Preliminary Study on the Analysis of Land Use/Land Cover of Yola North and South Local Government Areas of Adamawa State, Nigeria

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Abstract
This present paper is an attempt on the preliminary study on the analysis of land use/land cover (LULC) of Yola North and South Local Government Areas of Adamawa State, Nigeria. Landsat 8 imagery techniques was employed in acquisition, processing and analyzing of image and algorithm classification of LULC data for the year 2023 in order to fill in the gap in the area. It was revealed that the majority of the area is covered by vegetation (46.98%) and built-up areas (23.12%), followed by water bodies (13.54%), farmland (8.14%), and bare surfaces (8.22%). In addition, the confusion matrix and ground truth information were found to allow for an assessment of the accuracy of the classification algorithm, highlighting areas of agreement and discrepancy between predicted and actual land cover classes. Similarly, commission and omission errors further elucidate the reliability of the classified results, while class accuracy metrics provides detailed evaluation of the algorithm's performance for individual land cover classes. It is therefore recommends that government and different NGOs should take steps to provide training about the impact of land use and land cover change and to foster collaboration among stakeholders for effective planning utilization and management of land resources for sustainable development.

Keywords: Analysis, Land use, Land cover, Preliminary, Yola.

INTRODUCTION

Land use land cover change is a complex matter, which is caused by numerous biophysical, socio-economical and institutional factors (2017).
At present, the LULC pattern's changing scenario has become an immense issue for utilizing our natural capital and resources. Here, land use refers to human activity on the earth's surface such as infrastructure building, agricultural cropping and land cover refers to natural or manmade physical properties of the earth surface such as water body, vegetation covers etc. LULC has changed expeditiously for urbanization and overpopulation (Sikarwar and Chattopadhyay, 2016; Riggio *et al*., 2018). Land use/cover information is vital for the dynamic monitoring, planning and

management, and the reasonable development of land (Naeem *et al.*,, 2018; Thenkabail *et al.*,, 2005; Zhang *et al.*,, 2017a, 2017b; (Deng *et al.,* 2019).). Recently, due to rapid urban expansion, land cover information has changed dramatically in and around cities. Furthermore, construction land has become increasingly scarce, and the nonagricultural land has been highlighted (Fu and Weng, 2016; Dogan and Turkekul, 2016; Munshisouth *et al.*,, 2016). To better understand the impact of LULC change on earth surface area need to analyse the trend of land cover change near about the previous 30 years and predict the chance of future changes of land use (Ojima *et al*., 1994).

An urban environment can be characterized by two main classes namely, built-up areas (developed) which comprise of industrial, residential, commercial, parking areas, roads etc and non-built up areas (reserved) e.g. gardens, spots field, green areas, urban agriculture, etc. therefore, town planning departments attempt to incorporates these design plans (building and land use etc) depicting the type and extent of the permitted use of land and the corresponding constraints, where by any change is expected to conform to these plans. However, it is not uncommon to unveil that these plans particularly in developing countries like Nigeria are not adhered to due to problems associated with poverty, immigration, overpopulation, ignorance, lack of government participation in active planning/monitoring of any environmental changes, either positive or negative which also implies that the necessary infrastructure is not implemented.

Due to high population density which leads to intensive use of marginal land for urbanization, losses of vast agricultural lands, water bodies and forest areas which occur in recent years (Sadiq *et al.,* 2019). However, considering the fact that a research have been conducted to study the LULC in the study area by Babalola, *et al.*, (2014) and also of recent Aliyu *et al.*,., (2023) carried out similar researches covering many years up to 2022. Thus, the rapid changes of rapid construction of fly overs, bridges, roads, building of houses were experienced last year. Therefore, it is essential to fill in the gap and update the present LULC status of the area with the inclusion of one year data for proper data and information management and storage for effective land use planning, land management and sustainable development in the area. It is based on the aforementioned statement the authors choose to analyze LULC to find out the LULC changes pattern of the year 2023 in the area. Thus, this research work aimed to analyze Land Use/Land Cover of Yola North and South Local Government Areas of Adamawa State, Nigeria.

METHODOLOGY

Study Area

The study covers two local governments namely Yola North and South in Adamawa state, Nigeria. The local government areas are Jimeta: Lat.$9^0 6^/$N, Long.$12^0 27^/$ and Yola Lat.$9^0 14^/$, Long.$12^0 27$ as shown in Figure 1below.

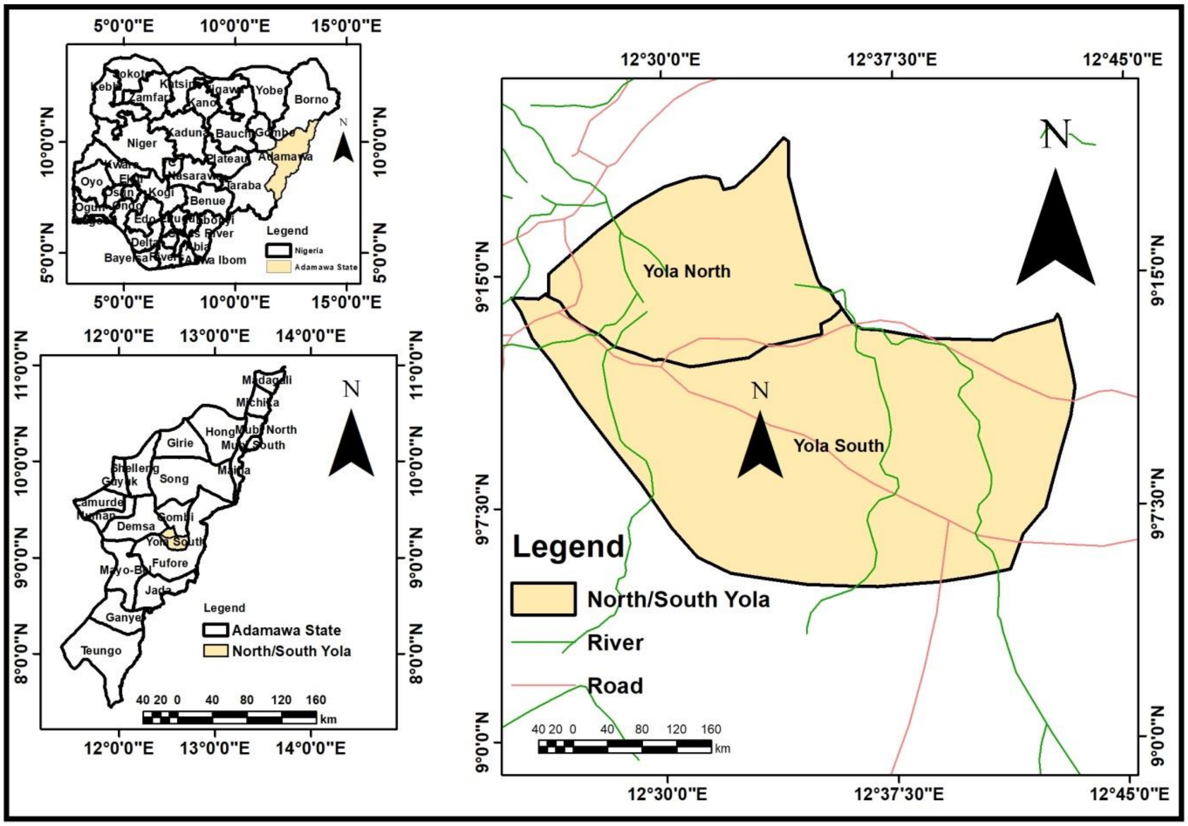

Figure1. **The map of the study area**

The cities have high density of buildings and have not earlier been developed according to periodic urban plans; thus, resulting in clusters of buildings with different sizes and shapes. The agricultural fields surround the cities and it is relatively flat in eastern and some northern part. This metropolis, with increasing institutional development (2 universities, colleges and various government departments); this together with good road network provided by the Industrial and residential areas with high population density are located in the northern part called Jimeta and spreading in the Lamido's city called Yola. (I.e. residential areas, both densely and sparsely built-up are located at the southern edge of the city). The general urban areas were built on a relatively flat surface, even though some hills with reasonable slopes are city center.

Data Acquisition

Landsat 8 imagery was downloaded using Glovis, setting the path/row with spatial resolution of 30m. The image was dated 1/3/2023 to 30/11/2023.

Pre-processing

Perform geometric correction to rectify geometric distortions caused by sensor and terrain variations. This step involves geo-referencing the imagery to a common map projection and datum. Radiometric Correction Correct for atmospheric effects, such as haze and clouds, using tools like Dark Object Subtraction (DOS) or FLAASH within ENVI.

Image Classification

Collect training data by using Region of Interest (RIO), select a classification algorithm, and perform classification. Collect representative samples of each land cover class within your study area. Anderson 1976 classification scheme was used and five classes were selected or trained; built up, farmland, vegetation, bare surface and water body. About 50 Region of Interest (RIO) were trained randomly.

Classification Algorithm

Support Vector Machine (SVM) was used because of its robustness with high-dimensional data, flexibility in handling various kernels, ability to manage imbalanced datasets, noise tolerance, and well-established track record in remote sensing.

RESULTS AND DISCUSSIONS

The LULC statistics provide valuable information about the distribution of land use and land cover in the area for the year 2023 were presented on Table 1 and also depicted on Figure 2 accordingly. These statistics reveal that the majority of the area is covered by vegetation (46.98%) and built-up areas (23.12%), followed by water bodies (13.54%), farmland (8.14%), and bare surfaces (8.22%). Understanding these statistics is crucial for land management, urban planning, and environmental conservation efforts. The presence of vast vegetation area shows the potentiality of the area for agricultural and other socio-economic infrastructural planning and development. An increase of built-up area signifies the presence of rapid urbanization in the areas. This result agreed with findings of Sadiq *et al.*, (2019).

Table 1: LULC Statistic for the year 2023

Land Use / Land Cover	Area (km^2)	Percentage (%)
Built-up	130,628	23.12
Farmland	46,016	8.14
Vegetation	265,478	46.98
Bare surface	46,464	8.22
Water body	76,515	13.54
Total	**565,101**	**100**

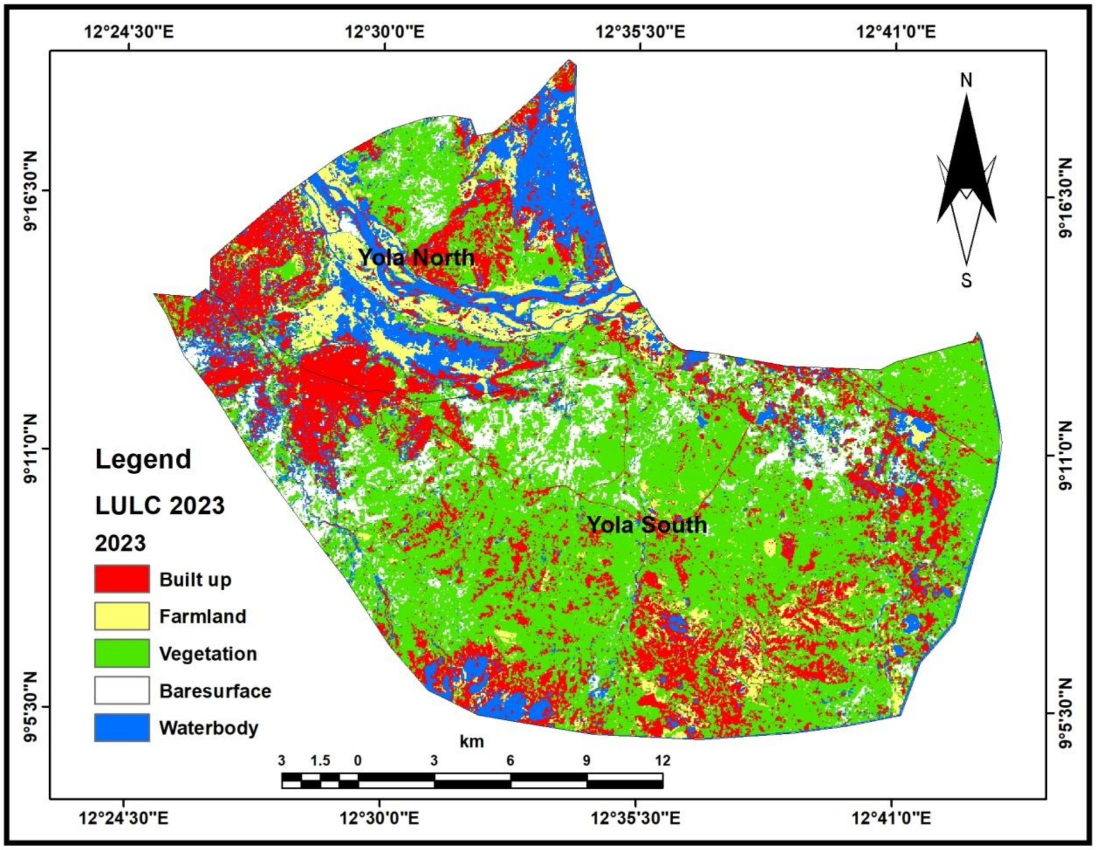

Figure 2. Classification of LULC for the year 2023

Confusion Matrix

The confusion matrix is a vital tool in assessing the performance of a classification algorithm by comparing the predicted classes against the ground truth. In this case, the confusion matrix shows the number of pixels classified into each land cover class compared to the actual ground truth. It provides insights into the accuracy of the classification process and highlights areas where misclassifications occur. The result on Table 2 shows clear accuracy of classification having total value of 4270 between the predicted and actual ground classes. Water bodies received high total value of 1733 with accuracy of 1616, followed by farmland (986) with accuracy of 864, built-up area received total of 751 having accuracy level of 596 then Bare surface (577) with 554 accuracy and vegetation having 223 with 191 accuracy respectively.

Table 2. Confusion Matrix

Ground Truth (Pixels)	Built up	Farmland	Vegetation	Bare surface	Water body	Total
Unclassified	0	0	0	0	0	0
Built up	596	1	19	0	135	751
Farmland	1	864	7	0	114	986
Vegetation	12	6	191	6	8	223
Bare surface	9	0	8	554	6	577
Water body	58	46	12	1	1616	1733
Total	**676**	**917**	**237**	**561**	**1879**	**4270**

Ground Truth

The ground truth information in the confusion matrix provides a detailed breakdown of the actual land cover types in the region. By comparing the ground truth with the classified results, it is possible to identify areas of agreement and discrepancy. This information is essential for evaluating the accuracy of the classification algorithm and refining it for future applications. Based on the results presented in Table 3 below revealed perfect agreement of land cover types and their areas classified with each holding 100 % and the overall total was also 100 %. It could be observed that water body received high percent (40.59 %), followed by farmland (23.09 %), buit up areas (17.59 %), Bare surface (13.51 %) and vegetation (5.22 %) respectively.

Table 3. Ground Truth

Class	Built up	Farmland	Vegetation	Bare surface	Water body	Total
Unclassified	0.00	0.00	0.00	0.00	0.00	0.00
Built up	88.17	0.11	8.02	0.00	7.18	17.59
Farmland	0.15	94.22	2.95	0.00	6.07	23.09
Vegetation	1.78	0.65	80.59	1.07	0.43	5.22
Baresurface	1.33	0.00	3.38	98.75	0.32	13.51
Waterbody	8.58	5.02	5.06	0.18	86.00	40.59
Total	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

Commission and Omission

Commission and omission errors are critical indicators of the accuracy of a classification algorithm. Commission errors represent pixels that were incorrectly classified into a certain class, while omission errors represent pixels of a certain class that were missed or not classified. Understanding and minimizing these errors are crucial for improving the reliability of land cover classification results. Based on the results presented on Table 4 below shows that built-up received high percent of 20.64 % commission followed by 14.35 % vegetation, 12.37 % farmland, 6.75 %

and 3.99 bare surface % respectively. For the omission class vegetation was found to have high percent 19.41 %, water body 14.00 %, built up 11.83 %, farmland 5.78 % and bare surface 1.25 % accordingly.

Table 4. Commission and Omission

Class	Commission (%)	Omission (%)
Built up	20.64	11.83
Farmland	12.37	5.78
Vegetation	14.35	19.41
Baresurface	3.99	1.25
Waterbody	6.75	14.00

Class accuracy measures the performance of the classification algorithm for each specific land cover class. It includes producer accuracy, which indicates the proportion of correctly classified pixels for a particular class out of all the pixels that belong to that class according to the ground truth. User accuracy, on the other hand, measures the proportion of correctly classified pixels for a particular class out of all the pixels classified into that class. The overall accuracy of the classified image is compared to how each of the pixels is classified against the demonstrated land cover established from their consisted ground truth data (Riggio and Ndambuki, 2017; Congalton, 1991; Unger Holtz, 2007). These metrics help to assess the effectiveness of the classification algorithm for individual land cover classes and identify areas for improvement. For the results depicted on Table 5 below described that for producer accuracy class was in order of bare surface >farmland > built up > water body >vegetation while for the user accuracy the percent class increased in order of bare surface >water body > farmland > vegetation > built up respectively. Thus, the actuality of the resulting data to a user is established by it (Fung and LeDrew, 1988).

Table 5. Class Accuracy

Class	Producer Accuracy (%)	User Accuracy (%)
Built up	88.17	79.36
Farmland	94.22	87.63
Vegetation	80.59	85.65
Baresurface	98.75	96.01
Waterbody	86.00	93.25

It is imperative to note that the cover types have a high accuracy in both the user and producer accuracies because all types are above 85% except built up with 79.36 % under user accuracy. This results is in conformity with the finding of Deng *et al.*, (2019) who also concluded that several types of land cover were above 85 % which shows high accuracy level

Generally, analyzing LULC statistics, confusion matrix, ground truth, commission and omission, and class accuracy provides valuable insights into the performance of land cover classification algorithms and aids in decision-making for land management and environmental planning initiatives.

CONCLUSIONS

The preliminary analysis of land use and land cover (LULC) for the year 2023 provides valuable insights into the distribution and composition of land cover types in the area. The LULC statistics reveal that vegetation covers the largest area, followed by built-up areas, water bodies, farmland, and bare surfaces. The confusion matrix and ground truth information allow for an assessment of the accuracy of the classification algorithm, highlighting areas of agreement and discrepancy between predicted and actual land cover classes. Commission and omission errors further elucidate the reliability of the classification results, while class accuracy metrics provide a detailed evaluation of the algorithm's performance for individual land cover classes. The analysis underscores the significance of accurate land cover classification for informed decision-making in land management, urban planning, and environmental conservation efforts. While the classification algorithm demonstrates high accuracy for certain land cover classes, there are areas of improvement identified through commission and omission errors. Enhancing the classification algorithm's performance in these areas can lead to more reliable land cover mapping results and improved resource allocation for sustainable development initiatives. It is therefore recommends that government and different NGOs should take steps to provide training about the impact of land use and land cover change and to foster collaboration among stakeholders for alignment with development goals with the aim of addressing challenges in land cover mapping and ensure the accuracy, currency, and relevance of land cover information for sustainable development initiatives.

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