Journal of Research in Forestry, Wildlife & Environment Vol. 15(4) December, 2023
E-mail: jrfwe2019@gmail.com; jfewr@yahoo.com
http://www.ajol.info/index.php/jrfwe
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ISBN: 2141 – 1778
Abwage and Sale, 2023

ASSESSMENT OF LAND USES AND LAND COVER CHANGE OF NGEL NYAKI FOREST RESERVE, NIGERIA

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ABSTRACT

Land use and land cover changes have become an issue of global interest, mainly as the results of unprecedented changes impacted on the environment by Man to satisfy his economic needs. Landsat imageries of Ngel Nyaki forest reserve for 2002, 2012 and 2022 were obtained, based on availability. The images were classified into five land use and land cover change (Dense forest land, Spares Forest Land, Grass Land and Bare Land). The results of the findings from the classification shows Dense forest land (680.13ha, 706.23ha and 542.52ha), Spares Forest Land (95.94ha, 137.07ha, and 188.73ha), Grass Land (224.64ha, 214.02, 223.83ha) and Bare Land (56.61ha, 0.00ha,102.24ha) for 2002, 2012 and 2022 respectively. The dense forest was observed to have greater proportion of the land cover compare to other classes, which is an indication of the potential of the forest reserve in carbon sequestration as well as species richness. Finally, remote sensing techniques was sufficiently deployed to estimate the land use and land cover classification of Ngel Nyaki Forest Reserve which is now available for the forest manager to make an informed decision in sustainable management of the forest reserve.

Keywords: Ngel Nyaki Forest Reserve, Landsat imagery, Land use and land cover classification.

Correct Citation of this Publication
Abwage, W.D. and Saleh F.A. (2023). Assessment of land uses and cover change of Ngel-Nyaki Forest Reserve, Nigeria. *Journal of Research in Forestry, Wildlife & Environment;* 15(4): 75 - 85

INTRODUCTION

Land Use and Land Cover Change (LULCC) have been identify to be one of the key drivers of deforestation and forest degradation across the Globe (Gasparri,*et al*., 2010). Deforestation and forest degradation processes, have received much attention in the recent decades, as a result of the roles played by forest in Aboveground Biomass (AGB) conservation, carbon sequestration and species diversity conservation in the phase of ever-increasing challenges of global climate change. These roles can never be overemphasized, as forest remain one of the key players in climate change mitigation and adaptation. Among these roles are; species conservation and diversity, flood control, water conservation, and increase in agricultural yields among others. On the other hand, Man's need for food, shelter, and other activities such as urbanization, industrialization, mining activities among others have exerted much pressure on the environment (forests) and consequently increase in global warming (Omofonmwan and Osa-Edoh, 2008). As such, most of the forest canopies have been reduced below 10% threshold to meet up with Man's needs (FAO, 2004). Furthermore, some forests land has been transformed for various purposes ranging from, residential area, farming land, logging site, industrial activities.

One of the most challenging issues faced by Mankind in 21st century is global climate change (Vashum and Jayakumar, 2012). This is not surprising, as most issues confronting Man and His environment have their roots in one way or the other linked to climate change. This makes studies related to roles played by forest ecosystem in combating global warming, a center of attraction where the world attention is focusing towards at a moment, alongside the pattern of use in which land is being put to, couple with inadequate documentation of the roles of forest biomass in Carbon sequestration. Ngel Nyaki forest reserve which is situated at Mambila plateau, in Taraba State with a reasonable amount of less disturbed forest area has no updated documentation of the trend of Land use and land cover change. Knowing the position of our forest, being one of the major renewable natural resources when used sustainably on the face of the earth, and being a major source of livelihood before and during 21st centuries will go a long way to mitigating global climate change.

National resources such as forests are expected to be documented and reported periodically and spatially alongside emerging mechanisms like Reducing Emissions from Deforestation and Degradation (REDD) which is in line with the United Nations Framework Convention on Climate Change (UNFCCC, 2008; Basuki *et al.*, 2009). This enables a Nation to know its worth, at every point in time as well as put an appropriate measure in place for sustainability purposes.

Generally, change is known as the increase or decrease in the state of an object over time. To detect the state of change of an object, it has to do with the general process of observing the differences that occur overtime on an object or features (Singh 1989).

The term Land Use and Land Cover (LULC) change connotes two entities that are mostly interchanged (Rawat and Kumar, 2015). The term Land Use can simply refer to the pattern or means in which Man tend to utilize land to meet his contemporary need at the moment while Land Cover Change is the differences, which occur as a result of human or natural phenomena on land thereby making it to lose out or gain into it formal status (McConnell, 2015). Similarly, LULCC is the various pattern in which land is been put into use, alongside natural occurrences which resulted in diverse forms of changes on land (Pielke *et al.* 2011).

In other to better manage our natural resources, there is a need for consistent and adequate studies on changes that occurs on the land features and how these are put to use by Human. To carry out change detection, the use of a multitemporal dataset becomes inevitable as it presents information on the former and latter status of the land cover and how man put it to use in other to meet up with his economic needs (Lu *et al.,* 2004). The relevancy of multitemporal data sets of Landsat has made waves in studies related to change detection across the board. As a result of the application of the knowledge of change on land features, studies related to that are currently a center of attraction which has brought about consistent innovativeness on various techniques related to LULC change.

Recently, LULC changes have become an issue of global interest, mainly as the result of unprecedented change impacted on the environment by Man to satisfy his economic needs. These changes affect forest the most and unfortunately, the rate at which these changes occurred within Ngel Nyaki forest reserve has not been quantified. Remote sensing has widely been applied in natural sciences in terms of resource monitoring and management which have played vital roles in policy making. These policies have gone a long way in salvaging the environment as these resources are kept under consistent watch periodically through the application of R.S. techniques (Silleos*et al*., 2006).

Overtime, Activities such as industrialisation, urbanization, farming, logging and mining activities among others have been the major causes of LULCC. These anthropogenic activities, alongside natural phenomenon have been the major drivers of global LULCC in our environment in the 21st century (Kumar *et al*., 2013). There is need to know the extent at which these changes have occurred overtime within our environment. On this note, information from aerial photographs can now be of help to the resource manager to facilitate managerial policy that can lead to optimal maximization of the natural resources alongside the various pattern at which LULC changes within the study site at a consistent interval (Opeyemi, 2006). Therefore, the goal of this study is to determine the Land use and land cover change of Ngel Nyaki Forest reserve for the year 2002, 2012, and 2022.

MATERIALS AND MATHODS

Study Area

Study was carried out in Ngel Nyaki forest reserve is located at Mambilla Plateau in Taraba State, Nigeria. The study area is located between longitude 11º 00'00" and 11 º 30'00" East, and latitude 6º 30'00" and 7º 15'00" North. The plateau has an area of approximately 31,000 km2 of grassland with islands of forests lying at 1400–1500 m (Chapman and Chapman 2001). Ngel Nyaki is currently gazetted as a Local Authority Forest Reserve under Gashaka-Mambilla Native Authority Forest Reserve, Order of 24 April 1969 with an area of 46 km^2 (Chapman and Chapman 2001).

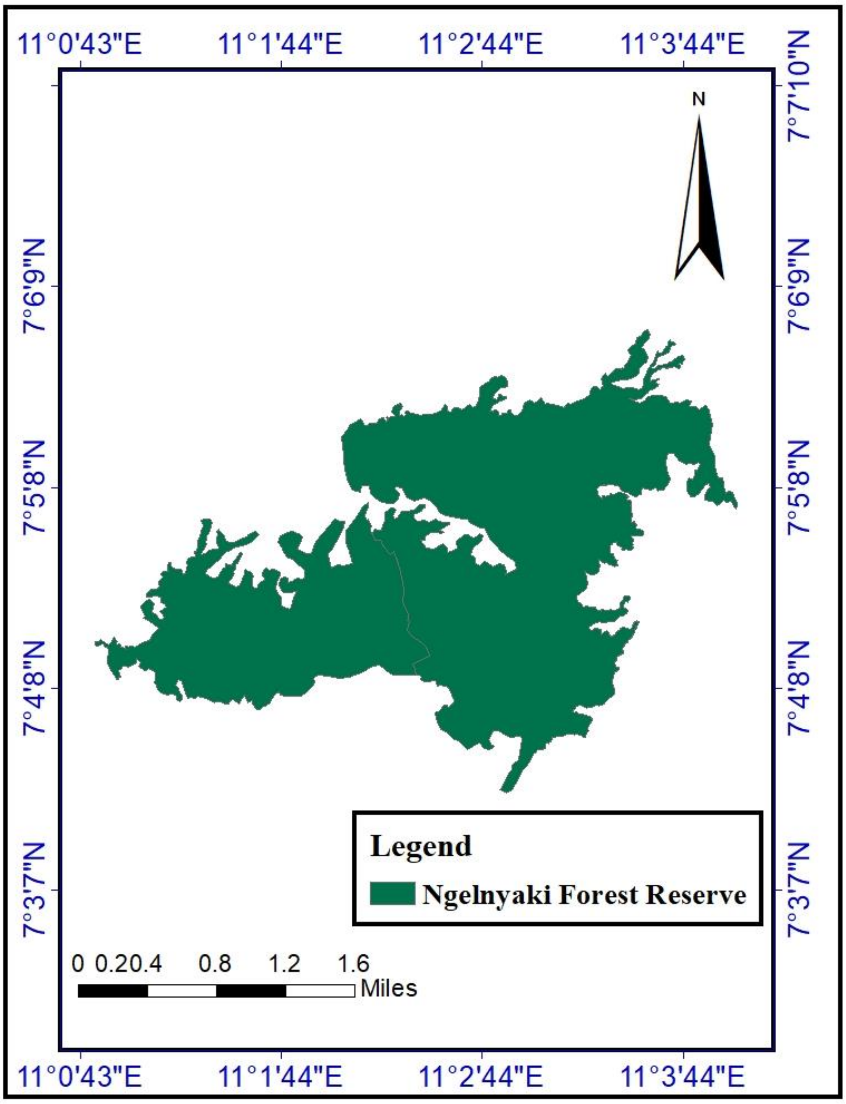

Figure 1: Map of Ngel Nyaki Forest Reserve

Spatial Data Acquisition

The imageries were gotten from *https://earthexplorer.usgs.gov*, through the path and row (186/55) search of the study area. The imageries were acquired from Landsat (ETM+ and OLI) at Level 1 and set at cloud cover of less than 10% for viewing download purpose. The data collected were

Landsat7 ETM+ of 2002, 2012 and Landsat 8 OLI of 2022 (Table 3.1). The choice of the Landsat satellite was made based on its wide-area coverage, the record of historical data for man's geographical area and free data policy.

Table 1: Spatial data imagers and the pattern of their collection.

Year	Sensor Type	Data Type	Resolution	Path and Row (scene/tile)
2002	ETM+	Spatial	30m	186/55
2012	ETM+	Spatial	30m	186/55
2022	OLI	Spatial	30m	186/55

Geometric Correction

This was carried out to correct some geometric distortion on the images arising from the sensor's platform instabilities, as well as to integrate the geo-spatial data into a compatible format. The various imagery ETM+ and Landsat8 of 2002, 2012, and 2022 respectively were registered to the WGS84 and UTM Zone32 coordinate system and geo-referenced.

Layer Stacking and Sub-setting of the study area.

This process brought in all the required bands together, so as to work with them as one entity by simply alternating the bands to get the desired composites.

The shape files of the study area were overlaid on the composite bands from the original or main data downloaded and the area of interest subset from it.

Digital Image Processing

Field surveys was carried out before and after the analysis, using the Global Positioning System (GPS). This was to help in ascertaining the truth location of each LULC classes pattern used. In order to obtain the required imagery data set for this study, sensors of Landsat (ETM+, and Landsat8) was used to collect data for 2002, 2012, and 2022. The images were pre-processed as stated earlier and was converted from Tag Image File Format (TIFF) to Imagine format using ERDAS in order to be compatible with the working environment. The multi-temporal data obtained were stacked and the study area were extracted for classification and process into a false colour composite of the imagery.

Subset and False Colour Composite of the Study Area.

The false colour composites was formed, by combining the required bands based on the LULC classes available or required for the study. The shape file of the study area was used to subset the satellite images downloaded with the address of the Area of Interest (AOI). This was achieved through overlaying the shape file on the satellite imageries and extracting the AOI from the satellite image covering the study site. The false colour composites was derived from the arrangement of bands in decreasing order (ranging from near-infrared to blue band) which turn vegetated area to red and non-vegetated (bare land) area to off-white.

Land Use/Cover Classification and Description process

Research work that has to do with LULCC needs prior knowledge of the various LULC in the study area before the analysis began. The various LULC within the study area were identified, and differentiated by the means of the available data sources such as; remote sensing imagery; Google earth, Landsat imagery and ground-truthing. Thereafter, the LULC system used were based on the LULC observed.

Image Classification

The different imageries collected were classified and a test of accuracy was carried out to ascertain the level of precision of the classification. This was done in order to take advantage and make good use of remote sensing data, so as to extract meaningful information for further findings.

Supervised Classification
Each of the pixel from the Satellite imagery enhanced, have its spectral signature which is usually determined by the spectral bands. As such, the imagery obtained were separated into different classes of interest through the supervised classification method. The choice of classes was based on various LULC within the study area which were in line with Anderson (1971) who made it known that number of classes to work with should be moderate in line with the needed information while considering the basic classes with most appropriate vital information that will meet the research objective.

RESULTS

Change Trend in Land Use and Land Cover in Ngel Nyaki Forest Reserve
The false colour composite for the study periods (2002,2012, and 2022) with greater area coverage with dark red is an indication of high proportion of thick or dense forest (Figure 2, 3 and 4). while the light red is an indication of spares of disturbed forest. The outcome from classified images from figure 5, 6 and 7 shows the various Land use and land cover in Ngel Nyaki, which were Dense Forest Land, Sparse Forest Land, Grass Land, and Bare Land occupying an area of 680.13 ha, 95.94 ha, 224.64 ha, 56.61 ha for year 2002; 706.23 ha, 137.07 ha, 214.02 ha, 0.00 ha 2012; 542.52 ha, 188.73 ha, 223.83 ha, 102.24 ha for year 2022 respectively (Table 1).

The area statistics of dense forest from the LULC was observed to higher across the study periods (2002, 2012, and 2022) with bare land from having the least of the area statistics across the same periods. This is an indication that the forest is still housing reasonable amount of dense forest. However, it was observed that the dense forest tends to be decreasing in year 2022 with an increase in the area statistics of bare land. The dark green areas from figure 6 to 7 are indication of the dense forest which are obviously of reasonable sizes, while the brown colour areas on the other hand are indications of bare land which were the smallest of all classes of LULC.

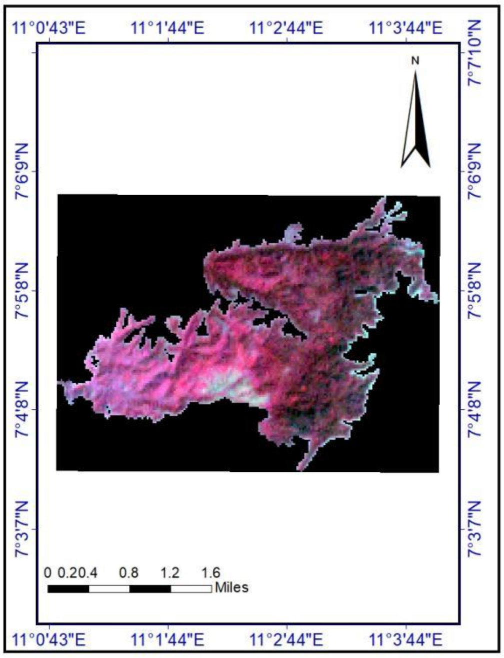

Figure 2: False Colour Composite Ngel Nyaki, 2002

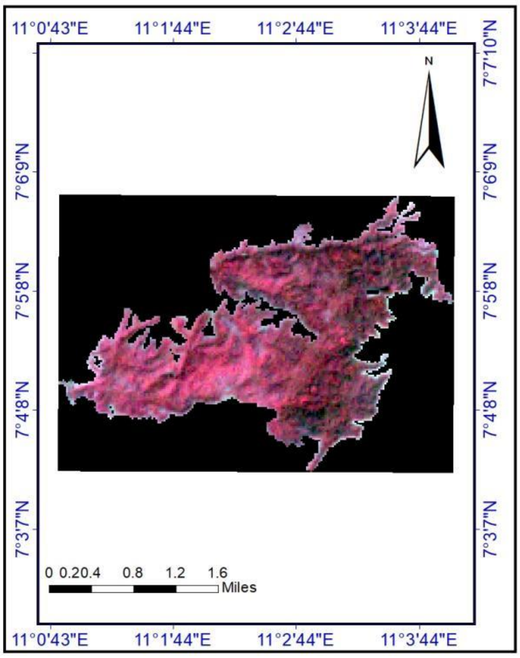

Figure 3: False Colour Composite Ngel Nyaki, 2012

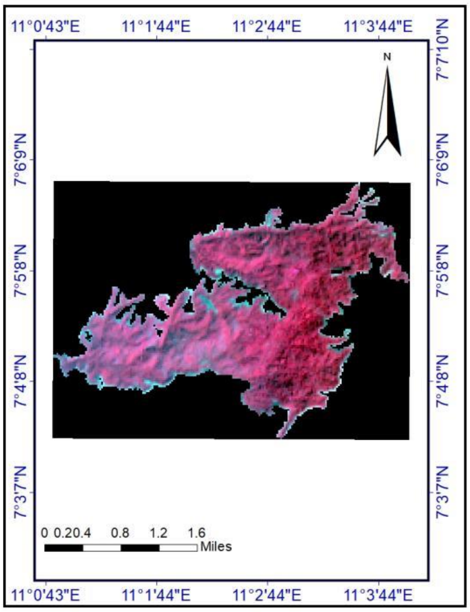

Figure 4: False Colour Composite Ngel Nyaki, 2022

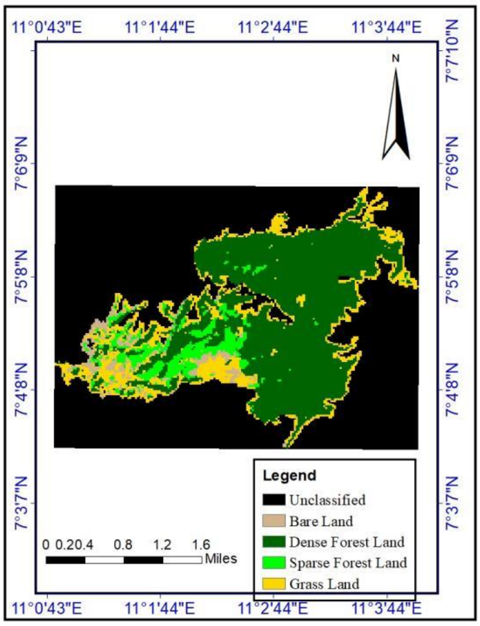

Figure 5: Classified Land Use Land Cover change of Ngel Nyaki, 2002

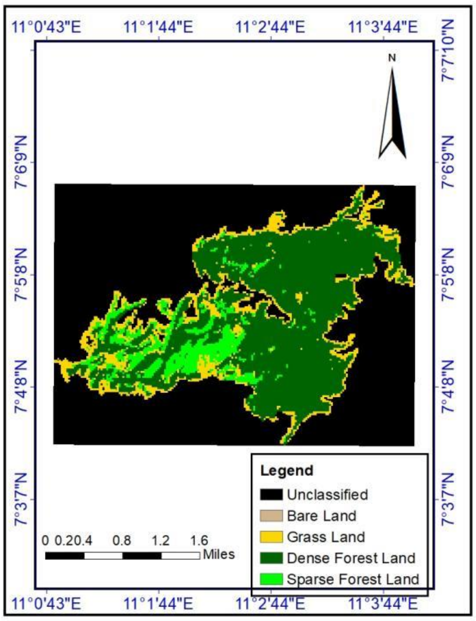

Figure 6: Classified Land Use Land Cover change of Ngel Nyaki, 2012

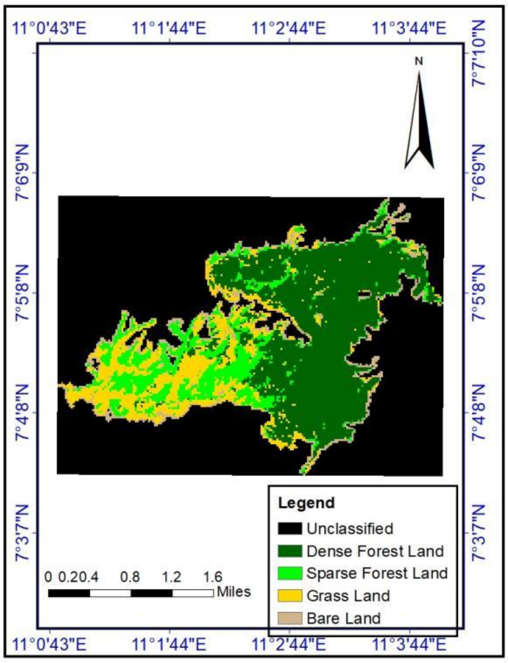

Figure 7: Classified Land Use Land Cover change of Ngel Nyaki, 2002

Table 1: Area Statistics of Land Use and Land Cover of Ngel Nyaki Forest Reserve for Year 2002, 2012, and 2022

	2002		2012		2022	
LULC Classes	**ha**	**%**	**ha**	**%**	**ha**	%
Dense Forest Land	680.13	64.3	706.23	66.8	542.52	51.3
Sparse Forest Land	95.94	9.1	137.07	13.0	188.73	17.8
Grass Land	224.64	21.2	214.02	20.2	223.83	21.2
Bare Land	56.61	5.4	0	0.0	102.24	9.7
Total	**1057.32**		**1057.32**		**1057.32**	

DISCUSSION

Land Use and Land Cover Change of Ngel Nyaki Forest Reserve

The study classified Ngel Nyaki forest reserve into four (4) land use/land cover namely; Dense Forest Land, Sparse Forest Land, Grass Land, and Bare Land. The selection of classes varied from location to location and is based on the objectives of the researcher as well as the nature of land use/land cover occupying the study area. Alo *et al.* (2020) classified Shasha forest into forest, shrubs, and built-Up areas. Oluwajuwon *et al.* (2021) classified Ogbese Forest Reserve, Ekiti State in Southwestern Nigeria into forest, plantation, farmland, grassland, and bare land.

In this study, the trend of increase and decrease varied across the study period (2002, 2012, and 2022). During the period of 2002 to 2012, Dense forest land experienced some level of increase (706.23ha to 706.23ha), which latter decrease from 2012 to 2022 (706.23ha to 542.52ha). The increase from 2002 to 2012 could be the period where in the forest was much protected, while the decrease observed from year 2012 to 2022 can be attributed to the recent demand of rose wood which were mostly found on montane forest. Similarly, Akinsoji (2013) affirmed that the forest is relatively undisturbed except the edges which are subjected to burning by incursions of grass land fires. On the other hand, the spares forest land experienced consistent increase during the study periods (2002, 2012, and 2022) with an area statistics of 95.94ha, 137.07ha, and 188.73ha respectively. This pattern of increase could be as a result of change in dense forest land as well as in-growth from the previous trees of smaller diameter class. Suprisingly, dense forest land still made up of the larger area coverage within the reserve. This could be as a result of the difficult terrain which might have contributed to its natural protection. The finding agrees with Oluwajuwon *et al.* (2021) who experienced a consistent decline in the amount of forest land with an increase in the farm land from 1998 to 2018 in Ogbese Forest Reserve. Similarly, Alo and Nwatu (2018) experienced a consistent decline in the green area of the Ibadan metropolitan during the LULC classification from 1985 to 2018. Most of the green areas were converted to built-up areas with an increase from 6.25 % to 21.77 %, while green areas decreased from 85.36 % to 67.88 %.

The classification accuracy obtained from this study ranged from 93.04 % to 95.41 % and was similar to that of Liping *et al.* (2018) who classified LULCC of Jiangle area in China, obtaining an overall accuracy of 94.94 %, 92.12 %, and 92.33 % in 1992, 2003 and 2014, respectively. Similarly, Alo and Nwatu, (2018) obtained an overall accuracy of 87.75 % to 88.75 % when they classified land use land cover of urban green space in Ibadan metropolis. Alo *et al.* (2020) also observed a classification accuracy ranging from 78.50 % to 86.55 % when modelling forest cover dynamics in Shasha forest reserve, Osun State, Nigeria. Hence, the classification accuracy obtained for this study is of high precision. This suggest that most of the features within Ngel Nyaki Forest reserve were sufficiently classified.

Human demand for wood of different kinds is a major driver of deforestation within the study area. This also implies that a slight increase in human demands for forest trees could lead to greater loss of the forest. Liping *et al.* (2018) opined that human activities were the cause of obvious changes in the Jiangle area of China, from 1992 to 2014. Ogundele *et al*. (2016) observed that in a quest to meet up with human needs, Nigerian forest resources were constantly under pressure.

The increase in sparse forest land could be at the expense of the dense forest from 2012 to 2022. This might be as a result of the fact that; dense forest usually transits to spares before being converted to other form of land use in most cases. This is similar to the findings of Kayet and Pathak (2015) who reported that the Very Dense Forest (VDF) of Saranda forest, Jharkhand reduced to 8.61% and Open Forest (OF) increased to 7.03% between the years 1992 and 2014 due to an increase in the built-up area and mining activity. This loss observed in the dense forest is in support of Li *et al*. (2016) who stated that people's demand can directly reflect on the nature of LULCC within a particular area.

CONCLUSION

In this study, five land use and land cover change (Dense Forest Land, Sparse Forest Land, Grass Land, and Bare Land) from Ngel Nyaki were classified from landsat images. Through the spatial classification, it was found that the most part of the dense forest land is more or less mountainous which could have played a role in the significant dense forest land observed. Finally, the loss of dense forest at Ngel Nyaki could affect the role of the forest in carbon sequestration as well as loss of biodiversity, and consequently environmental degradation.

Acknowledgement

This study was funded by Institution Based Research Grant of Taraba State University, Jalingo. I am immensely grateful. for this opportunity.

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