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A MULTI-SPECTRAL ASSESSMENT OF SUB-SAHARAN COVER CHANGE IN GEIDAM LOCAL GOVERNMENT AREA (LGA), YOBE STATE, NIGERIA

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ABSTRACT

Ecological degradation is an environmental challenge faced across the globe. Mitigation strategies are vital in any attempt to understand and regulate the process of land surface degradation. The study conducted a land use/cover assessment using multi-spectral datasets. The study adopted datasets from the Landsat programme as it provides an extensive platform for evaluating the effects of land degradation for Geidam LGA, Yobe State. To achieve the study objectives, the indices - land use, land cover and normalized difference vegetation index were extracted and assessed over 12 years. The assessment, at six 6 years interval, was based on the raster-based classification technique and certified Kappa statistics. Five classification schemes namely; bare land, built up, riparian, vegetation and water-body, were identified in the study area. The result revealed that the bare land rose from 8.52% – 46.89%; built-up covered 0.71% - 1.14%; riparian reduced from 40.37% - 24.50%; vegetation also reduced from 50.08% - 27.33% and finally waterbody 0.32% - 0.14%. The values indicate that the rate of desertification is high in vegetation and non-vegetation areas of the study area. The Normalized Difference Vegetation Index (NDVI) values for the study area revealed a disturbing desertification rate, that is, 6.82 per cent of the study area per year. These results show that the desertification is a driving force to the rapid decline of the study area ecosystem. The study recommends policymakers to advocate environmental enlightenment and campaign on the need for sustainable green vegetation planting.

Keywords: Environment; Land Use Land Cover (LULC) change; NDVI; Desertification; Geidam LGA

1. INTRODUCTION

Global policymakers continue to report the unregulated change in land cover change as an environmental threat (Lamqadem et al., 2018). The unregulated change in land cover is described as a threat peculiar to the arid, semiarid and dry sub-humid regions of the earth surface, due to environmental attenuations such as climatic disparities and anthropogenic actions (UNCCD, 2011).

The change analysis of any territorial land cover remains an active variable when evaluating the temporal interaction of natural/anthropogenic activities as they affect the earth surface (Brown et al., 2018). Desertification is one key activity that stretches the already less sufficient natural resources stand and climatic conditions of any sub-Saharan territory (Mohammed et al., 2018).

The United Nations Convention to Combat Desertification (UNCCD) has identified desertification that is described as the degradation of the land surface resulting from natural and anthropogenic activities, in arid, semi-arid and dry sub-humid regions (UNCCD, 2011). It has been established that the rate and change of desertification within any territory, does affect the available natural resources, its social-economic value, and most importantly the lives of the inhabitants (Oswald and Harris, 2016). Studies have established that regions with exposed topsoil over an extended time epoch are a good intermediary for desertification as a result of the unprotected topsoil is usually at risk to the incidence of severe environmental factors (Helldén, 2008).

Desertification is a form of land degradation and also a global phenomenon that is greatly affecting developing cities/regions with limited resources/strategy (Zemba et al., 2018). It is a key adverse contributor to environmental sustainability indicators such as poverty alleviation, malnutrition/food security (Azua et al., 2019). The process of desertification on any land cover continues to generate heightening concerns in drylands across the globe especially across sub-Saharan cities (Joseph et al., 2018). In most sub-Saharan cities, desertification remains an urgent environmental challenge (Ikeke, 2016, Umar et al., 2018). Additionally, the procedure to guide policy responses across these cities are limited due to the ambiguity that results from the processes involved (Mohammed et al., 2018). It is reported that cities across the northern region of Nigeria are affected by desertification to a tune of 50 – 75 per cent (Elazeh and Kabara, 2013). With the consensus that land degradation resulting from desertification is a major environmental challenge in the sub-Saharan parts of Nigeria. This effect of desertification continues to escalate the damage to natural resources with 60 per cent of the northern Nigerian states, suffering an estimated loss of $5.1 billion per year due to the effects of desertification (Joseph et al., 2018).

With rising human activities and climatic variables (rainfall, soil moisture and temperature) contributing to land degradation (desertification), there is a continuous need for research to seek for evidence that would assist in the monitoring/decision-making of the land cover changes over drylands for a sustainable ecosystem (Du et al., 2016; Tomasella et al., 2018). An effective approach to monitoring the rate and change of land desertification is the utilization of satellite remote sensing technology and geo-information systems for mapping desertification effects using verified classification techniques from spectral indices (Afrasinei et al., 2017; Lamqadem et al., 2018). Satellite-based measurements are presently being utilized for studying environmental hazards across territories with limited ground datasets (Aliyu and Botai, 2018).

The process of conducting land degradation surveillance within an ecologically sensitive environment is vital for risk assessment of land use land cover (LULC) that would aid spatial planning approaches (Higginbottom et al., 2018). Over the last decade, studies on desertification assessment have and are still utilizing the Landsat datasets, that includes the enhanced thematic mapper plus (ETM+) and the operational land imager (OLI) satellite images, as their data source for land degradation monitoring (Xu et al., 2009; Duan et al., 2019, among others). One of the main indicators that are utilized for desertification monitoring is the normalized difference vegetation index (NDVI). The NDVI evaluates desertification through trends-based relationships between land cover and the vegetation chlorophyll density (Higginbottom and Symeonakis, 2014; Tomasella et al., 2018). This can be achieved through mapping the land cover to understand changes within an ecologically sensitive environment is key to identifying, evaluating, and understanding the areas at risk (Lamchin et al., 2016).

In Nigeria, studies continue to report a rising trend of desertification across the sub-Saharan region of northern Nigeria (Gadiga and Dan, 2015; Ikeke, 2016; Elijah et al., 2017). In Yobe State, the causes of desertification are steady instigating an increased frequency of drought, thus, posing a challenge to territorial/ regional climate change. It is for this reason that this study aims to utilize multispectral datasets to understand the 21^{st}-century land cover dynamics on habitable land to evaluate the desertification effects in a sub-Saharan city of Nigeria. The study objectives are: (a) identify existing land cover classes within the study area, (b) determine the trend of desertification based on the extent of the identified land cover classes over the study period (c) evaluate the extent of land degradation based on the vegetation variable.

2. STUDY AREA

The study area is Geidam Local Government Area (LGA) of Yobe State, northern Nigeria. It is largely a sub-Saharan (desert) area whose terrain is depicted in Figure 1 below. It is situated within the approximate geographical coordinates' ranging from longitudes 11^{o}26'20" - 12^{o} 37' 80" and latitudes 12^{o} 25'30'' - 12^{0} 56' 15''. The study area has an approximate size of 4,356.6 km² and a projected 2014 population of 207, 127 based on the 2006 national provisional results with the state-specific growth-rate (NPC, 2010). The climate of the sub-Saharan locale is mainly hot and dry for most of the year. It exhibits a high annual range of mean monthly temperatures (33.5°C). The reported peak temperature (about 42°C) is experienced around April and the least temperature measurements (about 15.1°C) recorded in January. The peak rainfall is around August every year. Majority of the population are small-scale farmers, that produce food grain such as maize, millet etc. The minority of the population engaged in other forms of agricultural practices such as poultry farming, animal husbandry and fish farming, Non-agricultural occupations within the study area include black-smith, hunting, dying, weaving etc. (Musa, 2012; Mustapha, 2017; Eze, 2018).

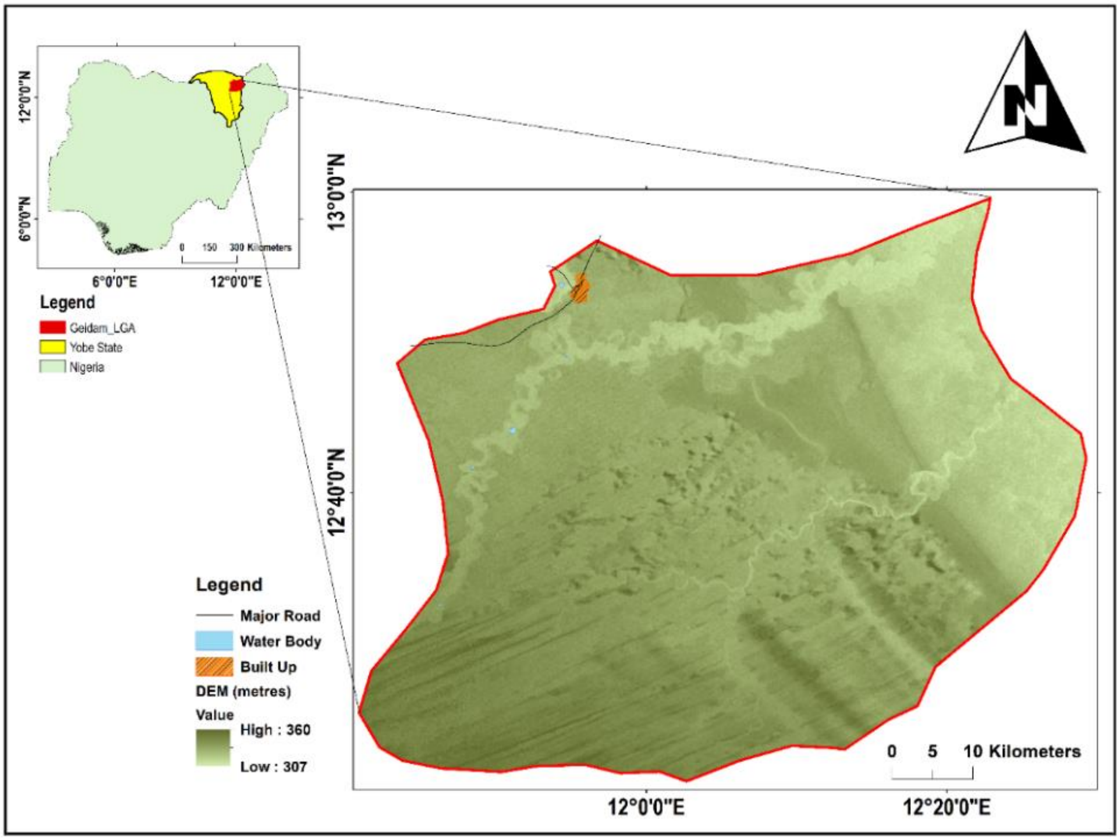

Figure 1. Digital Elevation Model of the Geidam LGA

3. METHODOLOGY

3.1 Study Datasets

The study utilized Landsat satellite datasets from the United States Geological Survey (USGS) website (Loveland and Dwyer, 2012), for the period 2003 to 2015 at 6 years interval (Table 1). For consistency and reliability of study analysis, cloud cover over image tiles was limited to less than 10 per cent and also the rainy season was adopted. This is because the rainy season will improve the evaluation that might the skewed as a result of the sub-Saharan terrain of the study locale. To evaluate the relationship between the LULC change and climatic variable (air temperature) collected at 2-m above ground level (Meng and Dou,

2016) from the National Centres for Environmental Prediction (NCEP) website was utilized for the study epoch of interest.

Table 1. Description of Landsat Datasets

S/N	Instrument	Path/Row	Data Date	Bands Stacked	Band Utilized
1	Landsat 7 ETM+	189/51	21 July 2003	1 - 8	Bands 3 / 4 (NDVI)
2	Landsat 7 ETM+	189/51	05 July 2009	1 - 8	Bands 3 / 4 (NDVI)
3	Landsat 8 (OLI)	189/51	28 June 2015	1 - 9	Bands 4 / 5 (NDVI)

The software utilized for this study is QGIS v2.18, Erdas Imagine v9.2, ArcGIS v10.3.

The framework of the methodology is illustrated in Figure 2.

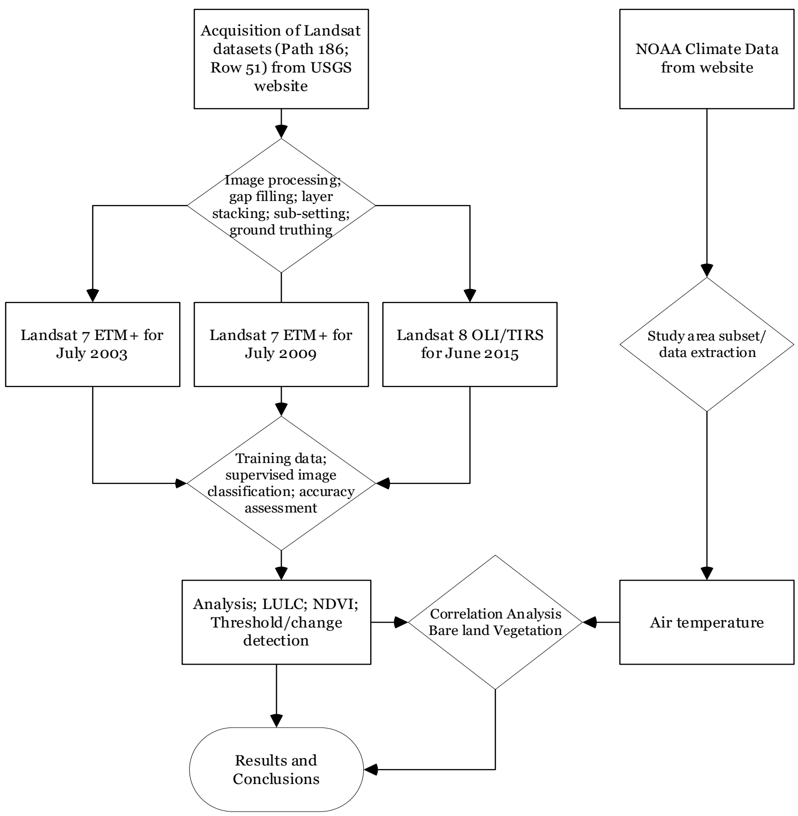

Figure 2. Study flow diagram

3.2 Dataset Processing and Study Analysis

Prior to the study analysis, datasets obtained from the Landsat 7 ETM+ instrument were gap filled to compensate for the scan line corrector off (SLC-off). Preliminary visual enhancements procedure was adopted to identify the extent of gap fill for the Landsat 7 ETM+ image(s) Scan Line Corrector (SLC) failure. A comprehensive gap-filling procedure was achieved in the QGIS version 2.18 software based on the vetted Semi-automatic Classification Plugin (SCP). This can be achieved through the conversion of image digital numbers to the top of atmosphere reflectance, as described in Yulianto et al. (2016). The need for the gap-filling procedure is as a result of the unfortunate failure of the Landsat 7 ETM+ scan line corrector (SLC) in May 2003. Various studies have acknowledged the SLC correction procedure (Vuolo et al., 2017; Obodai et al., 2019). Secondly, the multiple bands for the Landsat imageries were layer-stacked using the Erdas Imagine version 9.2 software. For the Landsat 7 ETM+, the 8 bands were layer-stacked while for Landsat 8 OLI, the 9 bands were layer-stacked. After the gap-filling and layer-stacking procedures, the study area (Geidam LGA) was subsetted using ArcGIS version 10.3 software.

Five LULC schemes were identified for the LULC analysis (Table 2 below) with emphasis on the rule-based feature extraction method. The LULC schemes adopted include bare land, built up, riparian, vegetation and water body. From these schemes, the training data were identified into the signature editor for the process of supervised classification using Erdas Imagine version 9.2. The supervised classification of the subsetted study satellite imageries (2003, 2009 and 2015) was utilized to identify the pattern of land use/land cover (LULC) over the study area with recommended accuracy (error/confusion matrix) assessment. Figure 2 describes the study workflow.

To evaluate the relationship between the LULC change and ground air temperature, a correlation analysis of the LULC climate significantly dependent variables (bare land and vegetation) were analysed with the processed collocating mean air temperature collected at 2-m above ground level.

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Table 2. The Study LULC scheme (modified Ibitoye et al., 2016)

Classes	Sub-class	Description
Bare Land	Bare ground; dry mud surface; dunes; cultivated land	Bare ground; dry clay; all types of dunes; harvested farmlands
Built-Up	Residential; commercial; and all types of settlements	All types of buildings
Riparian	Vegetation close to a water body	Vegetation situated close to a water body, flood plains and wetlands
Vegetation	Trees; shrubs; grass and grazing areas	All type of trees, shrubs, grass and grazing areas.
Water Body	River; lake; pond	A stream or standing body of water

The Landsat 7 ETM+ and Landsat 8 OLI data were used to evaluate the changes in the land use/land cover (LULC) types. Additionally, the Normalized Difference Vegetation Index (NDVI) was derived for the different epochs. This is to identify the rate of change on the NDVI properties over the study period. The NDVI can be obtained through the relationship between the reflectance (ρ) of the Near-infrared (NIR) and red (R) bands. This is illustrated with Equation 1 below (Tomasella et al., 2018).

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

4. RESULTS

4.1 Classification Accuracy Assessment

The accuracy of the classified Landsat imageries (the year 2003, 2009 and 2015) was obtained using computational statistics to derive the error matrix (i.e. user accuracy, producer accuracy, overall accuracy and Kappa coefficient), errors of commission/omission for the classification schemes, based on Congalton and Green (2019).

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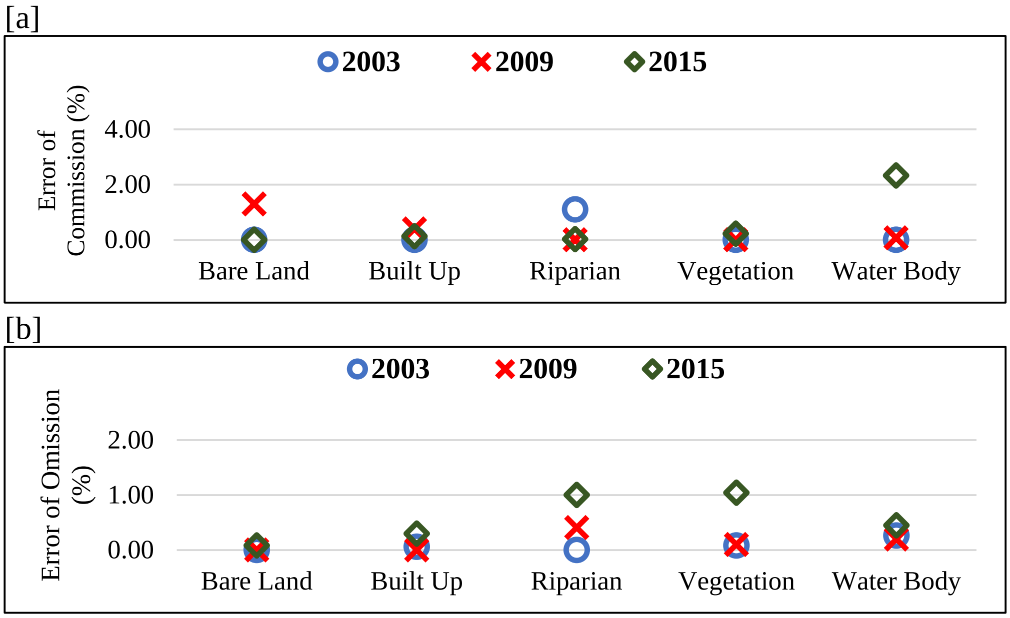

Figure 3. The classification scheme error of commission (a), errors of omission (b) for the year 2003, 2009 and 2015

The error of omission is achieved when any of the classified scheme pixels is omitted out of their true class, while the errors of commission represent any particular classified pixel that has been inappropriately captured under a different classification scheme. To achieve this process, ninety (90) stratified random points were identified for the generation of the reference points. Figure 3 illustrates the generated percentage error of commission (Fig. 3a) and percentage error of omission (Fig. 3b) while Table 3 highlights the error matrix for the Landsat study datasets.

Table 3. The confusion matrices of the Landsat classification scheme

Reference Data for July 2003							
Classified data	Bare Land	Built-Up	Riparian	Vegetation	Water Body	Total	User Accuracy (%)
Bare Land	**15**	0	0	0	0	15	100.00
Built-Up	2	**11**	0	0	0	13	84.62
Riparian	0	0	**12**	1	2	15	80.00
Vegetation	1	1	2	**29**	0	33	87.88
Water Body	0	0	1	0	**13**	14	92.86
Total	18	12	15	30	15	**90**	
Producer Accuracy (%)	83.33	91.67	80.00	96.67	86.67		

Overall Accuracy = 88.89%; Kappa coefficient = 0.84

Reference Data for July 2009

Classified data	Bare Land	Built-Up	Riparian	Vegetation	Water Body	Total	User Accuracy (%)
Bare Land	**21**	2	0	0	0	23	91.30
Built-Up	1	**13**	0	0	0	14	92.86
Riparian	1	0	**14**	1	1	17	82.35
Vegetation	0	0	1	**19**	0	20	95.00
Water Body	0	0	1	1	**14**	16	87.50
Total	23	15	16	21	15	**90**	
Producer Accuracy (%)	91.30	86.67	87.50	90.48	93.33		

Overall Accuracy = 89.99%; Kappa coefficient = 0.84

Reference Data for June 2015

Classified data	Bare Land	Built-Up	Riparian	Vegetation	Water Body	Total	User Accuracy (%)
Bare Land	**31**	1	0	0	0	32	96.88
Built-Up	3	**16**	0	0	0	19	84.21
Riparian	0	0	**11**	1	1	13	84.61
Vegetation	1	1	1	**9**	0	12	75.00
Water Body	1	0	3	1	**9**	14	64.29
Total	36	18	15	11	10	**90**	
Producer Accuracy (%)	86.11	88.89	73.33	81.82	90.00		

Overall Accuracy = 84.44%; Kappa coefficient = 0.81

From Table 2, the results indicate that the interval of the computed Kappa coefficient, ($K \geq 0.81$), indicates that the classification scheme procedure recorded strong agreement/accuracy between the classified map and the stratified points utilized. Additionally, the overall accuracy reached 88.89%, 89.99% and 84.44% for 2003, 2009 and 2015 Landsat data classifications. These statistics are similar to Kappa-coefficients reported in Bosquilia et al., (2018); Deng et al. (2019).

4.2 Land Use Land Cover (LULC) Evaluation

The LULC was derived with less 10% cloud-cover parameter on the Landsat 7 ETM+ and Landsat 8 OLI instruments using raster-based classification technique. The five-classification scheme was identified for the years 2003, 2009 and 2015. From Table 3, it can be seen that the water body represented the least all through the study period. The predominant LULC as of 2003 was vegetation. It comprised of 50.08% of the total area. In 2009, there is an increase for all the identified classification schemes except for vegetation. The trend of increase/decrease of the LULC can be seen in Table 4.

Table 4. LULC distribution of the study area

LULC	2003		2009		2015	
	Area (Ha)	**%**	**Area (Ha)**	**%**	**Area (Ha)**	**%**
Bare land	37099.77	8.52	65814.08	15.11	204282.57	46.89
Built-up	3078.38	0.71	4370.08	1.00	4980.77	1.14
Riparian	175882.69	40.37	204071.20	46.84	106730.31	24.50
Vegetation	218213.65	50.08	159887.60	36.70	119063.92	27.33
Water body	1381.66	0.32	1513.19	0.35	598.58	0.14
TOTAL	**435656.15**	**100.00**	**435656.15**	**100.00**	**435656.15**	**100.00**

5. DISCUSSIONS

From Table 4, the result shows that the trend of the built-up area increased by 40.99% to 2009. This could be due to anthropogenic factors most especially population increase. However, the increase of built-up from 2009 – 2015 revealed 14.76%.

For bare land, the study analysis shows a sizeable increase (77.68 per cent) from the year 2003 – 2009. This increase tripled from the year 2009 – 2015 by 210.39%. The average LULC variations for the 12-year study period (2003 - 2015) shows that bare land increased at 13,931.19 hectares per year; built up increased at 158.53 hectares per year; riparian reduced at 5762.70 hectares per year; vegetation reduced at 8262.48 hectares per year and water body reduced at 65.26 hectares per year. This analysis dictates the alarming rate of desertification over the study area.

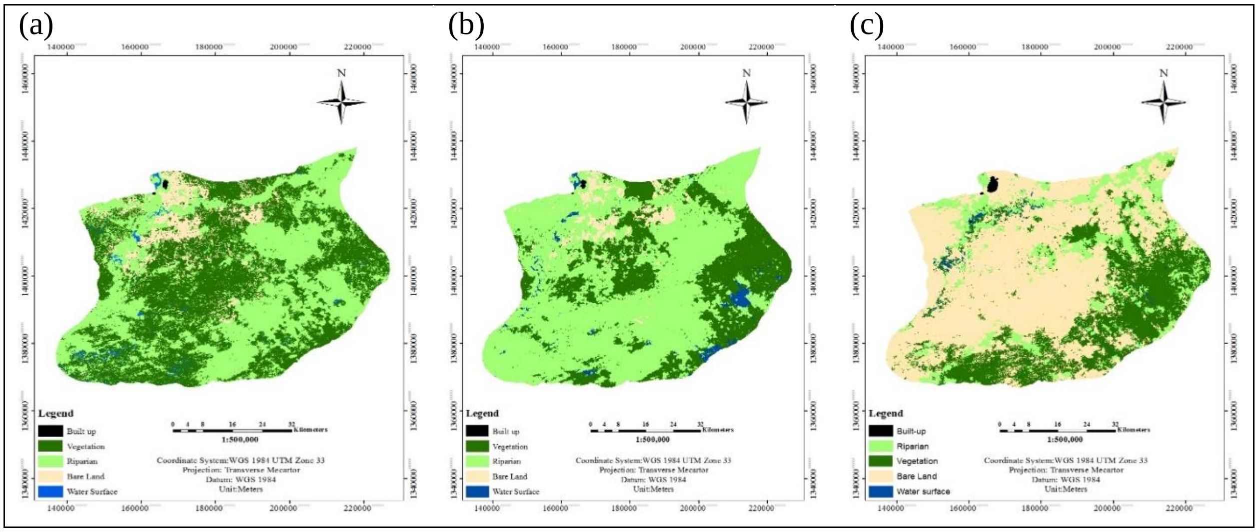

Figure 4. LULC changes of the study area (a) Year 2003 (b) Year 2009 (c) Year 2015

By the year 2015, key agricultural-related LULC variables (riparian, vegetation and waterbody) had faced drastic reduction when compared to the other classification schemes utilized for the study area. Riparian, vegetation and waterbody did reduce by 64.79%, 83.27% and 130.82% respectively. This is further illustrated in Figure 4.

5.1 LULC Interconversion

The LULC interconversion is presented in Figure 5. Figure 5 reveals the gains and losses that occurred between the epoch periods (2003 - 2009), (2009 - 2015) and (2003 - 2015) in hectares. A significant change occurred with the riparian and vegetation classes across the periods. These cover categories lost more land area than they gained in the period. From Figure 5a, it can be observed that there is a significant change that affected the LULC (riparian and vegetation), which are key drivers in mitigating desertification. Whereas the bare land gained the most across the 12-year study period. The interconversion transition between the LULC types for 2003 - 2015 is illustrated in Figures 5b. In Figure 5b, it can be observed further that the main desertification driver in the study area that is bare land, is the major beneficiary to net change (decrease) to the riparian and vegetation.

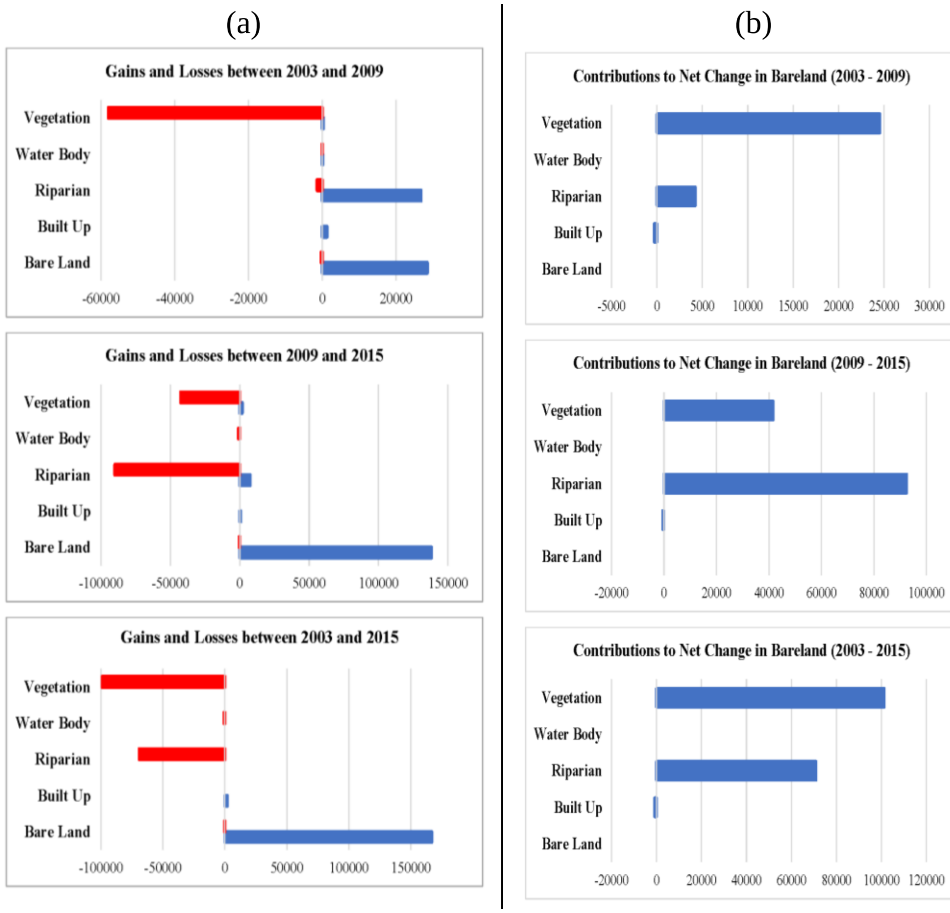

Figure 5. Change variation of land cover classes (in square metres). (a) Gains in blue and losses in red, (b) Contribution to the net change in bare land (desertification)

5.2 Land Degradation Analysis

The normalized difference vegetation index (NDVI) reflects the series of biophysical properties over agricultural land (Hasegawa et al., 2010). To determine the extent of degraded agricultural land, the study derived NDVI for the years 2003, 2009 and 2015 are shown in Figure 6. It highlights the distribution of vegetation indices that is recognised as a mitigating tool for agricultural land degradation from natural indices such as desertification (Masoudi et al., 2018). NDVI compares the chlorophyll content with the cell structure of the vegetation. In other words, reveals how luxuriant the vegetation is. The higher the index the more luxuriant.

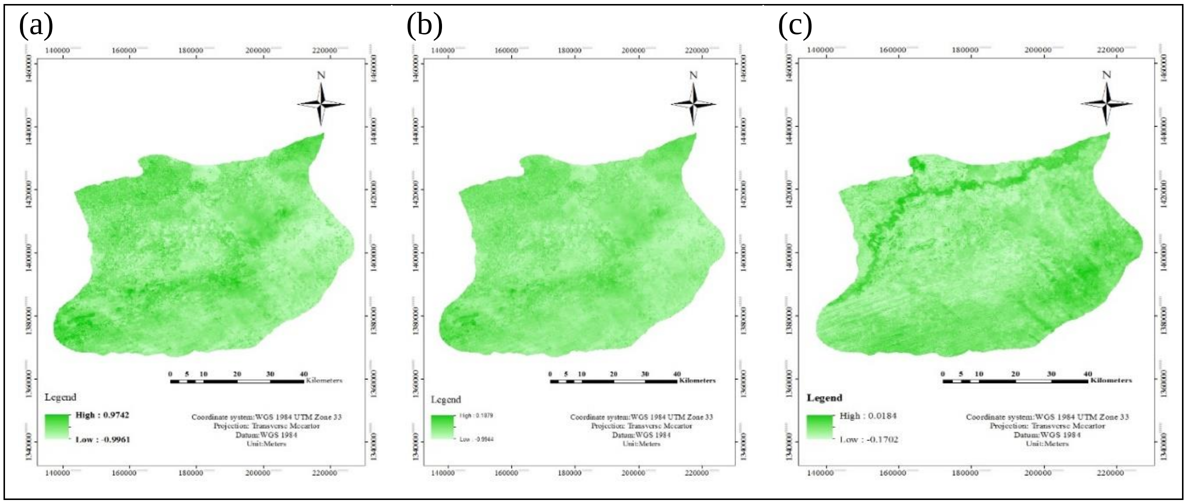

Figure 6. Landsat derived NDVI values for the (a) year 2003 (b) year 2009 (c) year 2015

Figure 6 above displays the trend pattern of the derived NDVI for the years 2003, 2009 and 2015. Threshold reflectance value of various pixels was identified and set to separate vegetation and non-vegetation area in the study area. It can be observed that the values for the non-vegetation to vegetation area ranged from (-0.9961 to +0.9742) for the year 2003, (-0.9944 to +0.1879) for the year 2009 and (-0.1702 to +0.0184) for the year 2015 respectively.

Table 5. Threshold values for NDVI indices (modified after Taufik et al., 2016)

Threshold Value of NDVI	**Value Description**
0 to ±0.1	Low NDVI
±0.2 to ±0.5	Moderate NDVI
±0.6 to ±1	High NDVI

Applying the information in Table 5 to interpret the derived-NDVI, it would be seen that the NDVI values for the non-vegetation area for the study period dataset reported a decreasing trend (that is, high (2003), low (2009) and low (2015)). Additionally, the vegetation area which describes the impact of agricultural land reveals high, high and low NDVI values for the year 2003, 2009 and 2015. It can be observed that the degradation of agricultural land for the vegetation and non-vegetation area averaged 42.39% for 2003 – 2009 and 81.81% for 2009 – 2015. Also, from Figure 5, the NDVI values reveal that the study area is experiencing low, high and severe desertification, based on the desertification grade rules described in Lamchin et al. (2016). This, therefore, demonstrates the extent of land degradation resulting

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from desertification, based on the rate of increase in the LULC of bare land (8.52% - 46.89%) from 2003 - 2015.

5.3 Climatic influence on LULC attenuation

To evaluate the relationship between the LULC change and climatic variable, a correlation analysis of the LULC variables was analysed with extracted daily mean air temperature collected at 2-m above ground level from the National Centres for Environmental Prediction (NCEP) (Meng and Dou, 2016) for the study epoch of interest. The analysis is shown in Table 5 below.

Table 6. Pearson correlation of LULC and climate temperature (* significant at 0.01 level)

	Air Temperature	Bare Land	Vegetation
Air Temperature	1.000	0.869	-0.999*
Bare Land	0.869	1.000	-0.894
Vegetation	-0.999*	-0.894	1.000

From Table 5, the analysis reveals that the reduction in the vegetation land cover over the 12-year study period produced a strong negative correlation with the independently retrieved air temperature data. Additionally, the increase in the bare land variable showed a strong positive correlation with the recorded air temperature for the study dates. This correlation result is in tandem with findings on the impact of desertification on climate change.

6. CONCLUSION

Mitigation strategies are vital in any attempt to understand and regulate the process of land surface degradation. This study conducted a post-millennial analysis of remotely-sensed data from Landsat 7ETM+ and Landsat 8 OLI to evaluate the extent of land degradation over Geidam LGA, Northern Nigeria. The study epoch was 2003, 2009 and 2015. Raster-based classification technique was utilized to determine the LULC classification scheme which comprised of bare land, built up, riparian, vegetation and water-body. Accuracy assessment of the procedure revealed average accuracy (0.87) and Kappa statistics (0.83). For the study period, the result revealed that the bare land rose from 8.52% – 46.89%; built-up covered 0.68% - 1.14%; riparian reduced from 40.40% - 24.50%; vegetation also reduced from 50.08% - 27.33% and finally waterbody 0.32% - 0.14%. NDVI values for the vegetation to non-vegetation area ranged from (-0.9961 to +0.9742) for the year 2003, (-0.9944 to +0.1879) for the year 2009 and (-0.1702 to +0.0184) for the year 2015. This indicates that the extent of land degradation resulting from desertification, based on the rate of increase of bare land from 2003 – 2015 is averaged at 81.81 per cent. These results show that desertification is immensely contributing to the rapid decline of the study area ecosystem. The study reveals the impact of land-use change, thus, the need for policymakers to advocate public enlightenment and campaign on the need for sustainable planting and replanting green vegetation. This will aid in reducing desert encroachment as well as serve as green belt, shelterbelt and alter heat source from gaseous exchanges.

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