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Using Landsat data to determine land use/land cover change and urban sprawl trend in Damaturu city, Nigeria.

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Abstract

This study investigated the trend of urban sprawl and land use land cover change in Damaturu city between 1986 and 2017 using the tools and techniques of Remote Sensing and Geographic Information Systems with the view to examining the direction of the continuous expansion of the city. Landsat imageries of the area were obtained, processed and classified and later overlaid to determine the pattern of changes in land use, direction and extent of expansion during the study period. Findings revealed that the city grows radially which had unprecedented effects on the agricultural lands close to the city. In view of this, the study suggested effective zoning strategy to check the indiscriminate nature of urban expansion whose effects on land use are prominent in the study area. Adequate monitoring by the Development Control Department and other stakeholders in urban planning is equally suggested to mitigate the incompatible land use change in the area.

Keywords: Remote Sensing, Geographic information science, Landsat, Imageries

1. Introduction

Urban sprawl is today viewed as one of the processes of urban development. The incident of urban development and growth is a very broad process with a wide range of concepts. The concept of urban growth and development is a global phenomenon, however, in developing countries, the rate of urbanization is very fast. Urban growth, especially the encroachment of residential and commercial areas to suburban and typically rural areas around the boundaries of city, has been viewed as a sign of economic growth. Bhatta et al. (2010) is of the opinion that apart from urbanization, urban growth is another processes of urban development, and the characteristics of this incidence are so broad, making its implications to be so extensive. Urban growth encompasses the spatial as well as demographic changes within a particular location whereas urbanization is a social and spatial process that happened in societal dimensions of an urban set up (Hegazy & Kaloop, 2015), as such, the rapid urban growth rate created diversity of urban forms.

Urban planning developed over long period (especially the twentieth century), creating different kinds of urban forms that often gave little consideration of the impacts on the environment. This era experienced the phenomenon of urban sprawl as one of the major sign of urban growth (Daneshpour & Shakibamanesh, 2011). The urban sprawl and the increase in size of the urban areas are the major worries of present-day cities. Nevertheless, when the development is increasing rapidly, the municipality will face new problems that are new to the authorities. Previously, cities had well defined boundaries, but with this trend of urban development, they lose their territories by tremendous rate of urban growth (Habibi & Asadi, 2011).

Multi-perspective urban sprawl scholars documented the intricate interaction and the driving force of urban development such as the economic, social, cultural as well as political factors as the main cause of sprawl. Among these driving forces consist of the rapid urbanization, population, economic development, traffic conditions, agriculture, government policy, migration, industrialization, income growth, as the key influencing factors (Osman, Nawawi, & Abdullah, 2009).

In Nigeria, one chief feature of cities is urban sprawl, resulting mainly due to unplanned and uncontrolled urban growth and urbanization. At present, there is no city in the Nigeria that is exculpated from this menace of urban sprawl. The urban sprawl in the country is usually characterized by unplanned housing development in the suburbs of the cities, where most of the buildings were done without authorities' consent or planning permit. Oftentimes, these buildings are a product of unlawful resident that choose to settle down at the outskirts due to their inability to acquire houses in the city (Nnaemeka-Okeke, 2016).

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One of the key driving forces of change on the global environment is the Land use and land cover change (LULCC), which is principal in the sustainable development debate. The rapid changes of land use and land cover, especially in developing countries, are usually characterized by land degradation and widespread urban sprawling, or the conversion of agricultural land to other uses that result in huge cost to the surroundings (Hegazy & Kaloop, 2015; Sankhala & Singh, 2014).

Two distinct terms which are used interchangeably in relation to urbanization are Land use/cover (Dimyati, Mizuno, Kobayashi, & Kitamura, 1996). The first concept 'land cover' refers to the physical features of earth's surface, comprising of soil, water, distribution of vegetation, and some other physical features of the earth surface, including those produced solely by human activities such as residential settlements. On other hand, the term 'land-use' refers to the way in which humans use their lands, on the basis of their functions for various social and economic activities. The natural as well as socio-economic features of the land is the outcome of the utilization of the land use/ land cover of given place by man in space and time. Providing vital information regarding land use and land cover and opportunities for their maximum use is important for the choice, planning and execution of various land use programs to meet the ever-increasing demands for basic man' welfare and need. Provision of such information would also help in monitoring the changing aspects of land use, especially the emerging demands of population increase (Rawat & Kumar, 2015).

Land use and land cover change is usually described as an important instrument for assessing diverse global change in spatiotemporal scales (Lambin, 1997). This concept is a dynamic and endless practice (Mondal, Sharma, Garg, & Kappas, 2016), thus, wider study on LULCC pattern is imperative together with their environmental and social consequences at different temporal and spatial scales (López, Bocco, Mendoza, & Duhau, 2001). It is a general, and important process that is driven by human activities, which in some instances, it as well pushes changes that affect society (Agarwal, Green, Grove, Evans, & Schweik, 2001). Research on the modifications taking place in different land uses are imperative for overall environmental monitoring and evaluation (Lal & Anouncia, 2015).
There are significant number of methods available for assessing and detecting land use and land cover change. Prominent among them and most widely used by researchers in the field is the GIS

and remote sensing technique (Dewan & Yamaguchi, 2009). With the discovery of remote sensing and Geographical Information System (GIS) as tools for land use change detection, it gave land use/cover mapping a useful and comprehensive way of enhancing the choice and selection of areas designed for urban, agricultural and industrial areas of a city (Reis, Nisnci, Uzun, & Yalçin, 2003). The use of remotely sensed data has made it possible to examine various changes taking place on land at low cost, in a lesser time, and also with high degree of accuracy (Kachhwala, 1985; Notti et al., 2018). Furthermore, this remote sensing, together with the GIS provides an appropriate platform for spatial data acquisition, update, analysis, and retrieval (Cihlar, 2000).

With the discovery of higher spatial resolution satellite images, more innovative image processing and GIS tools has occurred. Remote sensing technique has been extensively used in updating land use and land cover maps, which has become one of the most important applications of remote sensing. In this study, remote sensing and GIS techniques are also applied to detect urban sprawl and LULCC in Damaturu for the purpose of exploring how the land use has been changed and the extend of urban sprawl in Damaturu for the period of 1986 to 2017.

2. Study area

Yobe state is one of the 36 states in Nigeria, with Damaturu as the state capital. The state has 17 local government areas. It is located within latitude 11^{o} north and longitude 12.5^{o} East with a total land area of 47,153 square kilometres. The state shares boundaries with Borno State to the east and south-east, Jigawa State to the north while Bauchi and Gombe States to the south-west. It also shares an international border with the Republic of Niger. This boundary stretches over 180km to the north of the state. Yobe state had the population of 2.3 million in 2006 which was projected to be 3.3million in 2016 (National Bureau of Statistics, 2016).

The vegetation of Yobe state is generally Savannah Grassland. Grasses, sparse dwarf trees and shrubs are the most common features of the state. Human activities such as farming and grazing of animals are the major sources of household wealth and income in the state and are worsen desert encroachment. Yobe state government encourages tree planting campaigns in other to control desert enrichment especially at the northern part of the state. The state is multi-ethnic with Kanuri, Bade, Fulani, Ngizim, Bolawa, Kare-kare, Ngamo, Babur/Maga, Hausa and other Nigerian groups constituting the main groups in the state. The Hausa language is widely spoken in the state.

With regard to the economy the state Yobe is relatively small compared to her counterparts such as Lagos, Kano and Borno in Nigeria. The gross state product (GSP), which evaluate the output of annual economic activities of the state, was estimated to be about US$222.99 compared to the national average for the same year put at US$887.63. The state economy makes contributes about 0.42% to the National Gross Domestic Product (GDP).

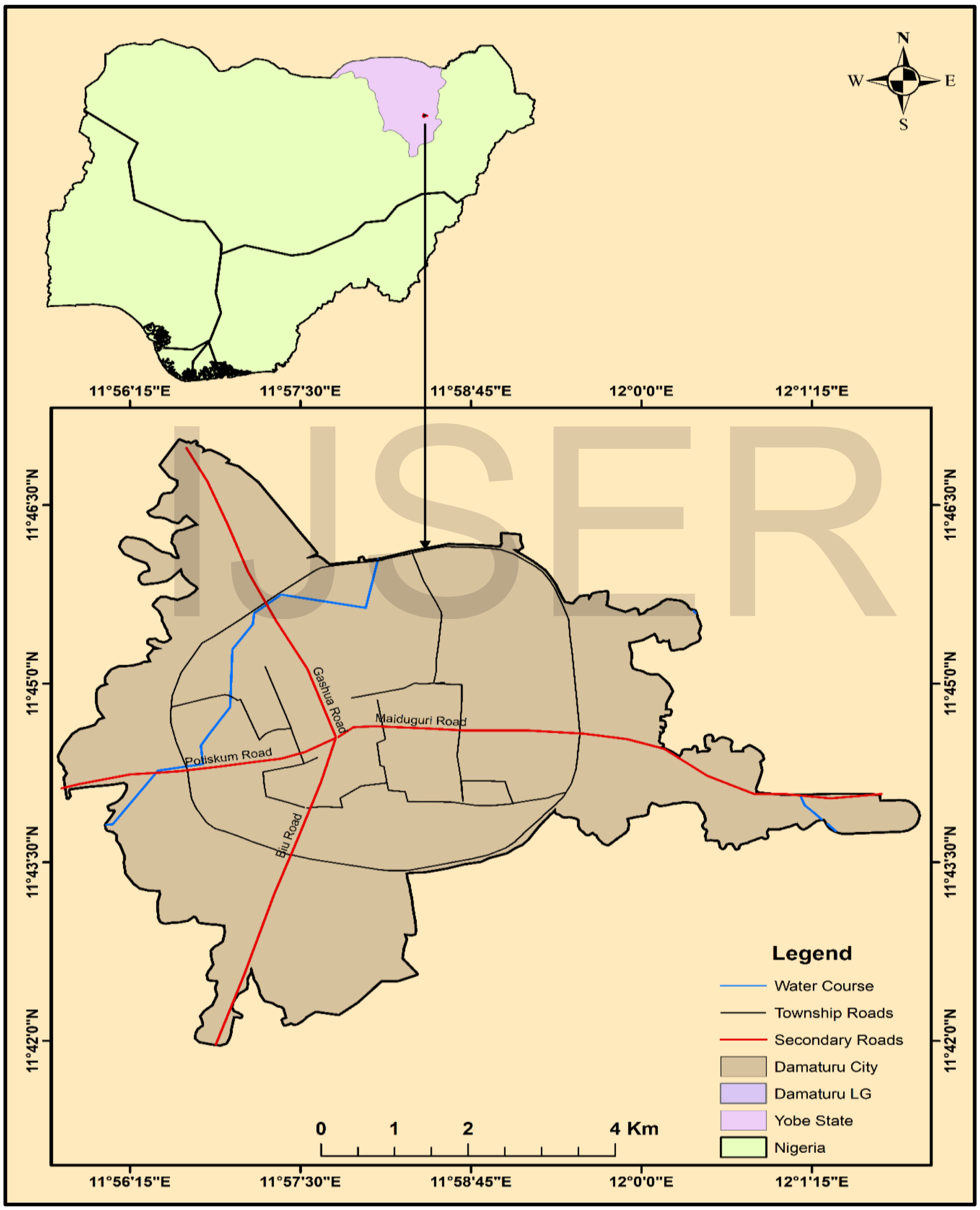

Figure 1: The Study Area

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3. Methodology

Data used for this study was primarily Landsat imageries which were acquired from the United States Geological survey (www.earthexplorer.usgs.gov). Landsat data has a global coverage and archive since 1972 and its freely available for public access since 2008 (Wulder, Masek, Cohen, Loveland, & Woodcock, 2012). The images for the study area (Path/Row 186/052) were downloaded free of charge at the end of the rainy season to eliminate the occurrence of clouds. These are presented in figure 2 and table 1.

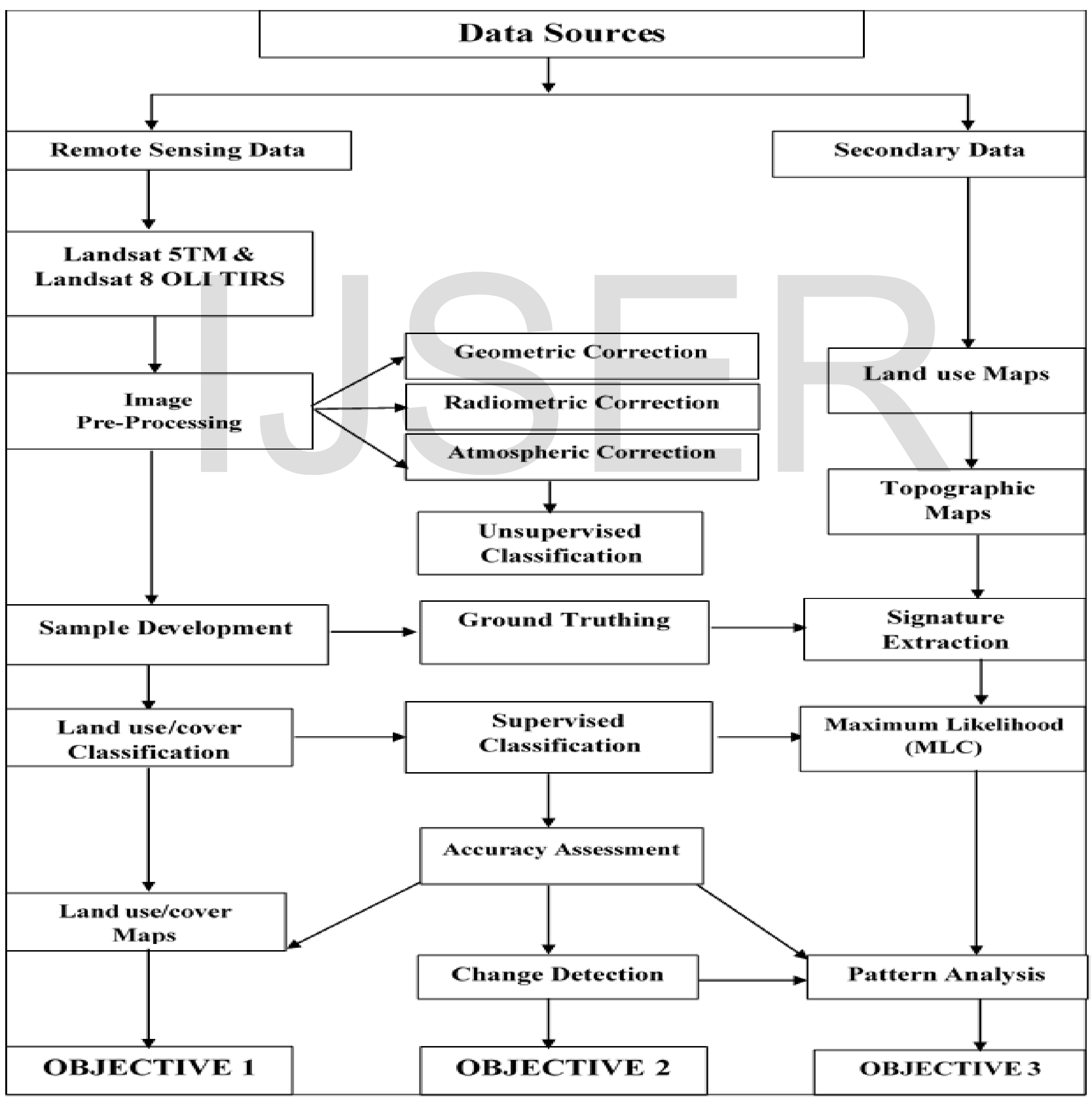

Figure 2: Study Flow Chart

Table 1: Landsat Data Used in the Study

	Type of Data	Spatial Resolution	Source	Acquisition Date
1.	Landsat 5 (TM)	30m	www.earthexplorer.usgs.gov	21/12/1986
2.	Landsat 5 (TM)	30m	www.earthexplorer.usgs.gov	04/11/1998
3.	Landsat 8 (OLI TIRS)	30m, Pan:15m	www.earthexplorer.usgs.gov	08/11/2017
4.	Google Earth images			

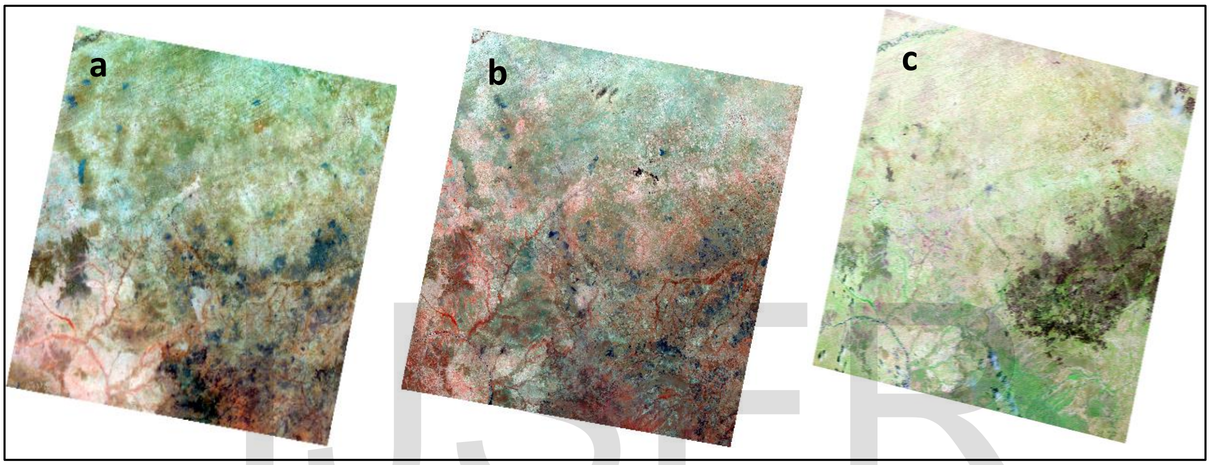

Figure 3: Landsat scenes used in the study: a (1986), b (1998) and c (2017)

Other data used include land use and topographic maps of the area obtained from the Department of lands and survey, Yobe state as well as historical Google Earth images which were used for verification and accuracy assessment.

3.1 Image Processing

The images were first orthorectified to the UTM 33N projection system and the World Geodetic System 1984 (WGS 84) in ArcGIS 10.2. The 1986 and 1998 images were then co-registered to the 2017 (L8 OLI TIRS) image which was taken as the reference image using GCPs collected on the topographic maps. The operation revealed an RMSE of 0.204 which is roughly 6m.

In addition, the images were corrected for atmospheric and radiometric distortions for possible haze, noise and other impurities that may affect the quality of a satellite image (López-Serrano et al., 2016). These operations were carried out using the following equations respectively as obtained from Eastman (2015).

$$L = \left(\frac{Lmax - Lmin}{255}\right) DN + Lmin \qquad \text{(Equation 1)}$$

where L is the radiance expressed in $Wm{-}2sr{-}1$

$$\rho_\lambda = \left(\frac{\pi . \mathrm{L}_\lambda . d^2}{E_{Sun_\lambda} . COS\ \theta_s}\right) \qquad \text{(Equation 1)}$$

Where

ρ = reflectance
$\boldsymbol{\lambda}$ = spectral band
L = radiance
d = Earth-Sun distance
Esun = the solar atmospheric irradiance and
θ = Solar zenith angle in degree.

3.2 Image Classification

The study employed both the unsupervised and supervised classifications. The unsupervised classification was used for initial clustering of the pixels and also to provide an insight of the land use of the area while the supervised classification was used for the actual land use classification using signatures that were generated from Google Earth images.

3.3 Unsupervised Classification

The unsupervised classification was performed using the K-Means clustering which uses Euclidean distance to find the most optimum positioning of the K centers and assign each point to the nearest center (Kim & Yamashita, 2007). K-Means is widely used in unsupervised classification and is computationally faster than many other clustering approaches (Ben Salem, Naouali, & Chtourou, 2018). It is given as:

$$\text{Kmeans} = \sum_{j=1}^{k} \sum_{i=1}^{n} (||v_i - c_i||)^2 \qquad \text{(Equation 2)}$$

where

n = number of data

k = number of centres

vi = data sample

|| || = Euclidian distance

3.3 Ground Truth Data

Ground truth data was obtained from the historical images of Google Earth. This data was used to generate training sites for the supervised classification and signatures for image accuracy assessment.

3.4 Supervised Classification

The supervised classification was carried out using the Maximum Likelihood Classification (MLC) scheme. The MLC is the most widely used classifier in image classification (Al-doski, Mansor, Zulhaidi, & Shafri, 2013). It is operationally simple, easy to use (Lillesand & Kiefer, 2015) and classifies pixels in the class with the highest probability (Lu, Moran, Hetrick, & Li, 2010). It is given as:

$$g_i(x) = \ln p(\omega_i) - ½ \ln|C_i| - ½ (x - m_i)^t C_i^{-1}(x - m_i) \qquad \text{(Equation 3)}$$

where:

gi (x) is the likelihood that a pixel belongs to a particular class

ci and mi are sample estimates of covariance and mean in class $\omega_i$and

p(ω_i) is the class probability which is estimated using the training data

The classification was performed in TerrSet software with 10 ground-truth polygons digitized in each land use class. Each polygon contains about 50 pixels to enhance the accuracy.

3.5 Accuracy Assessment

The classification accuracy was established with an error or confusion matrix. The error matrix quantitatively compares the relationship between the classified maps and reference data (Fonji & Taff, 2014). The accuracy assessment was calculated based on User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA) and the Kappa Index of Agreement (KIA) as derived from the formula given by Congalton & Green (Congalton & Green, 2009) as follows:

$$\text{UA} = \frac{nii}{Gii} \qquad \text{(Equation 5)}$$

$$\text{PA} = \frac{nii}{Cii} \qquad \text{(Equation 6)}$$

$$\text{OA} = \frac{\sum_{i=1}^{k} nii}{n} \qquad \text{(Equation 7)}$$

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$$\text{KIA} = \frac{N \sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n} (G_i C_i)}{N^2 - \sum_{i=1}^{n} (G_i C_i)} \quad \text{(Equation 8)}$$

where:

i = class number

n = total number of classified pixels that are being compared to ground truth,

nii = number of pixels belonging to the ground truth class i,

Ci = total number of classified pixels belonging to class i and

Gi = total number of ground truth pixels belonging to class i.

3.6 Change Detection

Change detection (CD) implies comparing the state of objects or phenomena at two or more different times in order to identify differences (Singh, 1986). This study used the Post Classification Comparison (PCC) which is the most widely used and most accurate approach to change detection in remote sensing (Mallupattu, Reddy, & Reddy, 2013). The proportion of each of the land use/land cover classes was calculated for each year (1986 and 1998, between 1998 and 2017 and between 1986 and 2017 as the overall change). The Land Change Modeler (LCM) of IDIRISI was also used to analyse land cover changes, the proportion of change from each land cover type and the overall losses and gains. The rate and pattern or direction of change were also determined.

4. Results and Discussion

4.1 Land use/land cover classification

The land use/land cover classification exercise generally revealed 5 classes of land use. These include the Built-up Area, Agricultural lands, Open Space, Vegetation and Water bodies and wetland. These classes are described in Table 2 below.

Table 2: Land Use/Land Cover Classes

S/N	Land use type	Description
1.	Built-up Areas	These include all built-up areas including houses, schools, shops, religious buildings, industrial premises and roads.

2.	Agricultural Land	These are farmlands and other cultivable lands for both dry and rainy season farming activities
3.	Open Space	These are Bare surfaces, rocks, sandy areas and uncompleted buildings
4.	Vegetation	These include trees, shrubs and other vegetation
5.	Water bodies and wetland	All water bodies, wetlands and marshy areas

4.2 land use/land cover change

Agricultural land use which occupied about 3844.4 hectares (78%) was the major land use around the city in 1986 (Table 3). The built-up area occupied 355.14 hectares (7.2%), the open space occupied 534.6 (10.8%) while vegetation occupied 4%. The water bodies and wetland on the other hand made up a very insignificant 2.34 hectares.

By 1998, the built-up area had increased to 570.5 hectares (11.2%) while agricultural lands reduced to 2686.2 hectares (54.4%). This may have been as a result of the creation of Yobe state in 1991 which brought into the city more people with numerous government establishments, parastatals and business activities. Similarly, the government embarked on massive allocation of residential and commercial plots which gave rise to more open spaces. Interestingly, the vegetation also increased to 517.3 hectares which could be attributable to increased planting of trees as more people who moved into the city. Trees were planted on the new residential and commercial areas to provide shade and protection against the harsh winds. The government also complimented these efforts by planting trees to curve the menace of encroaching desertification in the state. The water bodies and wetland increased to 31.4 hectares. This could however be due to increase in the amount of rainfall received in that year.

Table 3: Proportion of Land Use/Land Cover in Damaturu - 1986 to 2017 (Ha)

S/N	LUT	1986	%	1998	%	2017	%
1.	Built-up Area	355.14	7.2	570.51	11.6	1085.6	22.0
2.	Agricultural Land	3844.4	77.9	2686.2	54.4	2238.0	45.4
3.	Open Space	534.6	10.8	1128.6	22.9	1126.5	22.8
4.	Vegetation	197.6	4.0	517.3	10.5	477	9.7
5.	Water Bodies & Wetland	2.34	0.0	31.41	0.6	6.93	0.1

With increased growth of the city due to increase in population and commercial activities as well as improvement in infrastructure, the built-up area further increased to 1085.6 hectares by the year 2017 while the open space increased to 1128.6 hectares. Consequently, the agricultural land use further shrunk to 2238.0 hectares. The vegetation reduced slightly to 477 hectares. These details are shown in figure 4 and 5.

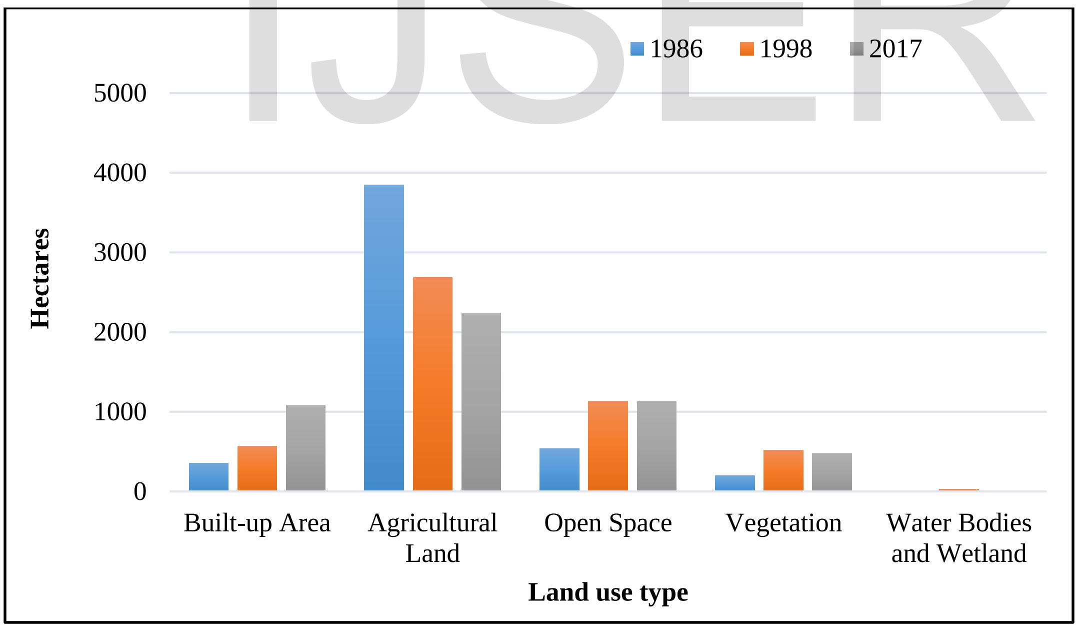


Figure **Error! No text of specified style in document.** : Proportion of Land use/cover in Damaturu between 1986 and 2017

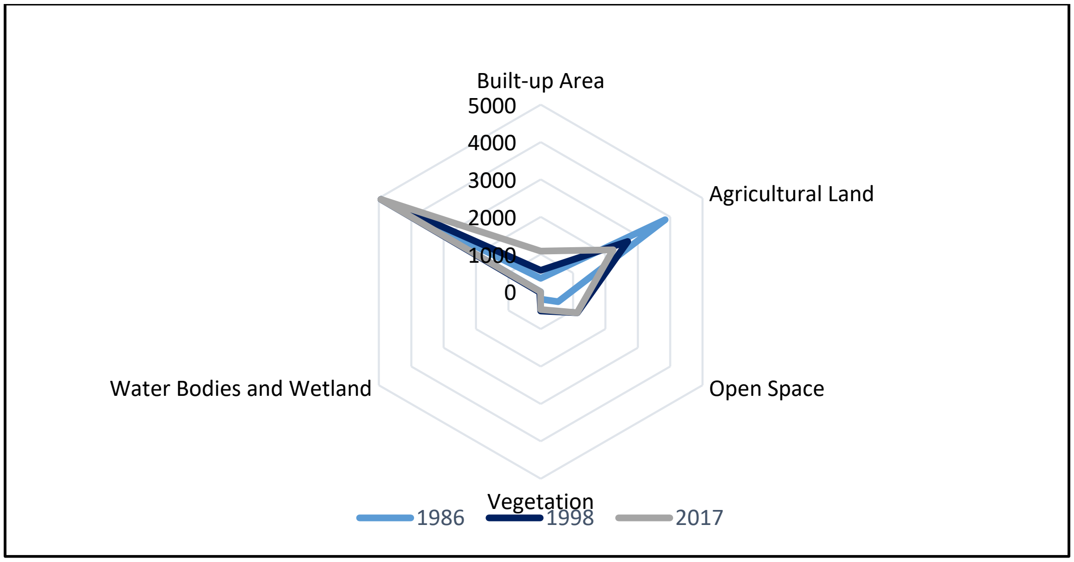


Figure 5: Land use/cover change for Damaturu between 1986 and 2017

The land use/land cover change matrix between 1986 and 1998 (Figure 6) revealed that agricultural lands and open spaces were the major land use types that have been converted. These were mostly converted to built-up area. In other instances, these land use types were also converted to vegetation when trees and other vegetation types were planted. Other forms of conversion during this period was from open space to agricultural lands and from vegetation to open spaces when trees were cleared for either agricultural or other purposes.

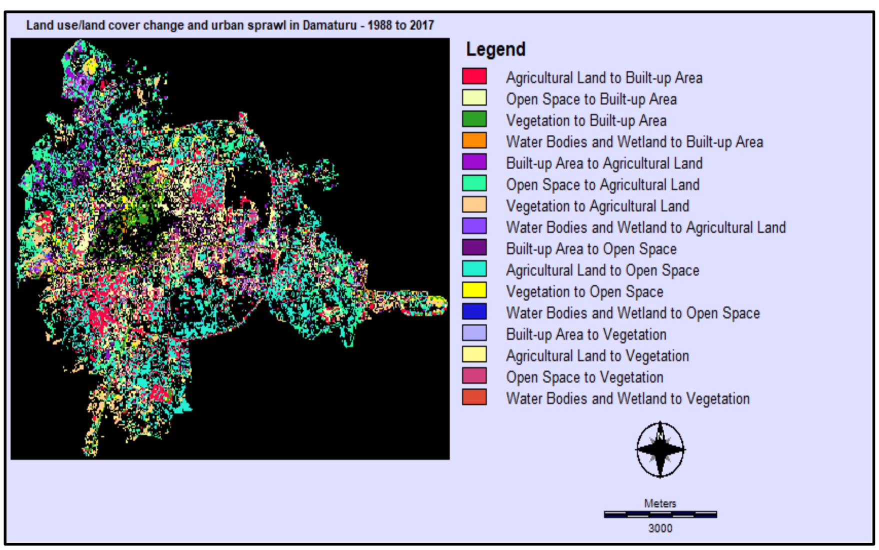
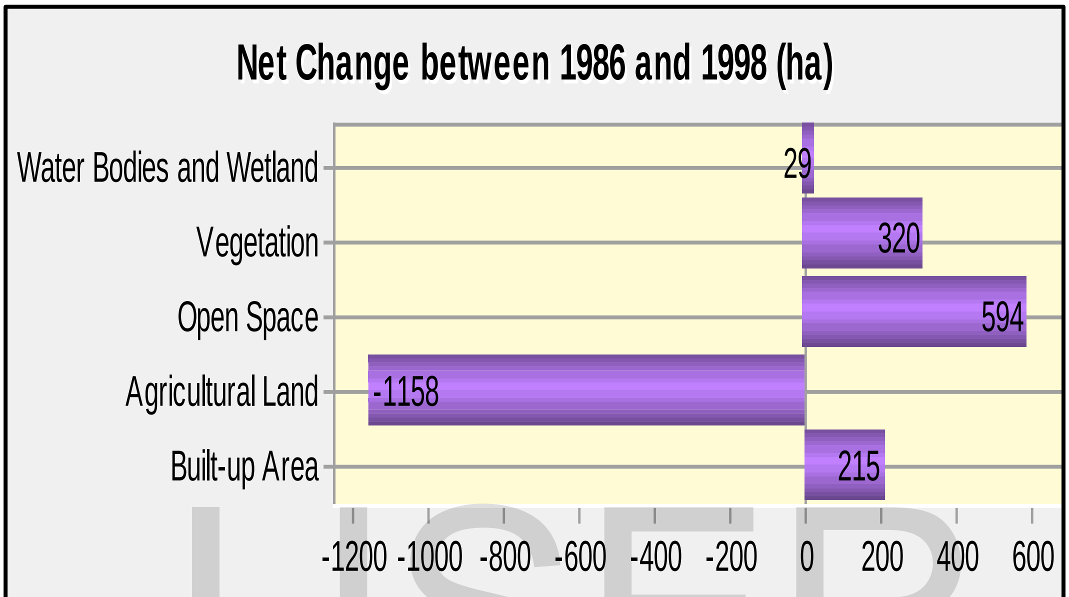


Figure 6: Land use/land cover change matrix in Damaturu for 1986 and 1998

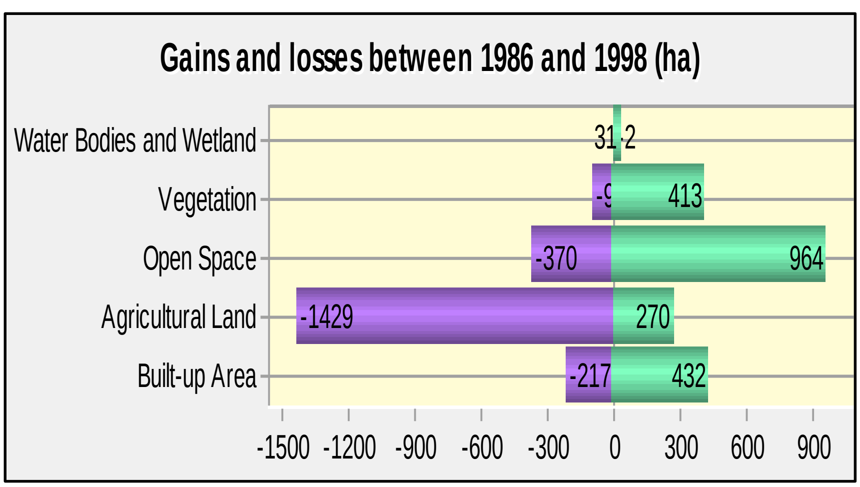
Net change (Figure 6) show an increase of 594 hectares for open space, 319.7 hectares for vegetation and 215 hectares for the built-up area. On the other hand, agricultural lands reduced by 1158.2 hectares.



Change in LULC

Figure 6: Net change of land use for Damaturu between 1986 and 1998

Net gains and losses during the period (Figure 4.5) therefore show that the highest increase was recorded in the open space while the highest loss was recorded in the agricultural lands. The built-up area and vegetation also appreciated remarkably during this period.



Losses

Gains

Figure 7: Gains and losses between land use types in Damaturu (1986 to 1998)

Between 1998 and 2017, the built-up area expanded dramatically to 1085.6 hectares which was 22% of the total land area of the city. This resulted to a further reduction of about 448 hectares of agricultural lands. The open space remained almost unchanged during this period but vegetation and water bodies reduced by 40.3 and 24.5 hectares respectively.

The change matrix (Figure 8) show that most of the changes were from agricultural lands, open space and vegetation to built-up area. There were also some parcels of water bodies and wetlands that have been converted to the built-up areas. Similarly, some open spaces and vegetation were also converted to agricultural lands while agricultural lands, open spaces and some built-up areas were converted to vegetation. This however does not imply total conversion but symbolises the appearance or growth of trees and other vegetation to cover the soil in these areas. The satellite sensors will thus capture vegetation as the prevailing land use class.

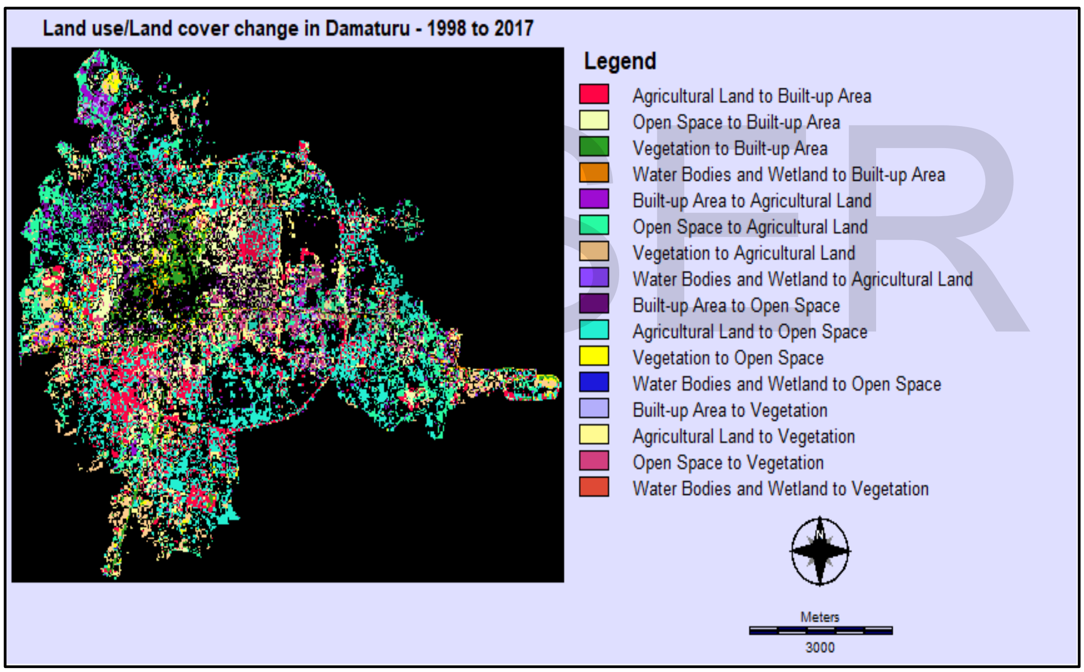
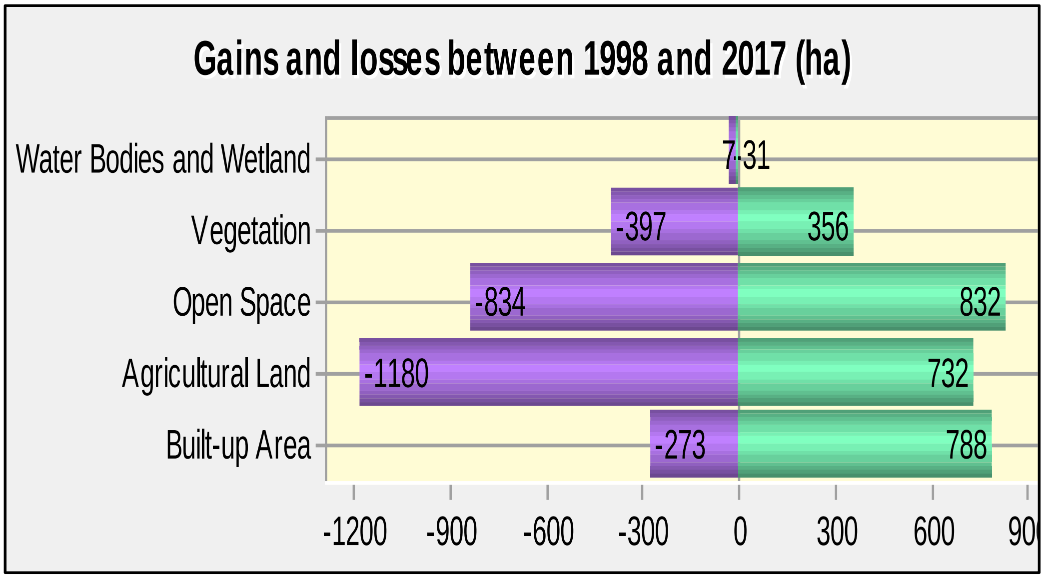


Figure 8: Change matrix between land use types for Damaturu from 1998 to 2017

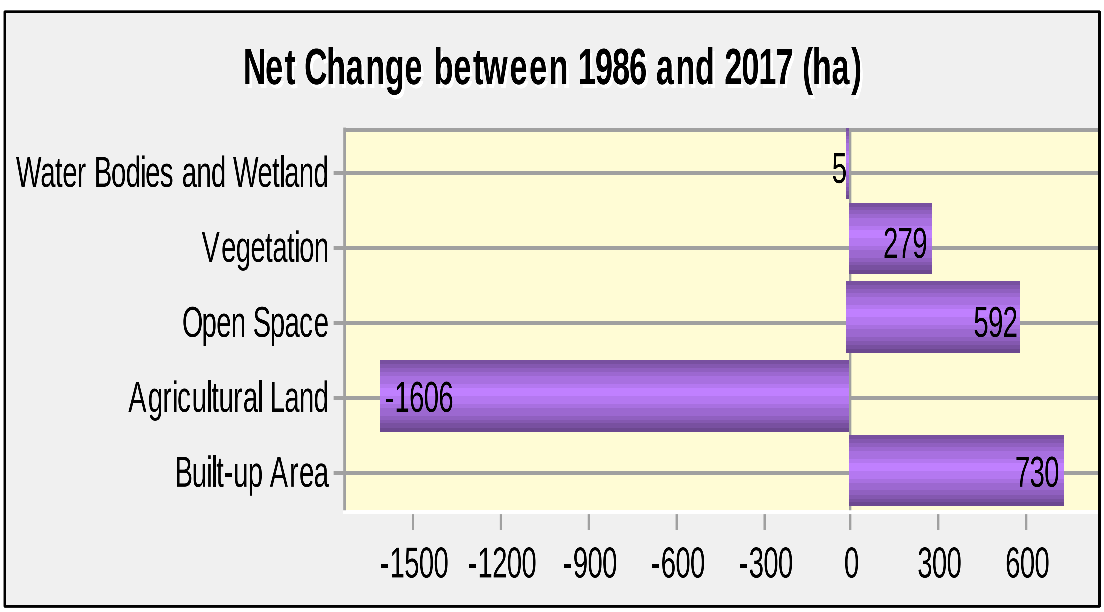
Gain and losses between land use types during the period 1998 to 2017(Figure 9) show that the built-up area and vegetation had the highest gains while the highest losses were recorded in the agricultural lands and water bodies and wetlands. The open space remained almost unchanged.



Losses
Gains

Figure 9: Gains and losses in land use for Damaturu from 1998 to 2017

Overall changes between 1986 and 2017 (Figure 10) show that the built-up area appreciated most, followed by the open space and the vegetation. The highest losses on the other hand were recorded in the agricultural lands. This shows that agricultural lands were more vulnerable to conversion while the built-up areas increased almost exponentially throughout the study period.



Change in LULC

Figure10: Overall land use/land cover changes in Damaturu from 1986 to 2017

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4.4 Urban expansion

4.5 Rate of urban expansion

The rates of urban expansion in Damaturu are presented in Table 3. Between 1986 and 1998, the highest expansion rate (28.9%) was recorded in the water bodies and wetlands. However, these increases were as a result of fluctuations in the amount of rainfall received around the city which varied between years. The vegetation also recorded a high growth rate of 10.7% during this period. This land use type expanded by an average of 26.7 hectares annually which shows the increased commitment of both the government and people towards tree planting in the city. Similarly, the government increasingly constructed roads and provided residential as well as commercial plots for the construction of offices, shops and residences to cater for the influx of governmental, commercial and residential needs of the people in the newly created state. Therefore, the open space and built-up area increased annually at 8.3% and 5.27% respectively. Conversely, the agricultural lands decreased at 3.98% or approximately 96 hectares per annum.

Table **Error! No text of specified style in document.** : Rate of Urban Growth in Damaturu between 1986 and 2017 (Ha)

S/N	Land use	1986	1998	Change	Growth Rate	2017	Change	Growth Rate
1.	Built-up Area	355.14	570.51	215.4	5.27	1085.6	515.07	7.15
2.	Agricultural Land	3844.4	2686.2	-1158.2	-3.98	2238.0	-448.2	-2.03
3.	Open Space	534.6	1128.6	594.0	8.30	1126.5	-2.07	-0.02
4.	Vegetation	197.6	517.3	319.8	10.70	477	-40.32	-0.90
5.	Water Bodies & Wetland	2.34	31.41	29.1	28.86	6.93	-24.48	-16.8

Between 1998 and 2017, the highest rate of expansion was recorded in the water bodies and wetland which reduced by 16.8%. This was earlier explained to be attributable to fluctuations in the annual rainfall. The built-up area increased at 7.15% or approximately 27.1 hectares annually.

The agricultural lands decreased at 2.03% (23.6 hectares) annually while vegetation and open space remained almost constant.

4.6 Pattern of urban expansion

The most practical conversion was between agricultural lands to built-up area. The trend and pattern of this conversion during the 1986 – 1998 study period (Figure 11) showed a southward and eastward pattern and direction. The city expanded radially but more intensely towards Maiduguri road where most of the developmental projects and residential plots were allocated. The dark brown areas show the old city while the lighter brown areas show gradual expansion of the city with increasing population and built-up areas. The yellow colour shows areas vulnerable to future expansions while the blue colour shows areas not possibly vulnerable to expansion in the nearest future.

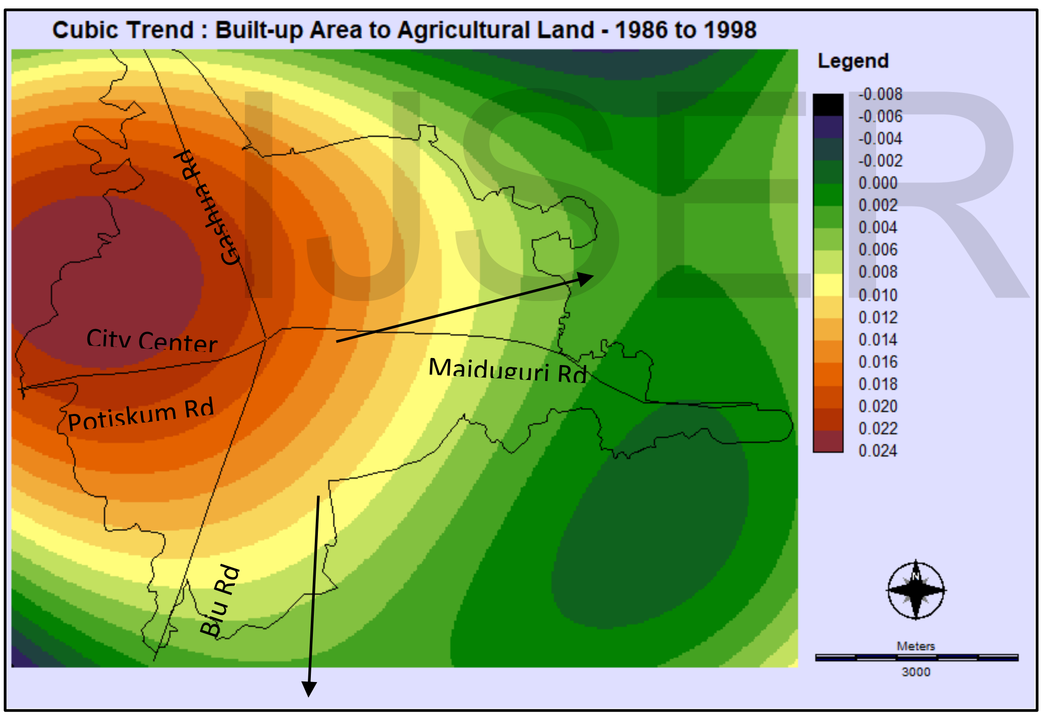

Figure 11: Trend of urban expansion and agricultural lands conversion in Damaturu between 1986 and 1998

The trend of this expansion widened up between 1998 and 2017, encroaching further into the adjacent agricultural lands. During this period however, agricultural lands in the northern and eastern parts of the city were mostly affected by the conversion (Figure 12).

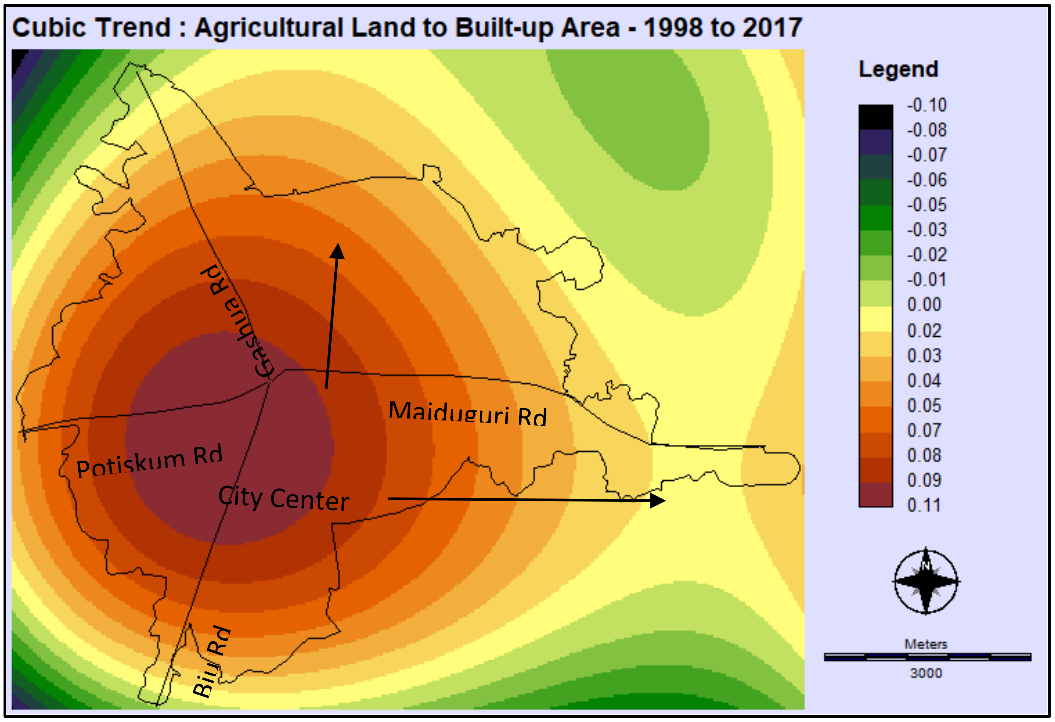

Figure 12: Trend in conversion of Agricultural lands to Built-up area in Damaturu between 1998 and 2017

4.7 Accuracy Assessment

Accuracy of the classification is presented in table 4.3. In the 1986 classification, the highest user accuracy (97.42) was achieved in the agricultural land use while the lowest (20.29) was obtained in the water bodies and wetland. In the same year, the highest producer accuracy (73.1) was achieved in the open space while the lowest was obtained in the built-up area. The overall accuracy for the year on the other hand, was 63.3% and the Kappa Index of Agreement (KIA) was 0.79 (79%). The Landsat image for 1986 and the historical Google Earth images used for the accuracy were not very clear. Thus, the classification accuracy was comparatively low.

Table 5: Accuracy Assessment (1986 to 2017)

S/N	Land use/cover type	1986		1998		2017	
		UA	PA	UA	PA	UA	PA
1	Built-up Area	52.30	51.93	39.12	66.93	99.10	84.33
2	Agricultural Land	97.42	63.58	85.33	83.71	78.68	95.21
3	Open Space	21.13	73.10	79.82	57.82	82.40	54.39
4	Vegetation	53.08	54.17	79.34	72.70	98.90	92.83
5	Water and Wetland	20.29	53.85	98.56	97.99	100.00	100.00
	OA	**63.28**		**74.80**		**84.60**	
	KIA	**0.79**		**0.82**		**0.89**	

Note:

UA = User Accuracy

PA = Producer Accuracy

OA = Overall Accuracy

KIA = Kappa Index of Agreement

In the 1998 classification, the highest user accuracy (98.6) was achieved in the water bodies and wetland while the lowest (39.1) was obtained in the built-up area. Similarly, the highest producer accuracy (97.9) was achieved in the water bodies and wetland while the lowest (57.8) was obtained in the open space. The overall accuracy for the year on the other hand, was 74.8% and the KIA was 0.82 (82%). This year coincided with high amount of rainfall which made water bodies clearer than was obtained in 1986. As such, the water bodies and wetland areas were more visible and thus, had higher classification accuracies.

The 2017 classification was the most accurate. The highest user and producer accuracies were achieved in the water bodies and wetland. This may not be surprising as the Landsat 8 (OLI TIRS) used was of much spectral quality than the previous images. In addition, the water bodies have lower spectral confusion than other land use/land cover classes. Therefore, the classification accuracy of water surfaces was 100%. The lowest user and producer accuracies on the other hand were recorded in the open space. This land use class has a lot of spectral confusion with farmland especially during the dry season when the images were acquired. The overall accuracy for 2017 was 84.6 and the KIA was 0.89 (89%).

4.8 Land use maps

The resultant land use/land cover maps of Damaturu city in 1986, 1998 and 2017 are presented in figures below:

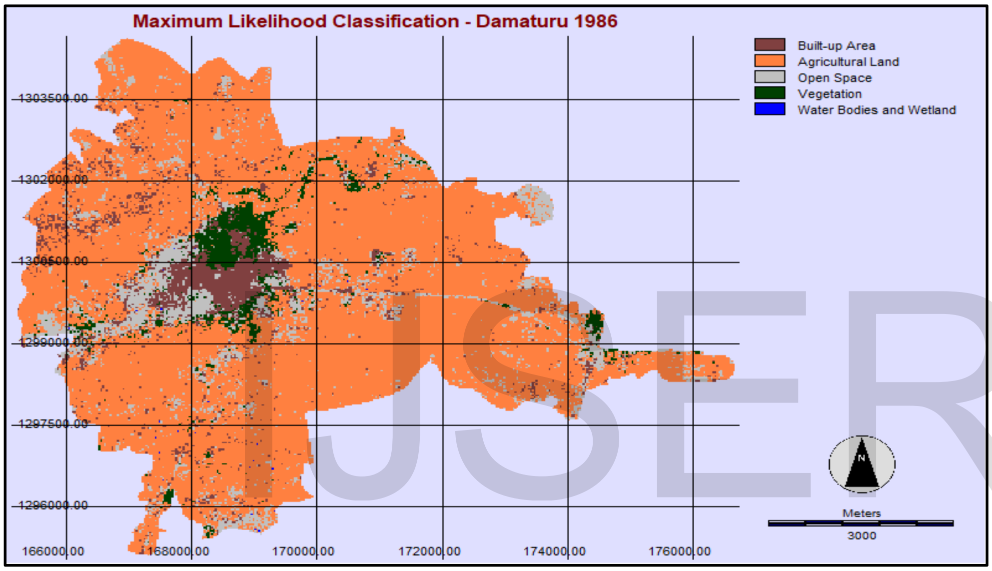

Figure 13: Land use/cover map for Damaturu 1986

In 1986 (Figure 13), the city was practically small, surrounded by vast areas of agricultural lands, scanty vegetation and some open spaces. By 1998 after the state was created, the city expanded to the west, south and eastern parts. The built-up area and vegetation increased noticeably towards the southern and eastern directions (Figure 14). The open space also expanded in all directions as new layouts were created by the government. Increases have also been spotted in the water bodies and wetlands in and around the city.

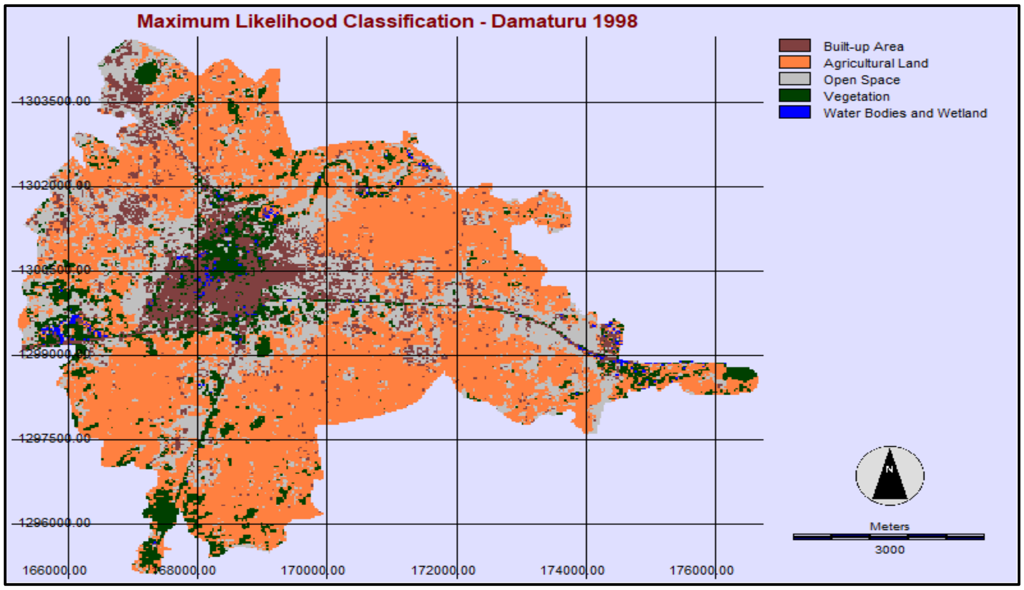

Figure 14 : Land use/cover map for Damaturu 1998

By 2017 (Figure 15), the city further expanded down south and to the east along Maiduguri road. The expansion of vegetation was seen to follow expansion in the built-up area.

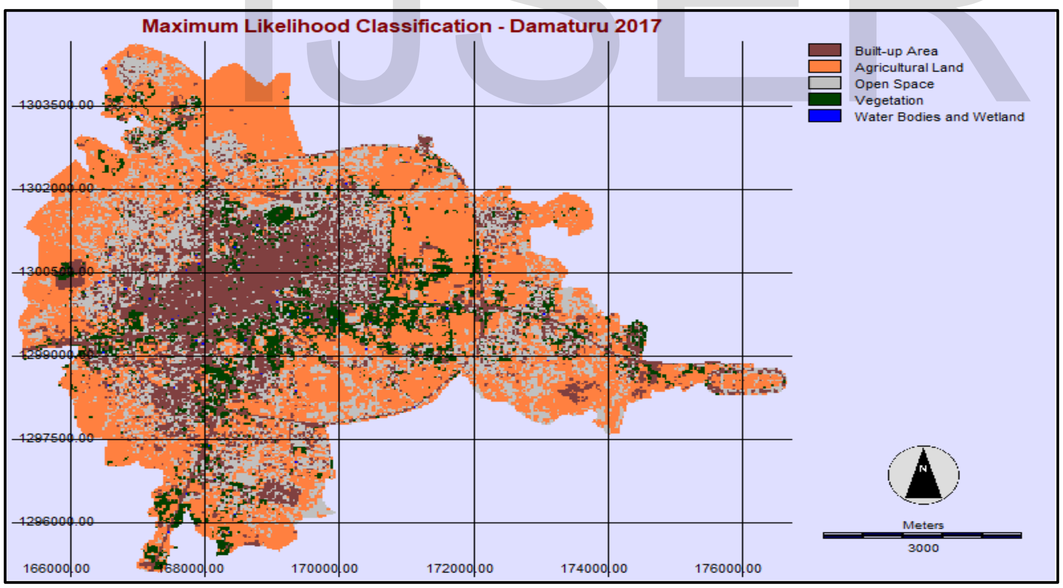

Figure 15 : Land use/cover map for Damaturu 2017

Conclusion

Land use and land cover changes are natural phenomena which occur in most cities around the world. In Damaturu, these changes took place between the various land use/cover classes at a slower rate between 1986 and 1998 but accelerated between 1998 and 2017. The most practical conversion was from agricultural lands to built-up area. The pattern of conversion was radial around the city but more prominently towards the eastern and southern parts of the city. The built-up area recorded the highest increased of 515ha while the agricultural lands reduced by 448.2ha between 1986 and 2017. These conversions were generally brought about by the creation of Yobe state and the location of its headquarters in Damaturu. This attracted a lot of people and their businesses to the city, hence the increase in institutional, residential and commercial constructions in the city.

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