On the Temporal Dynamic of Land use Land Cover Changes over Lake Chad Basin, Nigeria.

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Abstract

This study investigated the land use land cover changes around Lake Chad and its environs over a period of thirty-three years. Satellite images of Lake Chad from Landsat-TM, ETM+ and OLS/TIRS were used. The images are for years 1984, 1992, 2000, 2003, 2013 and 2017 in order to study the current state of the lake and its environs. In order to generate the land use land cover from the satellite images, supervised classification was performed using the maximum likelihood classifier for the land cover analysis. From the land use land cover maps, water body occupied about 8% of the area coverage, vegetation occupied about 11% while the shrub land and bare land occupied about 78% of the Lake Chad area in 1984. In a more recent year (2017), water body occupied about 9.5 % of the area coverage, shrub land occupied about 20% and bare land occupied about 29.5 %. Vegetation occupied the highest percentage of 41. Change detection was carried in order to quantify the changes in land use land cover for the years. For the period of study (1984 to 2017), water body increased from 154,000 (hectares) to 156,000 (hectares) with the highest area coverage in 2003 at 240,000 (hectares). Vegetation increased from 208,000 (hectares) to 682,000 (hectares), shrub land decreased from 686,000 (hectares) to 325,000 (hectares) while bare land decreased from 695,000 (hectares) to 486,000 (hectares). Classification accuracy was carried out on the classified images in order to reveal the level of accuracy of the classification. The overall classification accuracy was 84.78% for 1984, 83.72% for 1992, 81.08% for 2000, 82.61 for 2003, 82.76 for 2013 and 81.82% for 2017 confirming reasonable classification accuracy.

Keywords: Land use, land cover, Lake Chad, changes, increase decrease.

Introduction

In the past 50 years, West Africa has experienced large scale land-use changes including deforestation and increased irrigation (Li et al., 2007). Such land-use changes may have both immediate and long-lasting impacts on terrestrial hydrology, altering the balance between rainfall and evaporation. This will have a considerable impact on water resources which must be accounted for in water management plans (Jia et al., 2006). In addition, ongoing climatic changes are likely to also be influencing the regional water resources. Therefore, it becomes desirable to model water resource variations in African basins under strong human impact (Mekonnen, 2006) to better isolate the role of anthropogenic land use change from climatic changes in the water balance and to give some estimate of future water availability. Humans have been altering land cover since time immemorial through the use of fire to flush out game and, since the advent of plant and animal domestication, through the clearance of patches of land for agriculture and livestock. In the past two centuries, the impact of human activities on the land has grown enormously, altering entire landscapes, and ultimately impacting the earth's nutrient and hydrological cycles as well as climate (De Sherbin, 2002). In recent times, significant population increase, migration, accelerated socio-economic activities and increased demands on the landscapes for food and shelter and an increased number of products of man's living environment have led to unparalleled changes in land use and modification of rural and urban environments. Ifatimehin and Ufuah (2006) and Rimal (2001) asserts that, the change in land cover occurs even in the absence of human activities through natural processes whereas land use change is the manipulation of land cover by humans for multiple purposes; food, shelter, fuel wood, timber, fodder, medicine, raw materials and recreation. So many socio-economic and environmental factors inter play in land use and land cover dynamics Major consequences of the globally recognized rapid land use and land cover changes are; land degradation, agricultural yield depletion, loss of biodiversity and ecosystem functioning. Due to poorly planned human interference, many Africa countries have experience untold environmental degradation and ecological deterioration in the past century, with little or no real solution to alleviate many of these concerns. The understanding of land use and cover dynamics and interactions with socioeconomic and biophysical factors is a necessary tool that will aid the analysis of land-use and land-cover change across scales. Land use and land cover change is the quantitative changes in the areal extent (increases or decreases) of a given type of land use or cover type. It also includes alteration or modification and conversion from one type of use or cover to another (Briassoulis, 2000). Garba (2008) observed that land cover change provides a means of understanding and managing the problems of degradation and shortage of land and water resources. Land cover change has been described as the most significant regional anthropogenic disturbance to the environment (Roberts, et al, 1998). In additions, land cover change occur when one land cover type is converted to another, or is modified, such as a change in agricultural land to residential, or an intensification of existing use, such as from light to heavy industry. Land cover is continually influenced by land use due to human cultural, social, and economic activities (Lambin et al, 2003; Erle and Roberts, 2010). Land use change over time is an inevitable phenomenon occurring globally due to both temporary and or permanent interest of the inhabitants in a particular area. The phenomenon could be revealed either in a small or large scale but the most interesting and fundamental observation is that change occurs over time in a particular place. It has also been defined as "the arrangements, activities and inputs people undertake in a certain landcover type to produce, change or maintain it" (FAO, 1999). There is an increasing need to be able to precisely describe and classify land cover and land uses in order to define sustainable land use systems that are best suited for each place. The driving force for most land use and cover changes is population growth, although there are several other interacting factors involved (Ramankutty, et al, 2002). Humans have been modifying land to obtain food and other essentials for thousands of years, current rates, extents and intensities of land use and land cover change (LULCC) are far greater than ever in history, driving unprecedented changes in ecosystems and environmental processes at local, regional and global scales. These land uses exert pressure on the seemingly finite land resources in urban centres, thus land is fast becoming a critical resources, its demand remain a fundamental issue of both academic and policy discourse (Ujoh, 2008). Amongst the major global environmental changes observed around the world in recent decades is the drying of lakes (World Lakes Network, 2004). Drying has taken place in, for example, the Aral Sea in Central Asia (UNEP, 2014), Lake Chapala in Mexico (von Bertrab, 2003), Lake Chilwa in Malawi (Njaya *et al*., 2011) and Lake Chad in west central Africa (Odada *et al*., 2006). Freshwater lakes are valuable natural resources for human beings and have regional ecological and environmental functions, such as climate regulation, flood and drought control, and wildlife habitats (Williamson *et al*., 2009). Lakes hold more than 90% of the Earth's freshwater resources (Rast, 2014) and provide one or more of the supporting, provisioning, regulating and cultural services expounded within the ecosystem services framework (Millennium Ecosystem Assessment 2005). In the last few decades, numerous examples of decreasing water quantity, quality and disappearing of freshwater lakes and rivers have been reported across the world (Gorsevski, 2008). Many freshwater lakes throughout the world have been undergoing dramatic changes in their water inundation and morphology (Hampton *et al*., 2008; Lennox et al., 2010; Gao *et al*., 2011). These changes greatly affect the spatial availability of freshwater resources, which can disturb terrestrial and aquatic environments, thereby altering wildlife ecosystems and posing threats to regional sustainable development (Ariztegui *et al*., 2010; Du *et al*., 2011). Numerous studies have stated that the diminution of lakes shapes the well-being and security of lake dwellers (Bene *et al*., 2003; Nindi 2007; Kafumbata *et al*. 2014). There is need, to identify the nature of the changes, where and when they occur, the rates at which they occur, the social and physical forces that drive those changes, and to understand the effect of these changes on environmental systems (Lambin *et al.*, 2003; Munns, 2006; Dale *et al.*, 2008). It is therefore very important to estimate the rate, pattern and type of land use and land cover changes in order to predict future changes (Dewan and Yamaguchi, 2009; Mohan *et al.*, 2011). Environmental change manifested in terms of drought and desertification in the Lake Chad basin area is characterized by changes in the land use land cover around the lake which results into the drastic reduction in the volume of the water in the basin, with serious consequences both at the local and global environment. Climate change and anthropogenic activities on the entire Lake Chad environment results in the emergence of different land cover. These land uses and land covers keep on changing due to the changing behavior of the lake. There is therefore the need to assess the changes in the land use land cover over the lake.

Data and Methodology

The Lake Chad basin is located approximately between latitude 12^{o}N and 14^o 30' N and Longitudes 13^o E and 15^o 30' E (Figure 1) parts of four West African countries namely Chad, Cameron, Nigeria and Niger. In Nigeria's territory, the basin covers an area of approximately 200,000 km^2 with 720 km^2 attenuation westwards from the shores of the lake and a north-south width of about 300 km (Thambyahphillay, 1987). The Lake Chad basin comprises five bioclimatic zones, namely: Saharan, Sahelo-Saharan, Sahelo-Sudanian, Sudano-Sahelian and Sudano-Guinea ecological zones (LCBC, 2007). The south-west humid Atlantic (monsoon) and the north-east Egyptian hot and dry (harmattan) currents influence the climate and consequently the ecological zonation of the basin. The Sudano-Guinean climate in the south for example has average annual rainfall of over 950 millimeters, a rainy season of six to seven months (May-November) with an average annual temperature at Sarh (formerly Fort Archambault in Chad) of 28^{o}C (absolute minimum 10^{o}C, absolute maximum 45^{o}C) and annual Piche-recorded evaporation of 2027 mm in 1961. During the winter months the cool, dry, dust-laden "hamattan" blows from the Saharan in the north, bringing low humidity, cool nights and warm days. In summer months, moisture-laden winds blow from the Gulf of Guinea in the south bring high humidity, rains, and more uniform diurnal temperature. The monsoon advances from the south, so that rains start earlier, are heavier and last longer in the southwards, although in general there is high spatial and temporal variability over the entire area. The terrain of the study area is generally flat with a few shallow depressions and a few widely scattered elevated spots. The resulting surface drainage density is low (LCBC, 2007). According to LCBC (2005), there was a considerable shift in the rainfall pattern the Lake Chad region as a whole in the past 35 years which resulted into a reduction of the rainfall southward. Temperature around the Lake Chad region is high and humidity is low with the exception of rainy season between the months of June to august (LCBC 2005). The vegetation of Lake Chad region according to Sarch (2000) cited in Ayuba and Dami (2011) is made up of woodland species, however northward the woodland gradually reduces to few trees and shrubs. The presence of the Lake Chad supports an estimated 18 million people, units of livestock (cattle, goats and sheep, camel and donkeys). There are many ethnic groups, each exploiting the natural environment by a range of activities which serve as their source of livelihood. The major language spoken is Hausa, Kanuri, and Fulani and the major occupations the study area are farming, fishing and animal rearing (Usman *et al*., 2016)

Figure 1: Map of Lake Chad the Study Area (Adapted from Babamaaji and Lee, 2014)

The data used for this work includes cloud remotely sensed Landsat data from LandSat 5, LandSat 7 and LandSat 8 satellites. These collected from the archive earth explorer.

Table.1: Data used for this study

DATA	Path	Row	Source	Data acquired
LandSat5 TM	185	51	Earth Explorer	6th Nov., 1984
LandSat5 TM	185	51	Earth Explorer	22nd Dec., 1992
LandSat7 ETM+	185	51	Earth Explorer	31st March, 2000
LandSat7 ETM+	185	51	Earth Explorer	4th Feb., 2003
LandSat7 ETM+	185	51	Earth Explorer	1st July., 2013
LandSat8 OLS/TIRS	185	51	Earth Explorer	17th January, 2017

Radiometric characterization and calibration is a prerequisite for creating high-quality science data, and consequently, higher level downstream products (Chander *et al*., 2009). Landsat Satellite sensors capture images of Land cover as Digital Number (DN) value rather than Top of Atmosphere (ToA) reflectance units. The main purpose of this step was to convert the digital numbers to Top of Atmosphere reflectance units. Equations and parameters to convert calibrated Digital Numbers (DNs) to physical units, such as at-sensor radiance or Top-of-Atmosphere (TOA) reflectance, has been presented in a ‘‘sensor-specific” manner elsewhere, e.g., MSS (Markham and Barker, 1987), TM (Chander and Markham, 2003), ETM + (Handbook2). Different calibration values differ according to sensor ID and acquisition date. Total calibration procedures consist of two steps, the first one was converting DN to Radiance (L_λ) and the second one was converting radiance (L_λ) to Reflectance (ρ_λ).

Spectral radiance, L_λ:

$$L_\lambda = \left(\frac{LMAX - LMIN}{QCALMAX - QCALMIN}\right) * (QCAL - QCALMIN) + LMIN \quad (1)$$

Where; L_λ is the cell value as radiance; QCAL = digital number; $LMIN_\lambda$= spectral radiance scales to QCALMIN; $LMAX_\lambda$ = spectral radiance scales to QCALMAX; QCALMIN = the minimum quantized calibrated pixel value (typically = 1); QCALMAX = the maximum quantized calibrated pixel value (typically = 255).

Conversion from DN in Level 1 products back to at-sensor spectral radiance (L_λ) requires knowledge of the lower and upper limit of the original rescaling factors (Chander et al., 2009). During radiometric calibration, pixel values (Q) from raw, unprocessed image data were converted to units of absolute spectral radiance using 32-bit floating-point calculations. The second step of radiometric calibration operation was to convert the sensor spectral radiance (L_λ) to Top of Atmosphere (TOA) reflectance. When comparing images from different sensors, there are three advantages to using TOA reflectance instead of at sensor spectral radiance. First, it removes the cosine effect of different solar zenith angles due to the time difference between data acquisitions. Second, TOA reflectance compensates for different values of the exo-atmospheric solar irradiance arising from spectral band differences. Third, the TOA reflectance corrects for the variation in the Earth–Sun distance between different data acquisition dates.

$$\rho_\lambda = \frac{\pi . L_\lambda . d^2}{ESUN_\lambda . \cos\theta} \quad (2)$$

where; ρ_λ is Planetary TOA reflectance [unitless]; π is mathematical constant equal to ~3.14159 [unit less]; L_λ is the spectral radiance at sensor's aperture [W/(m^2 sr μm)], $ESUN_\lambda$ is the mean solar exo-atmospheric irradiance for each band [W/(m^2 μm)], cos θ is the cosine of the solar incidence angle and dis earth-sun distance [astronomical units]. A manual Radiance to reflectance model was constructed to measure TOA reflectance value of each bands. Earth sun distance value was collected from Julian Day Calendar.

Digital image classification is the process of assigning a pixel (or groups of pixels) of remote sensing image to a land cover class. There are various classification approaches that have been developed and widely used to produce land cover maps (Atkinson 2004). They range in logic, from supervised to unsupervised; parametric to nonparametric to non-metric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel, and pre-field (Keuchel et al. 2003a, Jensen 2005) [Table 2]. The classification techniques may be categorized either on the basis of training process (supervised and unsupervised) or on the basis of theoretical model (parametric and non-parametric). However, there are two broad types of classification procedure and each finds application in the processing of remote sensing images: one is referred to as supervised classification and the other one is unsupervised classification. These can be used as alternative approaches, but are often combined into hybrid methodologies using more than one method (Jia 2006).

Table 2: Summary of Remote Sensing Classification Techniques *(*Source Jensen, 2005)

Methods	Examples	Characteristics
Parametric	Maximum likelihood classification and unsupervised classification etc.	Assumptions: data area normally distributed prior knowledge of class density functions
Non-parametric	Nearest neighbour classification, neutral networks and support vector machines etc.	No prior assumptions are made
Non-metric	Rule-based decision tree classification	Can operate on both real-valued data and nominal scaled data statistics analysis
Supervised	Maximum likelihood, minimum distance, and parallelepiped classification etc.	Analyst identifies training sites to represent in classes and each pixel is classified based on statistical analysis
Unsupervised	ISODATA and K-means	Prior ground information not known. Pixels with similar spectral characteristics are grouped according to specific statistical criteria
Hard (parametric)	Supervised and unsupervised	Classification using discrete categories
Soft (non-parametric)	Fuzzy set classification logic	Considers the heterogenous nature of the real world. Each pixel is assigned a proportion of the in-land cover fond within the pixel
Pre-pixel		Classification of the image pixel by pixel
Object-oriented		Image regenerated into homogenous objects. Classification performed on each object and pixel
Hybrid approaches		Incudes expert system and artificial intelligence

Unsupervised image classification is a method in which the image interpreting software separates a large number of unknown pixels in an image based on their reflectance values into classes or clusters with no direction from the analyst (Gonzalez, 1974). There are two most frequent clustering methods used for unsupervised classification: K-means and Iterative Self-Organizing Data Analysis Technique (ISODATA). These two methods rely purely on spectrally pixel-based statistics and incorporate no prior knowledge of the characteristics of the themes being studied. On the other hand, supervised classification is a method in which the analyst defines small areas called training sites on the image, which contain the predictor variables measured in each sampling unit, and assigns prior classes to the sampling unit and assigns prior classes to the sampling units (Chytry, 2005). The Supervised Maximum Likelihood classification which is the most common method in remote sensing image data analysis (Richards, 1995), was used in this study. It identifies and locates land cover types that are known a priori through a combination of personal experience, interpretation of aerial photography, map analysis and fieldwork (Jensen, 2005). It uses the means and variances of the training data to estimate the probability that a pixel is a member of a class. The pixel is then placed in the class with the highest probability of membership (Ozesmi and Bauer, 2002). A classification scheme was developed for further analysis of the images, based on the characteristics of the area (Table 3)

Table 3: A detail classification scheme used for supervised classification)

Land cover types	Description
Water body	Lakes, rivers, reservoirs, and ponds
Vegetation	Forest, Cropland, farmland, grassland
Shrub	Open grassland with sparse shrubs
Bare land	Bare surface, dessert areas, barren land

After development of signature file, image classification was carried out. Maximum likelihood parametric rule was applied during classification. Maximum likelihood classifier (MLC) is the most widely adopted parametric classification algorithm (Jensen, 2005b; Bailly, 2007). Maximum likelihood algorithm (MLC) is one of the most popular supervised classification methods used with remote sensing image data. This method is based on the probability that a pixel belongs to a particular class. The basic theory assumes that these probabilities are equal for all classes and that the input bands have normal distributions. However, this method needs long time of computation, relies heavily on a normal distribution of the data in each input band and tends to over-classify signatures with relatively large values in the covariance matrix. The spectral distance method calculates the spectral distance between the measurement vector for the candidate pixel and the mean vector for each signature and the equation for classifying by spectral distance is based on the equation for Euclidean distance. It requires the least computational time among other supervised methods, however, the pixels that should not be unclassified become classified, and it does not consider class variability. Maximum likelihood Classification is a statistical decision criterion to assist in the classification of overlapping signatures; pixels are assigned to the class of highest probability. The maximum likelihood classifier is considered to give more accurate results than parallelepiped classification however it is much slower due to extra computations.

According to Anderson *et al*. (1976), the minimum level of interpretation accuracy in the identification of land use and LULC categories from remote sensing data should be at least 85%. The procedure is a very effective way to represent accuracy in that the accuracies of each category are plainly described along with both the errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification (Congalton, 1991). In this study, accuracy assessment was performed for the MLC classified maps. Stratified random sampling design was adopted for the accuracy assessment**.** Overall accuracy and the Kappa statistics were derived from the error matrices to find the reliability and accuracy of the maps produced. A pixel-based comparison was used to produce change information on pixel basis and thus, interpret the changes more efficiently taking the advantage of ‘‘-from, -to’’ information. The data from the classified images were exported to Microsoft excel, where they were compared using cross-tabulation in order to determine qualitative and quantitative aspects of the changes for the study periods. A change matrix (Weng, 2001) was produced with the help of ERDAS Imagine software.

Result and Discussion

Land use land cover change

The land use land cover of Lake Chad was mapped from LandSat imageries for 1984, 1992, 2000, 2003, 2013 and 2017. Figure 2- 8 shows the land use classification of the area for each period. The land use was classified under four different sectors which includes; water body, vegetation, shrub and bare land. It can be observed that shrub and bare land occupy majority of the Lake Chad area in 1984 (figure 2). Water body occupied about 8% of the area coverage, vegetation occupied about 11% while the shrub and bare land occupied about 78% of the Lake Chad area. In 1992 (figure 3), vegetation increased to about 24% of the area coverage while shrub decreased from about 23%. Bare land which occupied majority of the area increased to about 35% while the water body was 7%. Part of the land use occupied by shrub in 1984 where replace by vegetation in 1992. In 2000 (figure 4), vegetation and water body increased to about 10% and 41% of the area respectively while shrub decreased to 17%. In 2003 (figure 5), there was an increase in the area coverage of water body. Water body increased to 14.04%, vegetation was 35%, shrub was 16% and bare land was 40%. In 2013 as depicted in figure 6, water body shrunk to 10% of the coverage area, vegetation was 39%, and shrub was 19% while bare land was 31%. In the most recent year, vegetation occupied majority of the area coverage (%) as shown in figure 7. The increase in vegetation may be possible due to an increase of invasive species (Babamaaji and Lee, 2014). Two prominent invasive species, typha and water hyacinth,

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are observed in the Lake. In the Chari and Logone Rivers, water hyacinth is dominant while typha is dominant in the Komadugu-Yobe River. The Komadugu-Yobe River has been colonized; over 1,000 km2 of fadama land was covered by typha and has contributed immensely to the diversion of flows away from Lake Chad (Bdliya and Bloxom 2011).

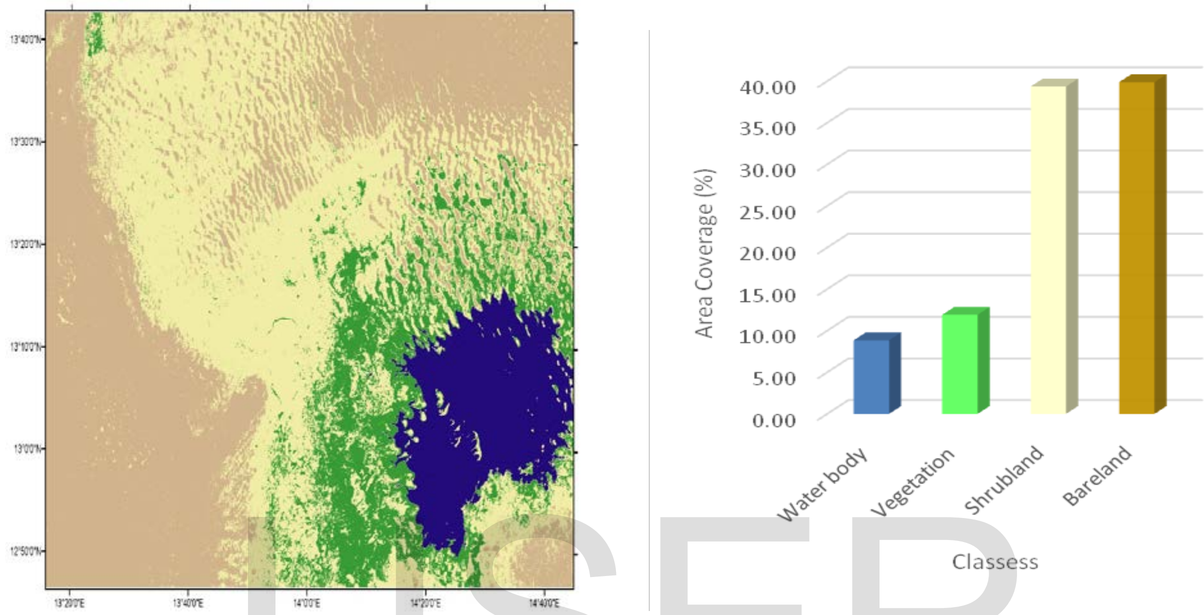

Figure 2: Land Use Land Cover Classification for 1984

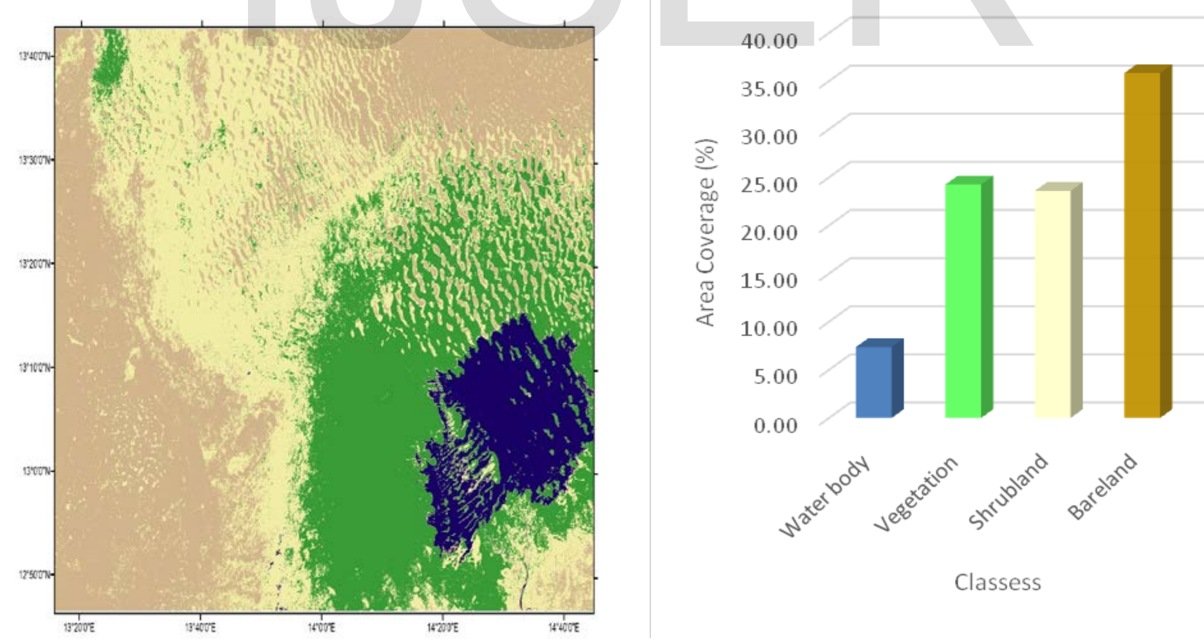

Figure 3: Land Use Land Cover Classification for 1992

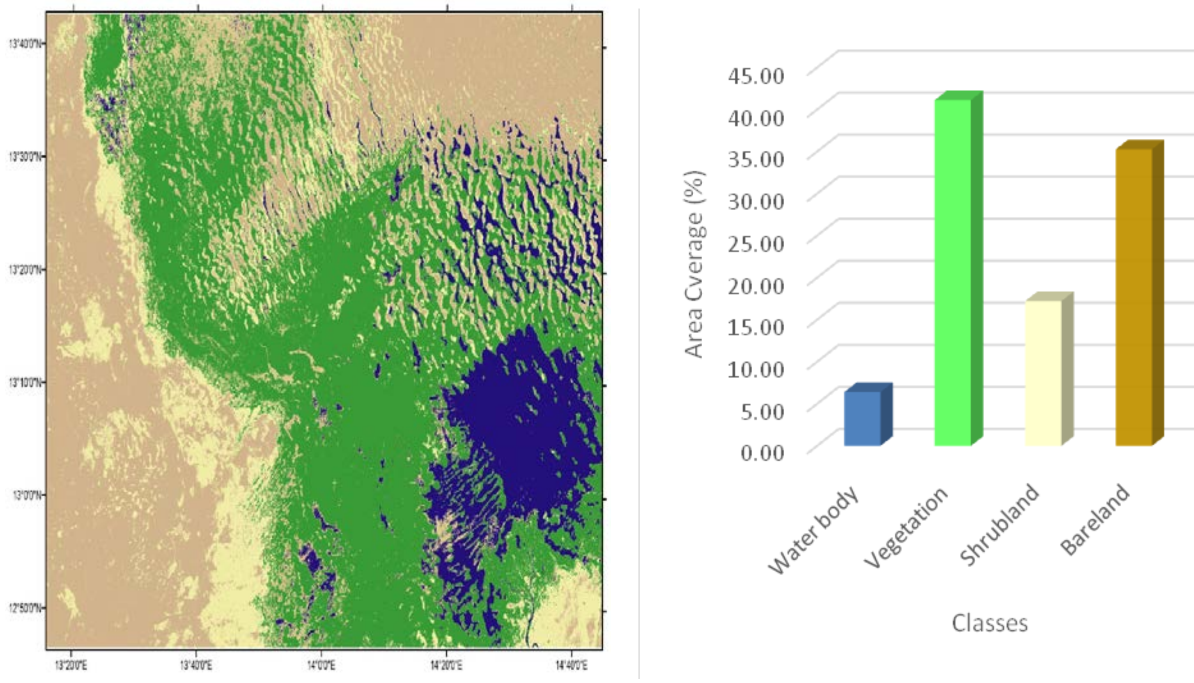

Figure 4: Land Use Land Cover Classification for 2000

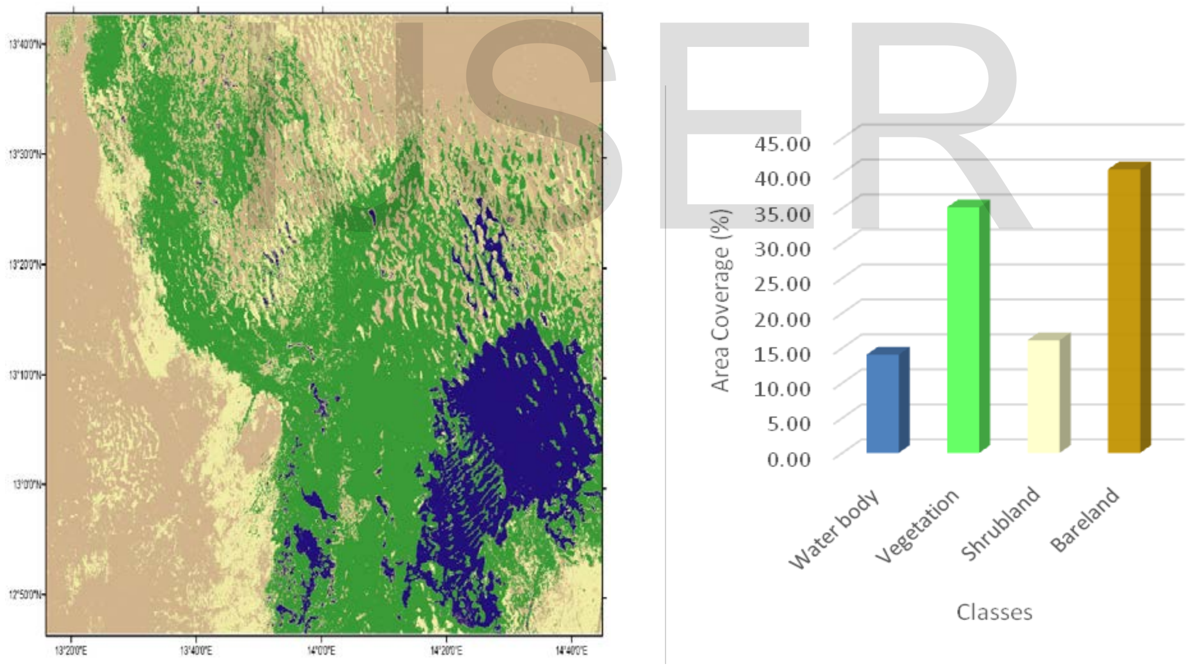

Figure 5: Land Use Land Cover Classification for 2003

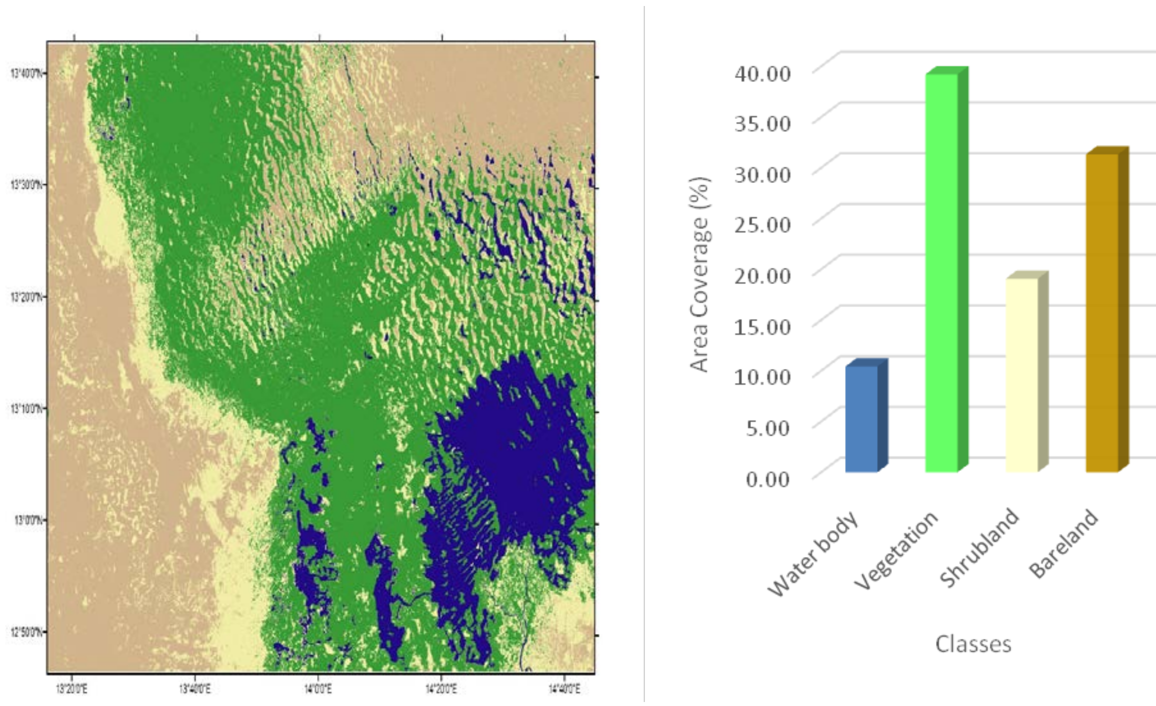

Figure 6: Land Use Land Cover Classification for 2013

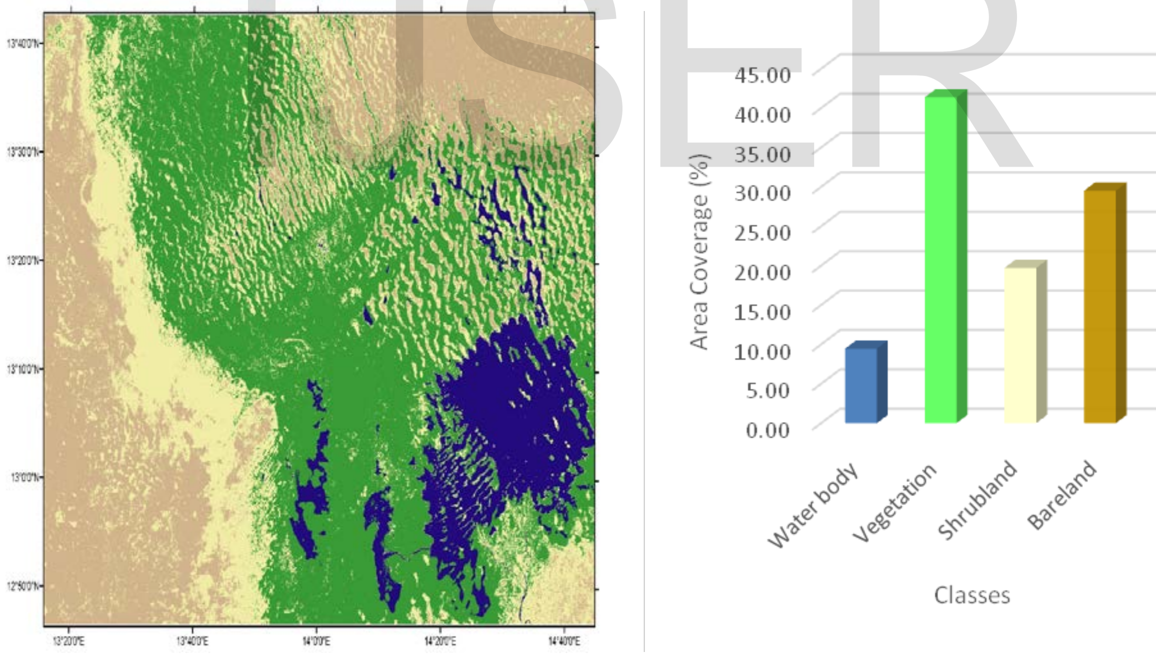

Figure 7: Land Use Land Cover Classification for 2017

Figure 8 reveals the rainfall around chad across the years. It can be observed that there was inter-annual variation in the rainfall around Lake Chad. Rainfall around Lake Chad was not constant, it varied from year to year. The lowest rainfall amount was in 1984 when it was about 180mm all through the year while the highest rainfall was in 1998 of about 650 mm. In order to determine the relationship between the lake (water body) and rainfall, the plot for both rainfall the area covered by water body class was plotted in figure 9. It can be observed from the plot that from 1984 to 1992, rainfall increased from 185 mm to 450 mm and there was a decrease in the area coverage of water body. From 1992 to 2000, when rainfall increased to 560 mm, water body also increased. From 2000 to 2003, rainfall decreased to 550 mm, but water body increased. From 2003 to 2013, rainfall further decreased to 450 and water body also decreased. The relationship between rainfall around Lake Chad and the water body (lake) was not fully direct as there was variation in the relationship. There shows that though rainfall is a factor that contributes to the change in the lake, there are other factors also responsible for the variation.

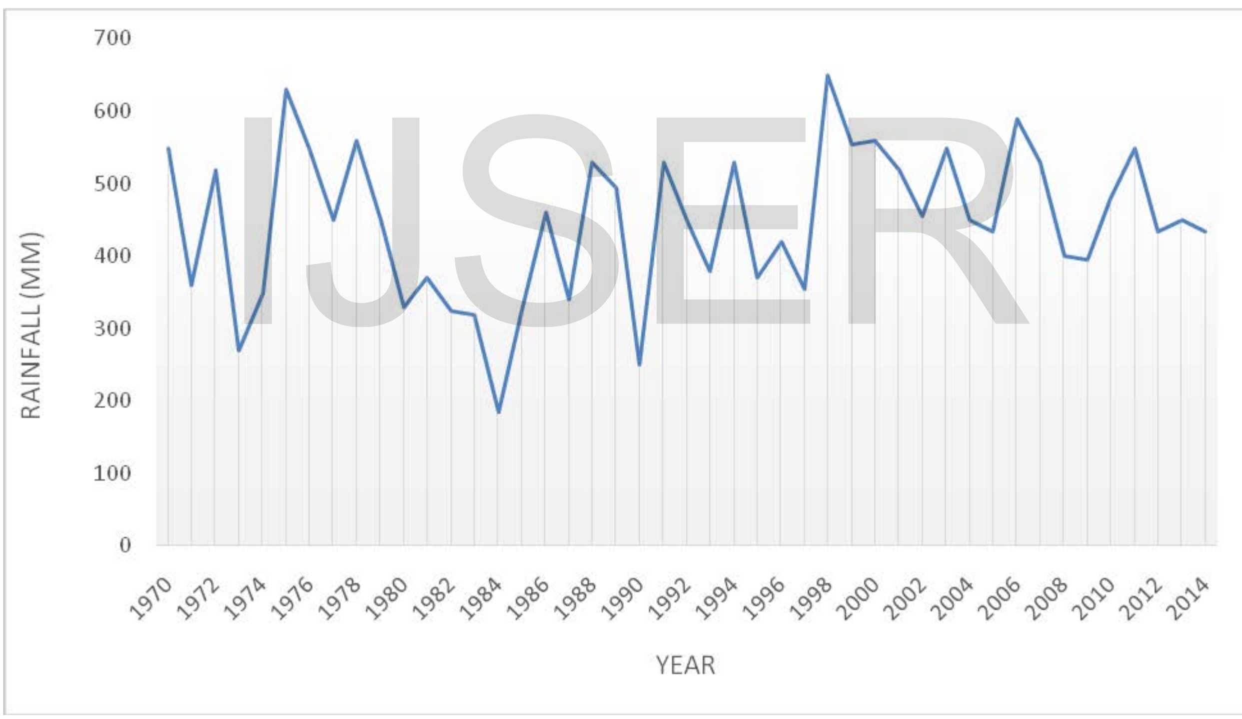

Figure 8: Inter annual rainfall variation between 1970 and 2014 around Lake Chad basin

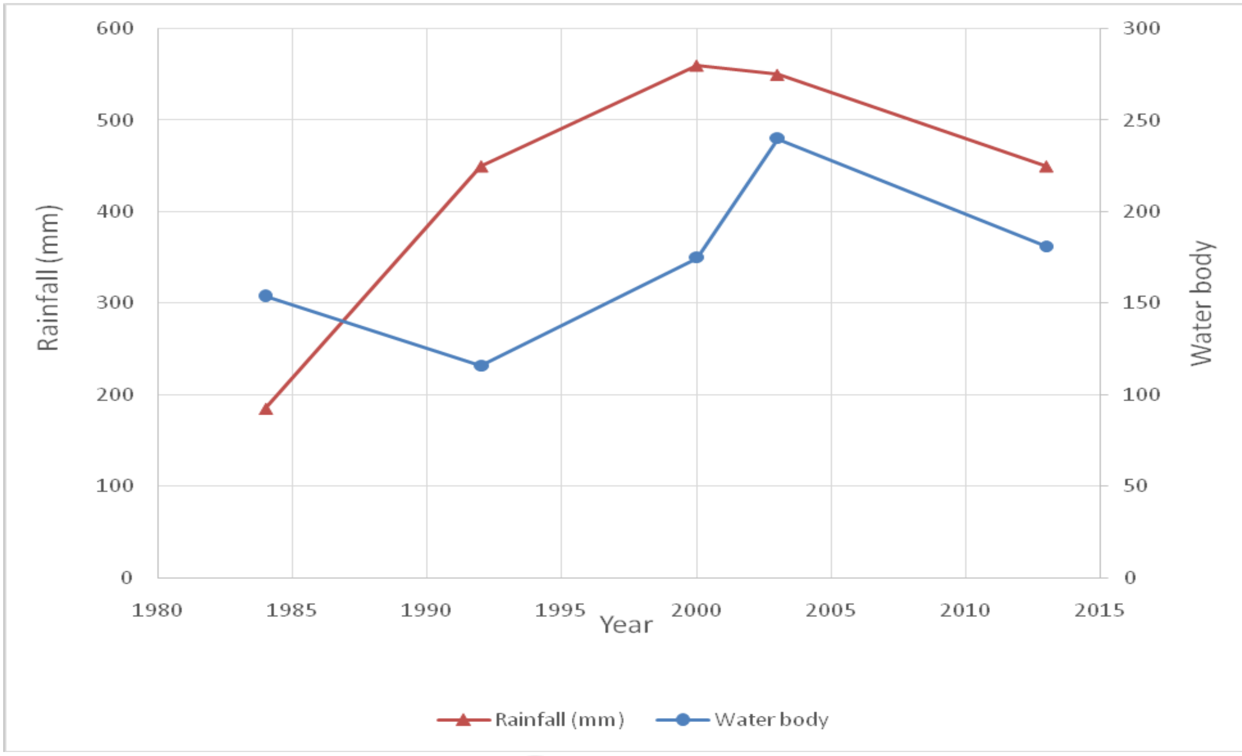

Figure 9: Relationship between rainfall (mm) and water body (area coverage) in Lake Chad

Change detection

Figure 10 reveals the area coverage (hectares in thousand) for each land use. The land use classes varied differently by the years. For the period of study (1984 to 2017), water body increased from 154 (hectares in thousand) to 156 (hectares in thousand) with the highest area coverage in 2003 at 240 (hectares in thousand). Vegetation increased form 208 (hectares in thousand) to 682 (hectares in thousand), shrub decreased from 686 (hectares in thousand) to 325 (hectares in thousand) while bare land decreased from 695 (hectares in thousand) to 486 (hectares in thousand). The increase in water body in recent years was also note by Babamaaji and Lee (2014) in the study over a period of 1991 to 2014. The change detection by land use is shown in Figure 11. This reveals the change in area (hectares in thousand) between the different study periods 1984 to 1992, 1992 to 2000, 2000 to 2003, 2003 to 2013, 2013 to 2014. There was no consistent change in any of the land use classes as there were variation in the change over the years. The change in area (hectares in thousand) from 1984 to 2017 a span of 33 years is presented in Figure 12. The positive values represent increase in area coverage as is the case of vegetation (474 hectares in thousand) and water body (2 hectares in thousand), while negative values represent decrease in area coverage as is the case of shrub (-361 hectares in thousand) and bare land (-209 hectares in thousand).

Figure 10: Distribution of Land Use by Area (hectares in thousand) for the study period.

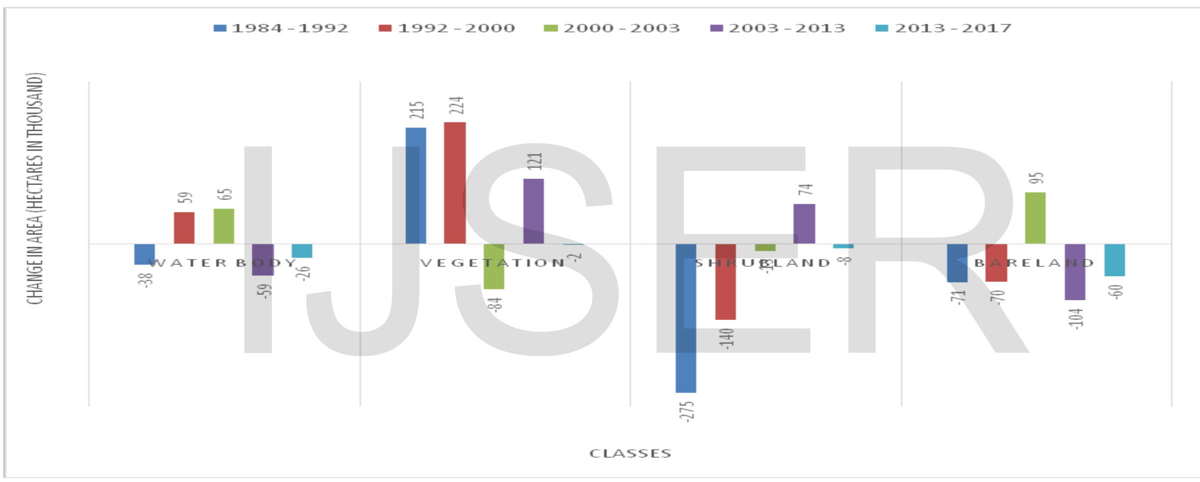

Figure 11: Change Detection by Land Use in Area (hectares in thousand)

Figure 12: Change Detection by Land Use in Area (hectares in thousand) for 1984 to 2017

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Table 4, reveals the rate of change per year for each time interval. From 1984 to 1992, vegetation reveals the highest change with a mean percentage change of 12.94 % change per year, water body at the rate of -3.11% change per year. Shrub changed at the rate at -5.01 % change per year and bare land decreased the least at -1.27% change per year. From 1992 to 2000, shrub and bare land decreased at the rate 4.26 and 1.40 % change per year respectively while vegetation and waterbody increased at the rate of 6.63 and 6.36% change per year. From 2003 to 2003, water body and bare land increased at the rate of 12.54 and 5.72 % change per year respectively while vegetation and shrub decreased at the rate of 4.32 and 1.56 % change per year. From 2003 to 2013, vegetation and shrub increased at the rate of 2.14 and 2.87 % change per year while water body and bare land decreased at the rate of 2.45 and 1.60 % change per year. From 2013 to 2017, all the land use classes decreased at the rate of 3.52, 0.06, 0.58 and 2.73 % change per year for water body, vegetation, shrub and bare land respectively.

Table 4: Change Detection of Land Use during the Study Periods

Land Cover Class	1984 - 1992			
	Change in area (Hectares in thousands)	Percentage change (%)	Mean area change (Hectares in thousand/year)	Mean percentage change (%/year)
Water body	-38.36	-24.87	-4.80	-3.11
Vegetation	214.97	103.52	26.87	12.94
Shrub	-274.92	-40.08	-34.37	-5.01
Bare land	-70.74	-10.17	-8.84	-1.27
Land Cover Class	1992 - 2000			
	Change in area (Hectares in thousands)	Percentage change (%)	Mean area change (Hectares in thousand/year)	Mean percentage change (%/year)
Water body	59.02	50.92	7.38	6.36
Vegetation	224.13	53.03	28.02	6.63
Shrub	-140.20	-34.10	-17.52	-4.26
Bare land	-69.77	-11.17	-8.72	-1.40
Land Cover Class	2000 – 2003			
	Change in area	Percentage	Mean area change	Mean

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	(Hectares in thousands)	change (%)	(Hectares in thousand/year)	percentage change (%/year)
Water body	65.35	37.36	21.78	12.45
Vegetation	-83.88	-12.97	-27.96	-4.32
Shrub	-12.70	-4.69	-4.23	-1.56
Bare land	95.11	17.15	31.70	5.72
Land Cover Class	2003 - 2013			
	Change in area (Hectares in thousands)	Percentage change (%)	Mean area change (Hectares in thousand/year)	Mean percentage change (%/year)
Water body	-58.87	-24.50	-5.89	-2.45
Vegetation	120.59	21.42	12.06	2.14
Shrub	74.11	28.70	7.41	2.87
Bare land	-103.86	-15.98	-10.39	-1.60
Land Cover Class	2013 - 2017			
	Change in area (Hectares in thousands)	Percentage change (%)	Mean area change (Hectares in thousand/year)	Mean percentage change (%/year)
Water body	-25.57	-14.09	-6.39	-3.52
Vegetation	-1.56	-0.23	-0.39	-0.06
Shrub	-7.68	-2.31	-1.92	-0.58
Bare land	-59.62	-10.92	-14.91	-2.73

Accuracy assessment

Table 5 comprises of the accuracy totals and kappa statistics for the classified images. Random points were generated for each classified image which was matched with the reference data. The accuracy report was generated for the images. The accuracy assessment for each classified image reveals on overlap in the classification for different classes, resulting from errors of omission and commission. The overall classification accuracy was 84.78% for 1984, 83.72% for 1992, 81.08% for 2000, 82.61 for 2003, 82.76 for 2013 and 81.82% for 2017. The overall kappa statistics ranged from 0.74 to 0.77 for all the classified images. The accuracy of the classification indicates reasonable classification accuracy, considering International Geosphere Biosphere Programme IGBP land cover map has an overall accuracy of73.5 % (Scepan 1999; Shao and Wu 2008).

Table 5: Accuracy assessment table

Year	Overall Classification Accuracy (%)	Overall Kappa Statistics
1984	84.78	0.75
1992	83.72	0.7782
2000	81.08	0.7413
2003	82.61	0.743
2013	82.76	0.7559
2017	81.82	0.7687

Conclusion

This study investigates the land use land cover changes around Lake Chad and environs. The objectives of study were to create a land use land cover classification scheme over the study area, derive land use land cover maps from the classified images of the study area and carry out change detection analysis of the land use land cover maps over the study area. This study utilized remote sensing data from LandSat for a period of thirty-three years. From the land use land cover classification and change detection, the land use classes varied in different periods. Waterbody decreased for three periods and increased for two. Vegetation increased in five periods and decreased only in one period; shrub land decreased in five and increased in one period while bare land on the hand also decreased in five periods and increased in one. The general distribution of the land use land cover across the years revealed variation in the water body, with increase and decrease in different years. The relationship between rainfall and water body area coverage was carried out to reveal the contribution of rainfall to the variation in the water body area coverage. It was noted that rainfall was a factor but there are also other factors contributing to the variation. Various factors could be responsible for this variation which includes natural and human factors. The accuracy assessment for the classification was carried out and it revealed reasonable level of overall classification accuracy for all the classified images with a minimum of 81%. The study revealed the variation in the land use land cover of Lake Chad. The variations are said to be caused by a number of factors and not just precipitation. Land use changes are caused by a number of natural and human factors. A change is precipitation pattern affects the lake extent. Also, human activities such as irrigation agriculture, over grassing, canalization, urbanization contributes extensively to changes and variation in the land use land covers. Natural effects such as rainfall (precipitation) changes are felt typically over a long period of time, the effects of human activities can be immediate and often radical.

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