

Research Article

Impact of Land Use and Land Cover Change on Deforestation in the Central Taraba State: A Geographic Information System and Remote Sensing Analysis

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Received: 4 July 2023; **Revised:** 8 November 2023; **Accepted:** 6 December 2023

Abstract: Deforestation, the widespread clearance of forests for various land uses, has become a significant global environmental issue with far-reaching consequences. Deforestation in the study area was identified, categorized, assessed, and interpreted using Landsat 5, 7, and 8 from the years 2008, 2014, and 2020, respectively. A geographic information system (GIS) database of land use and land cover categories and their changes were created. The results showed that several anthropogenic human activities, including agriculture and wood harvesting, were driving a general retreat of the forest area. The study further shows that between 2008 and 2020, forest area decreased by 8.5% with an annual rate of 0.33%, other vegetative areas increased by 2% with an annual rate of 0.077%, and non-vegetative areas increased by 1.5% with an annual rate of 0.58%. The hotspot map shows that the rate at which the reserve is deteriorating and the conversion of the forest area to other vegetation and bare ground are only a matter of time. The study recommended that the government should adopt rigorous policies to protect forest reserves from unauthorized habitation by encouraging the use of alternative firewood fuel sources to reduce the pressure on the forest.

Keywords: deforestation, GIS and remote sensing, land use, land cover change, Taraba State

1. Introduction

Forests are an essential, substantial, and valued part of the ecosystem that supports sustainable agriculture and stabilizes soils and the climate [1, 2]. Hosonuma et al. [3] state that it regulates water flows, provides shade and cover, and acts as a natural predator's habitat for agricultural pests and pollinators. Forests have made it possible for hundreds of millions of people to feed themselves and make a living, especially in developing countries like Nigeria and Africa. About 60 million indigenous people in Nigeria are almost totally dependent on the forest, and 350 million more rely on it to a considerable extent. Approximately 2.5 billion people in Africa rely on natural forest resources for a variety of services [4, 5].

However, man continues to harm forests through a range of anthropogenic activities, despite how essential they are to both human existence and the ecosystem [6, 7]. The dynamics of the forest and the tree density are disrupted by these operations, which speed up the process of deforestation. Deforestation is defined as the clearing and removal of forest trees when the land is used for non-forest purposes [8-11]. Examples of such uses include converting forest reserves into residential or commercial areas, removing forest trees due to road or rail construction, using the land for agriculture,

and cutting down forest trees for domestic and commercial purposes, such as firewood, timber, paper production, and charcoal.

The world's forests span over 4 billion hectares (ha), or 31%, of the total land area. Of the world's forests, 42% are found in wealthy nations, while 58% are found in developing nations [7, 12]. On the other hand, the average global per capita forest acreage fell from 1.2 ha in 2000 to 0.6 ha in 2010. Some experts predict that by 2025, there won't be as much as 0.2 ha, with the majority of the reduction taking place in developing nations [13-17]. Nigeria has the highest yearly deforestation rate in Africa, losing an average of 409,700 ha of natural forests annually [16, 18, 19].

Although deforestation occurred all over the country, Taraba State, which is less developed, was hardest hit [18, 20]. Deforestation impacts several aspects. Firstly, deforestation leads to the loss of biodiversity and the destruction of habitats for various plant and animal species. This loss of biodiversity disrupts ecosystems and can lead to the extinction of species, including those that may be important for providing ecosystem services such as pollination or pest control [10, 11]. The pattern of deforestation in Central Taraba State is similar to that of other areas of Africa. For example, studies including those have shown that deforestation rates are high in the Congo Basin, the Sahel, and the Ethiopian Highlands [11, 21]. The drivers of deforestation in these areas are similar to those in Central Taraba State, including agricultural expansion, logging, fuelwood collection, and infrastructure development [11].

Unchecked forest degradation appears to have increased over the past ten years, creating increasing problems for human life, welfare, and development. But the state's government has given it little to no attention, and over the years, neither a law nor an afforestation program have been initiated to put an end to the instances. For the purpose of implementing effective forestland usage, data on spatially explicit and thematically rich quantitative studies of changes in forest land cover over time and at a regional scale, such as this one, remains an essential resource. Therefore, geographic information system (GIS) and remote sensing will be used in this investigation. The goal was to complement existing similar studies in other regions of the country and to offer information on the occasions, types, and speed of harmful forestland use change. This information would also serve as a baseline for future research work in the study area.

2. Materials and methods

2.1 The study area

Taraba State is positioned roughly between latitudes 6°30' and 9°36' North and 9°10' and 5°0' East. Bauchi State borders it to the north, Adamawa State to the east, Gombe to the northeast, Nasarawa and Plateau states to the west, and Benue State to the southwest. An international border separates the Republic of Cameroon from the south and southeast. The entire area of land in Taraba State is about 54,473 km² [22]. The study area, which is a ward in Bali, a local government area of the state, has a total size of 15,104 km² (see Figures 1 and 2). The research area's undulating landscape is made up of flat, solitary, and mountain chains, with elevations ranging from 264 m to 934 m above sea level [22, 23]. The majority of the locals work mostly in agriculture, fishing, lumbering, hunting, sculpting, and the harvesting of trees for use as firewood in towns.

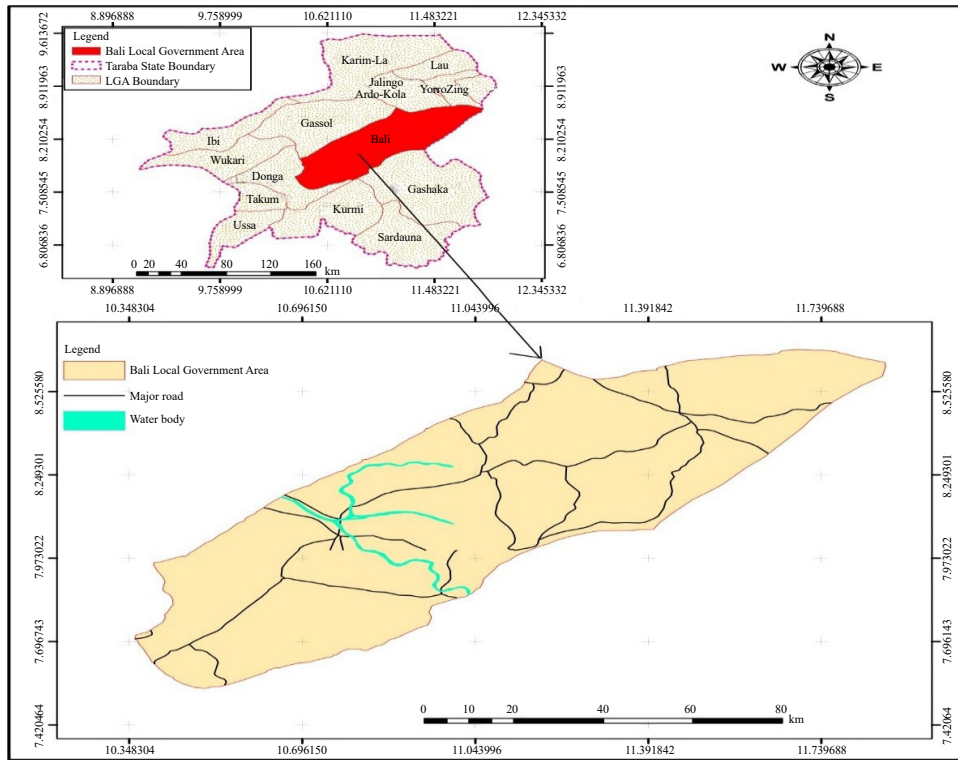


Figure 1. Map of Taraba State showing the Bali Local Government Area

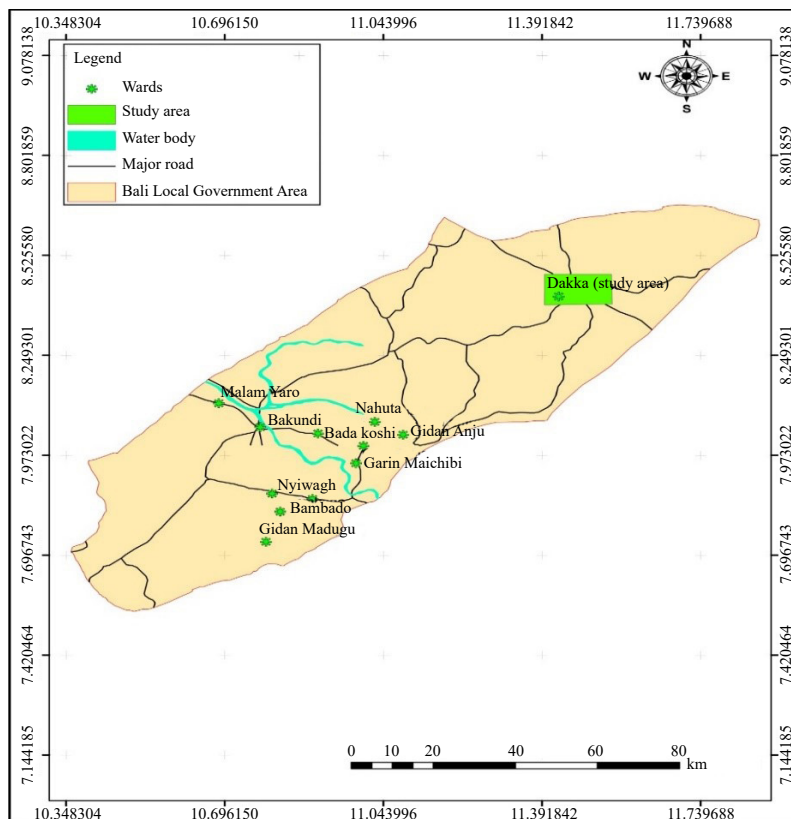


Figure 2. Map of the study area

2.1.1 Climate

The research region features climatic characteristics resembling a tropical climate with dry and wet seasons. In general, the wet season lasts from March until October [24]. The range of the mean annual rainfall is between 1,158 mm and over 1,500 mm. September and August are the wettest months. The dry season lasts from November through February, with December and January having the lowest relative humidity at 15%. The highest temperature ranges from 30 °C to 34.4 °C, with the average yearly temperature being around 28 °C. The minimum temperatures vary from 15 to 23 °C [22].

2.1.2 Vegetation

The primary kind of vegetation in the research area is Guinea Savanna vegetation, which is dominated by *Daniellia* and offers just a little shade [22]. The research area's vegetation pattern is primarily influenced by rainfall distribution and topography, with vegetation that is robust during the wet seasons but wilts in the dry. There are also numerous kinds of trees and bushes. The *Hymenocardia* and *Andropogon* communities, respectively, are the main shrub and grass communities. Shea butter (*Vitellaria paradoxa*), locust bean (*Parkia biglobosa*), sapele (*Entandrophragma cylindricum*), mahogany (*Khaya* spp.), afra (*Nectophryne afra*), and iroko (*Millicia excelsa*) are among the economic trees that are frequently seen. Mango (*Mangifera indica*), guava (*Psidium*), date palm (*Phoenix dactylifera*), and paw paw (*Asimina triloba*) are a few examples of cultivated plants.

2.2 Methods

The United States Geological Survey (USGS) provided satellite images of the research area. The Landsat images used were from 2008, 2014, and 2020. Google Earth provided ground control points (GCPs), which were used to verify the coordinates of the categorized images. The extent of land use and coverage of the area in 2008 was assessed using a Landsat 7 Enhanced Thematic Mapper (ETM+) image with a 30-m spatial resolution and 15-m spatial resolution (panchromatic), which had a total of 9 bands. The Landsat 7 ETM+ image of the year 2014 with 30 m spatial resolution and 15 m spatial resolution (panchromatic), which in total have 9 bands, was utilized to determine the extent of land use and coverage. Meanwhile, to ascertain the area extent of land usage and land cover coverage in 2020, Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI & TIRS) images with 30-m spatial resolution and 15-m spatial resolution (panchromatic) were employed. These images have a total of 11 bands.

2.2.1 Data pre-processing

Using Adobe Photoshop, all six images from 2008, 2014, and 2020 were enhanced in the pre-processing phase. Geometric and radiometric corrections were made when utilizing Erdas' theory [11, 25].

2.2.2 Image layer: stacked, mosaic, and sub-setting

The ArcMap 10.3 environment was opened after the satellite photos were imported. Layer stacking of the USGS images acquired in Path 186, Row 55, was done using ArcGIS's "composite band tool" to create a single image including all the information covered by the bands. Every photo that underwent this process was duplicated. Using the "mosaic to new raster tool" in ArcGIS, the images of the scene taken in 2008, 2014, and 2020 at Path 186, Row 55, and Path 186, Row 54 were combined into a single mosaic image by overlapping their edges. ArcGIS's "clip tool" was utilized for the categorization process; from the three mosaic scenes, a subset encompassing the area of interest was extracted.

2.2.3 Classification of images with the highest likelihood

The images were classified using a supervised classification method into multiple classes. This method is favored because it has 30 years of historical environmental data and allows the training data for the classification to be directed. Training data that was produced based on the predominant land use and land cover themes in the area served as the

classification’s guide [24, 25]. The recognized land cover types (training sites) were labeled with the names of the related theme characteristics. According to Adelalu et al. [20], land use and cover classification scheme, the various land use and land cover types in the research region were split into five categories: dense forest, bare land, shrubs, water bodies, and built-up areas.

2.2.4 Ground-truthing and accuracy assessment

To check the accuracy of the classed photos, GCPs were gathered from Google Earth and positioned in regions linked to the study’s classes in order to verify the correctness of the classified pictures. This was depicted in the images to demonstrate the effectiveness of the classification at the training locations. 10 GCPs were gathered for every class, totaling 50 points of truth data for each of the three Landsat pictures (2008, 2014, and 2020) and a total of 150 points for all three images.

2.2.5 Data analysis, presentation, and display

To detect the extent, type, and pattern of the land cover from 2008 to 2020, the research region’s images were overlaid in ArcGIS to identify changes caused by the classification of the land cover. The acquired values were converted into percentages and utilized as absolute data to illustrate changes in land cover and use and to determine the rate at which these changes happened between 2008 and 2020 [26, 27].

3. Results

There are four sections within this section. The amount and rate of deforestation in the study area are covered in the first and second parts, respectively. The third and fourth sections, respectively, list the study area’s most rapidly deforested areas and most endangered species.

3.1 The extent of deforestation in Taraba State

The level of deforestation was determined by assigning land cover classes to pixels and identifying three types of land use and cover: forestry, other vegetation (grass, bushes, and crops), and non-vegetative areas (built-up and bare surfaces). A color composite of the acquired images utilizing the bands 4 3 2 and 5 4 3 was then created, and supervised classification using the maximum likelihood approach was applied. The success of the classifier in classifying land use and cover led to its adoption. Table 1 displays the land use and land cover of the research region for the years 2008, 2014, and 2020 in ha and as a percentage.

Table 1. The area of land cover for the research region in ha and percentage for the years 2008, 2014, and 2020

Land use type	2008 land use		2014 land use		2020 land use	
	Area	%	Area	%	Area	%
Forestry	9,846	65	9,062.4	60	8,533.7	56.5
Other vegetation	3,927	26	4,833.3	32	5,135.3	34
Non-vegetative area	1,359	9	1,208.3	8	1,133	7.5
Total	15,104	100	15,104	100	15,104	100

The study area in 2008 was densely covered by forest, accounting for 65% (9,846 ha) of the land use cover, scattered other vegetative land areas accounting for 26% (3,927 ha), and spotted non-vegetative areas accounting for 9% (1,359 ha). These findings are presented in Table 1 as well as Figures 3, 4, and 5. Meanwhile, other vegetation increased by 6% (4,833.3 ha) and the non-vegetative areas increased by 1%, bringing the total area of the non-vegetative area to 8%

(1,208.3 ha). The land use and cover of the study show gradual deforestation from the center of the study area in 2014. At that point, the forestry area had decreased by 5%, leaving a total percentage of 60% (9,062.4 ha). However, in 2020, the area used for forestry further shrank or declined from the initial 65% to 56.5%, indicating a total loss of 8.5%. While non-vegetative areas decreased to 7.5%, other vegetation, which was initially 26%, rose to 34%. These results with regard to the extent of deforestation are consistent with studies elsewhere in Nigeria [4, 5, 11, 21, 26].

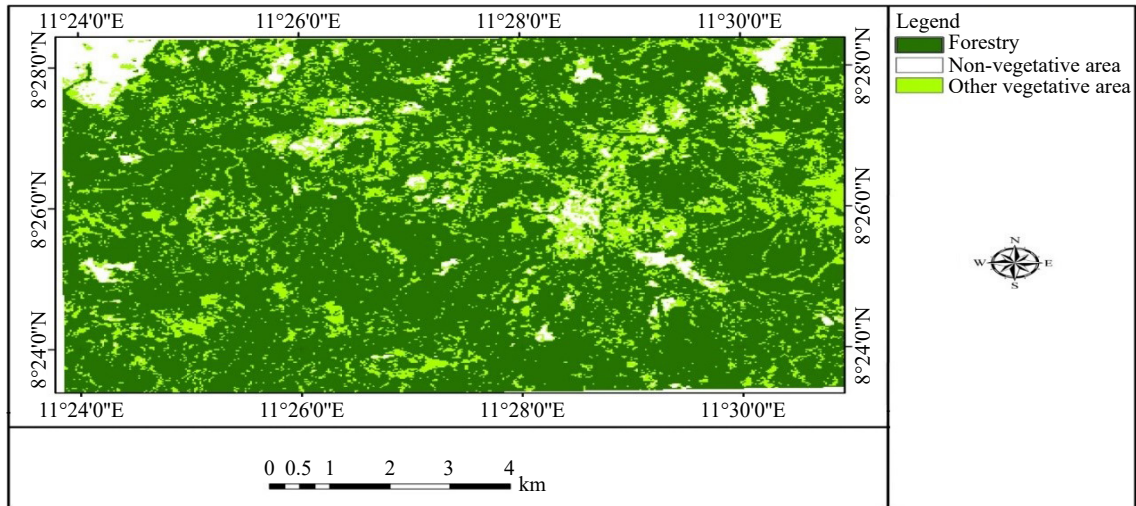


Figure 3. 2008 land use and land cover image of the study area

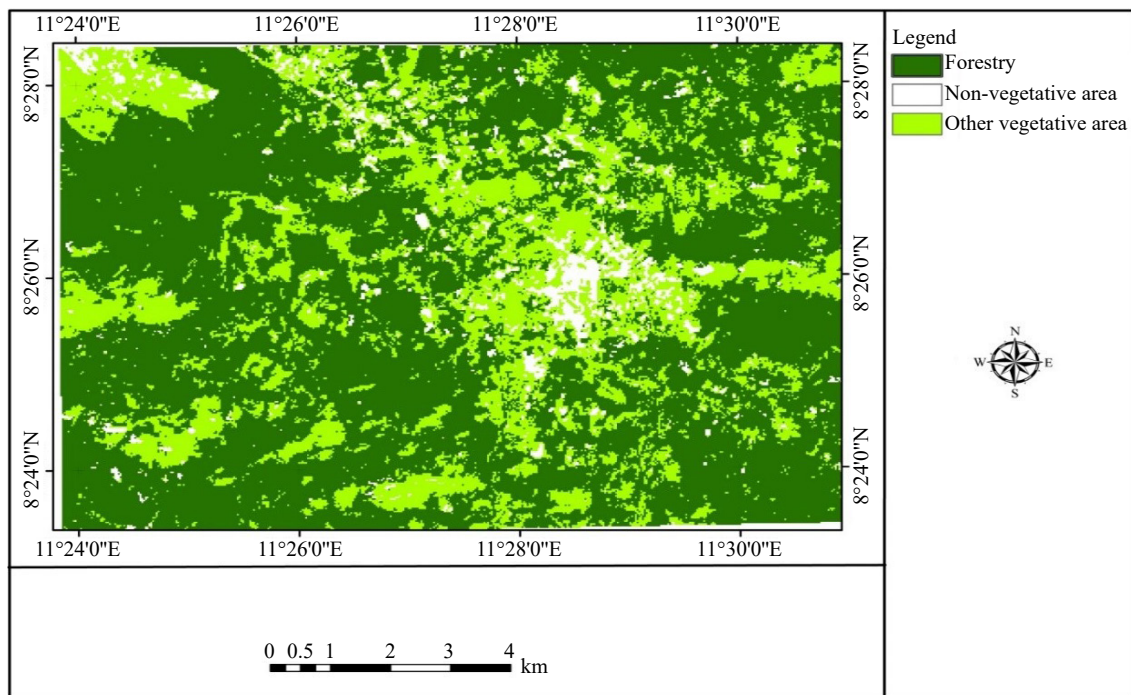


Figure 4. 2014 land use and land cover image of the study area

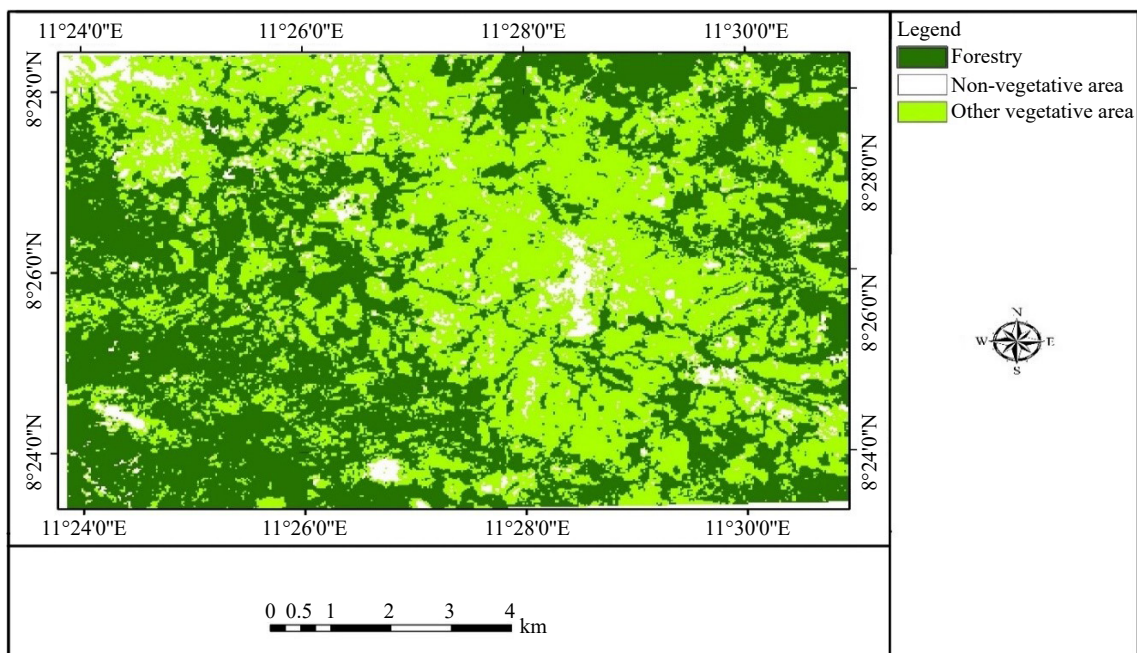


Figure 5. 2020 land use and land cover image of the study area

3.2 Rate of deforestation in the study area

The total number of cells in each category was determined from the attribute table of each study year in the ArcGIS environment to acquire the real area extent in hectares of the land use/cover categories for each study year. A cell's size is determined by using the characteristics option, and its total area is calculated by multiplying the number of cells in each category by that number. A detailed dataset in terms of land use type and changes throughout time is provided by tabulation and area computation. The annual percent increase or decrease in activity from 2008 through 2020 is shown in Table 2.

Table 2. Area, percentage, and the annual rate of decrease or increase in land use and land cover from 2008 to 2020

Land use type	Area covered (ha)		Difference (ha) 2008 to 2020	Increase or decrease (%) 2008 to 2020	Annual rate of increase or decrease 2008 to 2020
	2008	2020			
Forestry	9,846	8,533.7	-1,312.3	-8.5	-0.3269
Other vegetation	3,927	5,135.3	1,208.3	2	0.0769
Non-vegetative area	1,359	1,133	-226	-1.5	-0.0577

Results from Table 2 reveal that between 2008 and 2020, forest area dropped by 8.5% with an annual rate of 0.33%, other vegetative area increased by 2% with an annual rate of 0.077%, and non-vegetative area decreased by 1.5% with an annual rate of 0.58%. This finding is consistent with the results reported across the northeastern part of Nigeria [7, 14]. However, this is inconsistent with the findings of most studies carried out in southern and eastern Nigeria, where the rate of deforestation was minimal [10, 26, 28].

3.2.1 Image difference: change detection analysis

Areas with clearly varying brightness levels were found by comparing two categorized photos (2008 with 2014 and 2014 with 2020). This was accomplished by using the variations between newly made photos. Comparing spectrum changes with shifts in land cover was the fundamental tenet of the change detection method. By utilizing Erdas Imagine 9.2, change detection was carried out. Figure 6 depicts a high transition that occurs gradually from the northwest into a heavily populated area in the research area's center. Around the area of high change is a zone of low or no change. Figure 7 depicts the study area's high change as it moves from the north-west to the south-east, with patches of low or no, and moderate change surrounding the high change area.

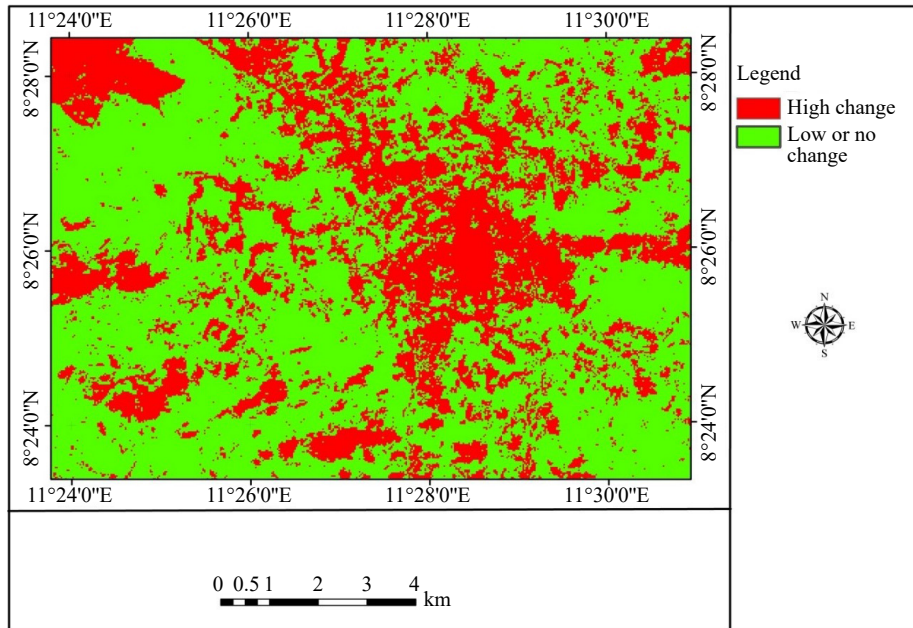


Figure 6. Map showing the image difference between 2008 and 2014

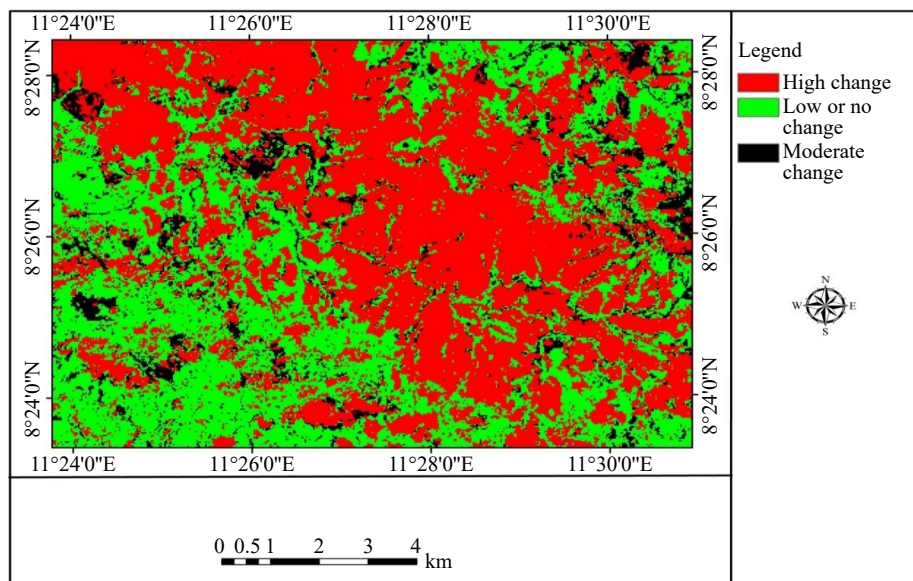


Figure 7. Map showing the image difference between 2014 and 2020

3.3 Analysis of the research area's deforestation hotspots

Results from Table 3 show that 1.6% of the study area has very high levels of deforestation, followed by 2.8% for a high level, 7.6% for a moderate level, and 20% for a low level. The remaining 68% of the study area has very low levels of deforestation. This concurred with the findings reported earlier [7, 14, 24] that there are very high levels of deforestation in the region.

Table 3. Deforestation class in area and percentage from 2008 to 2014

Deforestation class	Area (ha)	Percentage (%)
Very low	10,271	68
Low	3,021	20
Moderate	1,148	7.6
High	423	2.8
Very high	241	1.6

The evidence from Table 4 and Figure 8 indicates an increase in the area of very high deforestation levels. The central part shows the largest portion, accounting for 5.5%. High deforestation levels are observed in the northwest and southeast parts, constituting 7.5%. A moderate level of deforestation spans from the northwest to the southeast, covering 11%. Following this, low deforestation areas account for 14%, while very low deforestation areas cover 62% of the study area. These research findings clearly provide support for the previous study by Madaki and Sayok [14], who indicated that deforestation remains the major problem constraining the study.

Table 4. Deforestation class in area and percentage from 2014 to 2020

Deforestation class	Area (ha)	Percentage (%)
Very low	9,364	62
Low	2,115	14
Moderate	1,661	11
High	1,133	7.5
Very high	831	5.5

3.4 Endanger species

Based on observation, site visits, and community consultations, the African Rosewood (*Pterocarpus erinaceus*), also known locally as Madrid, was the study area's most endangered species. This is because of both local and worldwide demand.

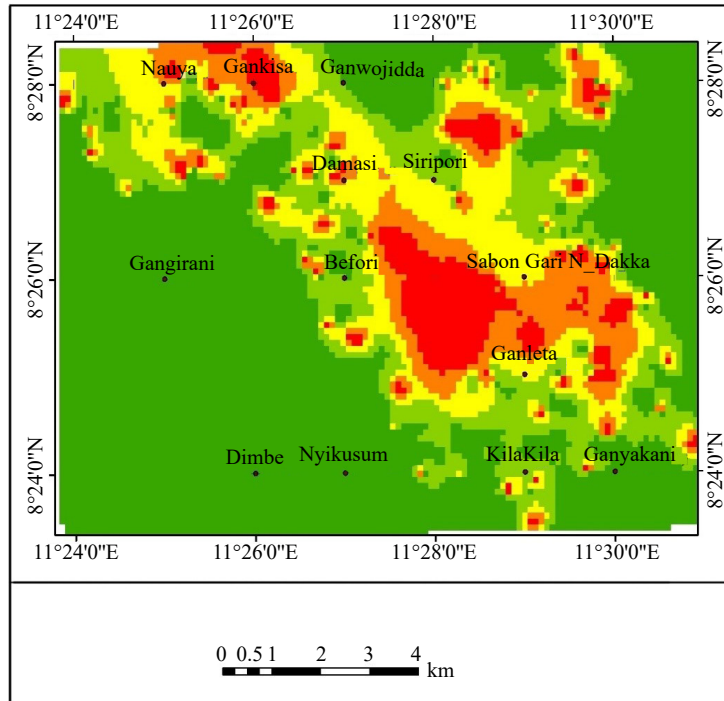


Figure 8. Map showing the hotspot from 2008 to 2020

4. Conclusion

Deforestation in the study area was identified, categorized, assessed, and interpreted using Landsat 5, 7, and 8 from the years 2008, 2014, and 2020, respectively. A GIS database of land use and land cover categories and their changes was created. The outcome demonstrated that various anthropogenic human activities, such as wood harvesting and agricultural operations, were causing the forest area to generally recede. The study shows that between 2008 and 2020, forest area decreased by 8.5% with an annual rate of 0.33%, other vegetative areas increased by 2% with an annual rate of 0.077%, and non-vegetative areas decreased by 1.5% with an annual rate of 0.58%. The change-difference map and hotspot reveal that the reserve is deteriorating at a concerning rate. The conversion of forest areas to other vegetation and bare ground appears inevitable, signaling a potential impending shift. The very high hotspot increased from 1.6 to 5.5% between 2008 and 2020; the high hotspot increased from 2.8 to 7.5%; the moderate hotspot increased from 7.6 to 11%; the low hotspot decreased from 20 to 14%; and the very low hotspot decreased from 68 to 62%. The study recommended that the government should adopt rigorous policies to protect forest reserves from unauthorized habitation by encouraging the use of alternative firewood fuel sources to reduce the pressure on the forest.

4.1 Limitations

A major factor that may constrain the generalization of the present study is that six random satellite images were used. A larger number would have been more reliable. However, despite the small number, the fact is that the study is the first of its kind examining land use and land cover change over a forested area in the research region. It is hoped that future researchers will contribute by using a larger number.

Conflict of interest

The authors have no competing interests.

Acknowledgment

The authors acknowledge and appreciate the financial support from the Nigerian Tertiary Education Trust Fund (TETFund), which has been instrumental to all our logistical and material requirements that make this research a reality. We also thank the management of Taraba State University, Jalingo, Nigeria, and the community members in the research region for their understanding and assistance.

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