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Geospatial modelling approach of water surface area fluctuations and sustainable strategies of Lake Chad Central Africa

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Abstract

Most of the Lake Chad areas have been affected by climatic and environmental changes. This has been worsened by land cover variations, thereby increasing the rate of their shrinkage. The Chad basin had supported business, economics and bourgeoning monetary task for around 30 million people in the area and it has shrunk to more than 20% of its original size and have devastated local economies, destroying livelihoods in farming, fishing and herding, leading to widespread poverty, food insecurity and displacement, as mentioned earlier millions of people depends on its resources. This research aims to model and investigate the effect of environmental variables which is very important that influences the surface and ground water, the variable include geological features of water surface area fluctuations using geospatial modelling approach in Lake Chad, Central Africa. In this study therefore, numerous software bundles were used at various processing stages. These include IDRISI selva, ENVI 5.1 and ESRI ArcGIS. Accordingly, ESRI ArcGIS, ENVI and IDRISI software were utilized for production of suitability maps/modelling, image classification and accuracy assessment, image correction and assessment of the outcomes. Meanwhile, ArcGIS also was utilized for geographic database, map production and presentation, on the other hand IDRISI software was used for CA-Markov chain analysis and modelling as well as forecasting of water surface area fluctuations. The changes to Lake Chad were analysed between the years 1985, 2000 and 2015 which uncovered a rapid shrinkage of water level in the study area. The expected outcomes revealed that the main accuracies of image classification of Landsat-TM was 93.80, Landsat-ETM+ was 90.80 and Landsat-OLI was 86.20 respectively. Furthermore, different information from different data sources with regards to geological variables of the study area were considered so as in having an updated map and the map layers were obtained to reveal diverse levels of geographical features details at various scales to facilitate uses of the map. The Cellular Automata model was used to predict the year 2030 land change of the area using some designed constraints, populations and geological features. Therefore, on validation, the overall model accuracy of 99.15% was achieved. Moreover, to analyse the gains and lost, land cover conversion results were also analysed within the year 2015-2030 and was attained by the aid of cross-tabulation analysis; with barren land having net loss of 695.57km^2 (6.69%), farmland has net gained of 586.63km^2 (1.1%), gallery forest has net gained of 365.71km^2 (3.61%), shrub has net loss of 146.41km^2 (2.6%) and water body has net loss of 110.36km^2 (3.93%). These findings highlight the urgent need for sustainable water resource management, as Lake Chad's decline threatens ecosystems, agriculture and water supply for surrounding communities. This study provides a geospatial framework for monitoring lake dynamics and informing policy interventions.

Keywords: Geospatial modelling, sustainable strategies, water surface fluctuations

Introduction

Surface water is crucial for environmental sustainability, economic development and human survival. It is fundamental to human, ecosystem and food crops (Yuan et al., 2015). Precise and timely/periodic observation of the Earth's surface features (lakes, forest and vegetation.) provides a coherent understanding of the interactions and relationships between humans and the environment for appropriate uses and management of the natural resources (Edwin et al., 2024). A few factors including climate change, over abstraction and part of droughts have led to decline in the water surface of Lake Chad in the Central Africa over some decades, that climate change allows the occurrence of drought through changes in weather, global temperatures, precipitation and water supply. Climate changes and drought are linked and influenced by climatic fluctuations and human-induced atmospheric changes. Lake Chad, once the sixth-largest lake in the world, has shrunk by approximately 90% over the past four decades due to climate change, over-abstraction and land cover variations (Gao et al., 2011; Mahamat et al., 2021). This decline threatens the livelihoods of 30 million people dependent on its resources. Geospatial techniques, combining remote sensing and GIS, offer robust tools for monitoring such dynamic water bodies (Arsanjani et al., 2015). However, existing studies often overlook the influence of geological features on water surface fluctuations, creating a gap in predictive modelling.

Investigation of lakes and surface water area fluctuations and patterns is a key component to findings and design, which requires facts about the present, past and future water surface positions (Rocha et al., 2018). Changes in shoreline position, such as regression and transgression, significantly impact coastal ecosystems and disrupt the balance between freshwater and marine systems. Effective coastal protection requires a thorough understanding of shoreline features, extent, evolution and environmental impact (Bruno et al., 2016, Kamta et al., 2021). Geospatial technologies, particularly the integration of Remote Sensing (RS) and Geographic Information Systems (GIS), offer efficient tools for analyzing spatial and temporal environmental data (Avila-Aceves et al., 2023; Ariffin et al., 2024). Remote sensing provides timely, accurate observations, while GIS enables the storage, analysis and visualization of spatial data through mapping and modelling. GIS combines geographic data, software, hardware and personnel to collect, manage, and interpret spatially referenced information. It facilitates the identification of patterns, relationships, and trends across diverse disciplines. As a result, GIS has been widely applied in fields such as ecology, hydrology, education, climate studies and economics. Its capacity to deliver reliable geospatial insights supports evidence-based decision-making for sustainable development and environmental management (Islam & Crawford, 2021; Jayabaskaran & Das, 2023).

The wide varieties of approaches and facilities used for improved management and monitoring of environmental resources by the naturalist and environmentalist have been provided through the recent improvement in geospatial innovations and models (Thodi et al., 2023). Landsat imagery from the rich temporal remote sensing datasets, also with geospatial modelling techniques, assist the procedure of studying and modelling environmental occurrence (Arsanjani et al., 2015; Hussaini et al., 2020; Tang & Mahmud., 2021). Geospatial techniques with field survey offer important spatial information to assess environmental variations on water bodies and their neighbourhood across the world from local to global scales particularly in the developing countries where numerous areas are not accessible. Water surface discrepancy is a measure of worldwide environmental change which happens in various temporal and spatial scales. Major contributing elements in the ocean level rise are global warming that prompts melting of masses of ice. These changes are the result of various factors in both here and now as well as long term scale (Rani et al., 2017). Surface waters from common lakes and basin are a noteworthy wellspring of freshwater for residential, industrial and farming purposes in various regions of the world. The dependability of such wellsprings/sources of water is frequently undermined because of anthropogenic and natural features. For instance, surface water resource can be easily polluted due to industrial events and farming activities, while changes in climatic conditions can regularly prompt vast fluctuations in the volumes of accessible water.

Surface water bodies are critical components of ecosystem services, including water supply, purification, flood control, climate regulation and coastal protection (Arsanjani et al., 2015). However, they are increasingly affected by severe atmospheric disturbances and environmental changes, leading to accelerated land cover transformations and unstable water surface. Such instability can expose lakebeds to erosion, occurring at low, normal or high-water surface fluctuations and negatively impact aquatic habitats and water provisioning. Fluctuations in lake levels can also influence wetland formation and disrupt human activities such as transportation, commercial shipping, and recreation (Altunkaynak, 2014). Lakes are dynamic systems sensitive to both natural and anthropogenic influences, and changes in lake levels can damage coastlines and alter human-environment interactions (Di Francesco et al., 2016). Despite their ecological and socio-economic importance, lake dynamics are often overlooked in decision-making. The unregulated use of surface water in watershed areas contributes to climatic shifts, such as reduced precipitation and elevated temperatures, which in turn affect lake water surface fluctuations (Su et al., 2022). Accurate forecasting of lake surface variations remains a persistent challenge for hydrographers and water resource managers (Li et al., 2016).

While prior studies have employed geospatial modelling to assess Lake Chad's shrinkage, few integrate geological variables as predictive constraints. This study addresses this gap by incorporating geological structures (e.g., basalt, clay) into a CA-Markov model to enhance the accuracy of water surface fluctuation predictions. This approach provides a novel framework for reservoir management under climate change.

This research aimed to investigate the impact of geological features of water surface area fluctuations using geospatial modelling approach in Lake Chad, Central Africa. The specific objectives were to: (i) investigate and map out water area extent in Lake Chad over the last three decades using multi-temporal satellite images of the basin, (ii) identify and map out reclassified geological features in the Lake using geospatial approach and (iii) model water extent using improve Cellular Automata/Markov Chain (CA-Markov) by integrating geological features

Obviously, more than fifty articles with respect to satellite remote sensing for water surface area fluctuations/dynamic have been critically reviewed in respect to this study. However, many of these researches have basic limitations. For example, the majority of them did not consider environmental variables such as Geology in relating water surface area fluctuations scenarios which is relatively new into Cellular Automata model.

Materials and methods

Study area

The Lake Chad Basin is located at longitudes 6°42’13.89’’ and 24°45’34.64’’ to the east of the Green Witch Meridian and latitudes 5°22’46.42’’ and 25°43’11.11’’ to the north of the Equator. Therefore, features of the lake are gradually changing as a result of the difference in temperature and rainfall which is obtainable based on its shape, size, and depth. The natural regions which are borders to the lake include wood forest, savannah, wetlands, desert, and mountains (Ovie et al., 2012). There are three (3) main drainage channels that provide water to the lake such as Ngadda/ Yedsaram River located in Cameroon, the River Komadugu of Yobe located in Nigeria and the last one called Chari Logone, is the river located in Central Africa Republic. Some lakes are associated with socio-political issues, therefore Lake Chad Basin can be seen as among them. For instance, some years around the 1960s the lake was regarded to be larger with respect to its size around 400,000km^2. Similarly, before it was known as Mega Chad, as of the whole 20th century. Around 1960 and 1963, the lake was regarded at its peak level of being utilised. Moreover, the investigation revealed that the nature of the lake has seriously declined in terms of its size, by around 25,000km^2 this is, greater than 90% declined from 1960s to the year 2011 (Gao et al., 2011). Further, accordingly the weather of the lake has been characterised by its evapotranspiration of around 2,200mm/year, erratic precipitation patterns, high temperature and solid breezes. There is also annual unstable rainfall spatially from 1400mm throughout the southern hemisphere to less than 150mm close to the north (Okpara et al., 2015). Thus, the region of the study area is depicted in Figure 1 below.

Figure 1. Study area

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The research was divided into six stages in accordance with the stated objectives Figure 2 portrays a detailed representation of every stage/phase.

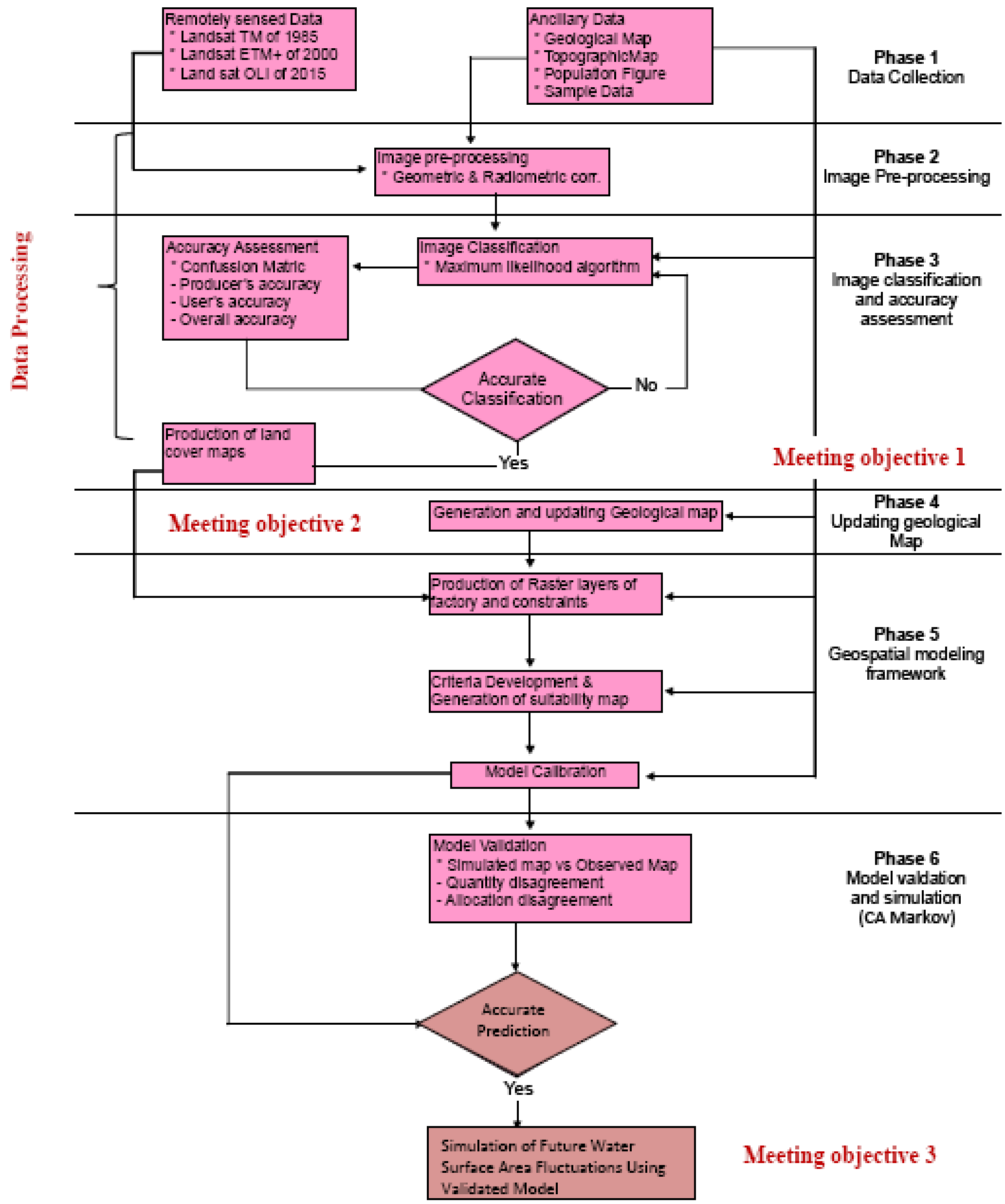

Figure 2. An outline of the methodology framework

Image pre-processing and data acquisition

Currently, the higher resolution satellites platforms were used to obtain information about the surface of the earth. Therefore, to appropriately analyse the past and present situations of water surface area fluctuations, it is important to have multi-temporal satellite images that cover some past decades' scenarios, such as Landsat imagery. To obtain the multi-temporal images, 3 decades of Landsat imagery have been employed in this research. The imagery comprises Thematic Mapper (TM) developed in the year 1985, followed by Enhanced Thematic Mapper Plus (ETM+) developed in the year 2000 and afterwards an Operational Land Imager (OLI) developed in the year 2015. Landsat imagery has been chosen in this research because of its global coverage, modest spatial resolution, free access and varied spectral band appropriate for dissimilar applications (Luca Cenci et al., 2018; Komeil Rokni, 2014). The entire Landsat sights selected as a key-in to this study were imaged amid the months of December and January, which is the winter period in that area. The Earth explorer and Global Visualization Viewer of the USA Geological Survey (USGS) served as the source of the images. The Landsat images employed in this research for detecting some changes and modelling water surface area fluctuations has been presented in Table 1.

Table 1. Landsat images with features including row, path and acquisition dates for 1985, 2000 and 2015

Path/	1985		2000		2015	
Raw	Sensor	Date	Sensor	Date	Sensor	Date
183/051	Landsat TM	19/11/1985	-	-	-	-
184/051	Landsat TM	20/10/1985	Landsat EMT+	19/11/2000	Landsat OLI	23/12/2015
184/052	Landsat TM	17/10/1985	Landsat EMT+	05/02/2000	Landsat OLI	23/12/2015
185/050	Landsat TM	10/11/1985	Landsat EMT+	10/11/2000	Landsat OLI	30/12/2015
185/051	Landsat TM	07/11/1985	Landsat EMT+	10/11/2000	Landsat OLI	30/12/2015
185/052	Landsat TM	26/11/1985	Landsat EMT+	31/3/2000	Landsat OLI	30/12/2015
186/050	Landsat TM	02/10/1985	Landsat EMT+	17/11/2000	Landsat OLI	21/12/2015
186/051	Landsat TM	21/10/1985	Landsat EMT+	03/12/2000	Landsat OLI	21/12/2015

Therefore, for the assessment of changes, the entire number of satellite imagery used were twenty-two (22) so as to have detailed information of the whole extent, the study needed the coverage of eight (8) scenes in 1985 and seven (7) scenes each in 2000 and 2015 respectively, this as a result of their scenes are larger in size than that of 1985. Then the scenes are illustrated in Figure 3 below.

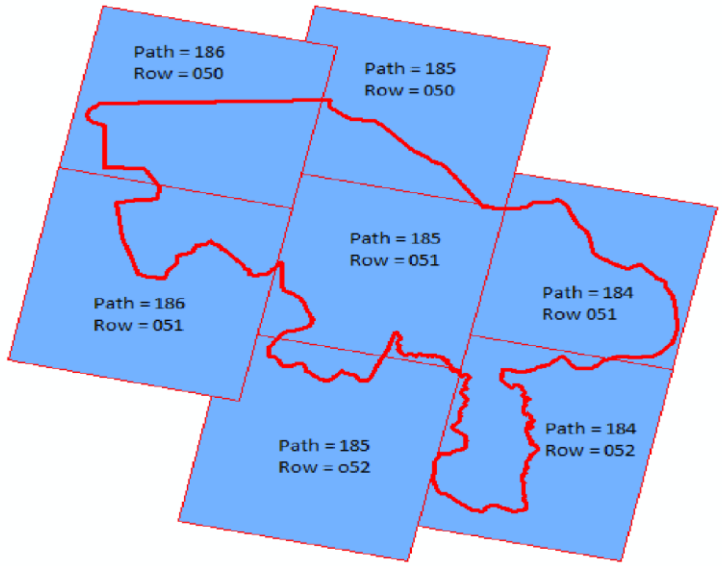

Figure 3. Landsat imagery scenes for Lake Chad and its Environs

Classification of image and assessment of accuracy

The classes of the land used were categorized into five parts: water body, gallery forest, shrub, barren land, and farmland. Subsequently, the training location for various kinds of land cover amid the 3 sets of images are developed using the gathered training samples and supplementary information (Eastman, 2012). ArcGIS software was employed to achieve the development through computerizing polygons across look alike land cover from the selected colour composites. The colour composite comprises 542 bands for Landsat TM developed in 1985, 542 bands for Landsat ETM+ developed in 2000, and also 753 bands for Landsat OLI developed in 2015 (Elhaja et al., 2017). Afterwards, for the purpose of statistical characterization of the various land cover, spectral signatures were created (Blaschke, 2010). Further, considering supervised classification based on maximum likelihood algorithm using the signature files, 3 groups of images were classified (Otukei and Blaschke, 2010), The 3 groups of images comprise the 2015, 2000, and 1985 land cover maps of the region generated.

Furthermore, in order to confirm the degree of suitability between ground features and the classified images, it is imperative to carry out accuracy evaluation. Thus, a confusion matrix has been employed for evaluating the correctness of the classification in this study due to its efficiency. (Gong et al., 2015). The confusion matrix was used to assess three accuracies, namely, producer's, user's and overall. The correctness of the producer's accuracy describes how well the study region is categorized. The correctness of the user's accuracy explains how consistent the pixel groups in the categorized maps denotes the ground characteristics. The total accuracy explains the correctness of the entire categorization. The three accuracies were computed using the following formulae (Congalton, 1991; Foody, 2002):

$$\text{Producer's accuracy} = n_{ii}/n_{+i} \qquad (1)$$
$$\text{User's accuracy} = n_{ii}/n_{i+} \qquad (2)$$
$$\text{Overall accuracy} = \sum_{i}^{q} \quad = 1^{n}{}_{ii}/n \qquad (3)$$

where n_{ii} = number of corrected pixels (diagonal pixels), n_{i+} = total number of actual pixels in a particular class (row total), n_{+I} = total number of predicted pixels in a particular class (column total), and n = total number of pixels in the confusion matrix.

For the purpose of evaluating the classification accuracy, five hundred (500) ground truth (reference) points were stochastically chosen in a manner that the 5 land cover classes employed in the categorization (classification) must have some pixel intensity at particular sites across the study region. The pixel intensity includes 90, 95, 100, 105, and 110 for water body, shrub, gallery forest, farmland and barren land, respectively. These pixel intensity values were converted and transformed to a ground truth map with 30m by 30m cell dimension by employing ArcGIS software (Zhang et al., 2011), Afterwards, the reference map was inserted into IDRISI software. Further, the confusion (error) matrices were generated by means of the ERRMAT component of the IDRISI software. Thus, using the years 2015, 2000, and 1985 categorized images as classified map images and ground truth images as reference maps (Foody, 2008).

Modelling framework (Geospatial)

CA-Markov (Cellular Automata/Markov Chain) model was employed in this study to predict the water surface area fluctuations in Lake Chad. The CA-Markov chain is mostly utilized for land change forecasting model that enhances spatial adjacency component and cognition of the probable spatial delivery of change toward Markov chain investigation by the mixed-up effectiveness of conventional sort of Cellular Automata/Markov Chain, Multi-Object Land Assignation approaches and Multi-Criteria (Eastman, 2012). Then the model (CA-Markov) inserted in IDRISI Selva package was embraced in the research as utilized by some scholars such as Al-sharif and Pradhan (2014); Mahmoud and Alazba (2016). The CA serves as a data driven (base up) model that produces an entire development by configuring basic principles in a specified location. Its incorporation by CA-Markov, which is an information driven (top-down) approach, advances its capacities of observing water surface/land variations (Arsanjani et al., 2015; Rocha et al., 2018).

The CA model has five elements which include neighbourhood, change rules, time steps, cells and cross section of cells. The CA element of a model is planned in a way that the conversion chances of a picture element dish out as a use of its encompassing components (Achmad et al., 2018; Wang & Murayama, 2017). Then essentially, three sorts of information inputs which are needed by the model CA-Markov model for forecasting of water surface area fluctuations/land variations, which consist of suitability maps, source land change maps and Markov transition domain file (Eastman, 2012). The land change maps were obtained via satellite images classification although the maps suitability was obtained through collection of maps (components and constraints) via Multi-Criteria Evaluation (MCE) as indicated by Kuter & Kuter (2015). The change domain files were organised via Markov model (Afrakhteh et al., 2016).

a. Generation of suitability maps and criteria development

To predict the influence of geological features on water surface area fluctuations in the research, the situations were evolved (factors and constraints). The instances help in determining which lands are constrained (limitation) or appropriate for upcoming development. The scenario was delegated to integrate a number of chosen environmental variables applicable to water surface by considering natural and socio-economic factors like geological features, easy to get to Central

Business Districts (CBD), proximity to navigable waters, proximity to high ways, population density and topographic slope as factors, so also existing settlements and existing water bodies are constraints. Therefore, appropriate maps were produced for different land cover classes by employing the procedure defined by (Hyandye & Martz, 2017). The appropriate maps were produced based on Multi Criteria Evaluation (MCE) through assimilating the data from various rules to attain a single index of assessment (El-Hallaq & Habboub, 2015; Hyandye & Martz, 2017; Said et al., 2021).

The preparation of vector layers denoting the factors and constraints, and rasterizing of every vector file were carried out by employing the ArcGIS software (Musa et al., 2019). Further, it is inserted into the IDRISI software and then a decision support wizard of the package is tied together. The standardization of the factors' layers was carried out to an ordinary data margin by employing fuzzy logic functions to simplify incorporation of factors (Mishra et al., 2018). A proper scale of suitability of 0 to 255 was allocated into the factors in the course of the standardization. Boolean attributes of 0 and 1 were assigned into the constraints. Then the extent of membership of a pixel that resides in the factors' layer is evaluated via control points, which are configured by bearing in mind the association between the water surface and the factors in question. Such associations determine the different shape including J-shaped, which is straight or Sigmoidal or trend, which is reducing or symmetric or rising of the fuzzy logic membership (re-scaling) factor (Eastman, 2012). Such that the functioning value rises and there is increase in the land area surface appropriateness for a specified land used category. Therefore, the system has been considered to be monotonically rising. The land surface appropriateness for a specified land cover category decreases, when the factor value increases thus, the system is considered to be monotonically decreasing. On the other hand, from a specified control point, land surface appropriateness for a certain land cover category rises when the factor value increases. It attains highest appropriateness at a certain value and then reduces thus, the system is considered to be symmetric.

In these findings, the configuration points of control points were carried out based on the ideas from the existing literature and the knowledge gathered via field survey (Alimi et al., 2016; Hyandye &Martz, 2017; Modibbo et al., 2019; Sangrat et al., 2020). For example, there is no fixed increasing or decreasing trend on suitability basis when considering distance from navigable water. The regions that are 300m of the navigable water were assumed to be less appropriate for future development in the case of sustainable developments. From the various literature and environmental information, it was observed that after 1000m distance from the navigable water, the appropriateness might not rise with proximity in a fixed scenario. It means that the regions that are 1000m away from sailable water could continue as fine as those regions that are 1500m far. Consequently, monotonically rising sigmoidal value was employed to re-scale the points in the distance-to-running water image. Thus, 300m was used as the preliminary control value at what appropriateness begins to rise swiftly from 0 and 1000m as the 2nd control value such that appropriateness reaches 255.

Equally, developers usually consider the areas that have 500m of roads as suitable. Regions within 50m of roads are often chosen as most suitable, which have constant decreasing suitability. Though, it is important to note that the decreasing trend cannot reach 0. The value 50 from the maximum of 255 was used as the preliminary control point since J-shaped function cannot reach 0. The value 500 is considered as the 2nd control point close to 0 for re-scaling the closeness-to-highway image. This implies that regions between 0 and 50m of the highways achieve the maximum suitability of 255. While the regions with beyond 500m attain less and lowest suitability approaching zero value. To re-scale the accessibility of the central business district image, the linear distance decay function was employed. Regions with shorter proximity to the CBD were determined to be more suitable against those regions that have longer proximity. In addition, regions (areas) with slope greater than 15% are considered not appropriate for growth by the developers, while the ones with less than 15% slope are considered suitable for development. Consequently, in re-scaling the values of the slope image, a monotonically reducing non quadratic function was employed. Thus, a value 7 was assigned as the value of the first effective point and 15.1 was assigned of the 2nd effective control valuesimilarly, subsequent factors were re-scaled using the same procedure.

Confirming the appropriateness of a certain land cover class is often attained by means of integrating the factors that needed weights to be allotted to the approved factors showing their significance in association to each other. Any of the three approaches can be used to achieve the establishment of the appropriateness of a given land cover category. User defined or Analytical Hierarchy and Process (AHP), or allocating the same weights (Eastman, 2012). Therefore, in this research, the AHP strategy based on pairwise contrasting has been employed. The pairwise contrasts were conducted by assessing the significance of the factors in association to one another. This is achieved by allocating a boundary of values from 1/9 to 9 that shows “exceedingly less significant” to “exceedingly more significant”, respectively (see Table 2). Subsequently, to produce the last weight of each factor, a principal eigenvector was employed. Also, to evaluate the pairwise matrix, an agreed consistency threshold of 0.10 was considered (Lin *et al.*, 2014). This means that a consistency ratio lower than 0.10 signifies good regularity. In the case that the ratio is greater than 0.10, then the pairwise matrix is re-evaluated.

Table 2. The comparison of pairwise matrix.

Variables	**Pop_Den**	**Geology**	**Acc-to-CBD**	**Slope**	**Prox-to-Highway**	**Prox-to-Nav. Water**
Pop_Den	1	-	-	-	-	-
Geology	1/3	1	-	-	-	-
Acc-to-CBD	1/3	1/3	1	-	-	-
Slope	1/3	1/3	1/3	1		-
Prox-to-Highway	1/3	1/3	1/3	1	1	-
Prox-to-Nav. Water	1/3	1/3	1/3	1/3	1/3	1
Consistency ratio = 0.09						

*NOTE: Acc = Accessibility, Nav = Navigable, Prox = Proximity, Pop_Den = Population Density CBD = Central Business Districts

Similarly, subsequent variables were re-scaled using the same procedure. Confirming the appropriateness of a certain land cover class is often attained by means of integrating the variables that needed weights to be allotted to the approved factors showing their significance in association to each other. Any of the three approaches can be used to achieve the establishment of the appropriateness of a given land cover category. User defined or Analytical Hierarchy and Process (AHP), or allocating the same weights (Eastman, 2012). Therefore, in this research, the AHP strategy based on pairwise contrasting has been employed. The pairwise contrasts were conducted by assessing the significance of the variables in association with others. This is achieved by allocating a boundary of values from 9-1/9 that shows exceedingly less significant to exceedingly

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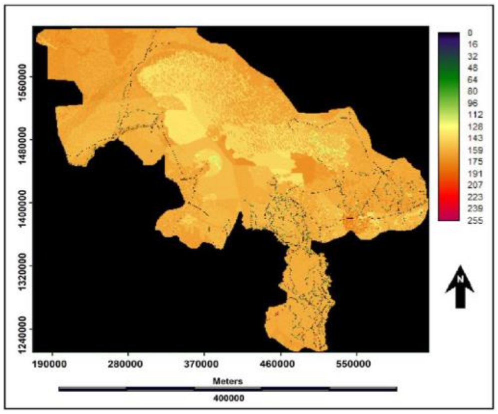
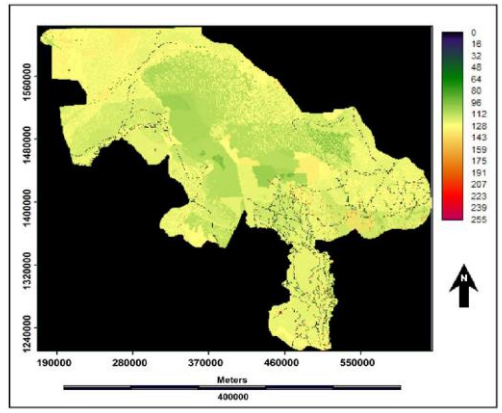
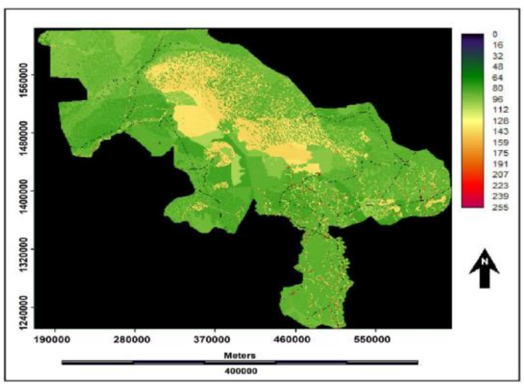


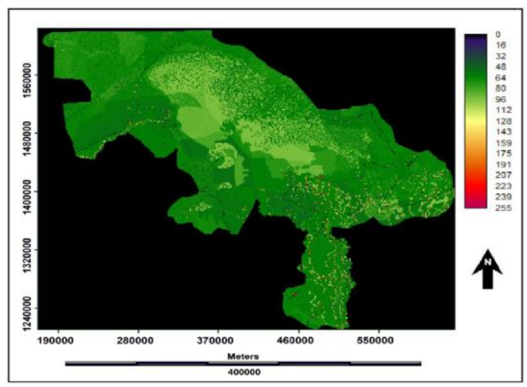
(i) Suitability map for barren land



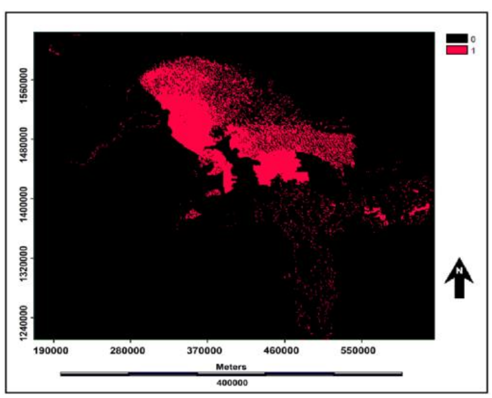
(ii) Suitability map for farmland



(iii) Suitability map for gallery forest



(iv)Suitability map for shrub



(v) Suitability map for water

Figure 4. Land-cover suitability maps

Lastly, to aggregate the whole of the factor layers, an MCE module was used, which forms the appropriateness maps for each of the land cover categories can be seen in Figure 4(i-v) presented the suitability maps of all classes. The scenario was designed to incorporate some environmental variables like geological features, topographic slope, and accessibility to central business districts, proximity to navigable, proximity to highways, population figure, existing settlements and existing water bodies. A number of user- defined decisions are obtainable in the MCE component for realizing the task specifically, a Weighted Linear Combination (WLC) was considered for this research. Generally, WLC is considered as a non-quadratic function, which is employed to superimpose approved value in agreement for their respective heaviness sight of significance, so the overall factor weights sum is equal to 1 (Eastman, 2012).

b. Prediction of future water surface area fluctuations

The year 2030 was predicted, for future water surface area fluctuations of Lake Chad, Central Africa by accommodating Cellular Automata model utilizing IDRISI software. Then the procedures start by managing modules in a (CA-Markov) utilizing land-use maps.

Results and discussion

Accuracy assessment and generation of land-use maps

The wide-ranging analysis using change detection method took place, and maximum likelihood algorithms through supervised classification were implemented in this research. The confusion matrices served as a tool for accuracy assessment through cross-validation statistics by utilising a bundle of 500 stratified random samples. Nonetheless, the standard procedures for acceptance considering United State Geological Survey procedures of classification is 85% and above of the overall accuracy. The outcomes of these classifications have attained the standard procedures. Therefore, the entire assessments of classification including the confusion matrices, user‘s and producer‘s, overall accuracies as well as kappa indexes. Figure 5 (a-b) presented the classified images assessment. Then, the 2015, 2000 and 1985, land-use maps obtained from the images classified and these includes five (5) land-use classes: barren land, farmland, gallery forest, shrub and waterbody then the derived change map for the year 1985, 2000 and 2015 it’s can be presented in Figure 6 (i-iii). The overall accuracies, user’s and producer’s accuracies coupled with kappa indices of images classified are illustrated in Table 3 below.

Correspondingly, Table 4 presents the variations obtained from the post-classification comparisons and the area sheltered in kilometre square. Barren land area covered was found to be 20678.40km^2 in 1985, while in 2000 it was 16153.14km^2 but in 2015 it was 10396.04km^2. Farmland area covered was found to be 27742.80km^2 in 1985, while in 2000 it was 40824.79km^2, but in 2015 it was 53513.20km^2. Gallery forest area covered was found to be 5237.10km^2 in 1985, while in 2000 it was 6546.46m^2, but in 2015 it was 10119.31km^2. Shrub area covered was found to be 20808.60km^2 in 1985, while in 2000 it was 14115.51km^2, but in 2015 it was 5566.26km^2. Finally, water body area covered was found to be 7943.30km^2 in 1985, while in 2000 it was 4767.65km^2, but in 2015 it was 2812.73km^2. Then the results revealed a remarkable increment of 92.91% of farmland and 93.22% of gallery forest from 1985 to 2015. While the decrement was recorded to be -49.73% of barren land, -73.25% of shrub and -64.59 of water bodies from 1985-2015 respectively.

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Error Matrix Analysis of 1985 REFERENCE MAP (columns : truth) against 1985 CLASSIFICATION (rows : mapped)

                 1          2          3          4          5     Total    ErrorC
          -------------------------------------------------------------------------
     1 |        47          1          0          0          2 |      50    0.0600
     2 |         1         47          2          0          1 |      51    0.0784
     3 |         1          0         47          0          0 |      48    0.0208
     4 |         1          1          0         49          0 |      51    0.0392
     5 |         0          1          1          1         47 |      50    0.0600
           -------------------------------------------------------------------------
 Total |        50         50         50         50         50 |     250
ErrorO |    0.0600     0.0600     0.0600     0.0200     0.0600 |              0.0520


         ErrorO     = Errors of Omission   (expressed as proportions)
         ErrorC     = Errors of Commission (expressed as proportions)

         90% Confidence Interval  =  +/-  0.0231    (0.0289 - 0.0751)
         95% Confidence Interval  =  +/-  0.0275    (0.0245 - 0.0795)
         99% Confidence Interval  =  +/-  0.0362    (0.0158 - 0.0882)

KAPPA INDEX OF AGREEMENT (KIA)
------------------------------

Using 1985 CLASSIFICATION as the reference image ...

    Category          KIA
------------     ------------

           1       0.9250
           2       0.9020
           3       0.9740
           4       0.9510
           5       0.9250

1985 REFERENCE MAP

    Category          KIA
------------ ------------

           1       0.9250
           2       0.9246
           3       0.9257
           4       0.9749
           5       0.9250

Overall Kappa =          0.9350
```

Figure 5a. Satellite image classification assessments in 1985

Error Matrix Analysis of 2000 REFERENCE MAP (columns : truth) against 2000 CLASSIFICATION (rows : mapped)

	1	2	3	4	5	Total	ErrorC
1	49	0	0	1	0	50	0.0200
2	0	48	0	1	1	50	0.0400
3	0	1	47	0	0	48	0.0208
4	0	1	1	48	2	52	0.0769
5	1	0	2	0	47	50	0.0600
Total	50	50	50	50	50	250	
ErrorO	0.0200	0.0400	0.0600	0.0400	0.0600		0.0440

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0213 (0.0227 - 0.0653)
95% Confidence Interval = +/- 0.0254 (0.0186 - 0.0694)
99% Confidence Interval = +/- 0.0335 (0.0105 - 0.0775)

KAPPA INDEX OF AGREEMENT (KIA)

Using 2000 CLASSIFICATION as the reference image ...

Category	KIA
1	0.9750
2	0.9500
3	0.9740
4	0.9038
5	0.9250

2000 REFERENCE MAP

Category	KIA
1	0.9750
2	0.9500
3	0.9257
4	0.9495
5	0.9250

Overall Kappa = 0.9450

Figure 5b. Satellite image classification assessments in 2000

Error Matrix Analysis of 2015 REFERENCE MAP (columns : truth) against 2015 CLASSIFICATION (rows : mapped)

	1	2	3	4	5	Total	ErrorC
1	47	0	0	1	0	48	0.0208
2	1	48	0	0	1	50	0.0400
3	1	0	49	0	0	50	0.0200
4	0	2	0	49	1	52	0.0577
5	1	0	1	0	48	50	0.0400
Total	50	50	50	50	50	250	
ErrorO	0.0600	0.0400	0.0200	0.0200	0.0400		0.0360

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0194 (0.0166 - 0.0554)
95% Confidence Interval = +/- 0.0231 (0.0129 - 0.0591)
99% Confidence Interval = +/- 0.0304 (0.0056 - 0.0664)

KAPPA INDEX OF AGREEMENT (KIA)

Using 2015 CLASSIFICATION as the reference image ...

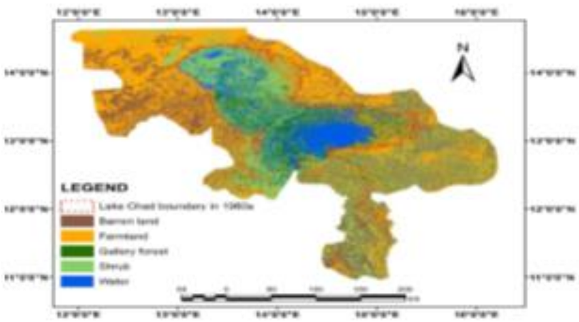
Category	KIA
1	0.9740
2	0.9500
3	0.9750
4	0.9279
5	0.9500

2015 REFERENCE MAP

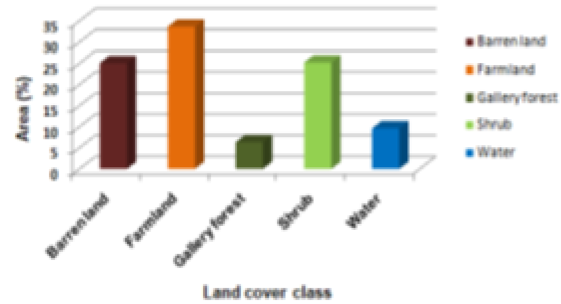
Category	KIA
1	0.9257
2	0.9500
3	0.9750
4	0.9747
5	0.9500

Overall Kappa = 0.9550

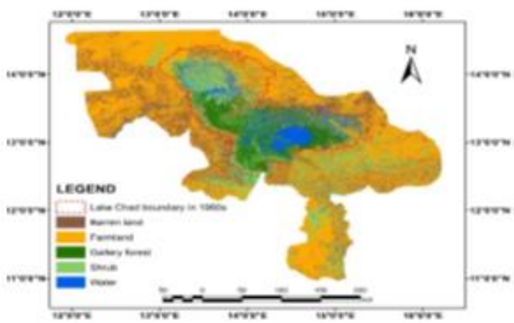
Figure 5c. Satellite image classification assessments in 2015



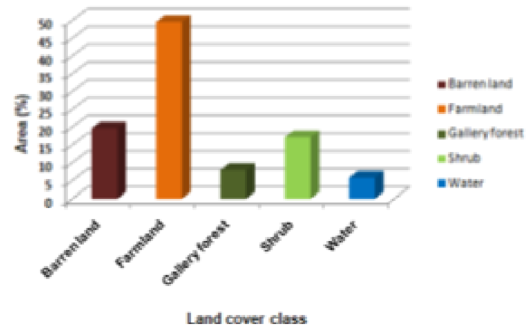
(a) Change map of lake Chad in 1985



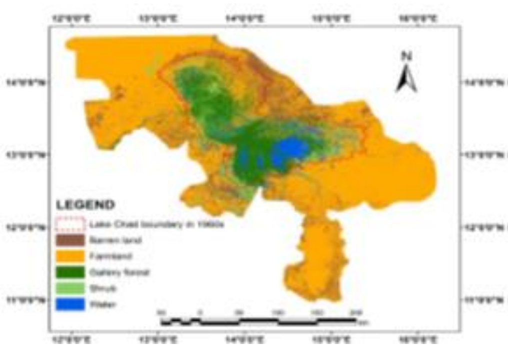
(b) Class percentage in terms of area covered in 1985



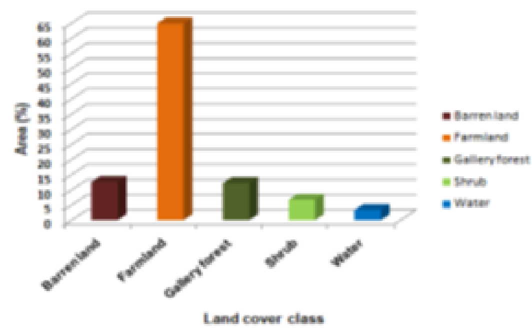
(c) Change map of lake Chad in 2000



(d) Class percentage in terms of area covered in 2000



(e) Change map of lake Chad in 2015



(f) Class percentage in terms of area covered in 2015

Figure 6. Land-use map from 1985-2015

Table 3. User's, producer's and overall accuracies with overall kappa indices of images classified

Land use category	1985		2000		2015	
	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)
Shrub	98.00	94.23	94.00	87.04	88.00	77.19
Water body	95.79	94.79	90.53	98.85	85.26	100.00
Barren land	87.78	95.18	96.67	93.55	97.78	95.65
Farmland	97.14	86.44	82.86	82.86	71.43	73.53
Gallery forest	90.00	100.00	90.91	93.46	90.00	89.19
Overall Kappa	**92.24**		**88.49**		**82.72**	

Table 4. Area covered in (km^2) and land cover changes from, 1985-2015

Land cover classes	Area covered in (km^2)			Changes in (%)		
	1985	2000	2015	1985-2000	2000-2015	1985-2015
Barren land	20,678.40	16,153.14	10,396.04	-21.88	-37.64	-49.73
Farmland	27,742.80	40,824.79	53,513.20	47.16	31.08	92.91
Gallery forest	5,237.10	6,546.46	10,119.31	25.00	54.57	93.22
Shrub	20,808.60	14,115.51	5,566.26	-32.16	-60.56	-73.25
Water	7,943.30	4,767.65	2,812.73	-39.97	-41.00	-64.59

The fact behind achieving very good accuracy as a result of standard classification by using five (5) justifiable classes, nonetheless, it can be realised that the changed maps have different classification accuracies, these due to various temporal diversity and multi-spectral bands that were utilized in the imageries.

Generation/map out geological features

It can be realized that the second one is to recognize and mapped reclassified geological features of Lake Chad by utilising geospatial approach. The purpose has been clearly achieved and the outcomes are discussed and illustrated here. Obtaining first-class information of geological attributes are very important, to find out and recognize the different geological features/ structures of the area which were used as an input into a predictive model for the forecasting of water surface area fluctuations, Figure 7 illustrated the geological attributes in the study.

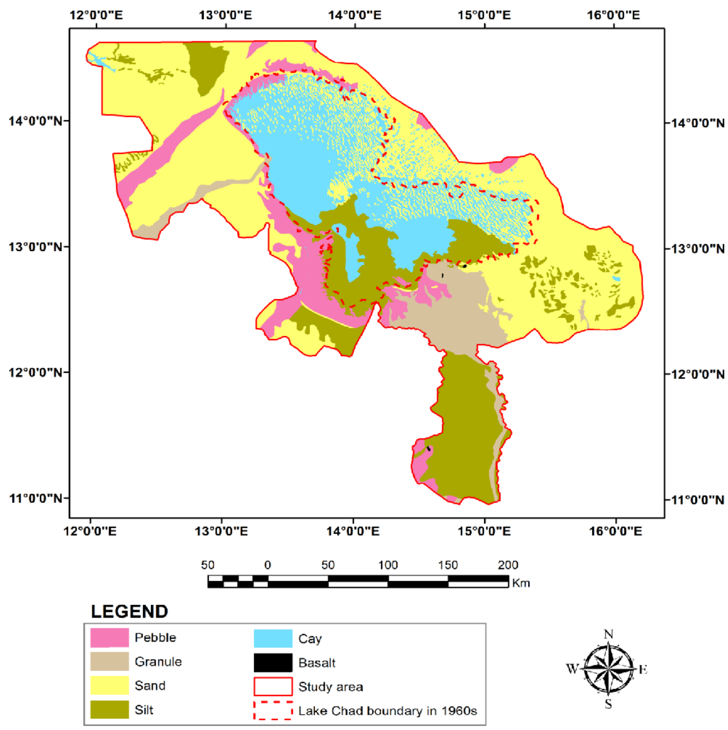


Figure 7. Geological map of the study area

The geological map of the study area presented the areas that were covered in terms of percentage for each class as depicted in Figure 8. Nevertheless, the percentage revealed the formation of geological features/types of the study area. The geological structures include six (6) categories namely: basalt, clay, silt, sand, granule and pebble. Table 5 has shown the areas occupied in terms of kilometre square for every class. Basalt it only covered 18.75km^2 with (0.02%), Clay it covered 15150.57km^2 with (18.38%), Silt it covered 16141.48km^2 with (19.59%), Sand it covered 36813.80km^2 with (44.67%), Granule it covered 6153.92km^2 with (7.47%) and pebble it covered 8131.63km^2 with (9.87%).

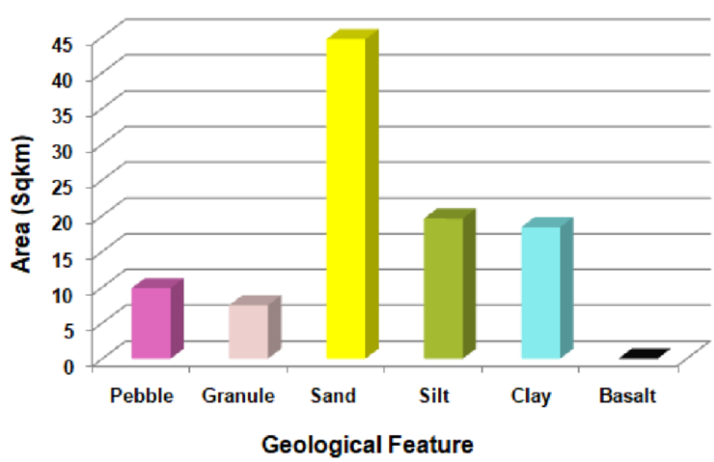


Figure 8. Areas that are covered in terms of percentage for each class.

Table 5. Area coverage in terms of kilometre square

Geological structures	Area (km^2)	Area (%)
Basalt	81.75	0.02
Clay	15150.57	18.38
Silt	16141.48	19.59
Sand	36813.80	44.67
Granule	6153.92	7.47
Pebble	8131.63	9.87
Total	**82410.15**	**100.00**

Cellular Automata Modelling (CA-Markov)

The last objective of this study is to model water extent using improved CA and Markov chains by integrating geological features identified and examining their impact on predicting water surface area fluctuations in the Lake. This objective has been accomplished. In attaining this objective, cellular Automata model (CA-Markov) was utilised to model the 2030 land use maps of the study area, as detailed mentioned in section Analysis of Projected Land Use Changes. Therefore, data inputs were used throughout the modelling process, which includes; Markov transformation area files, the assembly of suitable maps and basic land use map. Then the land cover map for the year 2000 was utilised as the basis. Also, the suitability maps are presented and discussed below coupled with the model validation results and predicted land cover changes.

a. Analysis of validation results

This model has the capability to predict the year 2030 land use map accurately and was validated by making comparisons between predicted 2015 land cover and observed maps. Therefore, the outcomes of the validation are presented in Table 6, whereby it reveals proper agreement among the initial and predicted land use map of 2015. The outcomes illustrate an overall agreement of 82.62% between the predicted maps of 2015. Then, it can be split into 24.33% (agreements in terms of quantity) and 58.29% (agreements in terms of allocation). Similarly, the results illustrate overall disagreement or prediction errors of 0.71%. Then, this can be split into 0.17% (errors due to quantity), 0.54% (errors due to allocation). Therefore, it can be realized that the predicted map varies further from the initial map with respect to the amount of cells in different classes than allocation of the cell (pixels).

Table 6. Elements of disagreement/agreement among the initial and simulated land cover map of 2015

Disagreement/agreement	Value	(%)
Quantity disagreement	0.0017	0.17
Allocation disagreement	0.0054	0.54
Quantity agreement	0.2433	24.33
Allocation agreement	0.5829	58.29
Chance agreement	0.1667	16.67

The strength of a model projecting was assessed by utilising Kappa variations (*K*-indices) for proper modelling process. The nearest of the procedures of *K*-indices to 100% shows healthy agreement among the different pieces of maps (Pontius Jr & Schneider, 2001). *Kstandard* was recognized to be 98.8%, which reveals that there is better agreement among the projected map of 2015 and the initial map. *Kno*, shows that the overall predicted accuracy was recognised to be 99.15%. *Klocation*, illustrates the model capability to identify location precisely, and was recognized to be 99.08%. Therefore, the figures of the *K-indices* acquired in the study has the similarities with the work of various scholars that used Cellular Automata model (CA-Markov) effectively for the forecasting of land use changes. For example, Musa et al. (2018) achieved 85.71%, 88.13% and 89.25% as *Kstandard, Klocation* as well as *Kno* values/figures respectively. Also, the research carried out by Gong, et al. (2015) whereas *Kstandard*, *Kno* and *Klocation* figures were achieved as 86.97%, 88.95% and 94.31%, accordingly. Consequently, the prerequisite standard criteria needed for predictive rule should be 80% and above (Viera & Garret, 2005) was attained in this case, the prediction of 2030 land cover map has been considered effective. Nevertheless, there were slight differences among the observed and predicted maps as illustrated in Figure 9 and 10.

When modelling or predicting the land cover changes, it is very vital to consider the observed classified land use map and it provides the basis to carry out the modelling process by predicted the exact year that is 2015, so that to assess the agreements and disagreements by using kappa variation (K-indices). Incontestably, Figure 8 is the observed land use map for the study area in year 2015.

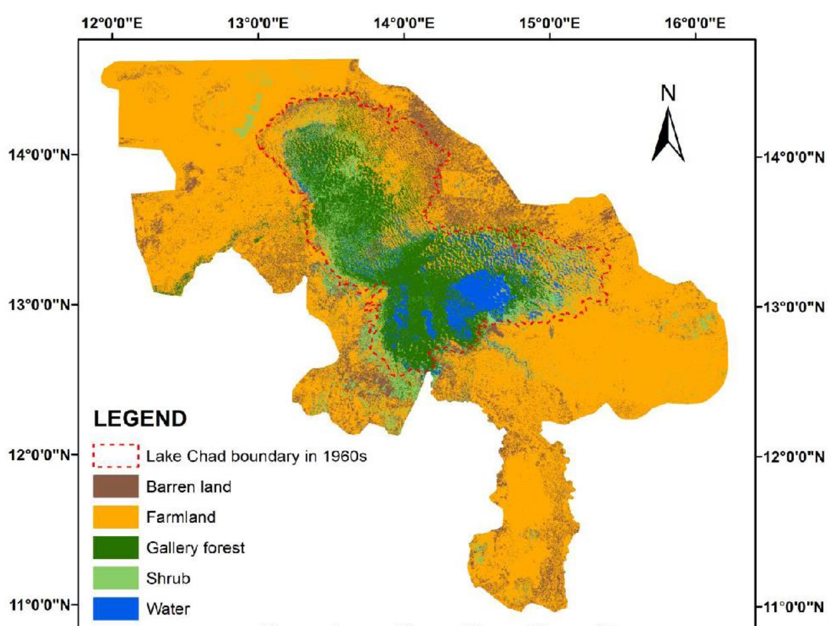


Figure 9. Predicted land use map of the study area for the year 2015

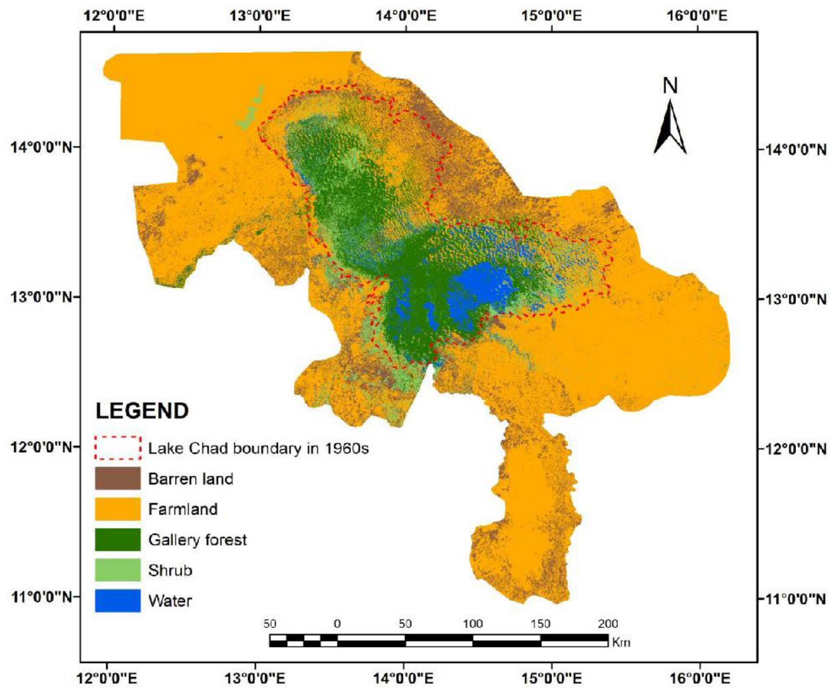


Figure 10. Initial land use map of the study area for the year 2015

b. Analysis of projected land use changes

The model outcome (changes of land cover) was analysed by making comparison among the predicted land cover map for the year 2030 and classified map for the year 2015. Therefore, the analysis discovered that barren land covered 10396km^2, and 9700.47km^2 in the year 2015, and 2030. Farmland covered 53513.2km^2, and 54100.1km^2 in the year 2015 and 2030. Gallery forest covered 10119.3km^2, and 10485km^2 in the year 2015 and 2030. Shrub covered 5566.26km^2, and 5419.85km^2 in the year 2015 and 2030. Water body covered 2812.73km^2, and 2702.37km^2 in the year 2015 and 2030, it has been illustrated in Table 7 and Figure 11.

Table 7. Projected Land use changes from the year 2015 to 2030.

Land cover category	**Area covered**		**Changes**
	2015 (km^2)	**2030 (km^2)**	**2015-2030 (%)**
Barren Land	10396	9700.47	-6.69
Farmland	53513.2	54100.1	1.10
Gallery Forest	10119.3	10485	3.61
Shrub	5566.26	5419.85	-2.63
Water Body	2812.73	2702.37	-3.92

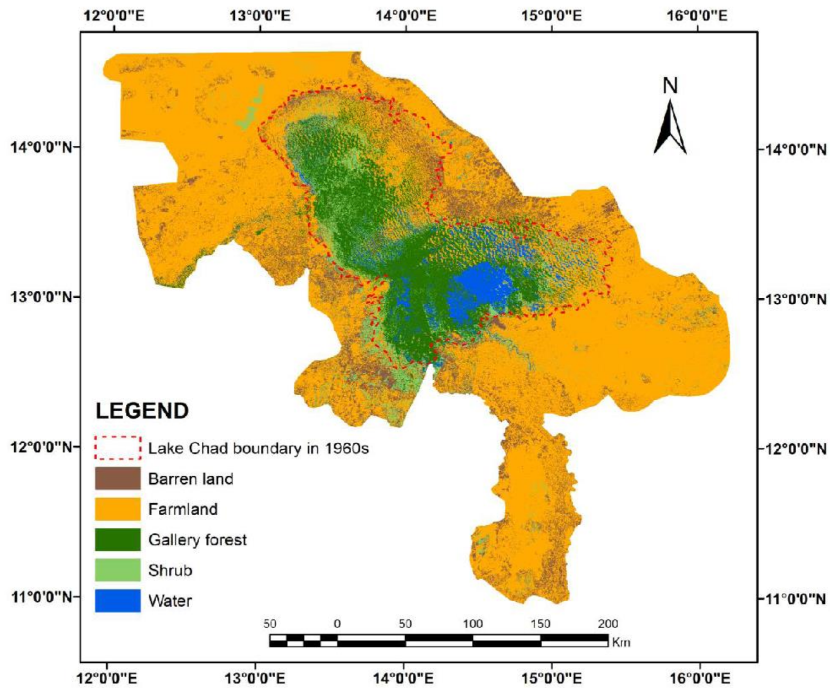


Figure 11. Predicted land use map of the study area for the year 2030

Table 8. Land cover gains and losses of 2015 and 2030

Land cover classes	Area in 2015 (km^2)	Gain (km^2)	Gain (%)	Loss (km^2)	Loss (%)	Net Change (km^2)	Net Change (%)	Area in 2030 (km^2)
Barren land	10396	1,156.81	11.13	-1,852.38	-17.82	-695.57	-6.69	9,700.47
Farmland	53,513.2	2,000.88	3.74	-1,414.25	-2.64	586.63	1.1	54,100.1
Gallery Forest	10,119.3	600.41	5.93	-234.7	-2.32	365.71	3.61	10,485
Shrub	5,566.26	586.27	10.53	-732.68	-13.16	-146.41	-2.63	5,419.85
Water Body	2,812.73	112.58	4.00	-222.94	-7.93	-110.36	-3.93	2,702.37

Then, the gains and losses, land cover conversion results of the study area were also addressed between the year 2015 and 2030. Thus, it was attained by means of cross-tabulation analysis, and it is very important when evaluating land cover changes because it defines cell-by-cell variations of two maps of divers decades that represent the similar features of the study (Mishra et al., 2014). The outcome reveals that the land cover classes have witnessed such losses and gains and in the year 2015 and 2030 as shown in Table 8. Barren land has gained 1156.81km^2 (11.13%) and lost 1852.38km^2 (17.82), with net lost 695.57km^2 (6.69%); farmland has gained 2000.88km^2 (3.74) and lost 1414.25km^2 (2.64), with net gained 586.63km^2 (1.1%); gallery forest has gained 600.41km^2 (5.93%) and lost 234.7km^2 (2.32%), with net gained 365.71km^2 (3.61%); shrub has gained 586.27km^2 (10.53) and lost 732.68km^2 (13.16%), with net lost 146.41km^2 (2.63%); water body has gained 112.58km^2 (4.00%) and lost 222.94km^2 (7.93), with net lost 110.36km^2 (3.93%)

Conclusion

Multi-temporal Landsat satellite images of three different epochs such as (1985, 2000 and 2015); population figure, geological features are the data required for the study. These data were obtained from internet website such as satellite images and relevant government agencies like population figure and geological features, with respect to acquisition of data, preparation and pre-processing. Then different software bundles were effectively utilised to process data at different processing stage. For example, ENVI 5.1, IDRISI selva and ESRI ArcGIS 10.3 were utilised for image classification, accuracy assessment, and image enhancement/correction of their results and production of maps suitability by utilised ENVI 5.1, IDRISI selva and ESRI ArcGIS 10.3. Similarly for geographic database design map production as well map presentation, ESRI ArcGIS were also utilized. Then IDRISI software was used for CA Markov chain analysis and modelling, forecasting of land change and spatial modelling. The reason behind software bundles was on the basis of their accessibility and extensive range of processing algorithm with good-quality performance.

Also, the study presented a novel geospatial modelling approach of predicting water surface area fluctuations using geological features and also illustrates the capabilities of GIS and remote sensing in evaluating the impact of the above-mentioned parameter (geology) on future water surface by the year 2030 and other social factor like population figures. Monitoring the Earth's surface water with the aid of remote sensing turned into a favourable technique within this decade due to two fundamental reasons: (i) there is overall vital need to survey existing water resource and its fluctuations because of the issues relating to water shortage, and (ii) the climate change effects and its straightforward influence on the water cycling, with regards to this more than sixty (60) articles were reviewed. Utilised existing GIS data or manual digitising to obtain the required water information, it is quite obvious that efficient extraction of water features and its variations from remote sensing data/information remains a challenging issue. This study therefore seeks to bridge the gap through investigating/embracing the geological features of the Chad Basin incorporated it in to the model so as to enhance the modelling process (Cellular Automata) and examine their impacts on predicting water surface area fluctuations with geospatial modelling approach. This was achieved through some specific objectives, which involve: (i) investigate the water surface area changes in Lake Chad over the last three decades using multi-temporal satellite images of the basin. (ii) identify and mapped reclassified geological structures/features in the lake by utilising geospatial approach. (iii) model water extent using improved CA and Markov chain by integrating geological features identified and examine their impact on predicting water surface area fluctuations in the lake.

Similarly, multispectral satellite imagery plays a vital role, and the land cover changes from 1985 to 2015 has been hitched in this research. The reasons behind the used of satellite imagery based on its temporal availability. Therefore, a well and effective assessment was attained with the used of geometric correction and image classification. The research demonstrated the capabilities of geospatial approach in assessing the influence of some selected environmental variables on the future water surface area fluctuations. It was achieved by involving environmental factors like topographic slope and population to forecast water surface fluctuations and the impact it could have on the change patterns by a mix of Chain Markov and Cellular Automata models. Assessing water surface area fluctuations is very important considering the role play by water bodies in supporting the natural ecosystem.

The research also has presented geological features of the study area, at this stage, all the information from various sources with regards to geological structure of this study, have been taken care for purpose of providing up dated map. The collected map layers were explained different aspect geographical structures/features at numerous scales to facilitate the of maps. The gathering enables the effectiveness of the map so as to make the visualization of all added instruments/elements at divers levels of details under that map compilation, GIS digitisation, and map production.

The simulation was carried out by incorporating topographic slope, proximity to highways, population, accessibility to central business districts and proximity to navigable water as factors, as well as existing water bodies and existing settlements as constraints were deliberated. The research out comes substantiated predicting the influence of the environmental variable can be easily attained at national level. Then, the model was validated and calibrated by utilizing initial land use map for the year 2015, nevertheless the outcomes delivered standard accuracies which were proved using quantity and disagreements, with numerous kappa indices. Then, more than 80% was achieved of predictive power with slight differences recognized among the observed and simulated maps. This has to do with insufficient suitability maps and over generalization during image classification. Subsequently, the land cover map of the study of the year 2030 was projected. Therefore, the results of predicted land cover changes justified some increase of the amount of Gallery Forest and Farmland as well as decrement of Shrub and Water body, Shrub and Barren land.

The proposed geospatial modelling approach in this study has been substantiated quite effective in predicting the spatial process of water surface area fluctuations of Lake Chad, Central Africa and can be implemented for predicting of spatial process of water surface fluctuations in a similar region. The study has been carried out in Lake Chad, as one of the largest inland lakes in Central Africa which experience highest level of shrinkage. Some scholars have investigated water shrinkage in the region, but none of them assesses the impact of environmental variables like geological features. Therefore, the main limitations for this research work were lack of land cover maps for image classification assessment and generation of suitability maps. Where its necessities the use medium resolution satellite imagery for assessment of the classification accuracy. Though the overall accuracies that fulfilled the minimum accuracy threshold of 85% required for effective and reliable analysis and modelling were attained.

Finally, the current conditions of the Lake have changed for the past decades and it is continuously changing in the upcoming decades due to factors like anthropogenic and climatic activities. The mapped-out geology of the Lake has provided the details of its features in the study area. Consequently, based on the geological features identified with their percentage in terms of compositions, proved that geology influenced the Lake shrinkage which, leads sand to have the highest percentage in the study area compared with other geological features to low retention capacity.

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Limitation

Therefore, the main limitations for this research work were lack of proper land use maps for image classification assessment and generation of suitability maps. Where its necessities the use medium resolution satellite imagery for assessment of the classification accuracy. Though the overall accuracies that fulfilled the minimum accuracy threshold of 85% required for effective and reliable analysis and modelling were attained.

Future work directions/ Recommendations

The following recommendations are suggested for future studies:

1. The mix of Cellular Automata, data driven model, with Markov Chain, a knowledge driven (top-down) model, has been effectively proved in assessing the impact of environmental variables like geological features on future water level fluctuations in the study area. Even though, this research established that idea, future research can consider the use of other models that offer them more freedom if the user's needs to amend much of the model.
2. This study provides the reasonable results on implementation of GIS and remote sensing in water level fluctuations, satellite images of high resolution like; QuickBird, IKONOS, GeoEye-1 and WorldView1-4 need to be considered for future studies. For their diversity and complexity of monitoring environment like water level investigation, the satellite image of higher resolution can facilitate feature extraction and provide more detailed map.

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