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SPATIO-TEMPORAL MAPPING OF DESERTIFICATION DYNAMICS IN THE FRONTLINE STATES OF NORTHERN NIGERIA USING REMOTE SENSING AND GIS

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ABSTRACT

Desertification remains a critical environmental challenge in Northern Nigeria, with far-reaching implications for livelihoods and ecosystem sustainability. This study employed remote sensing and Geographic Information Systems (GIS) to assess the spatio-temporal extent and trends of desertification across the frontline states from 1984 to 2022. Multi-temporal Landsat (TM, ETM+, and OLI) and Sentinel imagery were processed using supervised and unsupervised classification techniques, with the Normalized Difference Vegetation Index (NDVI) serving as a key indicator of vegetation health and density. Results revealed a substantial decline in vegetation cover, with 83.16% of the area exhibiting low NDVI values (0.12–0.22) in 2022 compared to 54.51% in 1984. Very high vegetation density (0.72–0.92) was virtually absent, while only 0.72% of the area retained high vegetation density. Land-use/land-cover (LULC) change analysis showed a 53.16% decline in dense vegetation (annual rate: –6.25%) and a 55.45% increase in light vegetation (annual rate: 2.37%). Bare land decreased slightly (–2.49%), built-up areas expanded by 0.63% (annual rate: 3.36%), and water bodies reduced by –0.43% (annual rate: –1.47%). These findings underscore the accelerating rate of vegetation degradation and the urgent need for sustainable land-use planning and afforestation interventions in Northern Nigeria.

Keywords: Desertification, NDVI, Remote Sensing, GIS, Land-Use/Land-Cover Change, Northern Nigeria

1.0 INTRODUCTION

Desertification is a progressive form of land degradation in which fertile land loses its biological and economic productivity, becoming arid or desert-like (UNCCD, 2012; Badapalli et al., 2023). It is driven by both natural processes and human-induced factors such as deforestation, soil erosion, urbanization, and unsustainable agricultural practices (Ferreira et al., 2018; AbdelRahman, 2023). Globally, desertification and land degradation threaten 20–40% of the planet's terrestrial ecosystems, with severe implications for food security, biodiversity, water resources, and human livelihoods (Global Land Outlook, 2022; Berdyyev et al., 2024). The United Nations' Sustainable Development Goal 15 (SDG 15) underscores the urgency of halting land degradation and restoring degraded ecosystems (Lucatello & Huber-Sannwald, 2020; Ajai & Bhnatnagar, 2022). Approximately 2.6 billion people across more than 100 countries are directly affected by desertification, with 1.5 billion at risk of displacement (UNCCD, 2008; Eswaran et al., 2019).

Africa remains one of the regions most affected by desertification, with over 45% of its land area degraded and more than half (55%) at high risk of further deterioration (Stavi & Lal, 2015; IPBES, 2018; IPCC, 2019). In Sub-Saharan Africa, land degradation exacerbates food insecurity, water scarcity, and migration pressures, disrupting livelihoods and socio-economic stability (Grishina, 2021; Lombe et al., 2024). The drivers—unsustainable land use, deforestation, and overexploitation of natural resources—intensify temperature rise and alter rainfall regimes in arid and semi-arid regions (Lal, 2001; Evans, 2022). Consequently, sustainable land management and ecological restoration have become central to regional and international policy agendas (Orr et al., 2017; Yahaya, 2024).

In Nigeria, desertification has been recognized as a major ecological crisis since the 1970s, particularly in the eleven "frontline states" of the north—Adamawa, Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, Kebbi, Sokoto, Yobe, and Zamfara. These states, which constitute about 43% of Nigeria's land area, are critical for national food security and livestock production but face rapid loss of vegetation and soil fertility (Yunusa, 2012; NAGGW, 2014; Ibrahim et al., 2022). The problem is aggravated by climate variability, population pressure, and unsustainable land-use practices, leading to the displacement of rural populations and encroachment of desert conditions on arable land (Audu & Adie, 2018; Yahaya et al., 2024).

Despite growing awareness of the problem, comprehensive regional-scale assessments of the spatio-temporal patterns of desertification in Northern Nigeria remain limited. Many existing studies are based on short-term datasets, making it difficult to detect long-term degradation trends driven by gradual climatic shifts and land-use changes (Huang & Kong, 2016; Arroyo-Ortega et al., 2022). This study addresses this gap by employing multi-temporal remote sensing and Geographic Information Systems (GIS) to map and quantify land degradation trends from 1984 to 2022 across Northern Nigeria's frontline states. Using vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Soil-Adjusted Vegetation Index (SAVI) (Shoshany et al., 2013; Ewunetu et al., 2021; Montfort et al., 2020), the research evaluates changes in vegetation health, identifies degradation hotspots, and explores the links between land-use transitions and ecological decline. The findings aim to provide empirical evidence to guide sustainable land-use planning, ecological restoration, and policy interventions to strengthen environmental resilience in Northern Nigeria.

2.0 MATERIALS AND METHOD

2.1 Study Area

Northern Nigeria is situated between latitudes 9° and 14° N and longitudes 3° and 15° E (Figure 2). The region, often defined politically and geographically, encompasses all states located wholly or partially within the northern part of the country (Abdulkadir, 2015). It shares borders with the Republic of Niger and Chad to the north and the Republic of Cameroon to the east. This extensive region lies within the Sudano–Sahelian ecological zone, which, together with parts of the northern Guinea savannah, forms Nigeria's dryland belt (Adeniran, 2020). The eleven states most affected by desertification—commonly referred to as the *frontline states*—include Adamawa, Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, Kebbi, Sokoto, Yobe, and Zamfara. These areas constitute approximately 43% of Nigeria's total land area and are the first to experience the southward advance of the Sahara Desert. The remaining northern states—Benue, Kaduna, Kogi, Kwara, Nasarawa, Niger, Plateau, Taraba, and the Federal Capital Territory (FCT)—are classified as *buffer states* because they absorb environmental pressures from the advancing desert (Federal Ministry of Environment, 2016).

The region's climate is characterized by distinct wet and dry seasons influenced by the seasonal migration of the Intertropical Discontinuity (ITD). The rainy season typically begins in June and ends in October, with annual rainfall decreasing from more than 2,000 mm in the southern Guinea Savannah to less than 400 mm in the extreme north (Federal Ministry of Environment, 2001). Rainfall variability contributes to desert encroachment and declining vegetation cover across the northernmost states. Temperatures are generally high, with a mean annual temperature of approximately 29 °C, minimum values around 13 °C in January, and maximum values reaching 38 °C in April (Mekala, 2023). The region experiences an average of nine hours of daily sunshine, and diurnal temperature ranges are pronounced due to seasonal and latitudinal variations (Folaji, 2007; Usman et al., 2013). Relief varies from 300 m to 900 m above sea level, except for the

Niger–Benue trough and the Sokoto and Chad Basins, which are below 300 m. Vegetation cover transitions from Guinea Savannah in the south to Sudan and Sahel Savannah in the north, with tree and grass density decreasing progressively northward in response to climatic aridity (Abdulkadir et al., 2013). The region's economy is predominantly agrarian, and the dependence on natural resources, coupled with climatic variability, exacerbates the vulnerability of livelihoods to desertification.

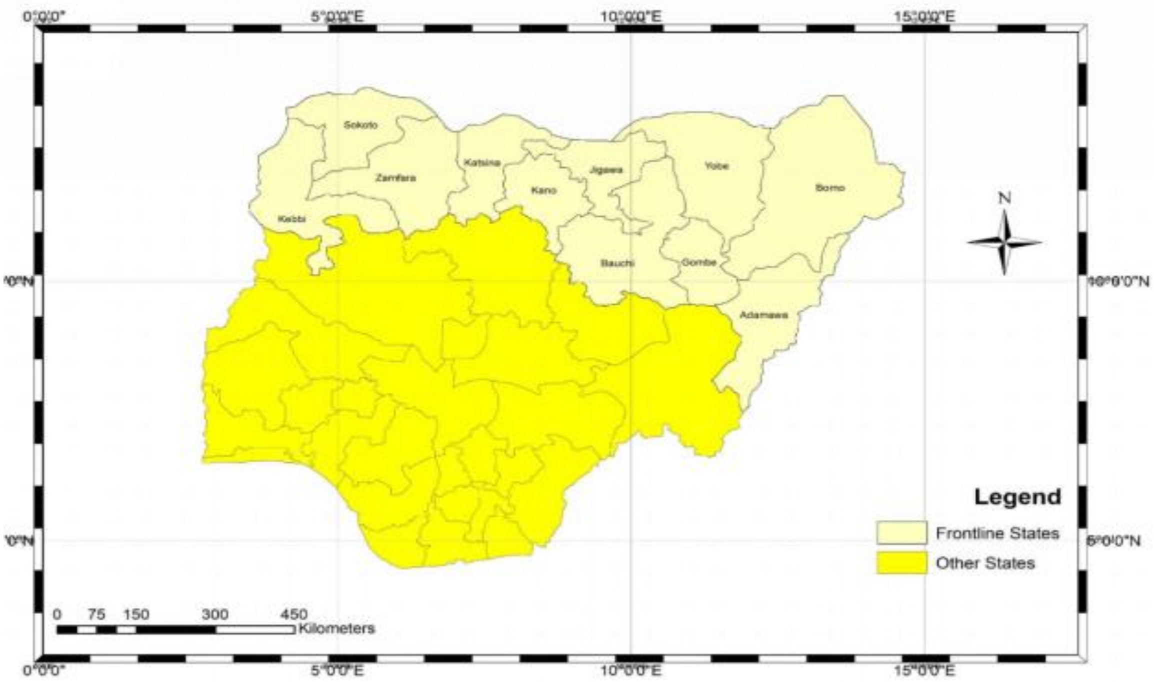

Figure 1: Map of the Frontline States of Northern Nigeria

2.2 Data Acquisition and Processing

This study utilized the Normalized Difference Vegetation Index (NDVI) derived from multi-temporal Landsat satellite imagery to assess and map land degradation across the frontline states of Northern Nigeria. The methodological workflow consisted of three main stages: (i) data acquisition, (ii) image preprocessing, and (iii) vegetation index computation.

2.2.1 Satellite Imagery Selection

This study used Landsat 5 TM (1984, 1994), Landsat 7 ETM+ (2004), Landsat 8 OLI (2014) and Landsat 9 OLI-2 (2022) imagery (spanning 38 years). Reflective bands are available at 30 m spatial resolution across sensors, with 15 m panchromatic data for Landsat 7/8/9, while thermal observations have coarser native sampling (TM: 120 m; ETM+: 60 m; Landsat 8/9 TIRS: 100 m, registered to the 30 m grid). Radiometric resolution improves from 8-bit (TM/ETM+) to 12-bit (OLI) and 14-bit (OLI-2), which increases sensitivity to subtle surface reflectance variation but also introduces cross-era differences in quantisation and noise characteristics. All data were sourced from USGS Landsat Collection 2 products, which incorporate updated calibration and improved geolocation intended to enhance interoperability through time; nonetheless, residual uncertainty arises from atmospheric correction (haze/aerosols), variable cloud contamination, and known cross-sensor spectral response differences between TM/ETM+ and OLI/OLI-2 that can shift reflectance-based indices. In addition, the Landsat 7 ETM+ scene is affected by the post-2003 scan line corrector failure ('SLC-off'), resulting in systematic missing data that can bias classification and change estimates unless gaps are masked or mitigated through compositing or gap-filled products (Roy et al., 2016). This temporal sequence ensures comprehensive monitoring of vegetation and land-cover changes over the study period.

2.2.2 Image Preprocessing

All imagery was preprocessed to enhance data quality and ensure cross-temporal comparability. Preprocessing steps included radiometric calibration to correct sensor-related distortions and atmospheric correction to minimize the effects of haze and atmospheric scattering. Images were georeferenced and projected to the Universal Transverse Mercator (UTM) coordinate system, Zone 32N, using the World Geodetic System (WGS 84) datum to maintain spatial consistency. Cloud-free scenes were prioritized, and mosaicking was performed where necessary to achieve full coverage of the study area. These preprocessing procedures ensured that variations in NDVI values accurately reflected real changes in vegetation rather than artifacts introduced by atmospheric or sensor discrepancies.

2.3 Vegetation Indices Calculation

2.3.1 Normalized Difference Vegetation Index (NDVI):

For this study, NDVI values were calculated using reflectance data from the red and near-infrared (NIR) bands of Landsat imagery. For Landsat 4–7 (TM and ETM+), NDVI was computed using Band 3 (Red) and Band 4 (NIR), while for Landsat 8–9 (OLI), Band 4 (Red) and Band 5 (NIR) were used. NDVI values were derived using the standard formula:

$$NDVI = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 1$$

Where:

R = the reflectance value at the subscripted satellite band

NIR = Near Infrared Band 5

Red = Band 3

NDVI values range from –1 to +1, where negative values represent non-vegetated surfaces such as water bodies, built-up areas, or bare soil, and positive values indicate vegetated areas. Higher NDVI values correspond to denser and healthier vegetation, whereas lower values signify sparse or degraded vegetation cover.

Atmospheric effects can significantly influence surface reflectance values and, consequently, NDVI accuracy. Myeni and Asrar (1994) demonstrated through vegetation–atmosphere radiative transfer modeling that NDVI values measured at the top of the atmosphere (TOA) are generally lower than those measured at the top of the canopy (TOC), due to atmospheric scattering and absorption. To minimize these effects, atmospheric correction procedures were applied prior to NDVI computation. Specifically, the NDVI analysis for the Landsat 8 OLI/TIRS imagery was adjusted following the approach recommended by Song et al. (2001), which corrects for variations in image spectral reflectance and digital number (DN) conversions caused by atmospheric interference. This ensured that the derived NDVI values more accurately represented ground-level vegetation conditions rather than atmospheric artifacts. For the NDVI analysis of the Landsat 8 OLI/TIRS, Eq. (3) is thus stated as follows:

$$NDVI = \frac{(R_{NIR} - R_{Red}) - (A5 - A4)}{(R_{NIR} + R_{Red}) + (A5 + A4)} \quad \ldots\ldots\ldots\ldots\ 2$$

Where:

A4 and A5 are the additive atmosphere effects of (Red, TM4) and (NIR, TM5) respectively. Eq. (3) takes cognizance of the atmospheric effects that contaminate NDVI signals/values and presents a satisfactory nonlinear modification (Myeni and Asrar, 1994; Song et al., 2001). For sentinel datasets, the expression is stated as follows:

$$NDVI = \frac{B8 - B4}{B8 + B4} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ 3$$

Where:

B8 = Band 8

B4 = Band 4

2.4 Supervised Classification and LULC Mapping

2.4.1 Supervised Classification Process

Supervised classification was performed to categorize each pixel in the imagery into predefined land-cover classes. Training samples were selected based on prior knowledge of the study area and visual interpretation of false color composites to enhance spectral separability. The classification process relied on the spectral reflectance properties derived from the NDVI and visible–infrared bands, enabling effective discrimination among vegetation, built-up areas, bare land, and water bodies. The Maximum Likelihood Classification (MLC) algorithm was applied due to its robustness and proven accuracy in multispectral data analysis.

2.4.2 LULC Map Generation

Land Use and Land Cover (LULC) maps were generated from the classified images for each reference year (1984, 1994, 2004, 2014, and 2022). These maps depict the spatial distribution and composition of major land-cover categories across the frontline states of Northern Nigeria. Temporal comparison of the LULC maps enabled the detection of significant changes such as vegetation loss, agricultural expansion, or urban growth, which serve as indicators of land degradation processes and desertification trends.

2.4.3 Accuracy Assessment and Validation

Classification accuracy was assessed using ground-truth data and high-resolution reference imagery obtained from Google Earth and field observations. A confusion matrix was constructed to quantify classification performance through standard accuracy metrics, including overall accuracy (OA) and the Kappa coefficient (κ). This validation step ensured that the classified maps reliably represented real-world land-cover conditions and could be confidently used for subsequent change detection analysis.

2.4.4 Interpretation and Mapping of Results

The final LULC maps and NDVI trend analyses were interpreted to provide a comprehensive overview of land degradation patterns across the frontline states. Spatial overlays and temporal comparisons were used to identify degradation hotspots, areas affected by urbanization, and zones of vegetation recovery. The resulting maps and trend charts serve as critical decision-support tools for identifying priority areas for ecological restoration, monitoring land-use dynamics, and promoting sustainable land management interventions in Northern Nigeria.

3.0 RESULTS

3.1 Spatial Extent of Desertification in the Frontline States of Nigeria

Table 1 presents the spatial extent of vegetation cover and the corresponding degree of desertification between 1984 and 2022. The analysis reveals substantial temporal variations in vegetation density across the frontline states. Areas classified as very low or non-vegetated (NDVI range: –0.25–0.12) decreased from 12.72% (5,032,829.46 ha) in 1984 to 1.25% (493,777.09 ha) in 2022, indicating a localized improvement in vegetation cover. Conversely, low vegetation areas (NDVI: 0.13–0.22) expanded markedly from 51.54% to 83.16%, representing a 31.62% increase. Moderate vegetation areas (NDVI: 0.23–0.42) declined from 30.06% to 14.81%, a reduction of 15.25%, while high vegetation areas (NDVI: 0.43–0.66) decreased from 5.69% to 0.78%, representing a 4.91% decline over the 38-year period.

Figures 2 and 3 illustrate the spatial distribution of vegetation cover for 1984 and 2022, respectively. NDVI values were categorized into four vegetation density classes for mapping purposes, differing slightly from the five statistical classes presented in Table 1. This variation reflects the absence of very high vegetation cover (NDVI: 0.72–0.92) in 2022, as none of the analyzed pixels fell within this range. Despite this, the spatial patterns are consistent with the quantitative results, revealing a discernible shift toward lower vegetation density across the study area.

Spatial comparison of the NDVI maps indicates that areas with very low vegetation cover decreased in 2022 compared to 1984, while low vegetation cover expanded significantly, dominating much of the landscape. Areas of moderate to high vegetation exhibited noticeable contraction, consistent with observed declines in NDVI values and reduced spectral greenness. These findings collectively suggest a progressive deterioration of vegetation health and density across the frontline states over time.

Table 1: Spatial extent of desertification in the study area

Vegetation health and density	NDVI Value	1984 Area (ha)	Extent (%)	2022 Area (ha)	Extent (%)	Indicator
Very poor	-0.10 – 0.12	5,032,829.46	12.72	493,777.09	1.25	Very low vegetation
Poor	0.12 – 0.22	2,039,8317.83	51.54	32,912,031.92	83.16	Low vegetation
Normal	0.22 – 0.42	11,895,721.82	30.06	5,861,744.91	14.81	Moderate vegetation
Good	0.42 – 0.72	2,250,588.65	5.69	309,903.46	0.78	High vegetation
Very good	0.72 – 0.92	-	-	-	-	Very High vegetation
	Total	39,577,457.75	100	39,577,457.37	100	

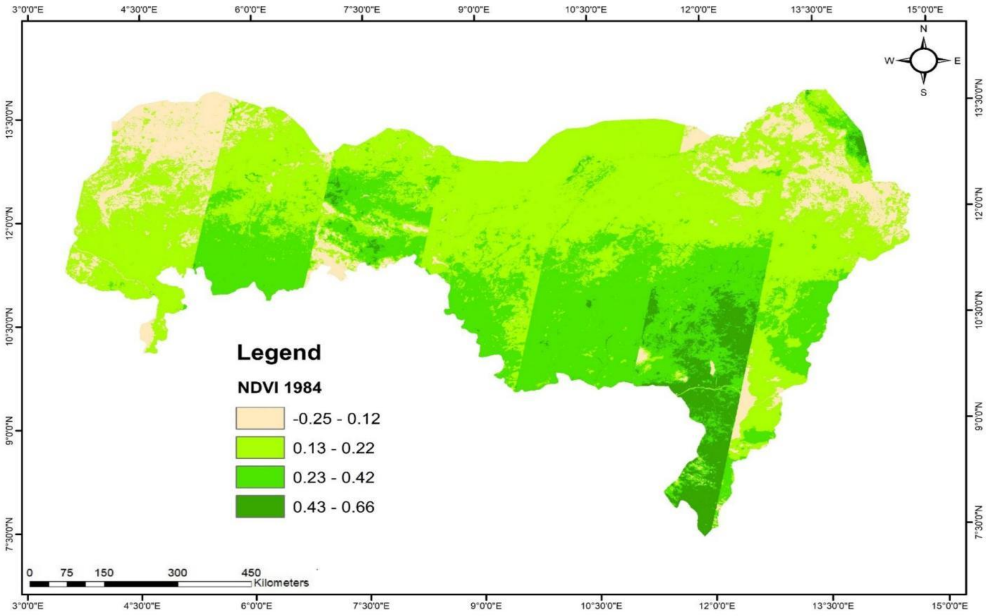

Figure 2: Spatial extent of desertification in 1984 in the Frontline States of Northern, Nigeria

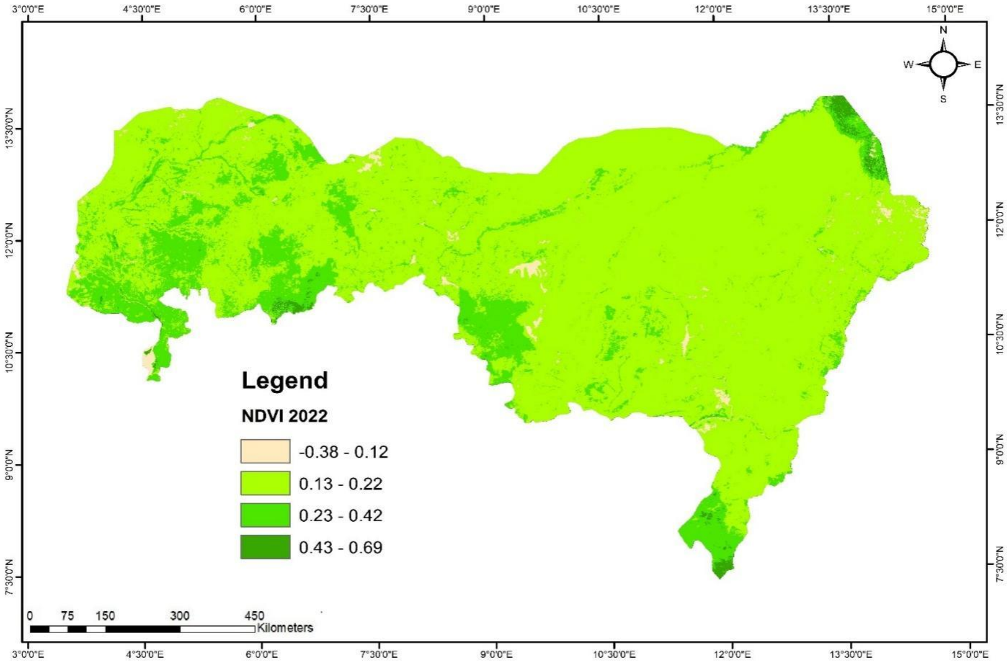

Figure 3: Spatial extent of desertification in 2022 in the Frontline States of Northern, Nigeria

3.2 Land Use Land Cover Analysis in the Frontline States of Northern Nigeria

3.2.1 Determination of Land Use Land Cover Change (LULC)

The analysis of Land Use and Land Cover (LULC) dynamics revealed substantial changes across the frontline states between 1984 and 2022 (Table 2). Five major LULC categories—dense vegetation, light vegetation, bare ground, built-up areas, and water bodies—were analyzed for each temporal dataset.

In 1984, dense vegetation dominated the landscape, covering 58% of the total area, followed by light vegetation (38%), bare ground (2.7%), water bodies (0.98%), and built-up areas (0.24%) (Figure 4). By 2022, these proportions had shifted markedly. Light vegetation expanded dramatically to 93.49%, becoming the dominant land cover type, while dense vegetation declined sharply to 4.84%. Built-up areas increased modestly to 0.87%, whereas bare ground (0.24%) and water bodies (0.56%) both decreased slightly (Figure 5).

The dominance of light vegetation in 2022 suggests a widespread conversion of dense vegetation areas into less productive or sparsely vegetated lands, reflecting extensive vegetation degradation and possible desertification processes across the study area.

3.2.2 Percentage Change and Annual Rates of Land Use Land Cover Change (LULC)

Between 1984 and 2022, light vegetation and built-up areas exhibited notable increases of 55.45% and 3.36%, respectively. In contrast, dense vegetation, bare ground, and water bodies declined by 53.16%, 2.48%, and 0.43%, respectively (Figures 12 and 13).

The estimated annual rates of change further underscore these divergent trends. Dense vegetation declined at an average annual rate of –6.25%, while light vegetation expanded at +2.37% per year. Bare ground and water bodies decreased at rates of –6.12% and –1.47%, respectively, whereas built-up areas increased at a rate of +3.36% annually. These contrasting rates highlight the accelerating conversion of dense vegetation to light vegetation and built-up surfaces, indicating ongoing landscape transformation driven by both natural and anthropogenic pressures.

Table 2: Area of Land Use and Cover Classes from 1984- 2022 in the Frontline States of Northern Nigeria

Land Cover Type	**1984**		**2022**		**1984-2022**	**1984-2022**
	Ha	%	Ha	%	% Change	Annual rate of Change
Bare land	1,080,316.27	2.7	95,353.83	0.24	-2.49	-6.12
Built-up	96,777.10	0.24	345,001.27	0.87	0.63	3.36
Dense Vegetation	22,954,682.02	58.0	1,915,475.72	4.84	-53.16	-6.25
Light Vegetation	15,057,535.33	38.05	37,001,925.3	93.49	55.45	2.37
Waterbody	388,146.61	0.98	219,701.21	0.56	-0.43	-1.47
Total	**39,577,457.33**	**100**	**39,577,457.33**	**100**		

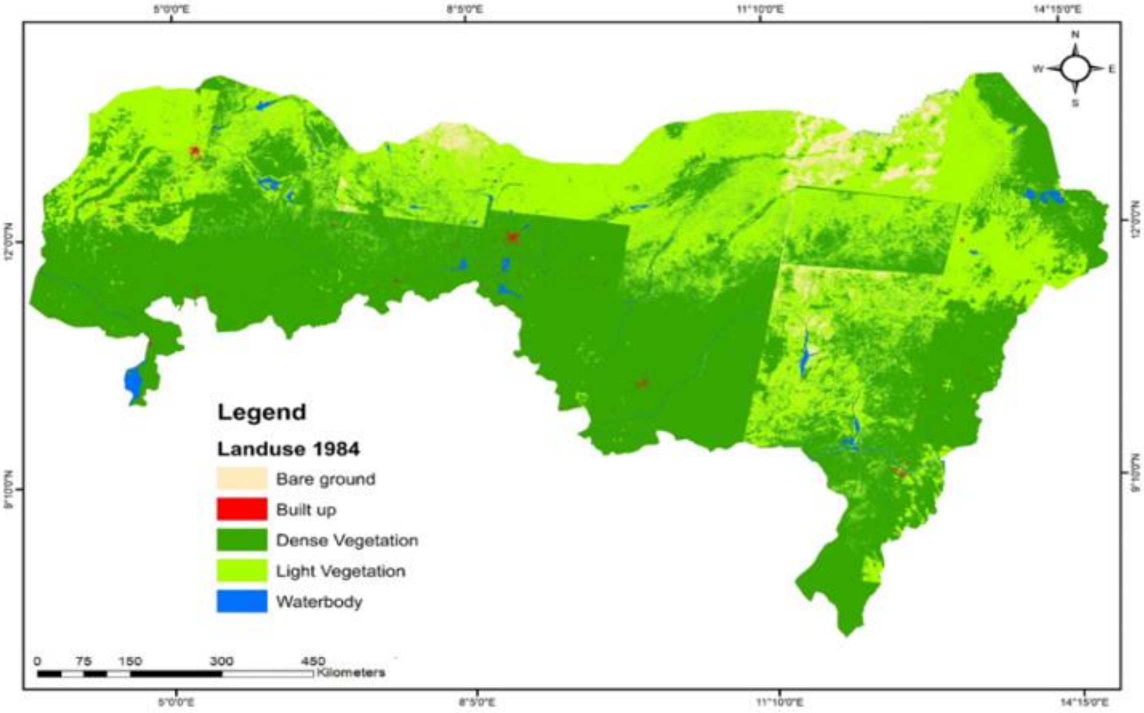

Figure 4: LULC Classes in 1984 in the Frontline States of Northern, Nigeria

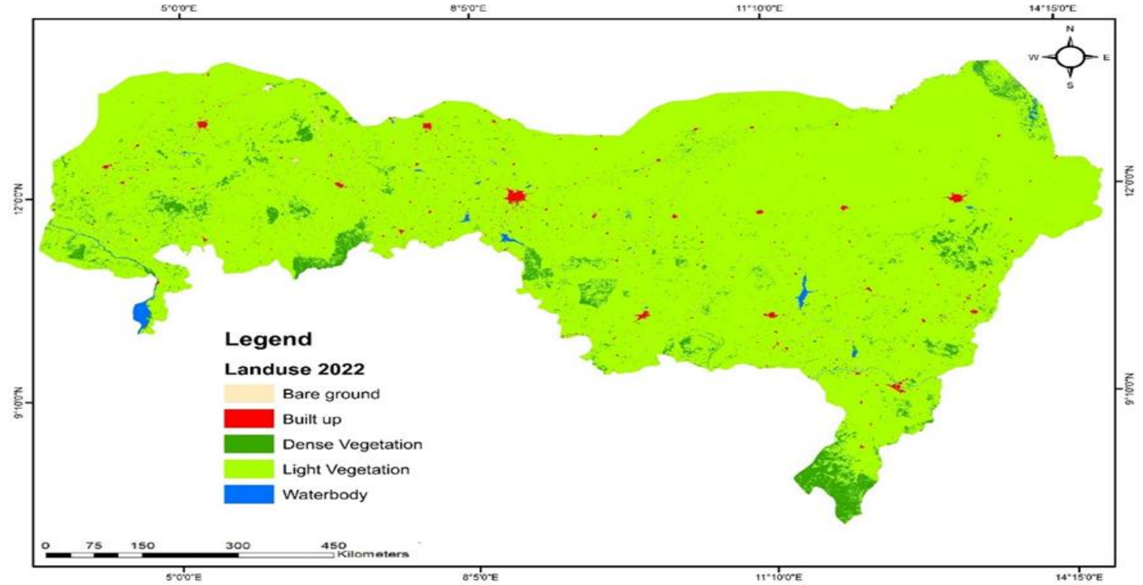

Figure 5: LULC Classes in 2022 in the Frontline States of Northern, Nigeria

4.0 DISCUSSION

The spatial and temporal analysis of vegetation and land-cover dynamics across the frontline states of Northern Nigeria reveals a consistent pattern of vegetation degradation and increasing desertification over the 38-year period (1984–2022). The NDVI results indicate an extensive decline in dense vegetation and a corresponding expansion of light vegetation, suggesting a gradual deterioration in vegetation health and cover. These findings align with those of Gakkuk (2014), Abubakar and Eniolorunda (2016), and Falaki et al. (2020), who also reported significant vegetation decline in Northern Nigeria due to combined climatic and anthropogenic factors. Comparable long-term remote sensing studies across the wider Sahel similarly report declining NDVI or a shift from dense vegetation to sparse cover in desert/grassland transition zones, with patterns often shaped by rainfall variability and land-use pressure (Wu et al., 2020). More broadly, Landsat-based desertification monitoring in semi-arid contexts such as Mongolia also documents persistent transitions among vegetation, semi-fixed sands and bare sandy surfaces over multi-decadal periods, reinforcing that vegetation decline and surface bareness expansion are common signatures of dryland degradation detectable from medium-resolution time series (Meng et al., 2021; Yu et al., 2020).

The observed reduction in vegetation density is likely influenced by declining rainfall, high temperatures, and unsustainable land-use practices, which exacerbate drought conditions and reduce soil moisture (Audu et al., 2021; Ahmed et al., 2020). Similar to the findings of Ndabula et al. (2018) in Borno and Yobe States, the increasing extent of sandy soils in the region reflects advancing desert conditions, with implications for agricultural productivity, food security, biodiversity loss, and rural livelihoods. This climate–land-use coupling mirrors evidence from other dryland systems where NDVI decline co-occurs with expansion of barren land and reduced ecosystem services, particularly where interannual rainfall variability interacts with population-driven land pressure (Sinare et al., 2022; Temesgen et al., 2022). In several African dryland contexts, vegetation decline is also reported to be strongly seasonal and can be misinterpreted if imagery dates are not phenologically comparable—highlighting the need to link NDVI trajectories to rainfall/temperature anomalies and drought indices to strengthen causal attribution (Wu et al., 2020; Daiman et al., 2025).

The variation in the proportion of each LULC class across the study period reflects the cumulative effects of socio-economic activities in the region, particularly agriculture and livestock rearing, which remain the dominant land uses. As noted by FAO (2014), Olagunju (2015), and Yahaya and Malik (2021), the high dependence on land-based livelihoods and poor land management practices have intensified land degradation. These pressures are further amplified by the region's role as Nigeria's key supplier of agricultural products such as beans, rice, tomatoes, and beef (James et al., 2018). Similar agricultural expansion dynamics—often at the expense of woodland/grassland—have been documented in other regions using Landsat-based LULC and NDVI analysis, where cropland/settlement growth and fuelwood demand are repeatedly identified as proximate drivers of vegetation loss (Seifu et al., 2023; Temesgen et al., 2022). Evidence from dryland Asia likewise shows that land management interventions and market-driven land conversion can shift landscapes between degradation and partial recovery, implying that socio-economic trajectories can modulate the direction and pace of desertification even under persistent climatic stress (Meng et al., 2021).

The decline in dense vegetation observed between 1984 and 2022 is punctuated by a brief recovery between 1994 and 2004, likely linked to the Forestry II Afforestation Project (1987–1996), which focused on shelterbelt establishment and farm forestry in the northern states (World Bank, 1998; Medugu et al., 2009; JIGAP, 2015). According to Ibrahim (2015), this was one of the most successful afforestation initiatives in Nigeria's history, though its gains appear to have diminished over time due to poor maintenance and renewed anthropogenic pressures. This "intervention-linked greening followed by decline" has parallels in other dryland regions where policy-driven restoration (e.g., shelterbelts, grazing controls, and ecological compensation) produced measurable vegetation recovery that weakened once enforcement or maintenance declined (Meng et al., 2021). Similarly, Sahel-wide analyses indicate that short-term "re-greening" signals can occur, but long-term trajectories remain mixed and sensitive to the combined effects of rainfall recovery, land management, and demographic pressure, underscoring why attributing NDVI changes to a single driver should be done cautiously and triangulated with policy timelines and climate records (Kusserow, 2017; Wu et al., 2020).

The overall increase in light vegetation, accompanied by the decline in dense vegetation, suggests extensive conversion of natural vegetation to agricultural and built-up areas, consistent with findings by Abdi et al. (2013) and Hussaini (2014). Meanwhile, the modest increase in built-up areas and decline in bare ground and water bodies align with regional studies in Sokoto (Ogunjobi et al., 2018), Yobe (Elijah et al., 2017), and Kano (Koko et al., 2021), which link these changes to rapid urbanization and infrastructure expansion. Comparable spatio-temporal studies elsewhere in Africa also report that settlement and cropland expansion can occur simultaneously with declining NDVI, particularly around transport corridors and peri-urban zones, reinforcing the interpretation that land conversion is a key mechanism behind the observed vegetation thinning (Seifu et al., 2023; Getaneh et al., 2024). In arid and semi-arid contexts beyond Africa, Landsat-based assessments similarly associate vegetation depletion and increasing bare soil fractions with expanding cultivation, settlement growth, and resource extraction—demonstrating that these land-change pathways are not unique to Northern Nigeria (Mukhopadhyay, 2024; Yu et al., 2020).

The persistent degradation of vegetation cover—particularly in northern localities such as Yusufari, Nguru, Karasuwa, and Bade—illustrates the compounding impact of overgrazing, rainfed agriculture, and shifting cultivation (Musa & Shaib, 2010). As noted by Abdulrashid (2017) and Musa (2012), shortened fallow periods and the expansion of cultivation into marginal lands have accelerated land degradation. Overgrazing in the Sahel zones, combined with fuelwood harvesting and weak local governance of rangeland resources, further intensifies vegetation loss (Goffner et al., 2019). Similar grazing–cultivation interactions are widely reported in drylands where rangeland fragmentation and biomass removal reduce vegetation resilience and accelerate transitions toward sparse cover or bare soil, particularly when drought events recur (Wu et al., 2020; Temesgen et al., 2022). Recent large-area dryland studies further suggest that integrating climate indices (e.g., SPEI) with LULC change improves evidence for desertification processes by separating climate-driven NDVI variability from human-induced land conversion—an approach that would strengthen causal interpretation in Northern Nigeria as well (Daiman et al., 2025).

Cross-border grazing by livestock from Niger, Chad, and Cameroon into the wetland patches of the Lake Chad Basin adds further strain to already fragile ecosystems (Murakami, 2020). The widespread dependence on firewood as a domestic energy source has also contributed to extensive deforestation around urban centers, inhibiting natural regeneration and expanding the radius of degraded land annually. Similar cross-boundary mobility pressures and fuelwood-driven deforestation are noted across many Sahelian landscapes, where livelihood dependence on biomass energy and transhumant systems increases landscape exposure to degradation during climatic shocks (Sinare et al., 2022; Kusserow, 2017). These cross-scale dynamics also help explain why localized restoration gains may be difficult to sustain without coordinated governance that matches the transboundary nature of grazing and resource extraction.

Collectively, these processes have accelerated the rate and intensity of desertification across Northern Nigeria, reducing the resilience of ecosystems and communities to climatic variability. The findings corroborate those of Gadzama and Ayuba (2016), emphasizing that both human-induced pressures and climatic stresses are driving the region's transition toward desert-like conditions. Comparable long-term Landsat-based desertification assessments in other arid and semi-arid settings also conclude that degradation trajectories are rarely linear: they often reflect alternating periods of decline and partial recovery depending on rainfall regimes, land management, and policy enforcement, underscoring the importance of interpreting NDVI/LULC change in relation to both climate variability and governance interventions (Wu et al., 2020; Meng et al., 2021; Daiman et al., 2025).

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study analyzed the spatial and temporal dynamics of desertification and land degradation across the frontline states of Northern Nigeria between 1984 and 2022 using multi-temporal Landsat imagery and NDVI-derived vegetation indices. The results demonstrate a persistent decline in dense vegetation and a substantial increase in light vegetation, reflecting a long-term deterioration in vegetation health and cover. The proportion of low vegetation areas expanded from 51.54% to 83.16%, while dense vegetation declined from 58% to less than 5% over the study period.

These changes indicate that desertification is intensifying across the region, driven by both anthropogenic pressures—such as deforestation, overgrazing, agricultural expansion, and urbanization—and climatic factors including reduced rainfall and rising temperatures. Although temporary improvements were observed during periods of targeted interventions such as the Forestry II Afforestation Project (1987–1996), the overall trend reflects a continued degradation of vegetation and land productivity. Spatial evidence of vegetation decline and sand encroachment should guide targeted shelterbelts, rangeland governance, fuelwood alternatives, and climate-smart farming, prioritising hotspots to restore forest cover, protect livelihoods, and strengthen cross-border dryland resource management.

The study confirms that the frontline states are experiencing a southward progression of desert conditions, threatening agricultural livelihoods, biodiversity, and rural sustainability. These findings underscore the urgent need for integrated land management policies and sustained ecological restoration efforts to reverse current trends and enhance the resilience of ecosystems and communities in Northern Nigeria.

5.2 Recommendations

1. **Strengthen Afforestation and Reforestation Initiatives:** Revitalize and expand afforestation programs such as shelterbelts, community woodlots, and farm forestry in the frontline states. Lessons from the successful Forestry II Project should guide the design of new, locally driven restoration efforts.
2. **Promote Sustainable Agricultural Practices:** Encourage conservation agriculture, agroforestry, and soil fertility management techniques to reduce pressure on fragile lands. Policies should promote the adoption of drought-tolerant crops and sustainable irrigation systems.
3. **Implement Integrated Land and Water Management Policies:** Strengthen institutional coordination among federal, state, and local agencies to manage rangelands, wetlands, and farmlands in a holistic manner. Integration of climate adaptation and land-use planning is crucial for sustainable ecosystem management.
4. **Enhance Environmental Monitoring Using Remote Sensing:** Establish a continuous, data-driven monitoring system employing remote sensing and GIS tools to track land degradation trends. This will improve early warning systems and guide evidence-based policy interventions.
5. **Strengthen Community Participation and Livelihood Diversification:** Support local communities through awareness programs, livelihood diversification, and capacity building in sustainable resource use. Women and youth should be prioritized in restoration and conservation initiatives.
6. **Develop and Enforce Environmental Governance Frameworks:** Strengthen existing desertification control policies, enforce anti-deforestation regulations, and improve rangeland management through cross-border collaboration, especially within the Lake Chad Basin region.

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