AN ASSESSMENT OF LAKE EXTENT CHANGES USING FOUR SETS OF SATELLITE IMAGERY FROM THE TERRALOOK DATABASE: A CASE STUDY OF LAKE CHAD, AFRICA

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Abstract

Lake Chad is located in Central Africa. This lake is shared by four countries namely÷ Cameroon, Nigeria, Chad and Niger. The population of the drainage basin is growing rapidly and was estimated at about 37 million people in 2004 with a high average growth rate of 2.4-2.6%. However, annual average rainfall over the entire basin is rather low at 320 mm and varying between 1, 500 mm in the southern parts of the region to less than 100 mm in the northern parts of Chad. This paper was to test if it is possible to estimate former changes in the spatial extent of Lake Chad using four sets of satellite imagery from the Terralook database (USGS, 2007). Satellite data (images) covering Lake Chad for four time periods÷ (Landsat MSS (1975), Landsat TM (1990), Landsat ETM$^+$ (2000) and ASTER (2007)) were used as data source. These images were classified using GIS and remote sensing techniques to create land cover maps which were used to estimate lake extent changes of Lake Chad. This study is unique as it tests the ability of a newly available, user friendly and publicly available dataset (Terralook) to be used in conjunction with remote sensing techniques. The results showed that Lake Chad has shrunk over the past 35 years. In the interval 1975-1990, lake area increased by 15%. The lake area declined by 9% in the interval 1990-2000. During the period 2000-2007, the lake area declined again by about 11%. The findings provide a useful tool to local stakeholders for decision making in the field of water management.

Keywords: Lake Chad, Lake extent changes, Remote sensing, GIS, Land cover classification

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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.

Previous studies have used remotely sensed data to estimate the areal extent of Lake Chad. A previous analysis of lake extent changes of Lake Chad is presented by Oluwafemi (2005). The analysis considers the period between 1963 and 2001 using five time series of remotely sensed data (1963, 1973, 1987, 1997 and 2001). Oluwafemi (2005) used images from Modis, Argon and Landsat satellites. Arc view 3.1, Arc map 8.1 and GIS tools were used to determine the lake extent. The results show shrinkage of Lake Chad between these referenced periods (1963 to 2001). Between 1963 and 1997 the lake was estimated to reduce from about 40,000 km^2 to 4,837 km^2 which is a loss of close to 88% of its areal extent. Oluwafemi (2005) estimate an increase in lake area between 1997 and 2001 of about 56%.

Fig. 1.1 Site location showing the central location of Lake Chad drainage basin in Africa, a zoom in of Lake Chad drainage basin.
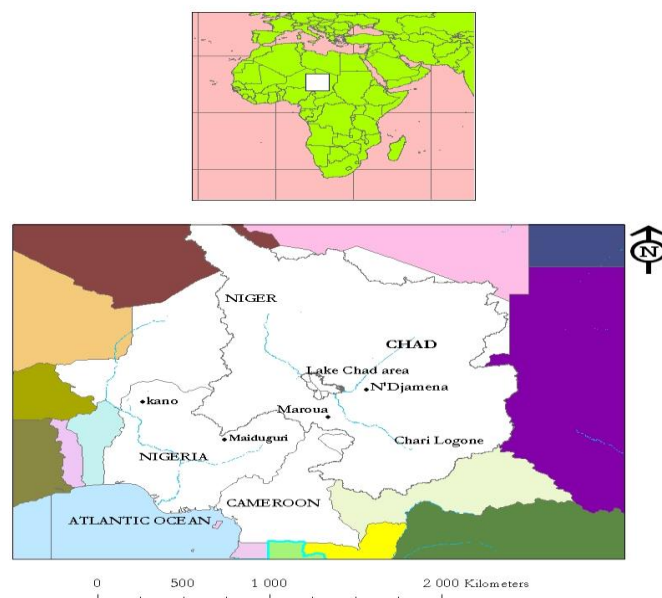
In a similar and recent study by Alfa et al. (2008) the extent of Lake Chad was estimated using satellite imagery. The analysis considers the period between 1963 and 2000 using four-time series of data (; 1963, 1972, 1987 and 2000). The corona space photograph for 1963 and Landsat imageries for 1972, 1987 and 2000 were

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used for this study. ERDAS Imagine environment was used to estimate the lake extent. They concluded that Lake Chad has reduced in size between the periods of study. In 1963 the lake extent was estimated to be 20,900 km^2 which reduced steadily until 2000 when the lake extent was estimated to be 304 km^2 corresponding to about a 95% loss in lake extent.

Coe and Foley (2001) used observations of lake level to estimate the lake area. Their analysis considers the period 1953 and 1994. They used two different models: IBIS that simulates the surface water balance from prescribed meteorological forcing and HYDRA that simulates transport of the runoff (simulated by IBIS) across the land surface to calculate the river discharge and lake and wetland area as a linked system. River discharge, surface water level and lake area were simulated and compared with observations for two periods 1953-1979 and 1983-1994. They concluded that the seasonal fluctuations of the lake level are primarily controlled by climate (accounting to about 95% of the total inflow variability) and not by water management practices. They concluded that water extraction due to irrigation had little effect on the lake system (Coe and Foley, 2001).

This study is unique as it tests the ability of a newly available, user friendly and publicly available dataset (Terralook) to be used in conjunction with remote sensing techniques. As such, the current study will answer the following question: Is it possible to estimate changes in spatial extent of Lake Chad using the four sets of satellite imageries available from the Terralook database? The major goal of this research is to analyse the lake extent changes in Lake Chad using four sets of satellite imagery. Hence the specific objectives included in this research are: Gather satellite data (images) for Lake Chad from available source specifically: Landsat MSS (1975), Landsat TM (1990), Landsat ETM$^+$ (2000), and ASTER (2007), perform a land cover classification for each data set to provide a land cover map for each reference time and an estimate of the total area covered by Lake Chad, quantify lake extent changes that have occurred within the referenced periods and compare them with already published estimates. Existing estimates are based on observations of lake levels used to generate lake extent from estimated ratios of area to lake level (Coe and Foley, 2001) and other remote sensing studies in the literature. The results showed that Lake Chad has shrunk over the past 35 years.

Materials and Methods

This study uses the newly available Terralook database (USGS, 2007). This database, developed by the United States Geological Survey (USGS) was first made public in 2007. The source of input data for this study is internet based and publicly available. The input data used in this study represents four time periods. The Terralook database was selected specifically to determine if this free, publically available database provides high enough resolution and consistency in data to analyze land use changes (specifically, areal extent changes in large lakes). According to Claudia et al. (2007) the bands, nominal and spatial resolutions with which the data included in Terralook were collected are as follows: Landsat MSS 1975 has bands 1- 3 with a spatial resolution of 80 m, Landsat TM has bands 4 & 5 with a spatial resolution of 30 m, Landsat ETM$^+$ has band 7 with a spatial resolution of 30 m and Aster has bands 1-3 and a spatial resolution of 15 m. These data while different in their time periods are similar in their datum (WGS 1984, Zone 33N). Terralook applies the same cubic convolution resampling technique and resample resolution (1000 m) across all data. According to Gurjar and Padmanabhan, (2005) resampling is a technique of generating an image on a system of coordinates, taking the input image from

a different set of coordinates. Despite these similarities, the images presented in Terralook are collected at different months, years, and days. Nine tiles were collected for each Landsat collection (Landsat MSS 1975, Landsat TM 1990, and Landsat ETM$^+$ 2000) while forty tiles were collected for the Aster collection. Images for Landsat MSS 1975 were collected from March, October, November and December. Landsat Thematic Mapper 1990 images were collected from August, September, October and November. Landsat Enhanced Thematic Mapper 2000 images were collected from October, November and December. The Aster 2007 data was collected during the period January, February, March, April, May, October, November and December. The Terralook database is also a collection of image scenes over a short period of time (months) that are considered as images of a certain time. For instance, Landsat MSS 1975 (circa 1972-1983) means a selection of images of best cloud cover and greenness between the intervals 1972-1983 to form a composite image for the year 1975. This choice of database has direct influence on the quality of results.

This study use only satellite imageries as data and uses remote sensing to estimate the spatial extent of Lake Chad. Thus computer assisted- interpretation of satellite imageries was integral to this study. Satellite imageries from Landsat MSS (1975), Landsat TM (1990), Landsat ETM$^+$ (2000), and ASTER (2007) were used (Table 2.1).For software; this study relied on a Geographic Information System (GIS) in the form of Arc map 9.2. Data was downloaded from Terralook database as georeferenced TIFF files. Terralook collections are ordered through the USGS Global Visualization (GloVis) Viewer. This begins by selecting a Terralook collection and clicking on the world map to select your area of interest and opening an image selection window. The option toolbar is used to access the various options prescribe to download the data. The selected image is highlighted in yellow and the scenes selected are highlighted in green. Selected images are added to the scene list. An order is made to move all the images from the scene list to the shopping basket (even though there is no cost) which is downloaded.

What follows is the step-by-step methodology used to process satellite images retrieved from Terralook into land use maps. These steps were repeated for each of the four sets of data retrieved from the Terralook database. The image files were imported into Arc catalogue. Here a geodatabase was created to manage each file. The images were then imported into Arc map where areas of no data were cut and the images can be combined (mosaicked) using the spatial analyst data management tool. This was done by the building of pyramids at the time the data was being mosaicked. These images were mosaicked before the unsupervised classification was performed.

The mosaicked image was imported into ENVI 4.3 for an unsupervised classification. The unsupervised classification was used to cluster pixels based on statistics only (i.e., with no user defined-training classes). Although the method requires no user input to create a classified image, the output needs post classification operations to make the results meaningful with respect to land use classification. The k-means clustering algorithm was used for the unsupervised classification. This method defines image classes by determining the optimal partitioning of the data distribution into a specified number of subdivisions and pixels are labelled using the closest-distance-to-centre decision rule (Mather, 2005).

Class statistics were generated in order to perform the classification. For a specified input file three bands (red, green and blue) are selected as a spectral subset. The initial number of classes was set to ten and the number of iterations to five. The influence of initial number of classes and iterations was tested and shown to be

minimal on the resultant lake area estimate. The initial ten classes corresponded to: 1) crop land, 2) thick vegetation or forest, 3) water, 4) urban, 5) sand, 6) wetland, 7) bare soil, 8) grassland, 9) marsh, 10) cultivated land.

Post classification consisted of combining classes. Here, the task was to decide which classes to merge so as to produce a five-class image and eliminate redundancy. The sensitivity to the number of classes specified was considered. To identify which classes to combine, the image was queried using the cursor location/value to label and identify classes of interest. The resulting five classes were: forest, cropland, water, urban, and soil.

The post-classified image was then sieved and clumped. In remote sensing, sieving is the process of removing classified isolated pixels occurring in classification image. The sieve class method looks at the neighbouring 4 or 8 pixels to determine if a pixel is grouped with pixels of the same class. Clumping is the process of adding adjacent similar classified areas together (Tou and Gonzalez, 1974). This was done by selecting classification in the ENVI main menu. The sieving was done first to remove isolated pixels based on a threshold (a number of pixels). Clumping of the sieved image was done to add spatial coherence to existing classes by combining adjacent similar classified areas.

The header file was edited to allow for easy visual comparisons of classification outputs. The labels of bands were changed based on final classification image. The file was saved as a georeferenced image file (geotiff) that can be imported into Arc map. This georeferenced image provides a land use map for the Lake Chad area and can be used to assess the percentage of area occupied by each land cover class.

The area covered by each land use was calculated in each map produced from the remote sensing images. Maps were trimmed to squares of approximately equal areas for all images. The attribute table of each map was exported into an Excel work sheet where a percentage for each land cover class was quantified. In addition, a shape of the historical Lake Chad extent was defined to estimate the water area (lake extent) for each map (i.e., defining a common area extent among the images). This was done to limit the influence of problems with the spatial projections between the satellite images.

The demarcation of the historical lake extent was done visually. This was based on the criterion that all blue pixels around the historical lake extent were considered as water. The shape of the historical lake extent was defined using the Landsat MSS 1975 image as a sample. This shape was overlaid on the other three images so that all the shapes have the same area. With the aid of the raster calculator, this historic lake extent shape was used to determine the number of water pixels in the historic Lake Chad extent. The pixels in the attribute table were multiplied by the resolution to get the lake area. This was then used to estimate the area of Lake Chad over the four time periods.

RESULTS

Effects of number of classes on land cover classification.

The choice of the number of land cover classes used in this study directly influences the estimated area of Lake Chad. The table below (Table 1) shows the land cover areas estimated using different numbers of classes over the Landsat MSS 1975 image (circa 1972-1983). Considering a change in the number of classes from three to four (Table 1), it can be noticed that the land cover class defining soil splits into two classes namely soil and urban classes. Adding the fifth class, the class forest splits into two land cover classes representing forest and cropland. Finally the sixth class test shows a split in the class water into two land cover classes namely water and wetland. This splits the class water into water and wetland having area coverage of 4,004 and 524 km^2

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respectively. Since adding this last class (i.e., having 6 classes) splits the class of water and does not significantly change the remaining classes, five classes were selected in this current study and used for the remainder of the analysis.

Table 1 Land cover classes and number of classes tested over Landsat MSS image.

| Land cover /number of classes tested	3 Classes	4 Classes	5 Classes	6 Classes
Forest	50,873	51,805	7,706	8,504
Cropland			40,567	43,586
Water	6,168	8,959	6,770	4,004
Urban		2,843	1,663	1,383
Soil	5,061	1,126	829	523
Wetland				524

Dynamics in land cover types

The land cover maps of Lake Chad area for the four reference periods are illustrated in Figure 1. Statistical summaries of the different land cover types are given in Table 2 for the entire extents of the scenes shown in Figure 1. Between 1975 and 1990, the category forest increased in area and receded between 1990 and 2000. Between 2000 and 2007, this class realised an increase in the area again. The category cropland reduced in area between 1975 and 1990.Between 1990 and 2000, the class cropland declined and increased in area from 2000 and 2007 according to the estimates in this study. The category water in the period 1975 to 1990 increased. During the interval 1990 to 2000, the area of the class water declined. The class urban area declined between 1975 and 1990. During 1990 to 2000, this category increased in area with a further increase in the period 2000 to 2007. The soil class increased in area during the interval 1975-1990. Between 1990 and 2000, the category soil increased and between 2000 and 2007; this class declined in area.

Table 2 : Changes in land cover area (given in km^2) of the Lake Chad are shown in Figure 1 from 1975 to 2007.

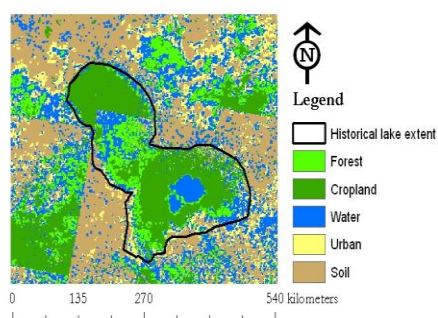| Class/ Data	Landsat MSS 1975 (circa 1972-1983)	Landsat TM 1990 (circa 1984-1997)	Landsat ETM$^+$ 2000 (circa 1999-2003)	Aster (2007)

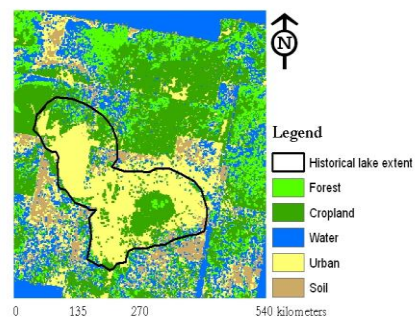|				
Forest	24,007	28,471	20,984	40,864
Cropland	67,813	47,630	38,754	90,410
Water	53,396	55,809	52,467	68,668
Urban	36,621	27,132	38,753	67,986
Soil	55,854	78,273	86,571	24,066
Total	**237,691**	**237,315**	**237,529**	**291,976**
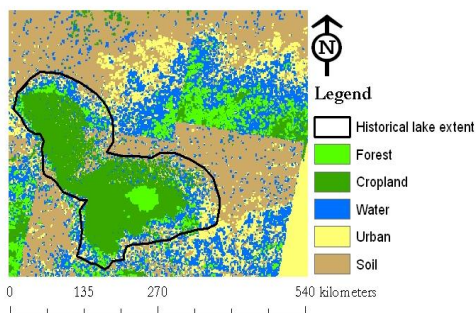
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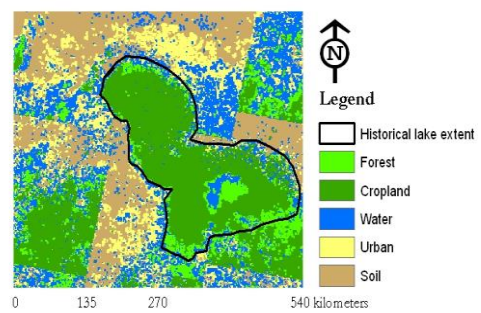
b

c

d

Fig. 1 : (continued) Land cover types in Lake Chad area in (a) 1975, (b) 1990, (c) 2000 and (d) 2007.

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Dynamics in lake area changes

It is obvious that there are many misclassified pixels in Fig 1 from the automated classification method used in this study. In addition, there is an apparent disagreement in projection of the maps between different time periods. To address these issues, the historic lake extent is defined in each image such that its area is constant between the different images. This historic lake extent is defined using the Landsat MSS 1975 classified image. The extent of this polygon (Figure 1a) most likely approximates the 1973 historical extent that marked the beginning of the 1973 to 1974 Sahelian drought (Fortnam and Oguntola, 2004). Table 3 summarises values of the calculated spatial area of Lake Chad over the four time periods used for the study within this historic lake extent. This Table (3) presents the total amount of water contained in the historical lake extent (Fig 1).

Table 3: Spatial extent of Lake Chad over four time periods.

Data/Item	Area (Km^2)
Landsat MSS 1975 (circa1972-1983)	8,065
Landsat TM 1990 (circa1984-1997)	12,813
Landsat ETM$^+$ 2000 (circa1999-2003)	10,011
Aster (2007)	8,251

The result of this study in relation to the actual size of the historic Lake Chad over the four time periods did not agree entirely with the results of some already published literature. However, it should be noted that there is much scatter in the various estimates of lake area extent and its change over time. Primarily, there is no similarity in the trends (Figure 2) showing a decrease in lake area with time. This is true because the other studies use different methods to estimate lake area from remote sensing or direct observation and because of the difficulties of using the automated classification scheme.

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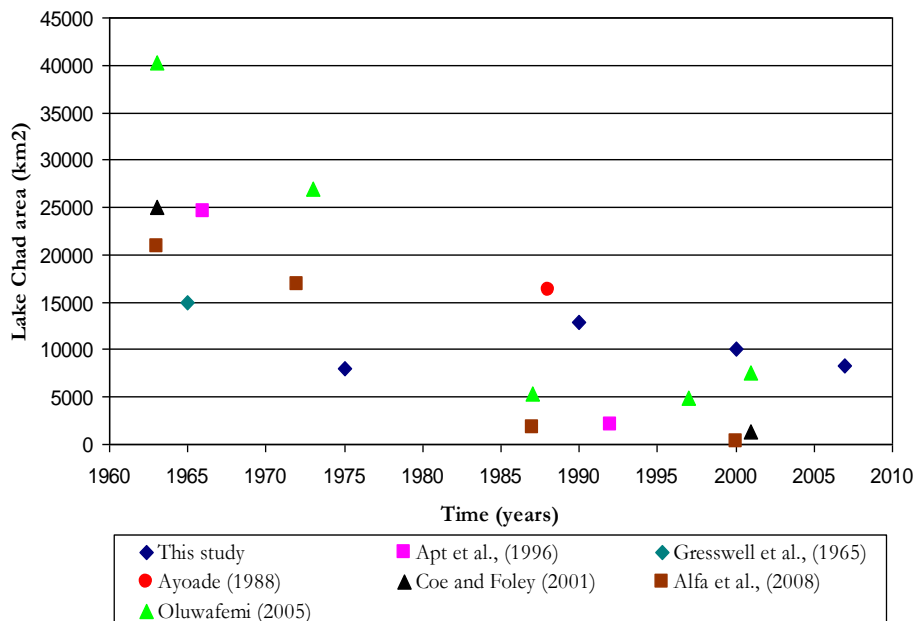
Fig 2: Comparing Lake Chad area estimates.

DISCUSSION

Land cover analysis

The land cover analysis was based on results from satellite image classification (Figure 1). The classification shows variation in all classes over the different time periods. Table 2 (that summarises Figure 1) displays the high uncertainty in these values. This is due to the problem of identification and separation of classes due to mixed pixels when using the automated land use classification scheme outlined in this study. For example, the forest class incorporated thick vegetation. Clusters of bushes were equally considered as forest. Similarly, the cropland category could possibly include cropland and grassland.

The water group, which is of primary interest in this current study, integrated open water, wetland and marshy areas. In the interval 1990 to 2000, the class water declined by 3,342 km^2 about 0.5% decrease in area. A possible explanation to this is a recurrent drought situation after 1982 (Fortnam and Oguntola, 2004). From the analyses between 2000 and 2007, the class water increased by 16,201 km^2, a 0.5 % increase in entire area given by the map shown in Figure 1. Counter to this, the urban class declined by 9,489 km^2, about 4% decrease in area, from 1975 through 1990. In the period 1990 to 2000, this category increased by 11,621 km^2, about a 5% increase in area, and further increases from 2000 through 2007. A credible explanation could be an encroachment of settlements (new towns) after the drought situation evident along the Cameroonian shore in 1989 (Fortnam and Oguntola, 2004) and the installation of large irrigation schemes. This could be explained by the encroachment of desertification from the north. This encourages southwards migration towards the lake and the building of homesteads around ancient lake area and around piedmont and dunal lakes for fishing and agriculture. Water abstraction through large irrigation projects resulted to a water loss and was replaced by urban and soil.

However, land classification using the automated method taken in this study is problematic as, on visual inspection, many pixels outside of the historical lake extent are misclassified as open water (Figure 1). Thus, it is not possible to accurately or realistically estimate changes in lake area using such a large region due to this issue of mixed pixels and/or misclassification. It is possible, however, to restrict the extent of area considered to the historic lake extent for Lake Chad.

Alternatively, soft classifiers could solve the conventional remote sensing classification of discrete pixels in this current study (Anna Haglund, 2000). According to Eastman (1997) soft classifiers express the degree to which a pixel belongs to each of the classes being considered. Accordingly, a single pixel is often a mixture of multiple surface types as land covers grade into one another (Lam, 1993). One of the motivations for using a soft classifier is to determine the mixture of land cover classes present and also to measure and report the strength of evidence in support of the best conclusion that can be made (Eastman, 2003).

Fuzzy classification methods, however, assign a set of probabilities to each pixel based on the likelihood that it belongs to each land-cover class. This information can then be used to determine more precise land-cover classes, including mixed pixel classes (Jensen, 1996). There are several types of fuzzy classification techniques, including linear spectral unmixing, mixed tuned matched filtering (MTMF), and spectral feature fitting (SFF).

Linear spectral unmixing is based on the assumption that the spectral reflectance of a pixel is a linear combination of the unique reflectance spectrum of each material present in the pixel in the proportion in which they cover the pixel area (Menke, 1984). Although this technique is often reserved for hyperspectral imagery, it has been used with multispectral imagery with limited success (Richards and Jia, 1986).

Generally, performing an unmixing requires the reflectance spectra of each land-cover type. These can be obtained in situ using a field spectrometer, or training sets can be established using the end members, or samples of pure cover type (Richards and Jia, 1986) found from the results of running a pixel purity index (PPI) algorithm. The PPI is performed on a minimum noise fraction (MNF) transformation of the image data (Green et al., 1988).

The MNF transform is a two step transformation. First, a principal component analysis (PCA) is performed on the data to decorrelate and rescale the noise. Any band-to-band correlation in the noise is removed and the resulting noise has unit variance. Next, a second PCA transformation is done on the noise-whitened data. The results are the MNF transformed image. The PPI procedure then continually re-projects the MNF transform result onto random unit vectors for a user-specified number of iterations (typically 1×10^4 to 1×10^8 times). Pixels at the ends of these vectors are tagged with each rotation. The number of times each pixel is tagged is recorded. Purer pixels tend to be tagged more often (Boardman, 1993; Boardman et al., 1995) and, thus, the highest scoring pixels are taken as potential end members. The user then rotates the purest pixels in n-dimensional space to identify end member clusters. This method is extremely time consuming, both in terms of operator time and processing time but is extremely useful in hyper spectral applications where spectral libraries are not available for all land-cover types.

The MTMF technique is a partial unmixing method that does not require all image end members to be defined. The algorithm returns a percent cover image for each defined end member as well as an infeasibility score for each to help reduce falsely classified pixels. End member mixtures can then be compared to their

infeasibility scores and pixels that have a high mixture score and a low infeasibility score are confidently classified as that end member (Albert, 2002).

One additional fuzzy classification technique is the spectral feature fitting (SFF) algorithm. This algorithm returns a scale image which is a measure of how well the spectral signature of a pixel matches each training set spectrum. The algorithm also returns a root-mean-square (RMS) error image for each training set. The RMS image can then be plotted against the individual end member scale images and pixels with low RMS error and high scale scores for a given class can then be assigned to that class (Albert, 2002).

Fuzzy sets are sets without sharp boundaries and they are applied to handle uncertainty in the process of classification (Palubinskas 1994). The result is often a more detailed and precise classification (Anna Haglund, 2000). Fuzziness can effectively extend the usefulness of map products developed from remote sensing imagery. The fuzzy set theory is particularly interesting as the analyst controls the degree of fuzziness (Foody 1996).

Table 3 summarises the calculated area of Lake Chad over four time periods used for the study. This represents (Table 3) the total area of water contained in the historical lake extent (Figure 1). From the result, the findings are fluctuating over the four time periods. The result is not concordant (Table 3) to those of already published literature on the lake in respect to the actual extent. (Figure 2) (Oluwafemi, 2005). The results show different rates of change over the four time periods showing a rise and fall over the time periods used. The results from this study are found to be within the range of those published in other studies (which appear to vary in their estimates of lake area to a large degree). For instance, Gresswell et al. (1965) put the size at 15,000 km^2. Ayoade (1988) estimated the size to fluctuate between 13,000 km^2 to 26,000 km^2. Apt et al. (1996) claimed the lake had shrunk from 24,500 km^2 in 1996 to 2,125 km^2 in 1992. Oluwafemi (2005) estimated the size to fluctuate from about 40,000 km^2 in 1963 to 4,837 km^2 in 1997 which is a loss of close to 88% of its areal extent. Oluwafemi (2005) estimate an increase in lake area between 1997 and 2001 of about 56%. Alfa et al. (2008) concluded that Lake Chad has reduced in size between the periods of study. In 1963 the lake extent was estimated to be 20,900 km^2 which reduced steadily until 2000 when the lake extent was estimated to be 304 km^2 about a 95% loss in lake extent. This current study estimates that the lake size fluctuated between 8,065 km^2 in 1975 to about 12,813 km^2 in 1990 showing a 15% increase in size. Accordingly, the size fluctuated between 10,011 km^2 in the year 2000 to about 8,251 km^2 in 2007 showing a decline of about 11%.

The result of this study does not attempt to refuse existing claims about the lake areal extent of Lake Chad. This is because the source and credibility of the data for the study may differ, likewise, the methods and date of the study. Oluwafemi (2005) used Arc view 3.1, Arc map 8.1 and GIS tools for data processing. In the same vein Alfa et al. (2008) used ERDAS Imagine environment to estimate the lake area. This current research uses remote sensing (the K-means unsupervised classification) and GIS techniques as the primary method and draws from the Terralook data base. These different methods produce different results in relation to the lake area. Still, there appears to be some convergence towards the general decreasing trend in the lake's extent. . This is regardless of the obvious difficulties encountered in this study using the Terralook data base and the K-means unsupervised classification technique.

Assessment of Terralook data and methodology

Terralook data stipulates it was already pre-processed with a geographic coordinate system (WGS 1984) and a projected coordinate system (WGS 1984 UTM ZONE 33N). Even though this was the case the data did not

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align when overlaid on each other. There is apparent discrepancy or error in the projection or re-projection of the data. Thus clipping exactly matching areas on the images was not possible. For example, the sum of the entire image extent boxes (Table 2) still shows some slight differences due to projection error. Also, it is clear the location of the historic lake extent changes between the four different images. Such an inherent projection discrepancy gives the use of Terralook data a disadvantage since it is limited to those with good knowledge in GIS with regard to re-projection of the data. This means it is impossible for those with little knowledge on remote sensing to make use of the data when considering small scale or finite comparison (such as the changes in areal extent of a lake). Also, the cubic convolution resampling technique will affect the radiometric values of images especially in this type of classification. This is because it alters the original digital number (DN) values of images.

Further, there are limitations of the method used in this study. For example, the sieve class process looks at the neighbouring 4 or 8 pixels to determine if a pixel is grouped with pixels of the same class. If the number of pixels in a class that are grouped is less than the value entered, those pixels will be removed from the class. When pixels are removed from a class using sieving, black pixels (unclassified) are left (Tou and Gonzalez, 1974). This leads to error in the estimate land covers.

Unsupervised classification identifies spectrally homogenous classes within the data that does not necessary correspond to the information category that are of interest. Thus it poses the problem of merging spectral classes generated by the classification to the informational classes that are required. This misclassification and the absence of user defined training sites make differences between the images (Figure 1) (Campbell, 2002). Furthermore the spectral properties of specific informational classes will change over time. This could be in a seasonal scale as well as over the years. Thus the relationship between informational classes and spectral classes are not steady (Campbell, 2002). This is a specific problem using this method for Terralook data which is made of a composite of various scenes from possibly different seasons of data. Also, the criterion for demarcating the historical lake shoreline was that all blue pixels at the historical shoreline were considered as water. The technique of overlaying the lake polygon of a particular period (1975) on the other three images to ensure having the same area for all polygons is different from methods used in the already published literature and is also somewhat subjective.

The Terralook database is also a collection of image scenes over a short period of time (months) that are considered as images of a certain time. For instance, Landsat MSS 1975 (circa 1972-1983) means a selection of images of best cloud cover and greenness between the intervals 1972-1983 to form images for the year 1975. Also, all images in the collection were selected without consulting the user only during the dry season since these are the periods of low cloud cover. This gives the method the disadvantage of assessing land cover changes over a long period of time. Specifically for lake extents, there is a general bias towards lower lake extents when considering a seasonal fluctuation in extent.

Image differencing is probably the most widely applied change detection algorithm to solve the problem of different dates of image collection (Singh, 1989). It involves subtracting one date of imagery from a second date that has been precisely registered to the first. Equally, geometric correction was not performed. Thus image to

image registration was not done. This is because the data was already georeferenced (according to the metadata of Terralook). This is disadvantageous in the sense that it did not help to reduce the positional error that is inevitably introduced during any resampling process (Alfred, 2009).

Again, the radiometric correction for this classification was not performed so as to homogenize and normalize the images. When performing change detection by differencing, the effect of solar angle, atmospheric conditions and instrument characteristics should be looked into since they hinder the consistency of radiometry (Eastman, 2003). One way of correcting this effect is to perform image normalization. That is adjusting the target image to match the base image. Through histogram matching, the adjacent scene is radiometrically homogenized with respect to the main scene.

The images used in this classification were mosaicked before being classified. This is disadvantageous because it distorts the spectral characteristics of the images thereby influencing the classification. Furthermore, the smaller the classified area, the more accurate the classification will be. Mosaicking a large area and attempting to classify the mosaicked image will be more confusing possibly based on the heterogeneity of a larger area. To this effect, the images were not calibrated since mosaicking was done before classification.

According to Lillesand and Kiefer (1994) classified data often manifest a salt-and-pepper appearance due to inherent spectral variability encountered by a classification when applied on a pixel-by pixel basis. In this situation, it is often desirable to smooth the classified output to show only the presumably correct dominant classification. This study failed to smooth the post classification (majority filter) so as to presumably have the correct classification. In such operations, if the classified pixel is not a majority class, its identity will be changed to a majority class. This gives the user the advantage of a user-specified minimum area for any given land cover type that will be maintained in the smooth output (Lillesand and Kiefer, 1994).

Among difficulties encountered in change detection are artifacts. According to Tsutoma et al. (1981) artifacts are angles caused by varying solar illumination condition and different viewing angles in remotely sensed images taken at different times. Correcting artifacts requires simulation of shading effects from a synthetic image. A digital elevation model is important since for any given sun angle, the image intensity is determined as a function of ground surface gradient (Tsutoma et al.,1981).To correct artifacts, the real image undergoes a low-pass filter so as to match with the resolution of the synthetic image. Later the image is de-shaded by subtracting the synthetically shaded image from the low-pass filtered image. The artifact correction is then complete by adding the low-pass filtered image to the shaded image. This clearly reveals useful information not present in original image (Tsutoma et al., 1981). This current study failed to correct artifacts that greatly influenced the results since the image analysis and interpretations were far from being accurate.

CONCLUSION

The Terralook database is not an adequate dataset for assessing lake extent changes over a long period under the methods used in this current study. The resulting estimates tend not to agree in trend and magnitude with published studies unless restrictions on the extent of area considered are put in place. Terralook suffers because of limitations with time of data collection and the resampling method used for data creation. As such, it is

difficult for Terralook data to be used 'off the shelf' by those with limited or no experience in remote sensing practice.

Again the methods used in processing data were limited because of the absence of training sites for the image classification and the difficulty to translate the reflectance spectrum to the appropriate informational classes. More so, the stages for data processing were incomplete or could be improved. For example, classifying each scene before mosaicking, performing geometric and radiometric corrections, image normalization, correcting artefacts and post classifications smoothing through the majority filter could improve the quality of the resulting land use classifications. All this put together helped to distort the spectral characteristics thereby influencing the classification results.

As a synopsis the study shows land use changes might be a main factor behind lake area changes. The methods and study itself could (with further development) contribute to knowledge of the specific changes that have occurred in lake area changes.

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