Engineering and Applied Science Research 2021;48(4):476-486 Research Article

EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

Geospatial modelling of land use/land cover dynamics in the Gongola basin for water resource applications through CA-Markov

AbdulRazaq Salaudeen*[1, 2], Abubakar Ismail[1], Babatunde K. Adeogun[1], Morufu A. Ajibike[1] and Musa Sulaiman Ibrahim[3]

[1]Department of Water Resources and Environmental Engineering, Ahmadu Bello University Zaria, Nigeria
[2]Department of Civil Engineering, Abubakar Tafawa Balewa University, Bauchi, Nigeria
[3]Department of Surveying and Geoinformatics, Abubakar Tafawa Balewa University, Bauchi, Nigeria

Received 11 September 2020
Revised 23 January 2021
Accepted 1 February 2021

Abstract

The Gongola basin has witnessed tremendous environmental changes over the last three decades as a direct consequence of urban growth, deforestation (including encroachment of existing forest reserves), agricultural expansion, overgrazing, bush burning, drought and recurrent flooding episodes. The impact of these changes is influential on the basin's hydrology, water resource and ecological process, yet, future land cover information to evaluate possible implications on its hydrology and the overall ecosystem is non-existence. Consequently, this study attempts to simulate future land cover demands of 2028 and 2038 for the basin, based on land cover images of 1988, 2003 and 2018 to develop land use/landcover (LU/LC) scenarios for possible hydrologic impact assessments. The method of the research therefore, premised on the use of cellular automata and Markov chain (CA-Markov) model, driven by a number of factors and constraints. Results indicate the land cover change to be mainly driven by rapid growth in urban and agricultural lands, contrary to the vegetation cover, which had been the dominant land cover type in the past. Besides, during the 30 years period, there were noticeable 37.05, 20.21 and 11.55 % increase in urban built-up, bare surface and agricultural land respectively, at the detriment of natural vegetation, which has itself decreased by 18.78 % over the period, with an estimated annual loss of approximately 330 km^2 of natural vegetation. The decrease in the coverage area of water body was significant (3.55 %) for the same period. Findings from future simulations of LU/LC trends in the basin, show that urban area would have increased by 39 % and agriculture by 34 % by 2028 relative to the baseline period of 2003. Conversely, the natural vegetation trailed a declining trend (39 %) higher in magnitude than the preceding years. The developed LU/LC scenarios for the basin can provide an opportunity for water resource managers and experts to understand the trends in changing land use for effective planning and management.

Keywords: CA-Markov model, Future land cover demands, Gongola basin, LU/LC scenario, Water resource management

1. Introduction

Like most other regions of Africa, one of the major challenges faced by the watersheds in Nigeria including the Gongola basin dwells in incessant conversions of natural forests to urban dwellings and agricultural lands to meet up the food needs of the growing population. There is no doubt that the Gongola basin is experiencing serious changes in its ecological process as a result of rapid changes in its land cover, which are attributed to both artificial and natural disturbances. The causes of anthropogenic land cover changes over the basin are not in any way different from those reported by Brink and Eva [1] over the larger Sub-Saharan Africa, which include rapid population increase and civil unrest leading to migrations. This is particularly true as most of the displaced persons on account of the crisis in the northeast of Nigeria now relocate to various communities within the basin. Thus, these scenarios have exacerbated encroachment of existing forest reserves [2], agricultural intensification, bush burning and overgrazing. Consequently, incidences of drought and recurrent flooding episodes in the Gongola basin are on the increase which has implications on its water resource and the overall ecosystem. Although, the remote cause of the devastating flooding in recent past (i.e. summer 2019) in the basin was majorly attributed to extreme meteorological conditions, with little or no attention paid to likely impacts from LU/LC changes.

The impacts of LU/LC change on water resource and hydrology of a watershed is significant [3], as it modifies the hydrological conditions as well as the ecological process in temporal and spatial scales [4, 5]. Moreover, the effects of land cover on key hydrological processes such as; interception, infiltration, and evapotranspiration have also been identified as influential [6]. Therefore, understanding these trends and impacts of land cover on watershed systems in the basin is vital to mitigate negative impacts [7], which can only be achieved through historical tracking and future projections. The main objective of this study therefore, was to simulate future land cover demands for Gongola basin, based on past land cover information to provide opportunities for simulating future water resource scenarios.

*Corresponding author. Tel.: +23480 8469 8123
Email address: asalaudeen@atbu.edu.ng
doi: 10.14456/easr.2021.50

LU/LC constitutes the major driver of landscape changes [8] on both regional and global scales. They are two distinct elements that are closely linked, as they are both products of interactions between natural and social systems [9], as such; they are often used interchangeably [10, 11]. Though, while the land cover describes the biophysical features of the global land surface [12] such as soil, vegetation, water etc.; the land use refers to the human influence on land, particularly for socio-economic activities – for example, urban dwellings, agriculture and forestry [13]. With the continuous increase in socio-economic activities as a result of persistent growth in human population, there are conflicts among the population, resources and the environment, which are believed to be on the increase, as such; much attention is being paid to research on land use changes [14] in recent decades at watershed scale.

For sustainable use of earth's resources, quite number of studies have revealed the importance of acquiring accurate, up-to-date and reliable spatial information on land cover changes [8, 15]. In this regard, remote sensing (RS) along with geographic information system (GIS) technology have become one of the most credible and reliable methods used in research and operation [16]. This is due to its cost effectiveness, practical data acquisition and application of spatiotemporal data as compared to field-based studies [8] which is capital intensive and at the same time require a lot of human efforts.

The research methods of land use dynamic change in literature included cellular based models, evolutionary models, analytical equation-based models, statistical models, system dynamic model and hybrid-based models [15]. Besides, agent-based, cellular-based or a hybrid of the two are the most widely preferred models by the scientific communities in recent literatures. The use of hybrid models now a days have become popular to overcome shortcomings in the application of single optimisation technique, due to their ability to develop skilful computational techniques that tend to cover up the weaknesses of the individual ones [17]. In light of this revelation, the Markov model is plausible in predicting changes in time dimensions [11], while, the cellular automata (CA) model has good skill in simulating the spatial variation of land cover. Thus, combining the strengths of these two models gave rise to a hybrid CA-Markov model, which ensures effective simulation of spatiotemporal dynamic of land cover changes.

To quantify the future land cover changes in regional watershed system, CA-Markov as an integrated modelling approach is used for this study. It incorporates GIS, statistical and simulation techniques to arrive at the future trends of land cover change [7]. The prospect of future LU/LC demands based on present-day change in Gongola basin is suggestive for a more in-depth research [7, 18]. In any case, improving the state of future water resource management of the basin becomes imperative, which can only be achieved through proper analyses and projections [18, 19]. Thus, the developed LU/LC scenarios in this study can provide opportunities for simulating future water resource scenarios for sustainable management.

2. Materials and methods

2.1 The study site

The study site lies in the northeast of Nigeria, between latitudes 9° 00' and 11° 30' north and longitude 9° 00' and 13° 00' east, with an estimated watershed area of 56,000 km^2. The basin is blessed with abundant water resource. The Gongola river originates from the Jos Plateau and flow past three other states namely, Bauchi, Gombe and Adamawa. However, there exist two major tributaries, one from Yobe state and the other from Borno – River Hawal, which took its source from Biu Plateau. The Plateau consists of undulating plains of between 610 and 914 m on the left bank. The middle and the lower reaches of Hawal lie over basement complex rock with isolated inselbergs. On a general note, the Gongola river falls from over 1,750 m above mean sea level on the Jos Plateau in the west to about 130 m at the confluence with river Benue after flowing a distance of approximately 570 km (see Figure 1). The catchment lies in two climatic zones: The Northern Guinea zone and the Sudan zone, with mean annual rainfall varying between 1600 and 700 mm [20]. The rainfall distribution is concentrated into the five summer months, May to September inclusive, representing about 80 % of the annual rainfall [21]. The rainfall and higher humidity are associated with south westerly winds, whereas the dry season hot winds blow down from the desert, and hence potential evaporation rates are high. The temperatures are low at Jos Plateau and are generally high at the lower catchment.

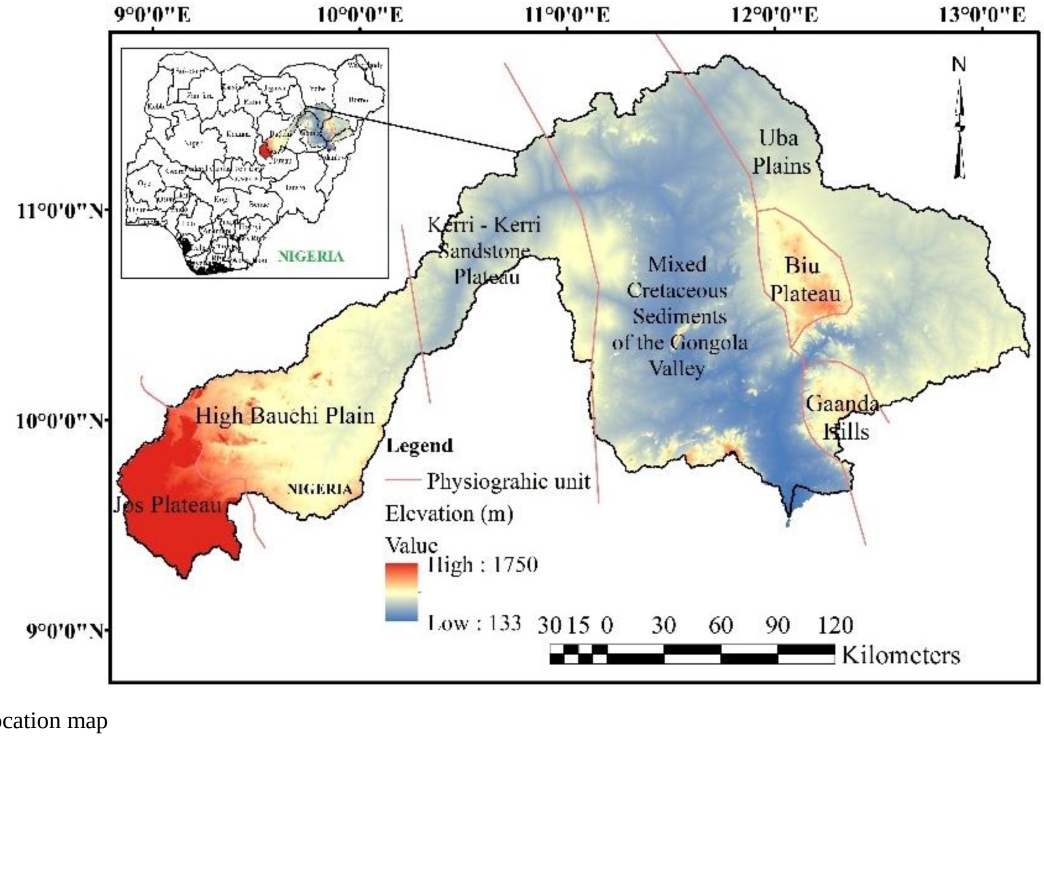


Figure 1 Location map

2.2 Data and data sources

The LU/LC change of Gongola basin was derived using three sets of temporal multispectral satellite images for different epochs; 1988, 2003 and 2018 which were acquired from the Global Visualisation Viewer (GloVis; https//: glovis.usgs.gov/) of the United States Geological Survey (USGS). The images are of 30 m x 30 m spatial resolutions, and were captured by Landsat 4-5, Landsat 7 and Landsat 8 of Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) sensors respectively. For accuracy and consistency, the remotely sensed data, imaged during the winter period (January-May) were selected to avoid effects of cloud and Scan Line Corrector's failure. The watershed boundary was generated from Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) of 30 m resolutions, downloadable from USGS earth explorer website (https//: earthexplorer.usgs.gov/). The data was processed using ArcGIS v10.3 software. Figure1 shows the study site's location map.

A field survey was carried out to obtain two sets of data for ground truthing as training samples, and reference data concurrently, though individualistically by hand-held Global Positioning System (GPS). Additional data were however collected through google earth to augment the field data for effective training. These were taken in the areas where the images have comparable features for the considered years for accuracy. A total of 1,200 ground control points were taken for the training, where about 800 control points were used as training samples and 400 for validation representing 70 % and 30 % respectively of the sampled dataset.

2.3 Classification and accuracy assessment of Landsat images

The preparation of LU/LC map from Landsat images requires classification scheme, which defines the LU/LC class of the study site. Basically, the number of LU/LC class depends on the nature of the project and its purpose [22]. In this study, changes in LU/LC were assessed in five broad classes as; built-up area, barren land, agricultural land, water bodies and vegetation. Incidentally, Interactive Supervised (IS) classification scheme was used for the classification using ArcGIS software package. The IS works the same as Maximum Likelihood (ML) classification, in the sense that both require training samples for known land use classes. The advantages of the IS lies in the fact that, it is fast, requires no signature file to run and it allows quick preview of classification result for a given training sample set. This enhances the classification accuracy of LU/LC maps produced [23]. Accordingly, training sites were developed within the three sets of images, using the collected training samples and ancillary data as discussed earlier, through polygon digitization around similar land cover type. In this regard, bands 542 were used for Landsat 4-5 and Landsat 7, while Landsat 8 considers bands 653. The resulting image through the IS classification scheme are the LC maps of 1988, 2003 and 2018.

The accuracies of the classified maps were assessed through confusion matrix and Kappa index to determine the extent to which the satellite images replicate the ground features, utilizing the method illustrated by Congalton [24] and adopted by references [8, 15, 18, 25, 26] In this approach, about 650 randomly selected reference points were considered, such that; the five LU/LC classes were adequately represented. These were rasterised and transformed into reference map with 30 m grids. The rasterised images were inputted to IDRISI Selva v17 software package to generate the error matrix using the observed images of 1988, 2003 and 2018 as the categorical map, and the reference map as the ground truth images as the case may be. The confusion matrix produces; the producer's, users and overall accuracies.

2.4 Prediction of future LU/LC change

The prediction of the LU/LC changes in this study for the future time periods of 2028 and 2038 considered the use of CA-Markov model as has been widely used in recent literatures e.g. Bozkaya et al. [8], Musa et al. [15], and Hyandye and Martz [18]. This is achieved by using two known land use of different time periods to project into the future. The CA-Markov is a hybrid land cover prediction model, which merges cellular automata and Markov chain, multi-objective land allocation (MOLA) and multi-criteria evaluation (MCE) procedures [27-29] to predict land cover change in time dimension. The CA model being a spatial dynamic model has basically four components, including cells, states, neighbourhood and rules [8]. It is expressed mathematically as [30]:

$$S^{t+1} = f(S^t, N) \quad (1)$$

where S^t refers to the state of the cell at time t, S^{t+1} defines the state of the cell at later time period t + 1, f is the transition function, and N represents the set of states of the cells in a neighborhood.

In the main, the CA model is based on certain assumptions which border on grid cells, urban growth, urban pattern and district time steps [28, 31]. The grid is assumed to be an isotropic plane with constant topography, geology including the geography and all other features, except land use which is presumably dynamic; unconstrained growth is assumed for the cities; the patterns for the urban land are assumed to be regular in shapes and sizes; while the progression in urban growth is assumed to occur concurrently, and at the same rate in every part of the city.

The process in Markov model involves relating stochastically, the future state of a system to the current state. In any case, the model describes the land use change from one period to another, consequently predicting the future trends of LU/LC change [32], by creating a transition probability matrix from time t to time t+1 as the basis for future projection. The Markov model is defined mathematically as [28]:

$$L_{(t+1)} = P_{ij} \times L_t \quad (2a)$$

but

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix} \quad (2b)$$

where Lt and Lt+1 signifies the land cover status at time t and t+1 respectively, Pij lies between the interval of 0 to 1, and the sum of 1 is identically equal to 0. i, j = 1,2, …, m which represent the probability transition probability in a state.

The three-input data generated for projection of LU/LC changes into the future include; basis land cover image (2003 map), Markov transition areas file and transition suitability image collection as illustrated by Eastman [27]. The basis land cover maps are products of classified Landsat images; whereas the transition areas file was prepared using Markov module of the software; and the MCE module was used to aggregate factors and constraints to arrive at suitability maps.

The forecast of future LU/LC dynamic change in this study considers topographic slope, proximity to highways, and proximity to central business district as factors, while; forest reserves, existing settlements, and existing water bodies were selected as constraints. The factors and constraints maps were first prepared in ArcGIS using Euclidean distance module of the package. Consequently, the image was transferred into IDRISI Selva environment in each case, after which a decision support wizard was utilized to standardize the images through fuzzy set membership function. For instance, slope gradient factor was standardized, using monotonically decreasing linear function, on a scale of 0-255, where areas between 0 and 15.1 % are considered suitable for urban development and areas greater than 15.1 are presumed to be otherwise. The proximity to highways factor map considers J-shaped monotonically decreasing function, which identified areas between 50 m to be most suitable; consequently, areas beyond 500 m have continuous declining suitability which though never reaches 0. To standardize the proximity to CBD on a scale of 0-255, a decreasing linear function was selected with control points of 400 m (most suitable) and 3000 m (least suitable) for urban growth. Similar trend was followed to arrive at the suitability maps for barren land, agriculture and vegetation. Each of the constraints was developed using Boolean character of 0 and 1. The 0 signifies areas restricted for development; while 1 depicts areas for suitability analysis [18].

Further analysis requires weights to be assigned to the factors to show their relative importance. Three options are available to achieve this based on insight from literature. They include: assigning equal weights, employing the user defined weights and finally using Analytical Hierarchy Process (AHP) [27]. The use AHP approach has been reported to be plausible and give satisfactory results by different researchers, hence, it was applied in this study. This is a pairwise comparison technique which evaluates the importance of the factors, by assigning values which varies between 1/9 and 9 inclusive, indicating “extremely less importance” to “extremely more importance” [24]. The eigenvector therefore, generated a weight of 0.6554 for proximity to highway, 0.2897 for slope gradient, and 0.0549 to proximity to CBD with consistency ratio of 0.07. Thus, a consistency ratio of less than 0.10 is considered acceptable [15, 29], and would have to be re-evaluated should the ratio exceeds this value.

Moreover, the Weighted Linear Combination (WLC) module was utilised to aggregate the factors and constraints to generate the suitability images for the individual LC category. In this approach, each factor is multiplied by its weight, after which the resulting product successively multiplied by each of the constraints, to arrive at weight sum of unity [27, 31, 33]. The combination of the various suitability maps results in suitability image collection.

The validation of the 2018 image through CA-Markov model utilised the results from Markov run as input data. The Markov module itself requires LC images of two time periods [14]. In this case, the 1988 image represented the earlier land cover image (t -1) whereas, the 2003 was used as the later land cover image (t =1). Nevertheless, the number of time period between the two images in the present-day and future time periods from the second image is 15 years, using a proportional error of 0.15. This produced the transition areas file. Combining the suitability maps and the transition areas file, using default iteration of 10 and standard contiguity filter of 5 x 5, yielded the projected 2018 map, which was compared with the observed 2018 LC map through VALIDATE module in IDRISI Selva. The validation process includes, determining statistically, the levels of agreement and disagreement between the simulated and observed land cover maps, as proposed by Pontius and Millones (2011). Using a minimum of Kappa threshold of 0.80, the 2028 and 2038 future land cover changes in the Gongola basin were projected.

3. Results and discussions

The results of the LU/LC changes in the Gongola basin are presented and discussed below:

3.1 Assessing the classification accuracy

The classified images of the study site (see Figure 2 (a-c)) were compared with the reference data in each case, to ascertain the level of accuracy of the maps through confusion matrix. Essentially, accuracy assessment is quantitative method used in research to compare the consistency of two images. Through this comparison, pixels which are wrongly included (error of commission), and those which are wrongly excluded (error of omission) are plainly presented. The Kappa indices for the maps are between 88 and 90 %, while the overall accuracies are 90.76, 91.68 and 92.22 % respectively for the land cover maps of 1988, 2003 and 2018. These are considered good, as they met the minimum 0.85 level of accuracy required for reliable prediction of dynamic land cover changes. The user’s accuracy and the producer’s accuracy of the individual LU/LC derived from the maps are as shown in Table 1. The results show that the images are credible, and can therefore be reliably used for future prediction of land cover change in the basin.

Table 1 Accuracy assessment of classified images using confusion matrix

Land Cover Class	1988		2003		2018	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Urban	98.40	95.35	98.43	100.00	95.45	92.65
Barren land	88.65	93.18	89.67	90.71	95.07	84.02
Agricultural land	90.94	80.94	84.36	80.43	81.80	88.03
Water bodies	100.00	78.81	100.00	95.45	98.23	87.41
Vegetation	74.33	94.09	82.74	87.26	86.67	93.60
Overall Kappa	87.69		89.35		89.70	
Overall Accuracy	90.76		91.68		92.22	

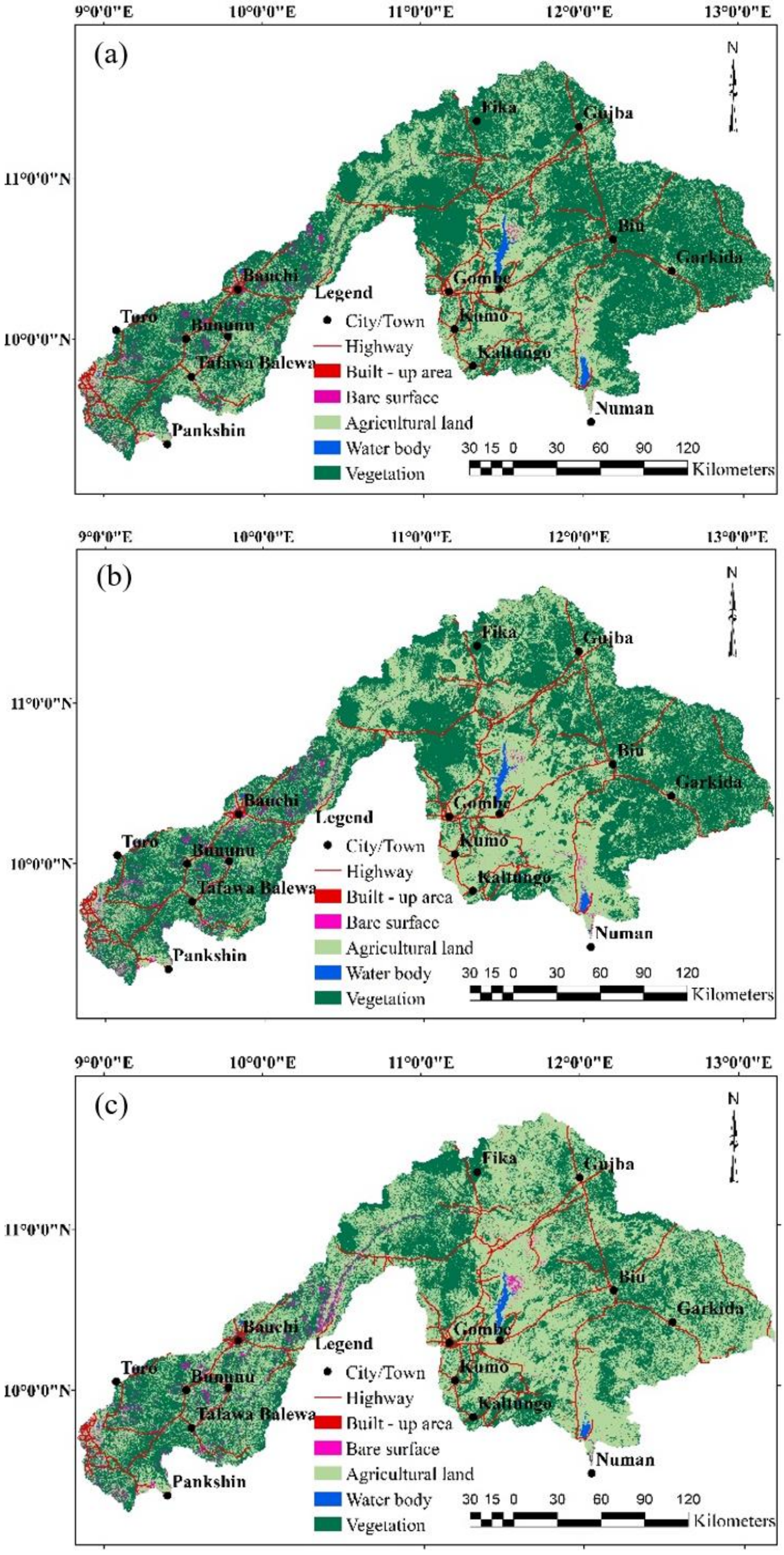


Figure 2 Classified images of (a) 1988 (b) 2003 (c) 2018

3.2 Change detection

The Gongola basin had witnessed tremendous changes in its land cover over the last three decades, resulting from human influence on its natural environment and ecosystems. The results obtained from the change detection analysis revealed accelerated increase in the areas of urban built-up, agriculture and bare surfaces; while, the land areas of vegetation and water bodies had continued to decline progressively. Evidently, the percentage increase in the built-up areas, bare surface, agriculture between 1988 and 2003 are +16.05, +9.01 and +14.65 % respectively, while the vegetation and water bodies experience a total decline to the tune of -11.92 and -1.99 % for the same period as clearly shown in Figure 3. The changes in land cover between 2003 and 2018 followed similar trends. Vegetation in the study area has continued to suffer decline, including the forest reserves as a result of human activities, which include, farming, bush fire, fuel wood extraction, logging and overgrazing [2], with consequent increase in agricultural land.

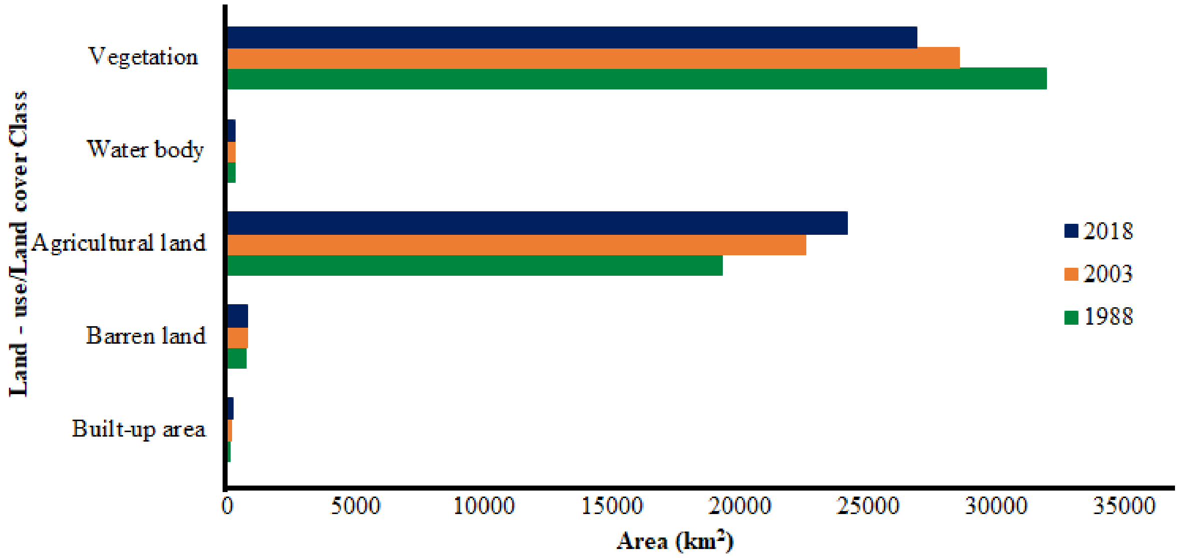


Figure 3 Dynamics of land cover changes in the study area from 1988 to 2018

Change analyses for the periods 1988-2003 and 1988-2018 were carried out using the Land Change Modeller (LCM). The LU change was evaluated through gains and losses by categories as used by Musa et al. [15] and several other researchers. In this case, the gain and loss in the urban built-up area from 1988-2003 are 61.71 % and 54.39 % respectively, with a net gain of 7.32 %. The barren land has a gain of 29.94 %, a loss of 23.00 % and a net gain of 6.94 %. The gain, loss and net gain in agricultural land are 32.35, 20.73 and 11.62 %; while water body gained 14.17 %, lost 15.84 %, with a net loss of 1.67%. The gain in vegetation area during the period was estimated to be 13.67 %, while the loss was 22.86 %, resulting in a net loss 9.19 %. The analysis for the period 1988-2018 revealed similar trend, with higher magnitudes of changes. The results from this study followed the research trends in many parts of the world and, is particularly similar to those conducted in Niger Delta region of Nigeria by Musa et al. [15], and Awoniran et al. [34] in Ogun, Southwest of Nigeria. It is therefore evident that there is continued growth in built-up area and agriculture; which have serious implications on the ecosystem and hydrology of the river basin.

3.3 Analysis of CA-Markov model results

The CA-Markov model was used to project the LU/LC maps of 2028 and 2038 in this study. The model requires suitability image collection, transition areas file, and the basis land cover map. The basis land cover map was the classified image of 2003 (see Figure 2), whereas the transition areas file was generated using combined images of 1988 and 2003; whilst the amalgamation of suitability maps (Figure 4) into one single folder produced the suitability image collection.

The images of 1988 and 2003 were used to produce the transition probability matrix for the projection of 2018 LC map and beyond. The study evaluates five classes of LC and their transitions occurring at district times. Thus, for any 15 years period, 66.72 % of the built-up area is expected to persist, and 7.8, 4.0, 9.97 and 11.5 % have the tendencies to change to bare surface, agriculture, water body and vegetation respectively. Similarly, the bare surface, agriculture, water body and vegetation have persistence of 75.51 %, 62.02, 71.48 and 74.58 % respectively as shown diagonally in Table 2. It was observed that the LC class with the highest probability to change to one or more other classes is barren land, followed by vegetation. In contrast, built-up area and agricultural land have the highest tendencies to remained unchanged. In any case, areas with high probability to change are reported to be influenced by the dominant LU/LC class.

Table 2 Markovian transition probability matrix based on LC maps of 1988 and 2003

	Probability of changing to				
LU/LC Category	**Built - up area**	**Bare surface**	**Agricultural land**	**Water body**	**Vegetation**
Built - up area	0.6672	0.0780	0.0400	0.0997	0.1150
Barren land	0.0076	0.7551	0.1061	0.0348	0.0964
Agricultural land	0.0008	0.0079	0.6202	0.0011	0.3700
Water bodies	0.0498	0.0965	0.0421	0.7148	0.0968
Vegetation	0.0026	0.0218	0.2278	0.0019	0.7458

The dominant LC class in Gongola watershed in the past was vegetation, followed by agriculture, then barren land, water bodies, with built-up area being the least. But due to persistent growth in human population, with consequent logging for construction activities, conversion of forest to agricultural land, encroachment and de-reservation of forests, bush burning and overgrazing, agricultural land appeared to be the dominant LC type in the basin in recent time, with no reversion back to vegetation.

3.3.1 Evaluation of model validation results

The observed and simulated 2018 LU/LC maps of the study site (Figure 5) was validated to ascertain the level of agreements/disagreements in terms of quantity and location of the cells, and also agreement by chance, in order to project into the future time periods. Results from the model validation give an overall agreement and disagreement as 90.13 % and 9.87 % respectively between the observed and simulated LU/LC maps in the basin, suggesting a valid model for land use change projection. Table 3 presents the model validation results.

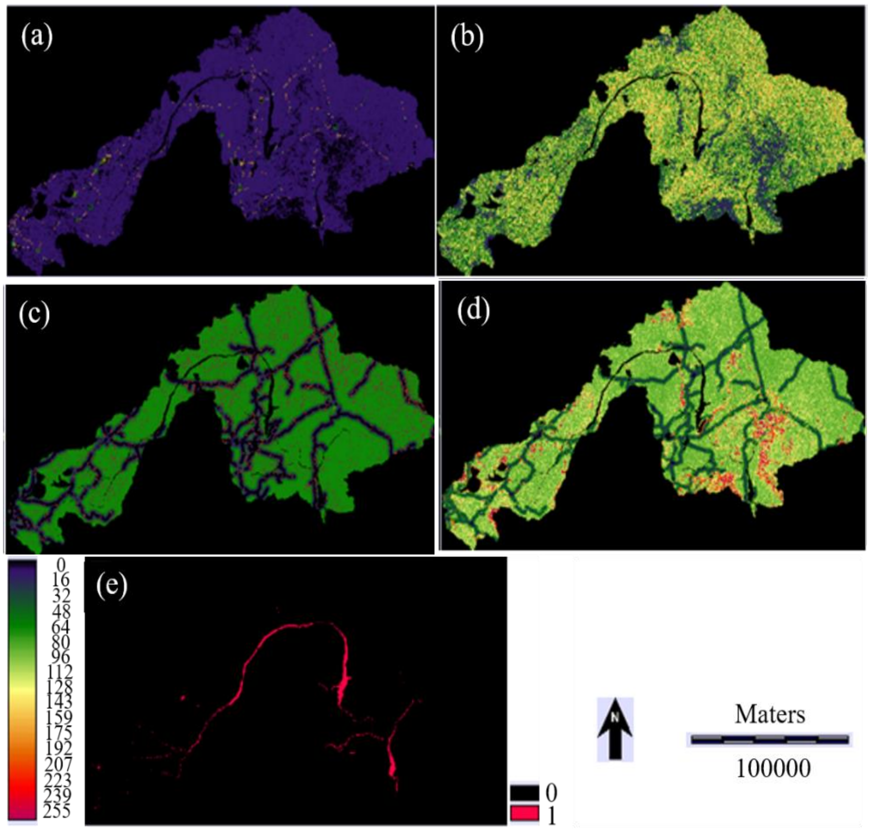


Figure 4 LU/LC category suitability maps for (a) built-up area, (b) barren land, (c) agricultural land, (d) vegetation, (e) water

These results show good agreements between the two maps in line with conditions outlined by Pontius and Millones [35]. The range of the Kappa indices for the simulation model is 0.8201-0.8815, suggesting almost perfect agreement according to Viera and Garrett [36].

The values as generated by the VALIDATE module of IDRISI Selva software package for K-standard, K-location and K-no (K for no information) are 0.8201, 0.8593 and 0.8815 respectively. The K-standard indicates the quantity agreement between the observed and simulated model, rather than by chance; the K-location shows the ability of the simulation model to accurately specify location; while the K-no defines the overall accuracy of the model. Some values of K-no reported in literature are 0.8856 [15], 0.9028 [18], and 0.8900 [37].

Table 3 Results of model validation for 2018 LU/LC maps

Name of component	Value (%)
Allocation disagreement	7.37
Quantity disagreement	2.50
Allocation agreement	45.01
Quantity agreement	28.45
Chance agreement	16.67

Since the predictive power of the simulation model is above the minimum threshold of 0.80 set, the model has the veracity to predict the future LU/LC changes in this study. Figure 5 shows the observed and simulated 2018 LU/LC maps.

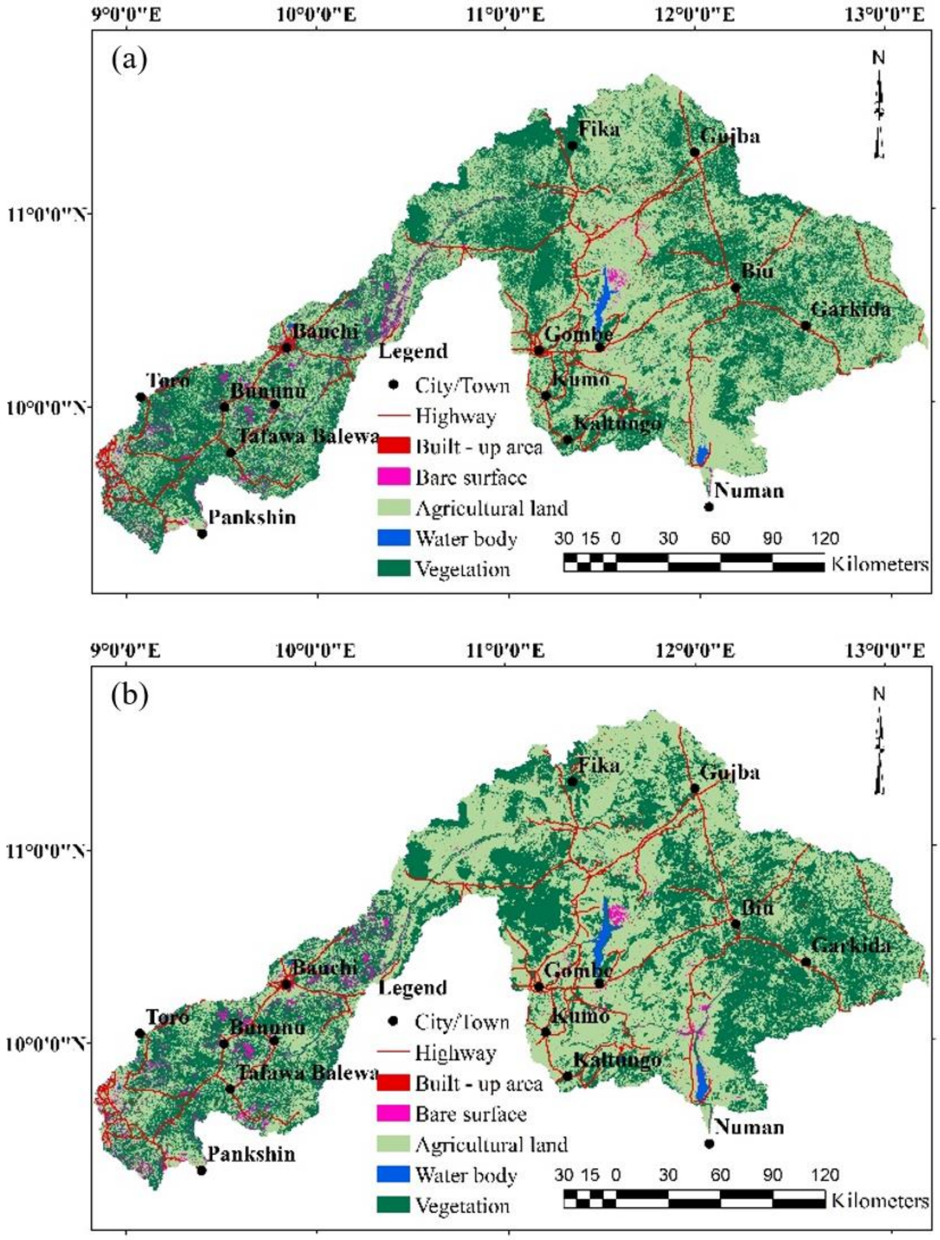


Figure 5 (a) Observed 2018 LU/LC Map (b) Simulated 2018 LU/LC Map

3.3.2 Future LU/LC prediction

The validated satellite derived LU/LC maps of 1988 and 2003 (Figure 2) were used to predict the LU/LC maps of 2028 and 2038 as shown in Figures 6 (a) and (b) with 2003 image as the baseline map. The assessments of the net change in LU/LC categories with reference to the baseline period of 2003 indicate 39 and 32 % growth in urban and agriculture respectively by 2028. Should appropriate measure not taken by the authority concerned, the human influence on LU/LC in the basin may lead to unsustainable environmental degradation in the basin as the natural vegetation is threatened and may suffer a decline of up to 39 % by 2028 relative to the baseline period. Furthermore, the findings from this research concur with the study on LU/LC change in sub-Saharan Africa over 25 years period by Brink and Eva [1], where they opined that expansion of croplands remained the major driver of LU/LC changes. Although, growth in agricultural outputs in Gongola basin has the tendency to impact positively on the socio-economic conditions of the dwellers, but this is without negative impacts. Thus, the continued expansion of urban area and croplands have serious consequences on the environment, the hydrology and the overall ecosystems of the watershed, which would only be discovered by further studies. The projected maps are shown in Figures 6 (a and b); while (c) presents the net change in LU/LC categories for the two considered future time periods.

In this study, the LU/LC dynamics of Gongola basin for a period of 50 years (1988- 2038) was examined. The results of the findings indicate persistent increase in the areas of urban built-up, bare surface, and agriculture. In contrast, the vegetation in the basin had suffered serious decline particularly in the last three decades and this trend may likely continue into the future time period, if there are no plans in place to reduce the pressure on vegetation. Continuous decline in water body for the past three decades was noted; however, the projections into the future shows slight increase. Figure 7 presents the graphical representation of LU/LC dynamics over the study domain

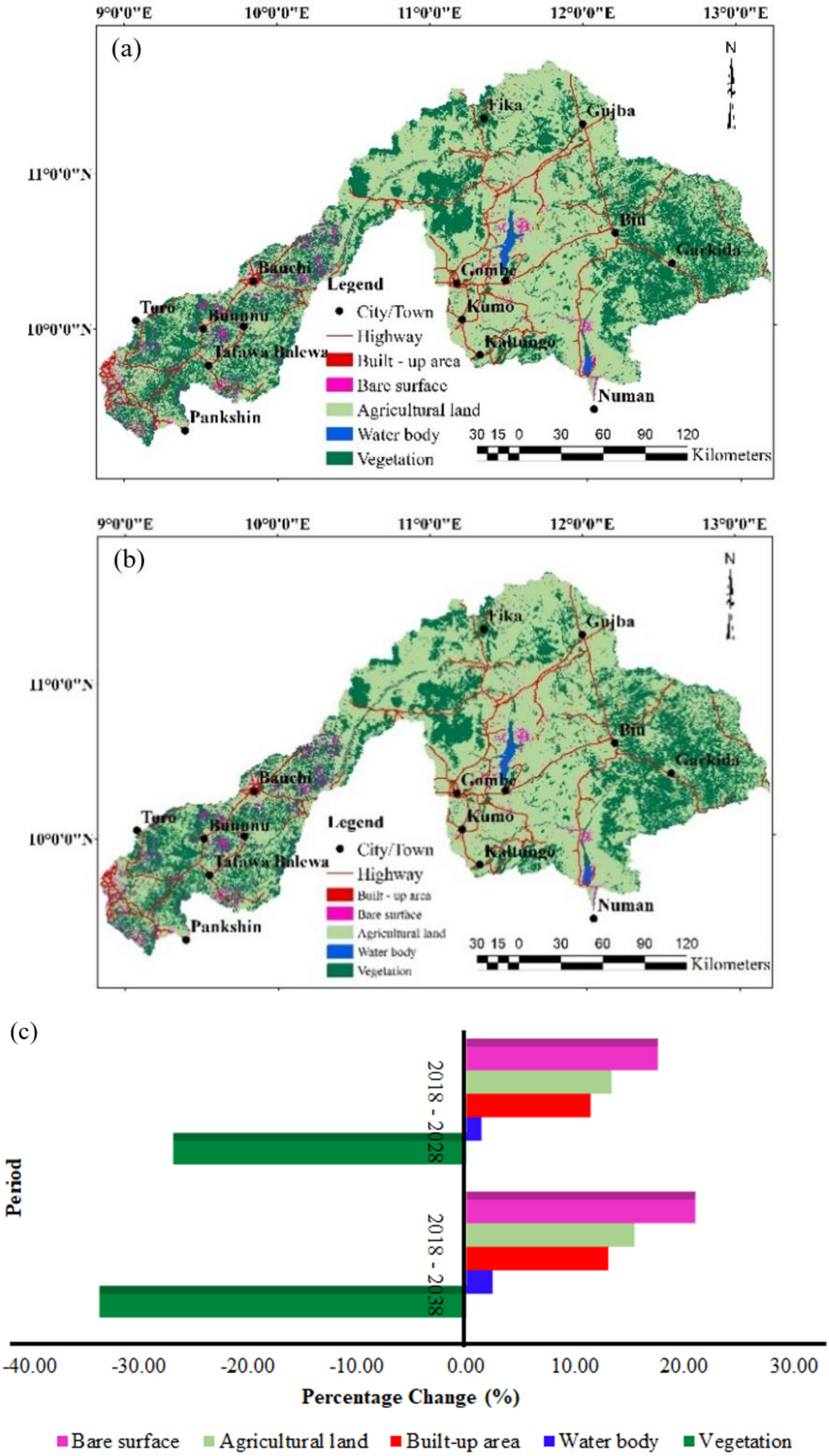
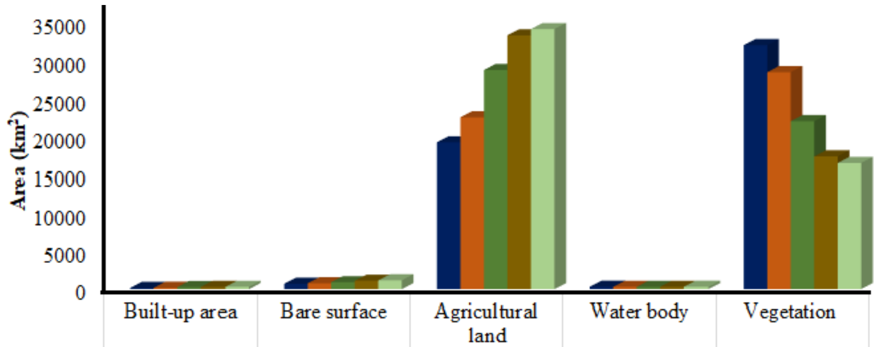


Figure 6 Projected (a) 2028 LU/LC map (b) 2038 LU/LC map (c) net change in LU/LC category



	Built-up area	Bare surface	Agricultural land	Water body	Vegetation
1988	151.61	711.22	19282.93	310.53	31975.45
2003	180.60	781.66	22594.07	304.47	28570.95
2018	261.41	920.04	28867.04	299.17	22084.08
2028	294.90	1115.28	33284.90	303.41	17421.65
2038	300.38	1163.49	34107.41	306.56	16542.30

Figure 7 Graphical representation of LU/LC dynamics in the study site

3.3.3 LU/LC scenarios for Gongola basin

An in-depth study of emerging changes in flow regimes and water resource of Gongola basin requires reliable information on LU/LC which can only be tracked through development of different land cover scenarios. We developed five LU/LC scenarios in this study denoted as G1, G2, G3, G4 and G5, which define the scenarios as baseline period, historical and future time periods to suite simulations of future water resource scenarios in the basin probably by hydrologists and water resource managers. The development of these scenarios is particularly important for the basin, being perhaps the first of such study as far as literature search is concerned. The classified land cover images as well as the simulated models produced plausible results that are deemed satisfactory for decision making. The maps representing the scenarios are shown in Figures 2, 5 and 6 of this article, while the summary of the LU/LC are presented in table 4 below.

Table 4 Summary of LU/LC scenarios for Gongola basin

Scenarios	Description	Period
G1	Baseline LU/LC	2003
G2	Historical LU/LC	1988
G3	Historical LU/LC	2018
G4	Projected LU/LC	2028
G5	Projected LU/LC	2038

4. Conclusions

This study has examined the changes in LU/LC pattern of Gongola river basin during the period 1988-2018 and simulated the LU demands in the future through CA-Makov model. We argue that the LU/LC in the basin has experienced substantial changes since 1990’s as a result of both human and natural factors. Thus, different LU/LC scenarios were developed for the basin for hydrology and water resource applications. Findings reveal rapid growth in urban built-up and agriculture to be the major drivers of changing LU/LC in the basin. Consequently, the change in urban built-up for the 30 years period (1998-2018) was 37.05 %. Likewise, the change in agricultural land was 20.21 % in consonant with rapid growth in population. The decline in vegetation cover in the basin was particularly significant (-18.78 %) and clearly noticeable all over the study area. This was however, more noticeable in the Sudan Savannah zone, where the physiographic features are identified as consisting of Kerri-Kerri sand stone and mixed cretaceous sediments - areas beyond high Bauchi plains up to Dadin Kowa in Gombe state. The water body, similar to vegetation, witnessed decline in area during the same period.

The LU/LC trends were simulated for the years 2028 and 2038. Results reveal that built-up areas and agriculture would have increased by 39 % and 34 % respectively by the year 2028, while the vegetation cover would have suffered serious decline to the tune of -39 %. This growth in urban and agricultural lands with consequent rapid decline in vegetation, if poorly managed has the tendency to cause adverse environmental impacts. The outputs from this study can be used by water resource managers and other stakeholders to track the trends in land use changes in Gongola basin, which may in turn provide opportunities for simulating future water resource scenarios for sustainable management.

5. Acknowledgements

The financial support to the first author by the Federal Government of Nigeria through Tertiary Education Trust Fund for Academic Staff Training and Development is greatly acknowledged. The Authors are thankful to USGS for making free the Landsat images and digital elevation models used in this research. The comments of two anonymous reviewers of this article are also acknowledged.

6. References

[1] Brink AB, Eva HD. Monitoring 25 years of land cover change dynamics in Africa: a sample-based remote sensing approach. Appl Geogr. 2009;29:501-12.

[2] Mbaya LA, Hashidu MS. Status of forest reserves (savannah woodland) biodiversity and rural livelihoods in Gombe state. Int J Dev Sustain. 2017;6:2173-92.

[3] Adnan NA, Atkinson PM, Yusoff ZM, Rasam ARA. Climate variability and anthropogenic impacts on a semi-distributed monsoon catchment runoff simulations. 2014 IEEE 10th International Colloquium on Signal Processing and its Applications; 2014 Mar 7-9; Kuala Lumpur, Malaysia. USA: IEEE; 2014. p. 1-6.

[4] Basarudin Z, Adnan NA, Latif ARA, Tahir W, Syafiqah N. Event-based rainfall-runoff modelling of the Kelantan river basin. IOP Conf Ser: Earth Environ Sci. 2014;(18):1-6.

[5] Wu F, Zhan J, Su H, Yan H, Ma E. Scenario-based impact assessment of land use/cover and climate changes on watershed hydrology in Heihe river basin of Northwest China. Adv Meteorol. 2015;2015:1-11.

[6] Croke BFW, Merritt WS, Jakeman AJ. A dynamic model for predicting hydrologic response to land cover changes in gauged and ungauged catchments. J Hydrol. 2004;291:115-31.

[7] Marshall E, Randhir TO. Spatial modeling of land cover change and watershed response using Markovian cellular automata and simulation. Water Resour Res. 2008;44.

[8] Bozkaya AG, Balcik FB, Goksel C, Esbah H. Forecasting land-cover growth using remotely sensed data: a case study of the Igneada protection area in turkey. Environ Monit Assess. 2015;187:59.

[9] Han H, Yang C, Song J. Scenario simulation and the prediction of land use and land cover change in Beijing, China. Sustain. 2015;7:4260-79.

[10] Liping C, Yujun S, Saeed S. Monitoring and predicting land use and land cover changes using remote sensing and gis techniques - a case study of a hilly area, Jiangle, China. PloS one. 2018;13:e0200493.

[11] Balzter H, Braun PW, Kohler W. Cellular automata models for vegetation dynamics. Ecol Model. 1998;107:113-25.

[12] Cihlar J, Jansen L. From land cover to land use: a methodology for efficient land use mapping over large areas. Prof Geogr. 2001;53:275-89.

[13] Aldhshan SRS, Shafri HZM. Change detection on land use/land cover and land surface temperature using spatiotemporal data of Landsat: a case study of Gaza strip. Arab J Geosci. 2019;12:1-14.

[14] Yang J, Chen F, Xi J, Xie P, Li C. A multimarket land use change simulation model based on cellular automata and its application. Abstr Appl Anal. 2014;2014:1-11.

[15] Musa SI, Hashim M, Reba MNM. Geospatial modelling of urban growth for sustainable development in the Niger delta region, Nigeria. Int J Remote Sens. 2018;40:3076-104.

[16] Das S, Sarkar R. Predicting the land use and land cover change using Markov model: a catchment level analysis of the Bhagirathi-Hugli river. Spat Inf Res. 2019;27:439-52.

[17] Chandwani V, Vyas SK, Agrawal V, Sharma G. Soft computing approach for rainfall-runoff modelling: a review. Aquatic Procedia. 2015;4:1054-61.

[18] Hyandye C, Martz LW. A Markovian and cellular automata land-use change predictive model of the Usangu catchment. Int J Remote Sens. 2016;38:64-81.

[19] Bello A-AD. Modelling the impacts of land-use and climate change in Skudai river watershed [dissertation]. Johor Bahru: Universiti Teknologi Malaysia; 2018.

[20] Federal Ministry of Water Resources and Japan International Cooperation Agency (JICA). The project for review and update of Nigeria national water resources master plan, Volume 4, National water resources master plan 2013. Nigeria: Federal Government of Nigeria; 2014.

[21] Diyam Consultants. Upper Benue development phase I - draft report on the Gongola basin. Nigeria: Diyam Consultants; 1977.

[22] Mishra PK, Rai A, Rai SC. Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. Egypt J Remote Sens Space Sci. 2020;23(2):133-43.

[23] Hassan Z, Shabbir R, Ahmad SS, Malik AH, Aziz N, Butt A, et al. Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan. Springerplus. 2016;5:812.

[24] Congalton RG. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens Environ. 1991;37: 35-46.

[25] Fenetahun Y, Yong-Dong W, You Y, Xinwen X. Dynamics of forage and land cover changes in Teltele district of Borana rangelands, southern Ethiopia: using geospatial and field survey data. BMC Ecol. 2020;20:55.

[26] Fentie SF, Jembere K, Fekadu E, Wasie D. Land use and land cover dynamics and properties of soils under different land uses in the Tejibara watershed, Ethiopia. Sci World J. 2020;2020:1479460.

[27] Eastman JR. Guide to GIS and Image Processing. Worcester: Clark University; 2012.

[28] Subedi P, Subedi K, Thapa B. Application of a hybrid cellular automaton-Markov (ca-Markov) model in land-use change prediction: a case study of saddle creek drainage basin, Florida. Appl Ecol Environ Sci. 2013;1:126-32.

[29] Iwuji M, Ibe C, Njoku J, Anyanwu S, Amangabara G, Ac-Chukwuocha N, et al. Analysis of land use and land cover dynamics in Orlu, Nigeria. Asian J Environ Ecol. 2017;4:1-10.

[30] Ahmed B, Ahmed R. Modeling urban land cover growth dynamics using multi-temporal satellite images: a case study of Dhaka, Bangladesh. ISPRS Int J Geo-Inf. 2012;1:3-31.

[31] Musa SI, Hashim M, Reba MNM. A review of geospatial-based urban growth models and modelling initiatives. Geocarto Int. 2016;32:813-33.

[32] Lu Y, Wu P, Ma X, Li X. Detection and prediction of land use/land cover change using spatiotemporal data fusion and the cellular automata-Markov model. Environ Monit Assess. 2019;191:68.

[33] Naschen K, Diekkruger B, Evers M, Hollermann B, Steinbach S, Thonfeld F. The impact of land use/land cover change (LULCC) on water resources in a tropical catchment in Tanzania under different climate change scenarios. Sustain. 2019;11:7083.

[34] Awoniran DR, Adewole MB, Adegboyega SA, Anifowose AYB. Assessment of environmental responses to land use/land cover dynamics in the lower Ogun river basin, southwestern Nigeria. Afr J Environ Sci Tech. 2014;8:152-65.

[35] Pontius RG, Millones M. Death to kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. Int J remote Sens. 2011;32:4407-29.

[36] Viera AJ, Garrett JM. Understanding Interobserver agreement: the kappa statistic. Fam Med. 2005;37:360-3.

[37] Memarian H, Kumar Balasundram S, Bin Talib J, Teh Boon Sung C, Mohd Sood A, Abbaspour K. Validation of ca-Markova for simulation of land use and cover change in the Langat basin, Malaysia. J Geogr Inf Syst. 2012;04:542-54.