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ARTICLE

Spatiotemporal Analysis of Land Use Land Cover Mapping and Change Detection in Dambatta Local Government Area

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ABSTRACT

This research studied the spatiotemporal changes in land use (LU)/land cover (LC) in Dambatta local government area, with a view to identifying the effect arising from the observable changes in land use patterns. The imageries used in the study were obtained from the National Space Research and Development Agency (NARSDA), Abuja. Spatial analytical techniques and descriptive statistical techniques were employed to analyze the data. The results showed 66.8% reduction in agricultural lands, 45.5% reduction in vegetation cover, 223.2% increase in built-up areas, 269.1% increase in bare lands and 70% increase in water bodies within the 20 years. Spatio-temporal analysis of the three imageries revealed that agricultural lands were largely been taken over by urbanization while vegetation had rapidly given way to bare lands within the 20 years. It was observed that these changes resulted from anthropogenic activities, environmental factors and climate change. These result in the loss of farmlands, inadequate food supply, unemployment, inadequate industrial raw materials, reduction in revenue generated, forest depletion, desertification, wildlife extinction and temperature increase. While it is recommended that reforestation, land reclamation and irrigation agriculture should be promoted in the area, it is also suggested that further research should focus on the impact of climate change on land cover change in the area.

Keywords: Dambatta; GIS; Land cover; Land use; Spatio-temporal changes

1. Introduction

Most often, land use and land cover are used interchangeably, however, there is a clear difference between them. Land cover refers to those things that cover part of the earth's surface like grassland and

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forest. Land use on the other hand refers to the manner in which the land is utilized. Land uses include activities such as wildlife management, agricultural practices, urbanization, recreation, etc. [1,2]. A given land use may take place on one, or more than one piece of land and several land uses may occur on the same piece of land [3]. Changes in land cover may occur when one type of land cover is totally replaced by another, while changes in land use may result from the modification of land cover types [4-6]. The predominant drivers of these scenarios include anthropogenic activities causing land subsidence, storms and sea level rise [7-10].

Remote sensing techniques and geographic information system (GIS) can be integrated into a single tool to perform different tasks including detecting land use and land cover changes [11-13]. Many researchers have studied the relationship between land surface temperature and land use/land cover NDVI using remote sensing and geographic information system (GIS). Amongst these, Campbell [14] studied the impact of urbanization on the thermal environment of the Bangkok Metropolitan Area. The study used normalized difference vegetation index (NDVI) to extract land use/land cover information from remote sensing images of different time periods and then analyzed the surface temperature retrieved from the thermal infrared band. The results showed that urban/built-up areas expanded dramatically with equally decreasing agricultural land. Moreover, temperature differences between the urban/built-up and the surrounding rural areas significantly widened. Similar studies with related results were conducted [15-20].

The use of remotely sensed data in the form of satellite imagery as a source of reliable information for surveying, classification, mapping and monitoring cannot be over-emphasized. Land use/cover mapping is one of the commonest uses of remotely sensed data. It has been extensively used in supervised image classification where a prior knowledge of all cover types to be mapped within the classified scene is assumed [1]. Other variants of supervised classification developed in recent years include decision trees [21-24]. It seems evident that when one knows what classes are desired and where they occur (at least a sample), supervised classification strategies are preferable. Due to its architecture, planting date, growing period and plant density, each crop has a unique spectral signature [1,25]. This is used during classification, crop identification and discrimination. In areas where land is scarce, the need to maintain food production with growing demand is achieved via technological changes in land use accomplishing higher returns per area of land [25]. In places of abundance, land conservation is the main strategy used. A better understanding of land use changes is essential to assess and predict its effects on ecosystems and society [26].

In Dambata LGA, it is revealed that the productivity of the land has declined by about 12% . This is mostly due to land degradation which translates to an economic loss of about ₦18 million [27,28]. It is the loss of agricultural land with consequent productivity reduction and economic loss that has necessitated this study. The study employed contemporary methods to detect and also analyze the rate of land use and land cover changes in the area. Thus, this research made use of land cover (LC) data of Dambatta LGA as it checked integrally, the spatial and temporal changes in land use and the rate of land cover change by analyzing the satellite images of 1997, 2007, and 2017 and also checking the vegetation dynamics within the study area. It is on this basis that the research work identified the spatio-temporal changes in land use and land cover (LULC) that occurred in Dambatta LGA between 1997 and 2017.

2. Materials and methods

2.1 Study area

Dambatta Local Government Area is positioned in the Northern part of Kano State. The approximate geographic location of the study area is between latitude 12°25'59" N and 12°30'00" N of the equator and longitude 8°30'00" E and 8°50'00" E of the Greenwich Meridian [27,28] (**Figure 1**). It has a total land area of 732 km^2 and lies within the "wet and dry"

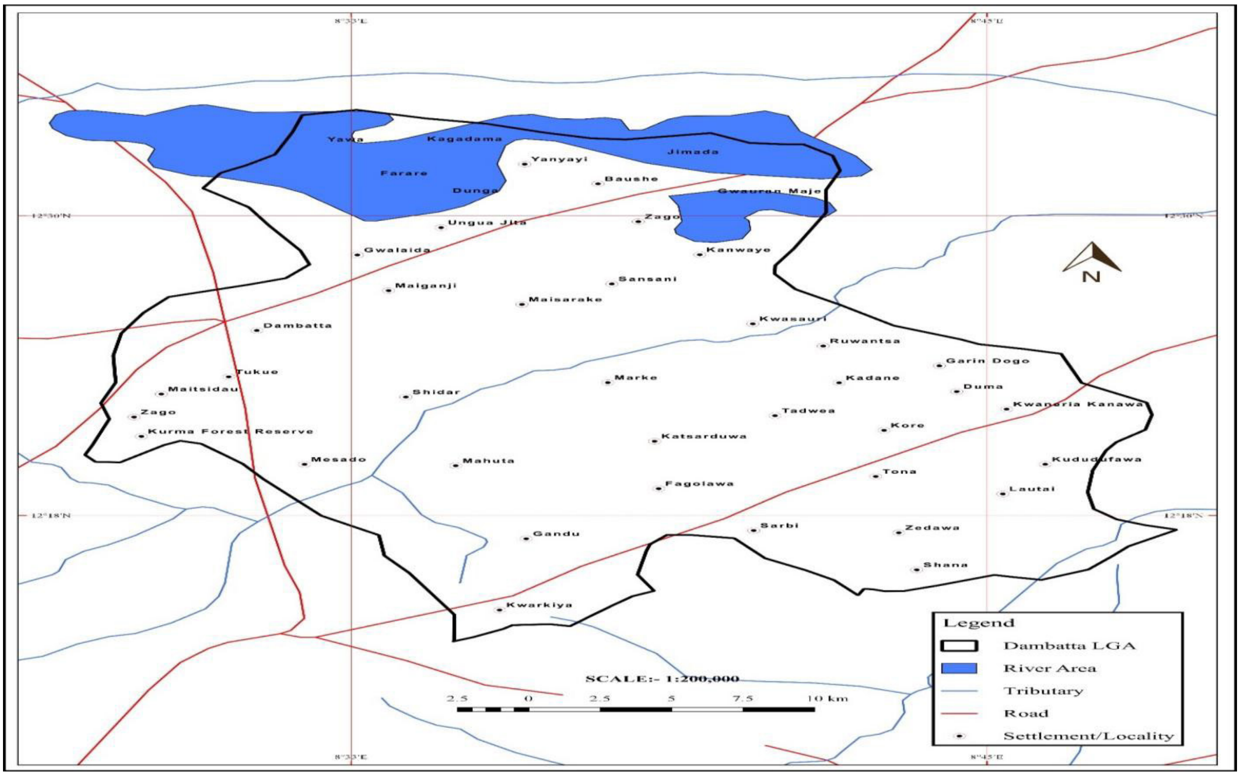

Figure 1. Dambatta LGA showing its localities.

Source: Researchers' field work.

climate with more dry months than wet months [29,30]. The climate of the study area is categorized under tropical savanna in Koppen's classification. The study area falls within the Sudan savannah as well as the chad formation underlain by sedimentary rocks of criterion origin. Agriculture forms the dominant land use.

2.2 Data collection techniques

The coordinates of the control points were obtained from a field survey using GPS device (GPSMap 76 CSx), while the spatial data was obtained from NASRDA, Abuja. These data sets were captured as shown in **Table 1**. Landsat imageries were chosen for this study because of their wider swath width which is required to display a larger area of Dambatta LGA in a single footprint. Hence, the number of footprints required for the study (per year) was reduced to two.

2.3 Image classification

A supervised classification procedure was used in the analysis of data. False color composites were developed for the individual images using three out of the respective bands in accordance with Jibril et al. [27,28]. These composites were used to separately classify 1997, 2007 and 2017 images. Sample sets were created for the individual land cover classes, using

Table 1. Landsat imageries for the study period.

Landsat imageries					
Sensor	Date	Resolution	Source	Path/Row	Satellite
MSS/TM	21st December, 1997	30 m	NARSDA	188/050 188/051	Landsat5
ETM+	4th November, 2007	30 m	NARSDA	188/050 188/051	Landsat7
OLI	24th November, 2017	30 m	NARSDA	188/050 188/051	Landsat8

Source: Authors' fieldwork (2018).

the 'create' icon on the sub-set image of the study area. The supervised approach was found useful in selecting the calibrated pixels. Training sets were cross-checked in the field to validate the various land cover classes for change detection assigned to each training sample set on the image. Thus, a classification scheme was developed for this research.

Subsequently, a maximum likelihood classifier (MLC) was used in this study because it uses a probability density function which enables it to accurately classify land cover categories that have residual ambiguity existing between overlapping classes in the measurement space. This ensured accurate classification in the analysis. Thus, the applied MLC in ILWIS academy software assumed that the image data exhibits normal distribution and thus, pixels should be made up of a single land use type. MLC allocates pixels in the image [31].

2.4 Accuracy assessment and field validation

The accuracy of classification is a function of the number of GCPs used for training. A useful rule of thumb is 30*n (n = number of bands) [32]. The rule was applied in this study and sampling was done using stratified random technique on the LC maps. The accuracy of the classification exercise was measured by analyzing both *commission* and *omission* errors that were supposed to have occurred during image classification. Out of the 700 GCPs, 400 were used for the accuracy assessment. It was assessed for each land cover type separately using an accuracy index (AI) that incorporated both omission and commission error into a single summary value: AI = ((n-o-c)/n) × 100.

2.5 Data analysis

Data processing was conducted using post-classification change detection technique in Integrated Land and Water Information System ILWIS 5.2, and later converted to shape files which was imported to Arc Map 10.2 GIS software. Landsat images of 30 metres resolution covering the study area in 1997, 2007, and 2017 were used for land cover classification to identify the spatio-temporal changes in land use (LU) land cover (LC) of Dambatta LGA between 1997-2017. Finally, descriptive statistical tools were used to analyze the spatio-temporal changes identified.

3. Results

The results of the analyses were corroborated by the ground truthing exercise and the satellite images of 1997, 2007, and 2017. Consequently, some maps were achieved and illustrated with Landsat MSS as of 1997, Landsat ETM+ as of 2007 and Landsat OLI as of 2017 respectively (**Figure 2**). **Figure 2** also shows the standard color code used to represent the five (5) LU LC classes. The green color represents agricultural land and the light green represents vegetation cover. The brown color represents a developed area, the milk color represents bare land while blue represents the water body.

3.1 Temporal analysis of land use land cover change in Dambatta LGA between 1997 and 2017

Land use (LU) land cover (LC) levels in Damnatta LGA in 1997

The agricultural land as at 1997 covered an estimate of about 51.7% of the lands in the area which was the highest spatial coverage, followed by vegetation cover at about 27.5%, developed area covered about 13.5%, bare land stood at 5.7%; while water body took 1.3% of the total land area (**Table 2**). This implies that, as at 1997, the level of anthropogenic disturbance in Dambatta LGA was minimal, and land degradation was very low with abundant agricultural farmlands and vegetation cover in virtually all corners of the LGA as shown by the statistical distribution of LU/LC. This, however, is an estimate and therefore not very suitable for conclusions, generalizations and decision making. A confusion matrix was created and used to assess the accuracy of image classification (**Table 3**).

It should be noted that, during classification, one-pixel value can enter another. Therefore, no image classification can be 100% accurate. This is why **Table 4** was created to establish the accuracy or oth-

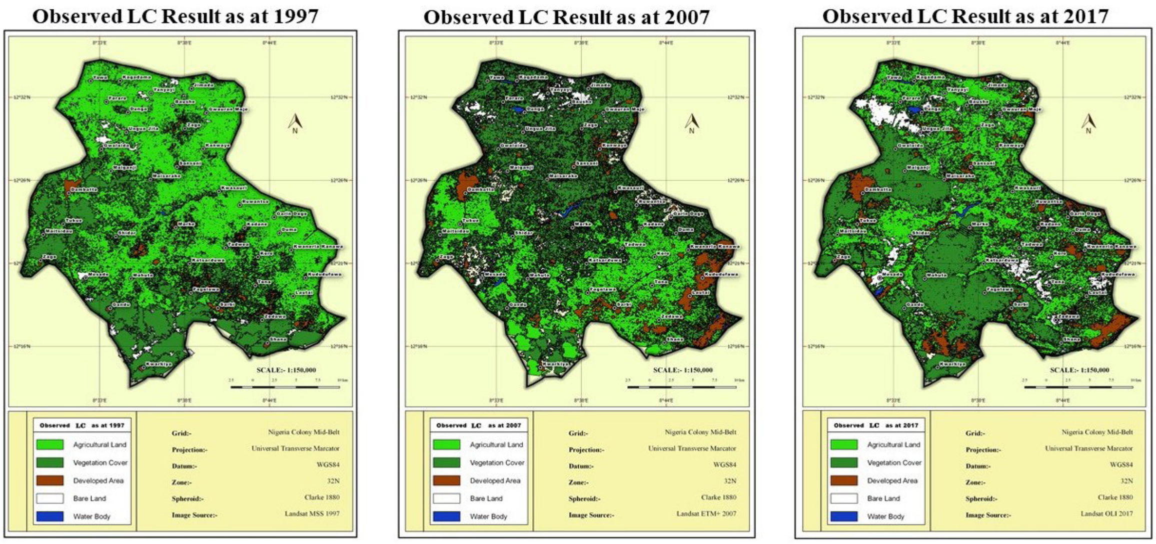

Figure 2. Land cover changes in Dambatta LGA between 1997-2017.

Source: Authors' fieldwork (2018).

erwise of the classification.

The diagonal columns in **Table 3** were added to obtain 340. The rows and columns numbers were also summed up to obtain 400. Therefore, the overall accuracy was computed as (340/400 × 100) 85%. This level of accuracy is indicative of an effective classification result. This method was repeated for 2007 and 2017 image classification.

Table 2. Estimated LU/LC distribution as of 1997.

S/No	LC observed	1997(km^2)	%
1	Agricultural land	379	51.7
2	Vegetation cover	202	27.5
3	Developed area	99	13.5
4	Bare land	42	5.7
5	Water body	10	1.3
	Total	732	100

Source: Authors' fieldwork (2018).

Land use (LU) land cover (LC) change in Dambatta LGA between 1997 and 2007

The land cover distribution as spatially displayed in **Figure 2** was represented in percentages in **Table 5**. The geospatial analysis of the classified Landsat ETM + image as at 2007 shows that vegetation cover occupied 25.1% of the total land in the study area. This was followed by agricultural land at about 24.5%, developed area had increased significantly to 33.4%, bare land had also increased to 13.7% while water body covered 3% of the total land mass as at 2007.

It was also observed that within a period of 10 years (1997 to 2007), agricultural land had decreased significantly by over 50%, while vegetal cover decreased by 10%. Developed area and bare land have increased by 147% and 140% respectively. This

Table 3. Error (confusion) matrix for landsat MSS 1997.

Classified data	Referenced data					
	Agricultural land	Vegetation cover	Developed area	Bare land	Water body	Total
Agricultural land	**182**	5	0	1	2	**190**
Vegetation cover	5	**42**	1	1	1	**50**
Developed area	4	10	**50**	6	0	**70**
Bare land	9	4	1	**31**	0	**45**
Water body	7	3	0	0	**35**	**45**
Total	**207**	**64**	**52**	**39**	**38**	**400**

Source: Authors' fieldwork (2018).

Table 4. Accuracy assessment for landsat MSS 1997.

Class name	Producer's accuracy	User's accuracy
Agricultural land	95.7%	87.9%
Vegetation cover	84%	65.6%
Developed area	68.8%	96.1%
Bare land	71.1%	79.4%
Water body	77.7%	92.1%
Overall accuracy	85%	

Source: Authors' fieldwork (2018).

Table 5. Land cover distribution as of 2007.

S/NO	LC observed	2007 (km^2)	Percentage (%)
1	Agricultural land	180	24.5
2	Vegetation cover	184	25.1
3	Developed area	245	33.4
4	Bare land	101	13.7
5	Water body	22	3.0
Total	732		100

Source: Authors' fieldwork (2018).

depicts that agricultural land and vegetal cover are giving way for built-up areas and bare lands.

It could be deduced from the observations that built-up areas are increasing obviously as a result of anthropogenic activities, while bare lands could be increasing as a result of anthropogenic activities or environmental factors like drought, less rainfall, wind and temperature. This, however, is an estimation based on observation. **Table 6** reveals the quality of the digital classification of the landsat imagery of the study area as at 2007. Producer's accuracy vis-à-vis user's accuracy was employed to arrive at the overall accuracy to ascertain the strength of the classification. Therefore, the overall accuracy of 93.7% was computed. This level of accuracy is indicative of an effective classification result (**Table 7**).

Land use (LU) land cover (LC) change in Dambatta LGA between 2007 and 2017

Supervised classification was also carried out on the Landsat OLI satellite image of 2017 as shown in **Figure 2**. The spatial distribution of land cover features resulting from the supervised classification of Landsat OLI satellite image of 2017 is shown in **Table 8**. On the basis of the digital image classification of Dambatta LGA as of 2017, bare land has increased progressively over time alongside built-up areas, while agricultural land and natural vegetation cover have continuously decreased over time. The implication of this result is that anthropogenic activities and environmental factors like drought, less rainfall, wind and temperature have increased over time and have affected vegetal cover in the environment leading to an increase in bare land and a consequential effect of land degradation. This has further led to a reduction in agricultural land. The accuracy assessment of the 2017 Landsat OLI satellite image computed is 83.25% (See **Tables 9 and 10**). This result is indicative of an accurate and effective classification process.

Table 6. Error (confusion) matrix for landsat ETM + 2007.

Classified data	Referenced data					
	Agricultural land	Vegetation cover	Developed area	Bare land	Water body	Total
Agricultural land	**90**	8	0	1	1	**100**
Vegetation cover	5	**68**	1	1	1	**76**
Developed area	0	2	**20**	0	0	**22**
Bare land	0	2	0	**99**	1	**102**
Water body	1	1	0	0	**98**	**100**
Total	**96**	**81**	**21**	**101**	**101**	**400**

Source: Authors' fieldwork (2018).

Table 7. Accuracy assessment for landsat ETM + 2007.

Class name	Producer's accuracy	User's accuracy
Agricultural land	90.0%	93.7%
Vegetation cover	89.4%	83.9%
Developed area	90.9%	95.2%
Bare land	97.0%	98.0%
Water body	98.0%	97.0%
Overall accuracy	93.7%	

Source: Authors' fieldwork (2018).

Table 8. Land cover distribution as of 2017.

S/NO	LC observed	2017 (km^2)	Percentage (93.7%)
1	Agricultural land	130	17.7
2	Vegetation cover	110	15.0
3	Developed area	320	43.7
4	Bare land	155	21.1
5	Water body	17	2.3
Total	732		100

Source: Authors' fieldwork (2018).

3.2 Spatial analysis of land use land cover change in Danbatta LGA between 1997 and 2017

Table 2 shows that Dambatta LGA had 732 km^2 of land in 1997. It also presents the result of spatial variation and distribution of land use land cover categories within the spatio-temporal frame from 1997 to 2017. **Table 11** shows that bare land and built-up areas witnessed remarkable increase which were also concentrated at the western and eastern parts (**Figure 2**). While bare lands occupied 5.7% of the land area in 1997, 13.7% in 2007 and 21.1% in 2017, built up areas had 13.5% of the total land area in 1997, 33.4% in 2007 and 43.7% in 2017 (**Table 12**). This means that bare lands had positive change differentials of 8% between 1997 and 2007, and 7.4% between 2007 and 2017. The built-up areas on the other hand had positive change differentials of 19.9% between 1997 and 2007 and 10.3% between 2007 and 2017. Generally, bare lands had increased by 269.1%, built-up areas had increased by 223.2%, and water bodies had increased by 70% within the 20 years. The implication is that the bare lands and built-up areas were increasing continuously throughout the period of the study. The increase in both bare lands and developed areas is not concentrated in one part of the area. The proportion covered by bare lands and built-up areas increased northwards of the southern part of the area and southwards of the northern part with few concentrations in the centre of the area (**Figure 2**). Very few water bodies were found around the central region of the imageries in 1997. A few more channels of water were found around the western, north western and south eastern regions besides the initial streams of the central region in 2007. The waters of the south western part of the land, however, disappeared in 2017. Thus, the water bodies in the area appear to be increasing and decreasing from 1997 to 2017.

Table 9. Error (confusion) matrix for landsat OLI 2017.

Classified data	Referenced data					
	Agricultural land	Vegetation cover	Developed area	Bare land	Water body	Total
Agricultural land	**80**	20	2	5	3	**110**
Vegetation cover	10	**40**	1	1	3	**55**
Developed area	0	8	**89**	3	0	**100**
Bare land	2	8	1	**39**	0	**50**
Water body	0	0	0	0	**85**	**85**
Total	**92**	**76**	**93**	**48**	**91**	**400**

Source: Authors' fieldwork (2018).

Table 10. Accuracy assessment for landsat OLI 2017.

Class name	Producer's accuracy	User's accuracy
Agricultural land	72.7%	86.9%
Vegetation cover	72.7%	52.6%
Developed area	89.0%	95.6%
Bare land	78.0%	78.0%
Water body	100%	100%
Overall accuracy	83.25%	

Source: Author's fieldwork (2018).

Agricultural land and vegetation cover decreased significantly over the period of study and were scattered around the study area. Agricultural lands occupied 51.7% of the total land area in 1997, 24.5% in 2017 and 17.7% in 2017 while vegetation cover had 27.5% in 1997, 25% in 2007 and 15% in 2017 (**Table 12**). The water bodies in the local government area took 1.3% of the total land area in 1997, 3.0% in 2007 and 2.3% in 2017. The comparison of the three satellite imageries (1997, 2007 and 2017) revealed a variation in the pattern of land cover. In 2007, the proportion covered by bare land increased southward of the northern area and northward of southern axis with few concentrations at the center when compared to 1997 with just a few scattered bare lands and more of vegetation cover with agricultural land (**Figure 2**). Less vegetation and agricultural land were visible in 2007 and the vegetation located in the northern and southern area of the study area had been lost to bare land and built-up area in 2007. In 2017, the area covered by vegetation decreased in both axis of the study area when compared to 2007. Generally, agricultural lands reduced by 66.8% and vegetation cover reduced by 45.5% within the 20 years.

4. Discussion

The spatio-temporal analysis reveals a number of changes. Initially (1997), the proportions of the land area were used in order of magnitude between agriculture, vegetation, urbanization, bare lands and water bodies. However, the year 2007 had a remarkable change, bringing the order to developed areas, vegetation, agricultural land, bare lands and water bodies. It means that development in the area had rapidly taken away almost half of the agricultural lands between 1997 and 2007. For example, the agricultural land left for cultivation is not enough to

Table 11. Land cover changes in Dambatta LGA between 1997-2017.

LULC types	1997 (km^2)	2007 (km^2)	2017 (km^2)	Changed area (km^2) 1997-2007	Changed area (km^2) 2007-2017	Overall change (km^2) 1997-2017
Agricultural land	379	180	130	–199	–50	–249
Vegetation cover	202	184	110	–18	–74	–92
Developed area	99	245	320	+146	+75	+221
Bare land	42	101	155	+59	+54	+113
Water body	10	22	17	+12	–5	+7

Source: Authors' fieldwork (2018).

Table 12. Percentage of land cover changes in Dambatta LGA between 1997-2017.

LC types	1997 (km^2)	%	2007 (km^2)	%	2017 (km^2)	%
Agricultural land	379	51.7	180	24.5	130	17.7
Vegetation cover	202	27.5	184	25	110	15.0
Developed area	99	13.5	245	33.4	320	43.7
Bare land	42	5.7	101	13.7	155	21.1
Water body	10	1.3	22	3.0	17	2.3
Total	732	100	732	100	732	100

Source: Author's wield work (2018).

produce food in quantities that are enough to feed all the people in the study area. The implication of this result is that most people in the area may partly depend on imported food for survival. This may result in famine due to the economic status of the people. Furthermore, the reduction in agricultural land has negative economic implications for the populace. A greater number of farmers would have been left jobless. The government would also record a huge reduction in revenue generated from the sale of farm produce. Industries that depend on agricultural products as raw materials for their products would rather have to import such raw materials in the midst of the scarcity created by agricultural land inadequacy. This will lead to a consequent rise in the prices of products in the market.

In 2017, there were still further changes, bringing the order to developed areas, bare lands, agriculyural land, vegetation and water bodies. This time, bare lands had taken over the lands previously occupied by vegetation cover. The implication is that the land has been exposed to erosion and its attendant consequences. This explains why there is much land left unoccupied in the midst of rapid development. Sand mining for building activities would have also exposed the land to erosion leaving a large portion of the land almost useless. In fact, continuous erosion on the exposed soil surfaces is more likely to displace settlers on such lands. Loss of vegetation cover implies loss of timber, wildlife, fire wood, medicine, employment and increased temperature. The loss of vegetal cover and developed areas are likely to generate high temperatures which can promote climate change. This is likely to be the reason why the rivers and streams in the area continue to increase and decrease over the years.

5. Conclusions

The study showed evidence of changes between 1997 and 2017. Spatiotemporal analysis of the three imageries showed that agricultural lands were largely been taken over by urbanization while vegetation areas had rapidly given way to bare lands. The study reached the conclusion that these changes are evident in almost all parts of Danbatta Local Government area, especially the northwestern, central and south eastern parts.

The strong and consistent occurrence of the changes is most likely due to anthropogenic activities like deforestation, urbanization, and environmental factors like drought, less rainfall, wind, temperature, erosion and climate change consequently. These results no doubt have negative implications for farmers, ruler dwellers, urban development boards, forest reserves and other policy-makers. This paper, therefore, suggests that further research should be conducted focusing on the impact of climate change on land cover change in the area. It also suggests that reforestation; land reclamation and irrigation agriculture should be promoted in the area.

Author Contributions

David Sesugh Aule: Besides serving as the corresponding author, David Sesugh Aule performed the analysis, wrote the abstract and introduction. He also did much of the discussion ensuring the application of the results to the study area in various ways.

Mamman Saba Jibril: Mamman Saba Jibril performed the supervisory role. He guided the ideas that culminated in the production of this paper from the beginning to the end. The methodology of this publication is his brainchild entirely.

Ali Husein Idris: Ali Husein Idris worked on data collection, processing and spatial analysis. He also produced the maps that are used in this study.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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