Results and Discussion

3.1 Trends of Land-cover Change in Study Area during the Period from 1986 - 2017

The NDVI value was computed for the period of study. In 1986, the value of NDVI varied from -0.24 to +0.69, while in 1996, the value of NDVI ranged from -0.61 to +0.16. Further, the 2006 and 2017 NDVI values ranged from -0.12 to +0.65 and -1 to +0.15 (Figures 2 to 5). In contrast, water / bare surfaces had the lowest value of NDVI in all the study years, owing to its larger visible reflectance over near-infrared reflectance. The spatial pattern of vegetative increase was observed in hilly areas and around plantation sites. Vegetative greenness decrease appeared in all the low land areas. The spatial pattern of greenness decrease was attributed to population growth and increase in settlement and farmland areas.



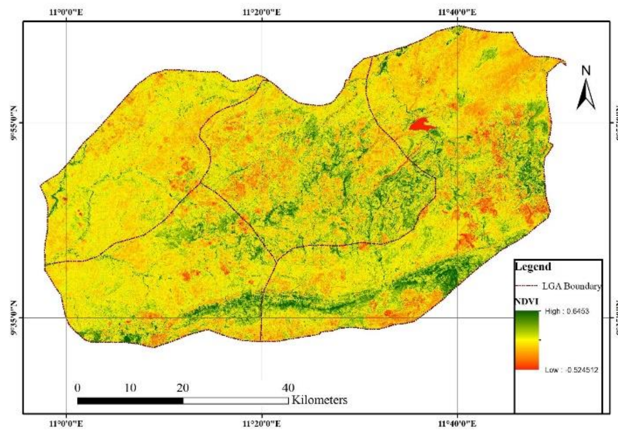
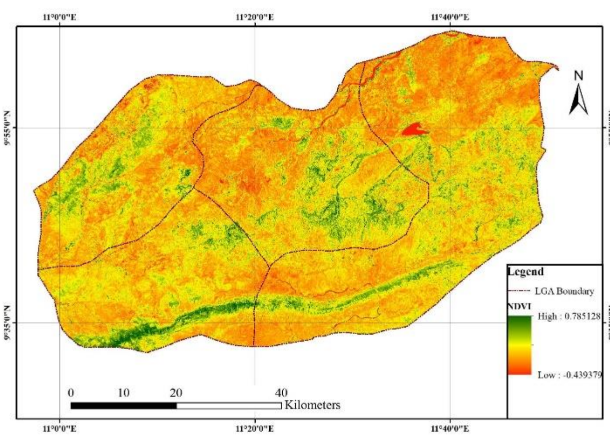


Figure 2: NDVI Map of 1986

Figure 3: NDVI Map of 1996



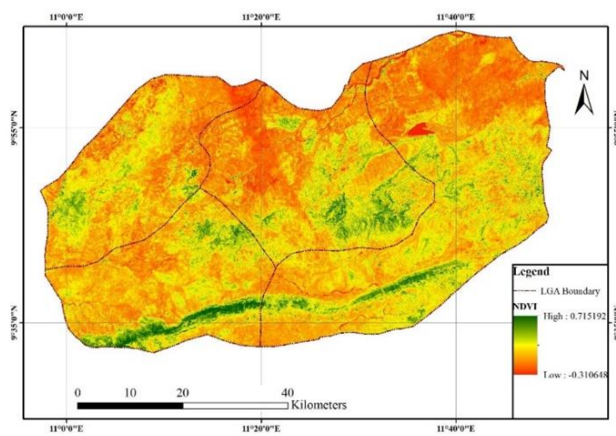


Figure 4: NDVI Map of 2006

Figure 5: NDVI Map of 2017

As observed from Table 1, the minimum reflectance values as measured from the LandSat sensor was -0.52451 in year 1986 and within the land use class of Bare surfaces/wetlands. The maximum reflectance was observed in year 2006 as 0.785128 and was within the land use class of woodlands/Dense vegetation attributed to higher reflectance in that year. The reason for the high reflectance was attributed to the thickness of vegetation as there were few afforestation programs in Shongom and Kaltungo within that period. Thus, the measure of incoming solar radiation using NDVI generally showed higher values as density of vegetation cover increases.

3.2 Characteristics of Vegetative Greenness Change

The vegetated and non-vegetated LULC classes obtained were based on data distributional assumptions which were cross referenced with aerial photographs. The results showed a variation of threshold (standard deviation) values between LULC classes from the NDVI for each of the years 1986, 1996, 2006 and 2017, respectively, as shown in Table 2.

Table 2: NDVI Classification

Landuse	1986		1996		2006		2017	
	Area	%	Area	%	Area	%	Area	%
Bare surfaces/ wetlands/settlement	105.73	2.48	548.77	12.89	654.60	15.37	1338.94	31.45
Grasslands	538.78	12.65	735.81	17.28	1119.41	26.29	1274.84	29.94
Shrubs	1705.19	40.05	1899.52	44.61	1696.11	39.84	1291.78	30.34
Woodlands	1907.97	44.81	1073.56	25.21	787.52	18.50	352.08	8.27
	4257.67	100.00	4257.65	100.00	4257.64	100.00	4257.64	100.00

Source: Author's Laboratory Analysis, 2017

The result shows that in 1986, woodland, shrubs and grasslands occupied about 44.81%, 40.05% and 12.65%, covering about 4,151.94Km^2 of the study area, while the bare surfaces/ wetlands/ settlements occupied about 2.48%. On the other hand, in 1996, bare surfaces/wetlands/settlements increased slightly to 12.89%, grasslands and shrubs also increased to 17.28% and 44.61% while woodlands dropped to 25.21% occupying relatively smaller surface areas. By 2006, the bare surfaces/wetlands/settlements increased to 15.37% as well as grasslands 26.29%, while shrubs and woodland decreased to 39.84% and 18.50% respectively. In 2017, bare surfaces/ wetlands/ settlements and grasslands recorded an increase of 31.45% and 29.94% while a reduction was noted in shrubs and woodland having 30.34% and 8.27% covering about 1643.86 Km^2 of the study area. The analysis of NDVI data indicates obvious decline in woody species except for grasslands that increased considerably over the years. Although, within the study area there was tree planting as shelter belts (Neem and Acacia) and plantation of economic trees (Mango, Guava, Palmea) in parts of Shongom, Kaltungo and Balanga which favored woodland conservation and thus accounted for some of the woody vegetal cover available. Related study by Adedeji and Adeofun (2014) in Omo Shasha Oluwa forest revealed that the natural forest which covers about 256,900 ha in 1986 reduced gradually to 225,300 ha by 2002. This shows a decrease in forest cover by about 10% of total land cover.

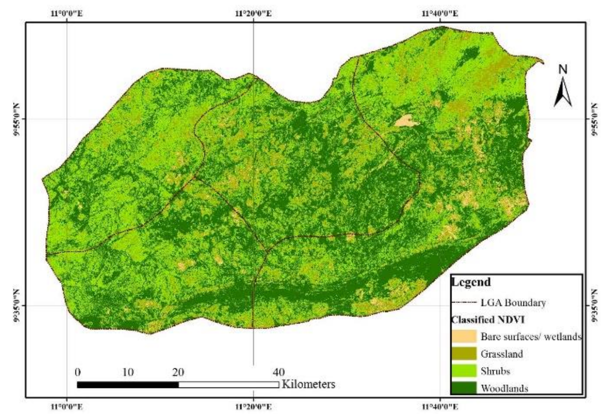


Figure 6: Classified NDVI Map of 1986

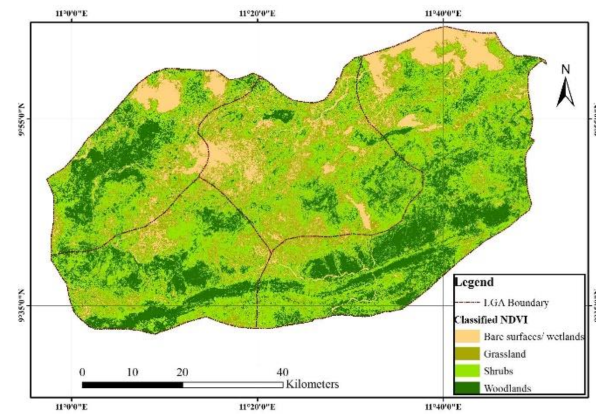


Figure 7: Classified NDVI Map of 1996

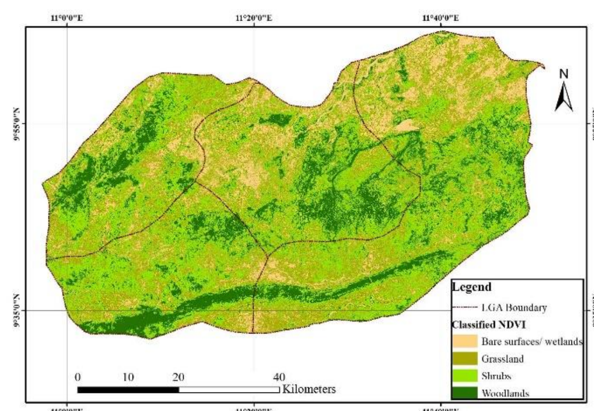


Figure 8: Classified NDVI Map of 2006

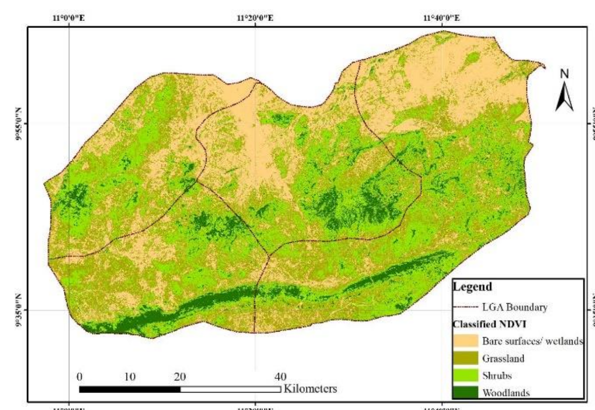


Figure 9: Classified NDVI Map of 2017

Table 3 shows surface area cover (Km^2) and corresponding percentages of the different LULC classes in the study area. In order to understand the results better and to make a healthier comparison, the NDVI were reclassified into four classes as shown in figures 6, 7, 8 and 9 respectively, while associated statistics were summarized in Table 3. When the results were assessed, it was determined that between 1986 and 2017, shrubs and woodlands had a net decrease of -1.03% and -14.26% while grasslands and bare surfaces/wetlands/settlements had increases of 1.86% and 2.97% respectively.

Table 3: Change rate of NDVI

Land use	Cover Changes						Annual rate	
	1986-1996		1996-2006		2006-2017		1986-2017	
	Area	%	Area	%	Area	%	Area	%
Bare surfaces/ wetlands	443.03	80.73	105.84	16.17	684.34	51.11	39.78	2.97
Grasslands	197.03	26.78	383.60	34.27	155.43	12.19	23.74	1.86
Shrubs	194.33	10.23	-203.41	-11.99	-404.33	-31.30	-13.34	-1.03
Woodlands	-834.40	-77.72	-286.04	-36.32	-435.45	-123.68	-50.19	-14.26

Source: Author's Laboratory Analysis, 2017

The results for NDVI differencing showed net negative patterns of woodlands (-50.19 Km^2) and shrubs (-13.34Km^2) and a net positive pattern for grasslands (23.74Km^2) (Table 3). This indicates that the underlying factors driving vegetal cover change in the study area from 1986 to 2017 resulted to a net shrub and woody cover loss rate of -1.03% and -14.26%. It could be suggested that, although changes occur naturally, anthropogenic factors including: extraction of wood, opening up of new agricultural lands, grazing, extension of settlements, occurring in different forms, has strongly influenced the trends in vegetal changes in the study area.

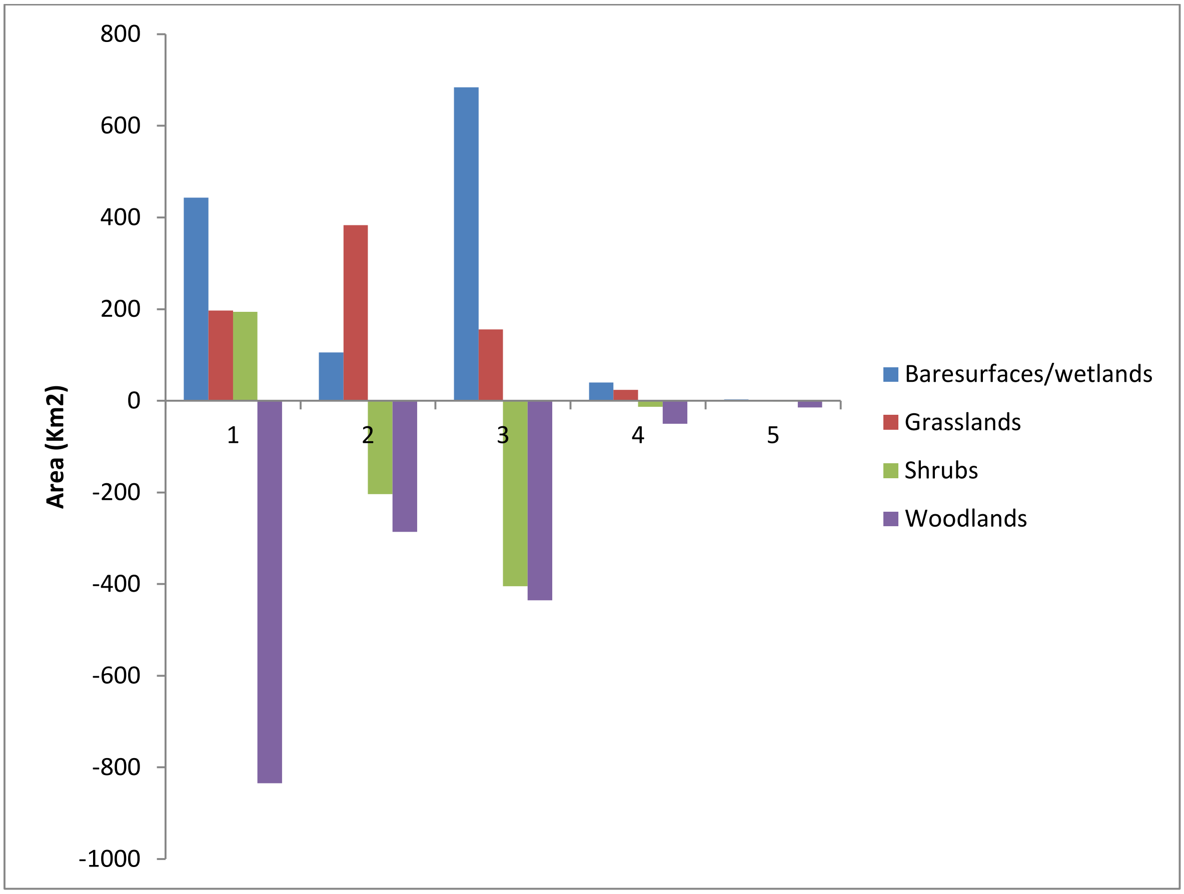


Figure 10: Trend of LULC (distribution of NDVI)
Source: Author's Laboratory Analysis, 2017

Figure 10 is a plot diagram showing the trends of LULC (distributions of NDVI) in the study area for three periods (1986- 1996, 1996 - 2006 and 2006-2017). The trends of LULC in the study area showed both positive and negative patterns for the classes. The results indicate that the trend in land-cover change in the study area was not a simple straightforward process because one cover class changes to other classes. However, it is worthwhile noting here that based on visual analysis, the reduction in the woodlands and shrubs did not preclude expansion of agricultural and built-up areas. The negative patterns of woodlands and shrubs corroborates the findings of Cheek et al (2000) and Harvey et al. (2004) who estimated that 96.5% of the original forest cover of Bamenda Highlands has been lost.

4.Conclusion

This study validates the application of Normalized Differential Vegetation Indices to measure vegetative potency and assess vegetal changes in Southern Gombe. The result revealed that there had been significant vegetal cover change in the study area during the last four decades. The values of NDVI were categorized as low density < -0.17 to -0.52 and high density from 0.12 to 0.79. The trends of vegetal cover change during the period from 1986-2017 showed negative patterns of woody cover. The analysis of NDVI data indicates obvious decline in woody species except for grasslands that increased considerably over the years. The NDVI multi-temporal analysis proved to be indispensable for detecting and monitoring vegetal changes in the study area. Therefore, it would be concluded that ongoing unsustainable land-use practices will cause loss and harm to vegetation systems.

5. Recommendations

Giving the state of vegetal cover loss within the study area, it is would be necessary that forest management should be considered by the stakeholders in discouraging logging and encourage afforestation. Government must encourage woodlots, hence the villages should be supported with the seedlings.

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