MODIS NDVI assessment of Forest Degradation in the Federal Capital Territory Abuja, Nigeria, Sub Saharan Africa: A Case Study of the year 2000 – 2022

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ABSTRACT

The Federal Capital Territory (FCT) Abuja is one of Africa's fastest-growing cities, and its rapid, unsustainable growth has led to forest degradation. This study aims to assess changes in Abuja's forest cover from the year 2000 to 2022 by analyzing annual averages of the Normalized Difference Vegetation Index (NDVI) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data. The data extraction and processing were conducted via JavaScript code editor on the Google Earth Engine (GEE) platform and ArcGIS 10.7.1. The user's accuracy (UA), producer's accuracy (PA), overall accuracy (OA), and kappa coefficient (KC) of the classified NDVI maps were computed via ArcGIS 10.7.1 and Google Earth Pro. The OA for 2000 and 2022 were 90% and 93%, respectively. The KC were 0.85 and 0.90, respectively. In the year 2000, the maximum value of the NDVI was 0.713, while the minimum value was -0.01. On the other hand, in the year 2022, the maximum value decreased to 0.634, while the minimum value increased to 0.05. A reclassified map was created using the NDVI threshold from the raster image. The NDVI threshold value was able to identify areas with no vegetation, sparse vegetation, or dense vegetation, which are the land cover classes considered in this study. In 2000, areas with no vegetation occupied 8 km^2, which later increased to 53.2 km^2 in 2022. Sparse vegetation occupied an area of 3,411 km^2, which later increased to 6,905 km^2 in 2022. Furthermore, in the year 2000 dense vegetation occupied an area of 3,936 km^2, which later decreased to 388 km^2 in the year 2022, which indicates massive forest degradation. The findings of this study have practical applications in the fields of environmental monitoring and forest management in FCT, Abuja, enabling policymakers to promote sustainable development.

Keywords: *Forest Degradation, MODIS, NDVI, Google Earth Engine*

1.0 INTRODUCTION

Forests play a crucial role in maintaining ecosystem services, offering a wide array of ecological, economic, and social benefits (Barua et al., 2020; Leal Filho et al., 2021; Chen et al., 2022; Oyediji and Adenika, 2022). However, unsustainable practices have resulted in widespread forest degradation, resulting in a significant land-use crisis, particularly in tropical ecosystems (Jeminiwa et al., 2020; Adeyemi and Oyeleye, 2021; Fotang et al., 2021). Key drivers of this degradation include forest clearance for agriculture (Amaechi et al., 2023), illegal logging (Hartoyo et al., 2022), and rapid population growth (Oyetunji et al., 2020), all of which contribute to the escalating demand for land and urban infrastructure (Sheikh et al., 2017).

Additional causes, such as overharvesting of forest products, overgrazing, wildfires, and invasive species, further exacerbate the degradation process (Bustamante et al., 2016; Vásquez-Grandón et al., 2018). An extensive analysis by Hosonuma et al. (2012) of 46 developing countries identified the primary drivers of forest degradation as timber harvesting, firewood collection, uncontrolled wildfires, and grazing. These factors may cause rapid forest degradation or occur gradually, as in selective logging where high-value trees are extracted over multiple harvests (Vásquez-Grandón et al., 2018).

Monitoring forest degradation is essential for understanding its progression, and the NDVI offers a reliable method for this purpose (Bid, 2016; Meneses-Tovar, 2011; Tarazona & Miyasiro-López, 2020). NDVI, which measures the difference between near-infrared and visible light, ranges from -1 to 1, provides an indication of vegetation cover and photosynthetic activity (Huang et al., 2021; Karaburun, 2010). Higher NDVI values correspond to dense vegetation like forests, while lower values are associated with barren areas or water bodies. The utility of NDVI in tracking forest cover changes has been widely adopted (Gandhi et al., 2009; Yang et al., 2010; Sidi Almouctar et al., 2021).

Several studies have demonstrated the effectiveness of NDVI in monitoring forest degradation. For instance, Thokchom (2008) observed a significant loss of forest cover in Imphal, India, with a decrease of 507 sq. km between 2008 and 2019. Othman et al. (2018) studied tropical deforestation in Pahang, Malaysia, revealing a forest degradation from 8.9% to 6.6% between the year 2002 and 2015. Khalile et al. (2018) reported a 52.09% decline of the Nfifikh Forest in Morocco between 1987 and 2015, while Salisu et al. (2024) noted a net vegetation degradation of 8,533.05 km² (-39.43%) over 29 years in Kebbi State, northwestern Nigeria.

This study employs NDVI data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) to assess forest degradation in the Federal Capital Territory (FCT), Abuja, over a 22-year period (2000–2022). MODIS, a part of the

Earth Observation System onboard NASA's Terra and Aqua satellites, provides NDVI and enhanced vegetation index (EVI) products with a spatial resolution of 250 meters, making it ideal for long-term monitoring of vegetation across large areas (Eckert et al., 2015). While the spatial resolution of MODIS is relatively low, its high temporal resolution compensates for this by enabling the detection of temporal trends in vegetation cover (Muktar and Yelwa, 2020; Gu and Wylie, 2015).

Although NDVI has been widely used to monitor forest degradation globally, there remains a gap in long-term temporal studies specific to Abuja. By conducting a 22-year analysis, this study aims to fill that gap, providing unique insights into forest degradation patterns in the region. The findings are expected to contribute significantly to the development of effective forest management strategies, supporting informed environmental decision-making in Abuja.

2.0 METHODOLOGY

2.1 Study Area

Abuja, Nigeria's capital, has six area councils: Abaji, Abuja Municipal (AMAC), Bwari, Gwagwalada, Kuje, and Kwali (Figure 1). The total land area of these six councils is approximately 7,354 km^2, with GPS coordinates of 9°5′ N and 7°32′ E. According to Euromonitor (2010), the growth rate of the city between 2000 and 2010 was 139.7%, positioning it as one of the most rapidly developing cities globally. According to Abuja Facts (2015), the city experienced a minimum annual growth rate of 35% in 2015, making it the most rapidly expanding metropolis in Africa. The city is characterized by both rainy and dry seasons (Adams and Bamanga, 2020). The short harmattan season, which is characterized by dry and dusty northeast trade winds sweeping through West Africa from the Sahara, results in chilly and dry weather conditions, particularly from November to early March. Daytime temperatures in cities range from 28°C to 40°C, whereas nighttime temperatures range from 12°C to 23°C (Chibuike et al., 2018). Abuja presents a unique case study for this research, as it has experienced significant urban growth since becoming Nigeria's capital. This expansion has led to considerable land use changes, including deforestation to make way for infrastructure and residential areas (Amaechi et al., 2023). In addition, Abuja's rapid population growth has increased the demand for resources, leading to activities such as illegal logging and agricultural expansion. These socioeconomic pressures have the potential to drive forest degradation (Oyetunji et al., 2020).

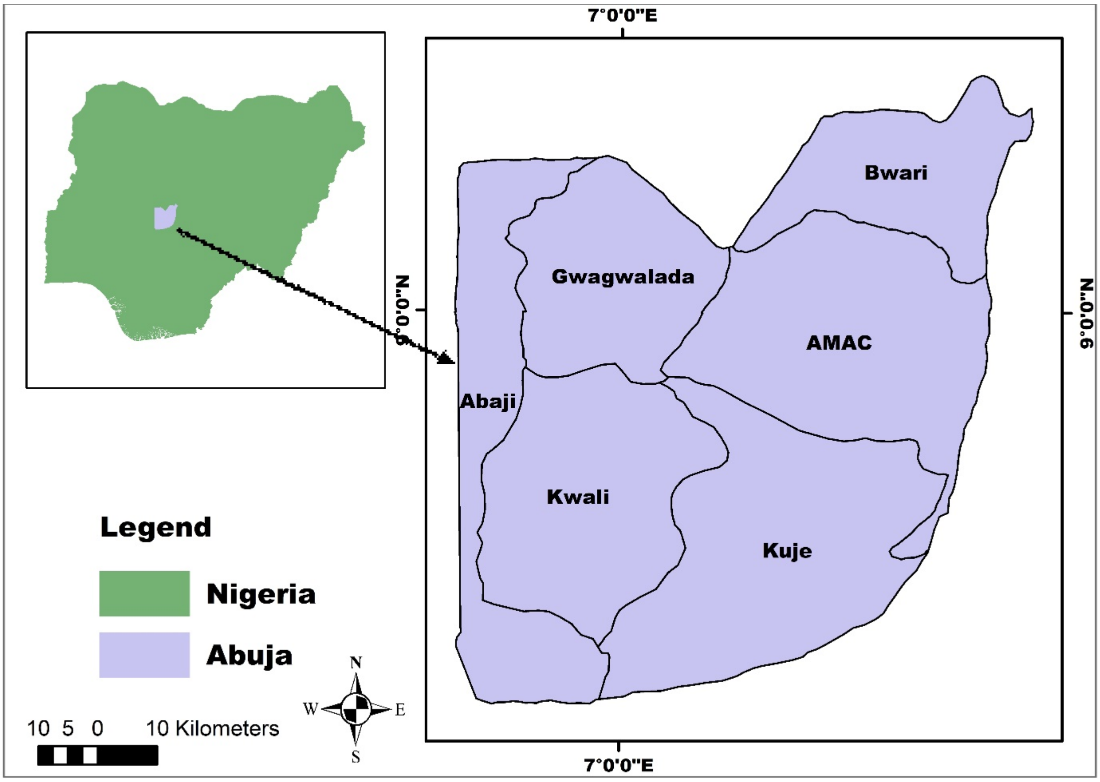

Figure 1: *Map of the study area (FCT, Abuja)*

2.2 Data sources and analysis

MODIS NDVI data were selected for this study because of their comprehensive temporal coverage and spatial resolution of 250 m, which is suitable for monitoring vegetation changes over large areas such as Abuja. This study utilized annually averaged MOD13Q1.061 Terra Vegetation Indices 16-Day Global 250 m datasets for the period from 2000 - 2022. These datasets are archived in the Google Earth Engine (GEE) as an image collection. The data extraction and processing were conducted via the JavaScript code editor on the GEE platform (Figure 2).

To estimate vegetation degradation in Abuja, the MODIS NDVI data were processed by averaging the 16-day composite data to obtain annual mean values for each year. This approach helps minimize the effects of short-term anomalies and provides a clearer picture of long-term trends. The use of GEE facilitated the efficient handling and analysis of large datasets, enabling us to visualize and analyze spatiotemporal changes in vegetation cover over the study period.

While MODIS NDVI data offer extensive temporal coverage and consistent data quality, it is essential to acknowledge certain methodological limitations inherent in the use of these data for assessing forest degradation: the 250-meter resolution of

MODIS NDVI data may not capture small-scale vegetation changes within the study area. This can potentially lead to underestimation or overestimation of localized degradation events.

```
Modis_NDVI *                                   Get Link   Save   Run   Reset
Imports (1 entry)
  var ROI: Table users/kingsleyhormone/Abuja
var modis = ee.ImageCollection("MODIS/061/MOD13Q1").select('NDVI').filterDate('2022-01-01','2022-12-31');

//Map.centerObject(country, 8)
print(modis.size());
Map.centerObject(ROI,10);
print;

var scaled_ndvi = modis.map(function(image){
  return image.multiply(0.0001)
  .copyProperties(image, ['system:time_start','system:time_end']);
});

print(scaled_ndvi.size());

var average_ndvi = scaled_ndvi.reduce(ee.Reducer.mean()).clip(ROI);
var ndviVis = {
  min: -1,
  max: 1,
  palette: [
    'blue','white','green'
  ],
};
Map.addLayer(average_ndvi , ndviVis);
Export.image.toDrive({
  image:average_ndvi ,
  description:'Abuja_ndvi_2022',
  folder:'GEE',
  region:ROI ,
  scale: 250,
```

Figure 2: *JavaScript code for extracting NDVI images.*

After the NDVI raster images for 2000 and 2022 were exported and downloaded, both were imported into ArcGIS 10.7.1 for further processing. The images were projected to UTM Zone 32 via the ArcGIS Projection Tool (Data Management). Mask (spatial analyst) extraction was used to extract the cells of the raster images that correspond to the Abuja boundary shapefile. The raster images for 2000 and 2022 were reclassified into three classes (no vegetation, sparse vegetation, and dense vegetation) on the basis of the observed pixel values. To obtain the exact area covered by each classified class, the Raster to Polygon conversation tool was employed. After conversion, the dissolve tool (data management) was used to aggregate all pixels with similar values together. After all the pixels were aggregated, change detection (intersecting tool) was performed to detect areas with no change, positive change, or negative change.

2.3 Accuracy assessment

The user's accuracy (UA), producer's accuracy (PA), overall accuracy (OA), and kappa coefficient (KC) of the classified NDVI maps for 2000 and 2022 were computed via ArcGIS 10.7.1 and Google Earth Pro. The steps involved are as follows:

1. Accuracy assessment points that were randomly distributed within each NDVI class were created.
2. *Converting Points to Keyhole Markup Language (KML):* The accuracy assessment points were converted to KML file format via the “Layer to KML” conversion tool.
3. *Opening KML in Google Earth Pro:* The KML file was opened via Google Earth Pro. The “show historical imagery” feature in Google Earth Pro was used to backdate the displayed image to 2000 and 2022 (Figures 3 and 4).
4. *Cross-Referencing and Computing the Confusion Matrix:* After cross-referencing all the points with the classified NDVI class in Google Earth Pro, confusion matrix tables (Tables 1 and 2) were computed. The UA, PA, OA, and KC were calculated via Equations 1- 4.

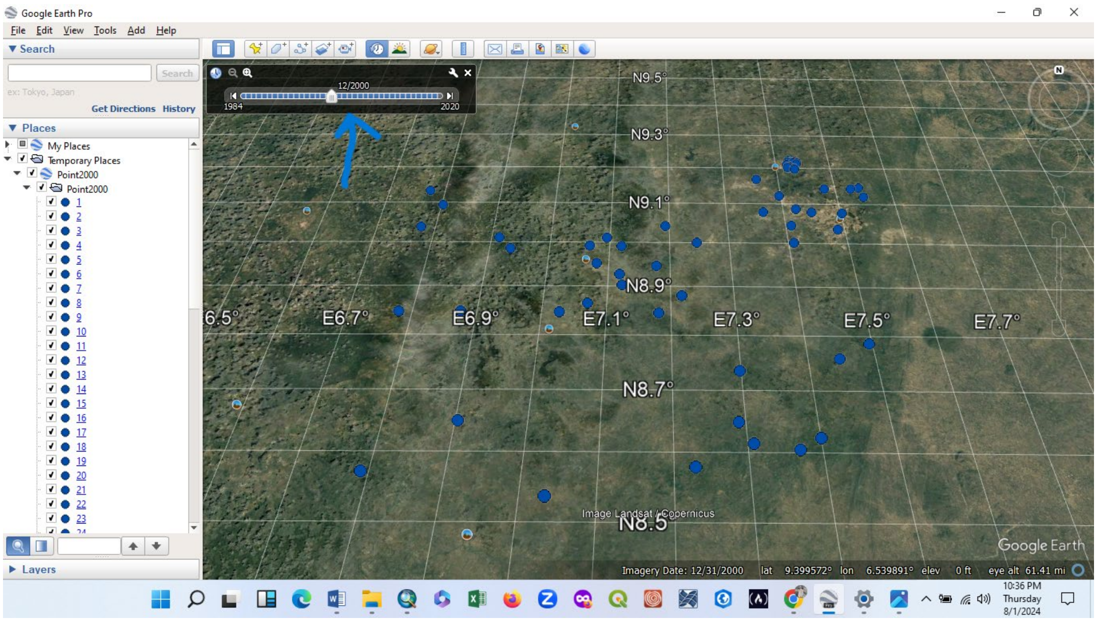

Figure 3: *Accuracy assessment points for 2000*

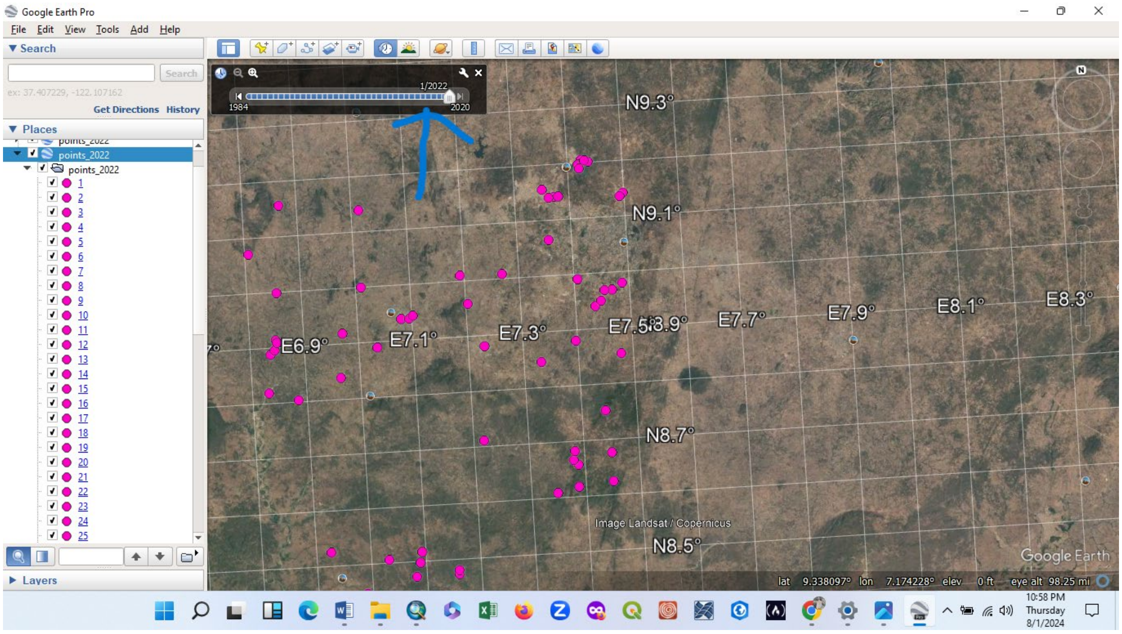

Figure 4: *Accuracy assessment points for 2022*

Table 1: *Correct and incorrect numbers of accuracy assessment points for 2000*

LULC Class	No vegetation	Sparse Vegetation	Dense Vegetation	Total
No vegetation	**20**	0	0	**20**
Sparse Vegetation	2	**15**	2	**19**
Dense Vegetation	0	2	**19**	**21**
Total	22	17	21	**60**

***Table 2**: Correct and incorrect numbers of accuracy assessment points for 2022*

LULC Class	No vegetation	Sparse Vegetation	Dense Vegetation	Total
No vegetation	**21**	0	0	**21**
Sparse Vegetation	2	**18**	0	**20**
Dense Vegetation	0	2	**18**	**20**
Total	23	20	18	**61**

Formulas for accuracy assessments

$$\text{User Accuracy} = \frac{\text{Number of correctly classified samples in each class}}{\text{Total number of classified samples in that class (row total)}} * 100 \quad (1)$$

$$\text{Producer Accuracy} = \frac{\text{Number of correctly classified samples in each class}}{\text{Total number of reference samples in that class (column total)}} *100 \quad (2)$$

$$\text{Overall accuracy} = \frac{\text{Number of correctly classified samples (diagonal)}}{\text{Total number of reference samples}} * 100 \quad (3)$$

$$\text{Koppa Coefficint} = \frac{\text{TS} * \text{TCS} - \sum(\textit{column total} * \textit{row total})}{TS^2 - \sum(\textit{column total} * \textit{row total})} \quad (4)$$

TS = total samples

TCS = total correctly classified samples

3.0 Results and Discussion

3.1 Accuracy assessment

Table 3 presents the classification accuracy for two years: 2000 and 2022. The overall accuracies were 90% and 93%, respectively. The kappa coefficients were 0.85 and 0.90, respectively, which are considered acceptable (Okoduwa and Amaechi, 2024).

Table 3: *UA, PA, OA, and KC results in 2000 and 2022*

Class	2000		2022	
	UA	PA	UA	PA
No vegetation	100	91	100	92
Sparse vegetation	79	88	90	90
Dense vegetation	90	90	90	100
Overall Accuracy	**90**		**93**	
Koppa Coefficient	**0.85**		**0.90**	

3.2 NDVI Range between 2000 and 2022

The range of the NDVI values is presented in Figure 5 (a and b). In 2000, the maximum value of the recorded NDVI was 0.713, whereas the minimum value was -0.01. In 2022, the maximum value decreased to 0.634, and the minimum value increased to 0.05. A comparison of Figure 5 (a and b) reveals that the NDVI values decreased from 2000 - 2022. A decrease in the NDVI value indicates a decrease in dense vegetation cover, whereas an increase in the minimum NDVI value indicates a reduction in water bodies. According to Nath and Acharjee (2013), anthropogenic activities and pressure from the human population have a significant impact on positive or negative changes in NDVI values. As population pressure increases between 2000 and 2022, so will anthropogenic activities, which must have led to a demand for forest trees and forestland for agriculture (Mutolib et al., 2017), leading to changes in NDVI values.

3.3 Reclassified map with the NDVI threshold

From the raster map (Figures 5a and 5b), the reclassified map (Figures 5c and 5d) was created using the NDVI threshold. The NDVI values of the land cover class observed through pixel inspection in GEE were used to determine the threshold for each class. The NDVI threshold value was able to identify areas with no vegetation, sparse vegetation, or dense vegetation, which are the land cover classes considered in this study. Table 4 presents detailed information about the classes and their NDVI thresholds.

Table 4: *NDVI thresholds for different classes from 2000–2022*

Class	2000 NDVI Threshold	2022 NDVI threshold
No Vegetation	-0.01 to 0.2	0.05 to 0.2
Sparse Vegetation	0.2 to 0.5	0.2 to 0.5
Dense Vegetation	0.5 to 0.713	0.5 to 0.634

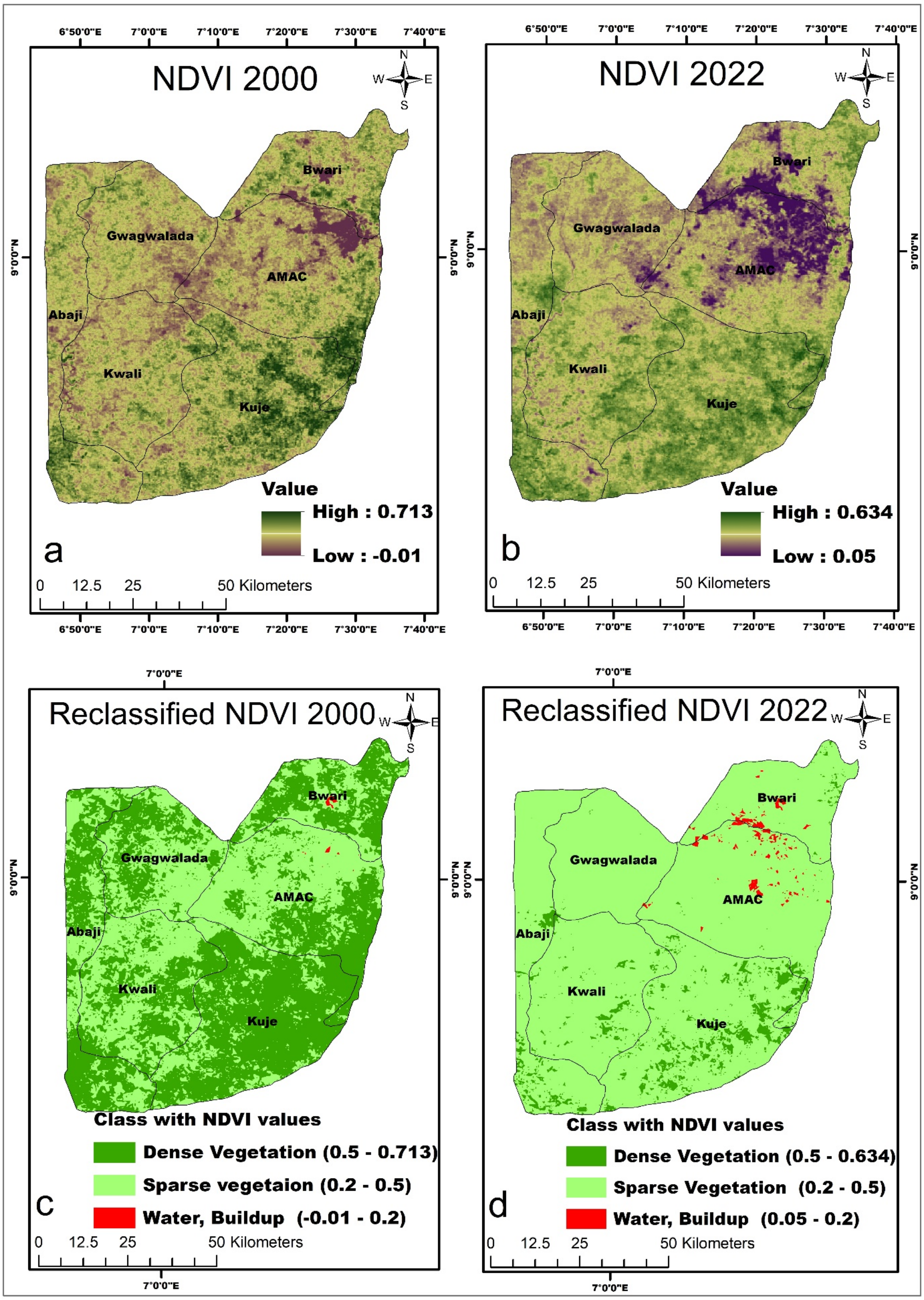

Figure 5: *NDVI map of FCT Abuja in 2000 and 2022 (a and b) and the NDVI reclassified map 2000 and 2022 (c and d)*

Other studies have also employed a comparable threshold. Al-doski et al. (2013) used NDVI threshold values ranging from -1 to 0 to represent water bodies, 0 to 0.2 to represent no vegetation, 0.2 to 0.4 to represent sparse vegetation, 0.4 to 0.6 to represent moderate vegetation, and greater than 0.6 to represent dense vegetation. Jeevalakshmi et al. (2016) demonstrated that the NDVI thresholds for water bodies range from -0.0175 to 0.328, built-up to range from -0.019 to 0.060, those of bare soil ranging from -0.001 to 0.166, those of sparse vegetation ranging from 0.244 to 0.44, and those of dense vegetation ranging from 0.5 upward. According to a recent study by Hashim et al. (2019), NDVI values between -1 and 0.199 indicate nonvegetated areas. On the other hand, the study identified low vegetation areas in the range of 0.2 to 0.5 and dense vegetation areas in the range of 0.5 to1.0.

3.4 Change Detection in Vegetation Cover

Three classes were generated from the resulting change detection (Fig. 6). Negative changes in vegetation occurred in all six regions that make up Abuja. This result contradicts previous findings of Muktar and Yelwa (2020), who, in their study titled Application of MODIS NDVI for vegetation across Nigeria from 2000 to 2019, reported only vegetation loss in Akwa Ibom, Rivers, Delta, Cross River, Edo, Abia, Imo, Osun, Lagos, Ekiti and Ondo State.

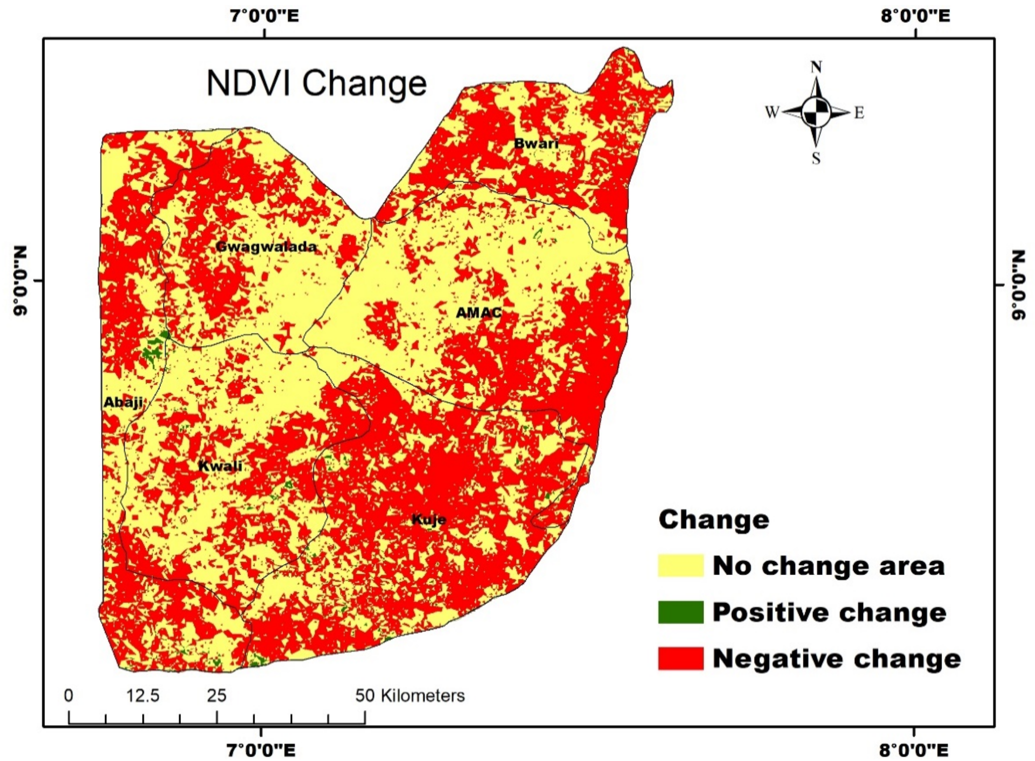

Figure 6: *Change detection from 2000-2022*

3.4 Net Change between 2000 and 2022

The net change shows a massive decrease in dense vegetation. Areas with sparse vegetation increased significantly at the expense of dense areas (Fig. 6). In 2000, areas with no vegetation occupied 8 km^2, which later increased to 53.2 km^2 in 2022. Sparse vegetation occupied an area of 3,411 km^2, which later increased to 6,905 km^2 in 2022; While in 2000 dense vegetation occupied an area of 3,936 km^2 which decreased to 388 km^2 in 2022 implying a 90.11% reduction in dense vegetation cover (Table 5).

Table 5: *Net change between 2000 and 2022*

	2000		2022		
Class	**Area km^2**	**Percentage (%)**	**Area km^2**	**Percentage (%)**	**Net Change in km^2 and %**
No Vegetation	8	0.1	61	0.9	53.2 (662.5%)
Sparse Vegetation	3411	46.4	6905	93.9	3494.9 (102.5%)
Dense Vegetation	3936	53.5	388	5.3	-3547.7 (-90.11%)
Total	**7354**	**100**	**7354**	**100**	

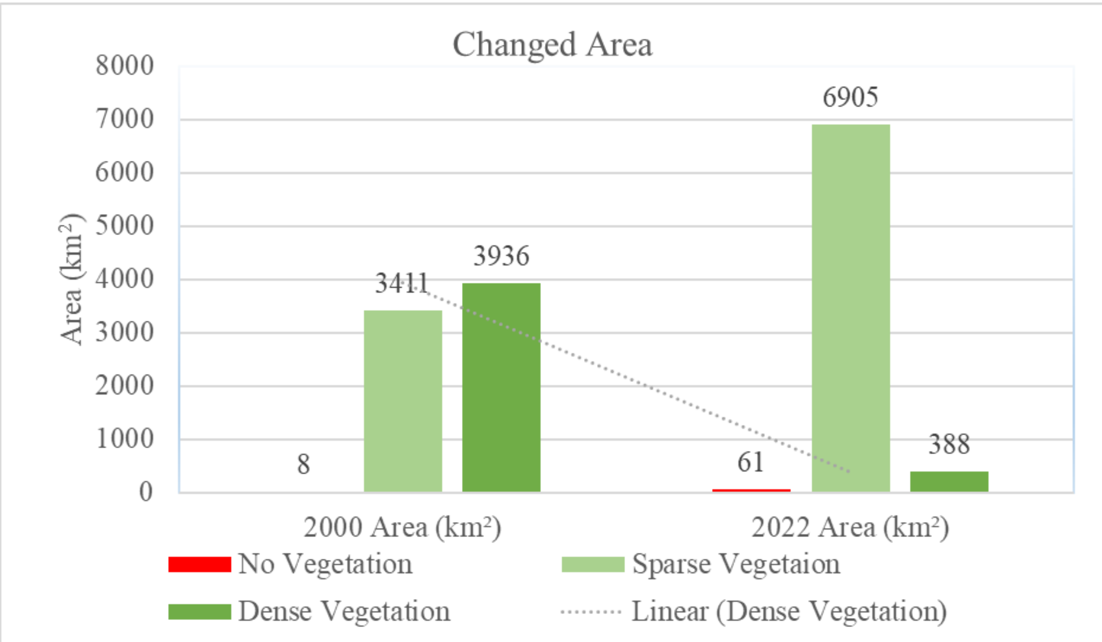

Figure 7: *Changed area from 2000--2022*

The results of this study indicate a significant decline in dense vegetation cover in Abuja from 2000 to 2022. This decline is likely driven by several socioeconomic and environmental factors, including urbanization, agricultural expansion, and deforestation.

3.5 Drivers of Forest Degradation in Abuja

The rapid urbanization of Abuja is one of the primary drivers of forest degradation in the region (Amaechi et al., 2023). As the capital city of Nigeria, Abuja has experienced unprecedented population growth since its designation as federal capital in 1991, with its population surging to over 2.1 million in 2020 (Bashir et al., 2021). This growth has necessitated the expansion of residential areas, commercial buildings, and infrastructure such as roads, which has directly contributed to the loss of dense vegetation (Du et al., 2019; Yao et al., 2019). As more land is cleared to urban sprawl, natural habitats have been fragmented or destroyed, leading to significant declines in NDVI values. The city's rapid urbanization is fueled by population growth, migration from rural areas, and economic opportunities. This migration however, places significant pressure on land resources, contributing to unplanned and unsustainable urban expansion.

Urbanization not only reduces forest cover but also has cascading effects on the environment. As forested areas are replaced with impervious surfaces such as concrete and asphalt, the region's microclimate changes, often resulting in the urban heat island effect (Cui & Shi, 2012; Singh et al., 2017). This further alters local temperature and precipitation patterns, exacerbating the degradation of vegetation in surrounding areas (Zhou et al., 2019; Liu et al., 2021). Moreover, urban sprawl contributes to increased carbon emissions, as transportation and energy demand rise in line with population growth. These emissions can aggravate the local climate, intensifying heat stress on vegetation and accelerating forest loss (Ahmed et al., 2020).

Agricultural expansion could be another significant driver of forest degradation in Abuja. The demand for agricultural land has grown alongside the city's population, driven by the need to ensure food security. As rural areas surrounding Abuja are converted into farmland, vast tracts of forest are cleared to make way for crops and livestock. This process, while necessary for feeding a growing population, has contributed to widespread deforestation and land degradation in Abuja (Amaechi et al., 2023).

The shift from forested land to agricultural land often results in the depletion of soil nutrients, increased soil erosion, and reduced biodiversity (Nunes et al., 2020). Smallholder farmers frequently employ unsustainable agricultural practices such as slash-and-burn techniques, which can result in the rapid degradation of forests.

Deforestation for timber and other forest resources also plays a crucial role in driving forest degradation in Abuja. Commercial logging activities, both legal and illegal, contribute to the rapid removal of trees and dense vegetation, further compounding the decline in forest cover. The demand for timber is often driven by the need for construction materials in urban and rural areas, especially as urban expansion and development continue to grow (Maijama'a et al., 2020).

In addition to timber extraction, fuelwood collection by local communities also contributes to deforestation. As a significant portion of Abuja's population relies on fuelwood for cooking and heating, forests are often exploited unsustainably, leading to further declines in NDVI values. These activities not only deplete forest resources but also disrupt wildlife habitats, reducing biodiversity and altering ecosystem dynamics (Kemppinen et al., 2020).

3.6 Implications of Forest Degradation in Abuja

Forests provide essential ecosystem services, including carbon sequestration, biodiversity conservation, and water regulation, all of which are critical for mitigating the impacts of climate change (Nunes et al., 2020). As forests disappear, Abuja will become more vulnerable to extreme weather events such as floods and droughts. The loss of forest cover can increase surface runoff, exacerbating soil erosion and flooding risks (Zhang et al., 2021).

Additionally, the reduction in forest cover impacts biodiversity by threatening the survival of plant and animal species that depend on forest ecosystems for their habitats (Kumar et al., 2022). The loss of these species can disrupt food chains and weaken ecosystem resilience, making the region more susceptible to environmental disturbances (Timpane-Padgham et al., 2017). The decline in vegetation also results in the loss of carbon sinks, contributing to higher atmospheric carbon concentrations and intensifying global warming (Tian et al., 2023; Yang & Pan, 2023).

Addressing the drivers of forest degradation in Abuja requires coordinated efforts between the government, civil society, and local communities. Implementing sustainable land-use planning and promoting agroforestry practices can help balance the need for agricultural production with forest conservation. In addition, policies that promote afforestation and reforestation can restore degraded landscapes, helping to mitigate the environmental impacts of deforestation. There is also a need for greater enforcement of laws regulating logging activities and fuelwood collection to prevent further depletion of forest resources.

4.0 CONCLUSION

These findings suggest that the NDVI threshold technique is a viable method for monitoring forest degradation. The results have practical applications in forest management and conservation, enabling policymakers to enhance their effectiveness and promote sustainable development. However, to address the complex challenges of forest degradation in Abuja, it is crucial to implement sustainable land-use planning and promote agroforestry practices, which can balance the need for agricultural production with forest conservation. Additionally, policies that encourage afforestation and reforestation can help restore degraded landscapes and mitigate the environmental impacts of deforestation (Prevedello et al., 2019). Stronger enforcement of regulations on logging and fuelwood collection is also needed to prevent further depletion of forest resources. Future research, particularly in regions like Abuja, should explore how changes in temperature, precipitation patterns, and extreme weather events influence forest degradation.

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