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Spatio-Temporal Dynamics of Fractional Vegetation Cover Change in Zamfara State, Nigeria (1985–2020): A Landsat and CLASlite Approach

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ABSTRACT

Vegetation degradation remains a critical environmental issue in semi-arid regions of Nigeria, where population growth, agricultural expansion, and climatic variability drive land-cover changes. This paper quantified the spatio-temporal dynamics of vegetation cover across Zamfara State over a 35-year period (1985–2020) using multi-temporal Landsat imagery (TM, ETM+, OLI) processed with the CLASlite algorithm to derive fractional vegetation cover. Eight epochs (1985, 1990, 1995, 2000, 2005, 2010, 2015, and 2020) were analysed using change-vector analysis and accuracy assessment through confusion matrices and Kappa statistics. Results indicate a consistent decline in photosynthetic vegetation cover from 65.3% in 1985 to 34.8% in 2020, with the central and northwestern parts of the state showing the most pronounced losses. The findings highlight accelerating vegetation degradation particularly after 2000, correlating with increased anthropogenic pressures. This long-term assessment provides a valuable baseline for sustainable land-use planning, ecological restoration, and policy development toward combating desertification in semi-arid Nigeria.

Keywords: Remote sensing, Vegetation cover, Change detection, CLASlite, Landsat, Fractional cover

INTRODUCTION

Vegetation resources constitute one of the most critical components of terrestrial ecosystems because they regulate hydrological processes, maintain biodiversity, sequester carbon, and support rural livelihoods. In the Sudano–Sahelian belt of Nigeria, however, vegetation systems have experienced sustained pressure from agricultural expansion, fuelwood extraction, overgrazing, artisanal mining, rapid population growth, and climate variability. These pressures have accelerated land degradation and increased vulnerability to desertification, particularly in northwestern states such as Zamfara.

Previous investigations in Nigeria have employed conventional land-use and land-cover classification approaches using remotely sensed imagery to examine environmental change. While these studies have provided valuable insights, categorical classifications often oversimplify heterogeneous semi-arid landscapes where vegetation, bare soil, and senescent biomass coexist within individual pixels. Fractional-cover approaches provide a more robust alternative by estimating the proportional abundance of photosynthetic vegetation, non-photosynthetic vegetation, and bare substrate. (Daniel, and Ayobami, 2017).

The Carnegie Landsat Analysis System-Lite (CLASlite) offers an effective framework for such analyses through automated spectral mixture modelling and Monte Carlo unmixing procedures. (Asner, Knapp, Balaji, & Páez-Acosta, 2019). Despite its demonstrated utility in tropical and semi-arid environments, few studies have applied CLASlite to long-term vegetation assessment in northwestern Nigeria, and no harmonized 35-year evaluation currently exists for Zamfara State.

MATERIALS AND METHODS

Zamfara state is located in northwestern Nigeria between latitudes 100^{o}15’N and 13^{o}45’N and longitudes 5^{o}00’E and 7^{o}15’E, covering approximately 39,762 km^{2}. The state falls within the sudano-Sahelian ecological zone and experiences a tropical continental climate characterized by distinct wet and dry seasons. Annual rainfall ranges from 600 to 1000 mm, occurring predominantly between May and October, while mean annual temperatures vary between 28^{o}c and 35^{o}c.

The vegetation consists mainly of Sudan savanna in the southern parts and Sahel savanna toward the north. Dominant species include Acacia, Parkia, Faidherbia, and various drought-resistant grasses. Agricultural activities, livestock grazing, fuelwood collection and artisanal mining constitute major land-use practices and have contributed significantly to vegetation modification and environmental degradation across the state.

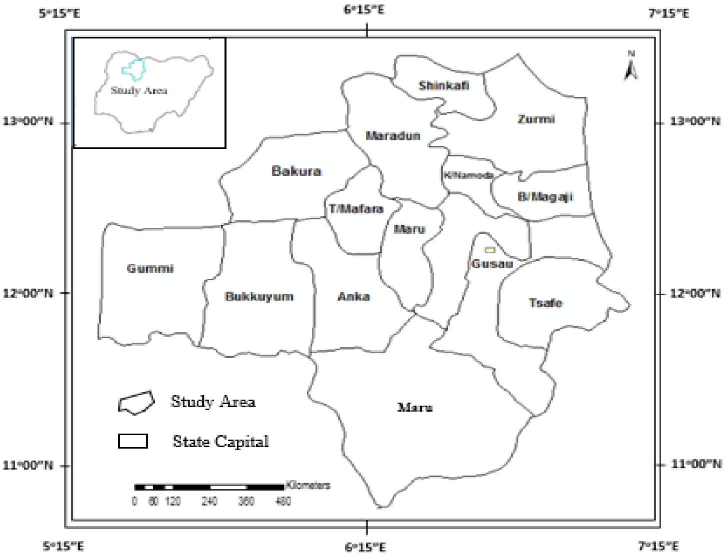

Figure 1: Map of Zamfara State

Data Sources and Image Pre-processing

Multi-temporal Landsat imagery obtained from the United States Geological Survey (USGS) Earth explorer database formed the principal dataset for this study. Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI scenes corresponding to eight epochs (1985, 1990, 1995, 2000, 2005, 2010, 2015, and 202) were selected.

All images were acquired during the dry season (November-January) to minimize cloud contamination and reduce seasonal variability in vegetation phenology, thereby ensuring inter-annual comparability. Atmospheric correction procedures were applied prior to analysis, while cloud and shadow pixels were removed using Fmask algorism. Individual scenes were mosaicked, georeferenced to the Universal Traverse Mercator projection (WGS 84, Zone 31N), and clipped to the administrative boundary of Zamfara State.

Table 1: Landsat Data Acquired For Analysis

S/N	Satellite Imagery	Path	Row	Day/Month/Year
1	Landsat 5 TM	189	051	27 November, 1985
		189	052	27 November, 1985
		190	051	27 November, 1985
		190	052	27 November, 1985
		191	052	27 November, 1985
2	Landsat 5 TM	189	051	10 January, 1990
		189	052	10 January, 1990
		190	051	10 January, 1990
		190	052	10 January, 1990
		191	052	10 January, 1990
3	Landsat 5 TM	189	051	22 December, 1995
		189	052	22 December, 1995
		190	051	22 December, 1995
		190	052	22 December, 1995
		191	052	22 December, 1995
4	Landsat 7 ETM+	189	051	21 November, 2000
		189	052	21 November, 2000
		190	051	21 November, 2000
		190	052	21 November, 2000
		191	052	21 November, 2000
5	Landsat 7 ETM+	189	051	27 November, 2005
		189	052	27 November, 2005
		190	051	27 November, 2005
		190	052	27 November, 2005
		191	052	27 November, 2005
6	Landsat 7 ETM+	189	051	21 December, 2010
		189	052	21 December, 2010
		190	051	21 December, 2010

S/N	Satellite Imagery	Path	Row	Day/Month/Year
		190	052	21 December, 2010
		191	052	21 December, 2010
7	Landsat 8 OLI	189	051	2 January, 2015
		189	052	2 January, 2015
		190	051	2 January, 2015
		190	052	2 January, 2015
		191	052	2 January, 2015
8	Landsat 8 OLI	189	051	20 December, 2020
		189	052	20 December, 2020
		190	051	20 December, 2020
		190	052	20 December, 2020
		191	052	20 December, 2020

Source: United State Geological Survey (2021)

Data Sources and Image Pre-processing

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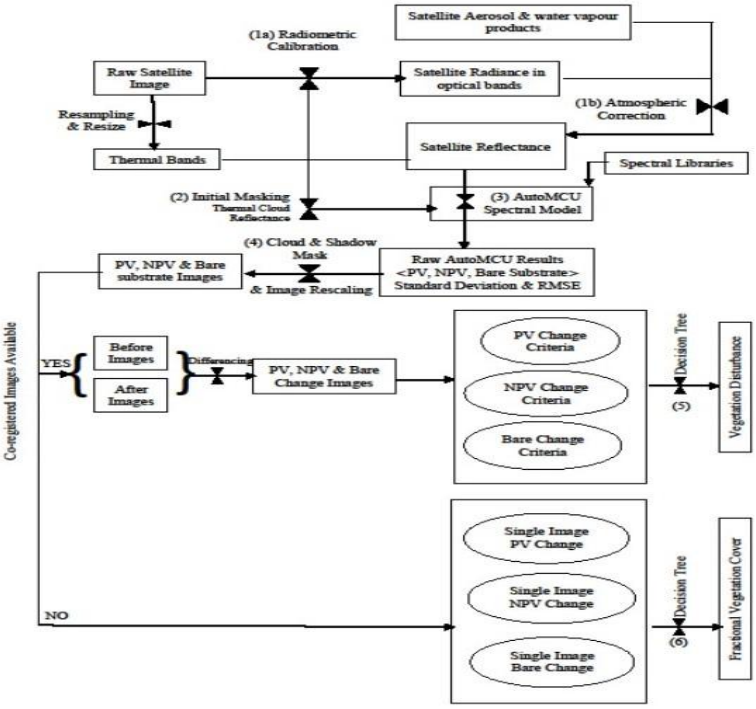

Figure 2: Claslite Processing Streams

Change Detection Procedures

Vegetation change analysis was conducted using post-classification comparison and fractional-cover differencing. Photosynthetic vegetation fractions from successive years were compared to quantify gains and losses in vegetation cover over time. (De Jong, Bruin, de Wit, Schaepman, & Dent, 2021).

Although Change Vector Analysis (CVA) was employed to support interpretation of vegetation dynamics, the present study emphasizes changes in fractional vegetation abundance rather than multidimensional spectral trajectories. Consequently, changes were classified into: Vegetation gain, Vegetation loss, and No significant change. This approach provided a robust framework for identifying long-term spatial patterns of degradation and regeneration across Zamfara State.

$$\Delta G = G - H \quad (1)$$

Where k = the number of bands;

$G = (g_1 \quad g_2 \quad \cdots \quad g_k)^T$ = image pixel vector of t1 period, containing 6 bands; (2)

$H = (h_1 \quad h_2 \quad \cdots \quad h_k)^T$ = image pixel vector of t2 period, containing 6 bands; (3)

Then the strength of change is calculated by (2), and we get the angle between each band and its spectral brightness axis using (3):

$$\|G\| = \sqrt{(g_1 - h_1)^2 + (g_2 - h_2)^2 + \cdots + (g_k - h_k)^2}$$

$$\cos\theta_i = \frac{x_i}{\|X\|} (i = 1,2,3,4,5,6) \quad (5)$$

Where $X(x_1, x_2, x_3, x_4, x_5, x_6)$ = change vector with 6 bands;

$$\|X\| = \sqrt{x_1^2 + x_2^2 + x_3^2 + x_4^2 + x_5^2 + x_6^2}\ ; \quad (6)$$

The technique was employed to discern alterations in spectral characteristics between two scenes that are ostensibly identical but were captured at distinct points in time. The number of bands per image in CVA is restricted to a maximum of two. The change vector in the two-dimensional spectral space is computed for every individual pixel. The findings derived from the implementation of the Change Vector Analysis methodology illustrate its effectiveness in identifying and categorizing various forms of change based on their impact on biomass, encompassing both gains and losses. The analysis of the change vector image for the two periods under investigation has facilitated the verification of a total degraded area of 12,820 km^2 during the time span from 1985 to 2020.

RESULTS AND DISCUSSION

Temporal Dynamics of Vegetation Cover Change

Over the 35-year period, vegetation cover in Zamfara State showed a consistent downward trend. The total area of photosynthetic vegetation declined from approximately 25,963 km² (65.3%) in 1985 to 13,847 km² (34.8%) in 2020. Significant declines were observed between 2000 and 2010, corresponding to a period of population growth and expansion of artisanal mining activities.

Spatial Distribution of Vegetation Cover Change in the State (1985 - 2020)

Spatial analysis revealed heterogeneous patterns of vegetation change across the state. The central and northwestern regions experienced the highest vegetation losses, particularly in Anka, Maru, and Talata Mafara LGAs. Conversely, minor vegetation gains were recorded in parts of the southeastern region, attributed to reforestation efforts and reduced agricultural intensity.

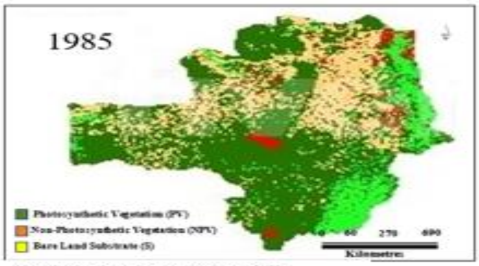

Fig. 3: Fractional cover image, 1985

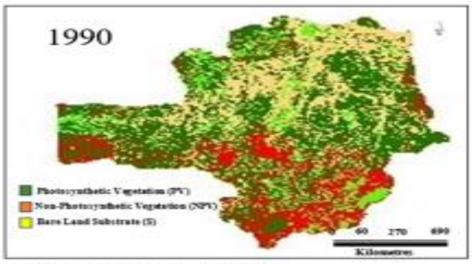

Fig. 4: Fractional cover image, 1990

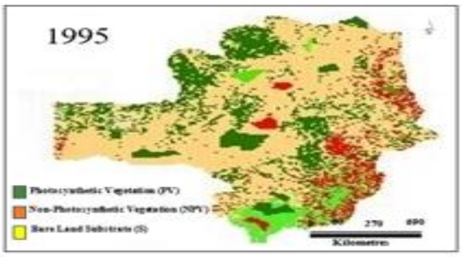

Fig. 5: Fractional cover image, 1995

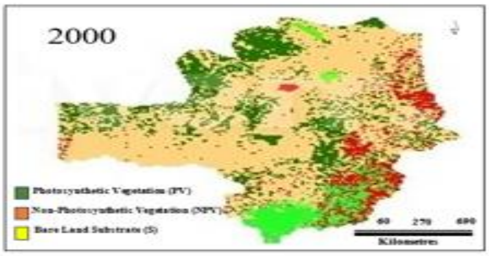

Fig. 6: Fractional cover image, 2000

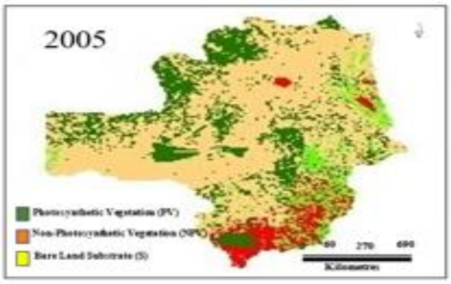

Fig. 7: Fractional cover Image, 2005

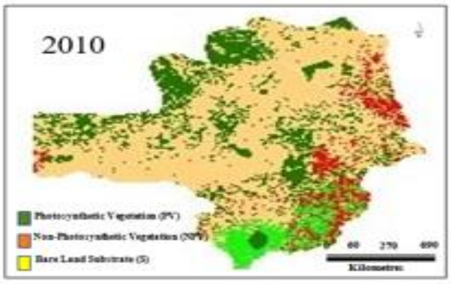

Fig. 8: Fractional cover Image, 2010

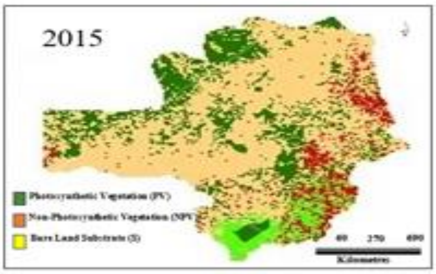

Fig. 9: Fractional cover Image, 2015

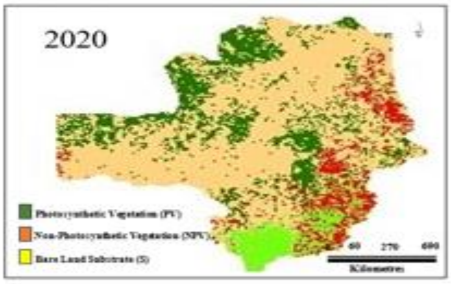

Fig. 10: Fractional cover Image, 2020

Vegetation change cover detection was performed to identify and quantify changes in vegetation cover over the whole of the state to monitor and assess environmental changes due to any of these; Deforestation or afforestation, Urbanization, Agricultural expansion, Climate variability and Natural disasters. Using Image differencing: Subtract pixel values of two images (1985 - 2020). This helps in Quantification of area gains and losses in vegetation classes.

The vegetation cover change detection map above in Fig. 10, illustrates the spatial dynamics of land cover over a 35-year period, focusing on three key categories: areas of vegetation gain, vegetation loss, and no change. The interpretation provides a breakdown of these transformations and their implications for ecological and land management concerns.

Table 2: Possible Change Classes from both Input Components and Related Type of Change

Classes	Greenness	Brightness	Themes
PV	+	-	Thick Vegetation
NPV	-	+	Light Vegetation
S	-	-	Non-vegetated

Author, (2023)

Class 1 is characterized by an increase in greenness and a decrease in brightness, signifying a vector direction primarily associated with the augmentation of vegetation biomass. On the other hand, class 2 exhibits a decrease in greenness and an increase in brightness, which point to a strong correlation between the decline in vegetation biomass and the degradation brought on by clear-cutting of vegetation. Class 3, which demonstrates a decline in both greenness and brightness, is primarily associated with a significant loss of vegetation cover. (Thapa *et al.*, 2023)

Change Detection

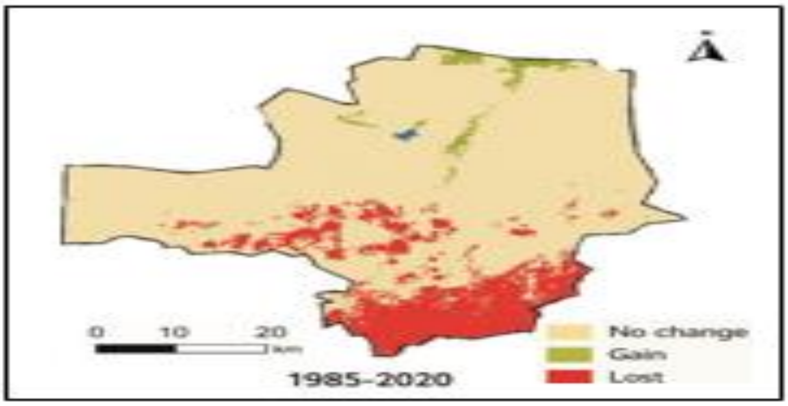

Figure 11: Change Detection Map of the Study Area Over the Study Period

Vegetation loss (Marked in Red), shows its geographic distribution which concentrated heavily in the southern and central-southern portions of the region (Tsafe, Gusau, Bungudu and some part of Maru, Anka, Bukkuyum and Gummi LGAs). The extent and impacts indicate widespread deforestation or land degradation in areas that were formerly vegetated in 1985. The large red coverage suggests significant vegetation retreat, possibly due to agricultural expansion (example, shifting cultivation, permanent farming), logging or fuelwood extraction, urban or rural settlement growth and climate-related stress such as droughts or wildfires. Some of the ecological implications may include; loss of biodiversity and wildlife habitat, increased soil erosion and land vulnerability, reduction in carbon sequestration potential.

Vegetation gain (Marked in Green), shows the geographic distribution of patchy but evident in the northern, northeastern (Maradun, Bakura, Shinkafi and Zurmi LGAs), and some part of central zones. The extent and impact although smaller in area compared to losses, these green patches indicate areas where vegetation has either naturally regenerated or been actively restored. Potential drivers include; reforestation or afforestation programs, abandonment of agricultural land allowing natural succession and improved rainfall patterns or soil moisture conditions. The ecological implications may be positive for local microclimates, soil health, and habitat restoration and some signals success of targeted conservation efforts or climate adaptation strategies.

No change (Marked in Beige), shows the geographic distribution which covers northern and western regions (some part of Talata Mafara, Gummi and Maradun), including some part of central corridor in far northern boundary Maru LGA. Extent and meaning represents zones where land cover remained relatively stable throughout the study period. These areas were likely either consistently barren or sparsely vegetated**,** protected or resilient vegetative zones not subjected to disturbance. And may also reflect inherent ecological constraints such as soil type, terrain, or rainfall availability limiting vegetation dynamics.

Water body (Blue Spot), the persistent presence of a blue feature in the north-central area represents a permanent water body**.** Its unchanging nature across the period may have acted as a buffer zone for surrounding vegetation gain, particularly visible in the nearby green patches.

The map provides compelling evidence of significant land cover transformation from 1985 to 2020. Vegetation loss dominates the south, reflecting a need for urgent intervention to prevent further degradation. Gains, though localized, demonstrate the potential for recovery through strategic environmental management. Stable areas offer critical ecological benchmarks for understanding land system resilience. Some recommendations may include targeted reforestation; efforts should focus on the most degraded zones (red areas). Areas showing vegetation gains should be monitored and supported to maintain momentum. Long-term land use policies must address both socio-economic drivers of vegetation loss and natural restoration dynamics. (Fragou *et al.,* 2020).

Accuracy Assessment

In Table 3. According to a general guideline, RMSE values ranging from 0.5 to 0.8 indicate that the model is capable of making reasonably accurate predictions of the data from the minimum of ± 0.800 and the maximum is ± 0.910 translating to a range of ± 0.11 and average of ± 0.841. Furthermore, an adjusted R-squared value of correlation which exceeds 0.75 is indicative of high accuracy of the Claslite model with a minimum correlation value of 0.78 and maximum of 0.98 translating to a range of 0.2 and the average of 0.891 (Deng *et al.,* 2019).

Table 3: Analysis of Accuracy Assessment from 1985 to 2020

Vegetation Class cover (year)	Total Area (ha)	Correlation (R^2)	P- value	Accuracy Assessment (RMSE)	Remark
1985	3,561,430	0.780	0.005	± 0.910	Moderate accuracy
1990	3,561,430	0.857	0.001	± 0.880	Good accuracy
1995	3,561,430	0.819	0.001	± 0.830	Good accuracy
2000	3,561,430	0.901	0.001	± 0.858	Very good accuracy
2005	3,561,430	0.911	0.001	± 0.820	Very good accuracy
2010	3,561,430	0.980	0.001	± 0.810	Excellent accuracy
2015	3,561,430	0.980	0.001	± 0.800	Excellent accuracy
2020	3,561,430	0.900	0.001	± 0.820	Very good accuracy

Table 4: Present the Outputs Showing Vegetation Change Detection Across Five Zones of Zamfara State between 1985 and 2020

Zone	Vegetation in 1985	Vegetation in 2020	Loss	Gain	Net Change (%)
Zone 1	817	630	558	371	-26.9
Zone 2	797	583	549	335	-22.9
Zone 3	782	608	552	378	-22.3
Zone 4	745	611	530	396	-18.0
Zone 5	751	640	502	391	-14.8

Table 4 summarized the gain and loss in Zone 1 which comprises Gusau, Tsafe, Bungudu, Maru and some part of Kaura Namoda. Zone 2 comprises Gummi, Anka, Bukkuyum and some part Maru. Zone 3 comprises of Talata Mafara, Bakura and Maradun. And Zone 4 and 5 comprises of Birnin Magaji, Zurmi and Shinkafi. All zones experienced net vegetation loss from 1985 to 2020. The highest rate of decline occurred in Zone 1 (-26.9%), while Zone 5 saw the least (-14.8%). Vegetation gains occurred in every zone but were insufficient to offset losses.

The primary alteration in vegetation cover observed in the state was the transformation of vegetated landscapes into more spaces and urban settlements, accompanied by a reduction in Trees Outside Forest (TOF) areas. The decrease in Ecological Service Values (ESVs) can be ascribed to the conversion of vast heavy vegetated surfaces into patterning patches of vegetation covers. This increase in unproductive land that led to a decrease in ESVs. However, the growth of different vegetation cover features near the rural community had a significant positive influence on ecosystem services, outweighing the negative effects of the reduction in agricultural land.

However, quantifying these effects is challenging. The study utilized Landsat image data in conjunction with published coefficients pertaining to global and Chinese ecosystems to accurately measure changes in land use and ecosystem services within the specified area. A sensitivity analysis was conducted to assess the impact of manipulating these coefficients on the estimated values. Their findings indicate that between 1973 and 2004, there was a conversion of heavily vegetated cover surfaces and grasslands into shrubland and cropland, respectively. This conversion led to a consistent decline in ecosystem service. The researchers discovered that the primary factor contributing to the decline of ecosystem service in the study area was the significant reduction in mixed vegetation covers. Hence, they suggest that forthcoming land-use policy should prioritize the vital ecosystem functions of these vegetation covers and strive to achieve a harmonious balance between the livelihood of local farmers and environmental preservation, in order to sustain a robust and stable ecosystem.

Accuracy Assessment of CVA

The overall classification accuracy across epochs ranged between 85% and 91%, with Kappa coefficients of 0.78–0.86, indicating good reliability of the CLASlite-derived fractional vegetation maps. Accuracy tended to decrease slightly in areas with complex land-use mosaics or sparse vegetation cover.

Table 5: Accuracy Assessment of CVA Method

Veg. Class	CVA	Number of Visual Interpretation Pixels	Accuracy %)
PV – NPV	9,072	9,126	96.06
NPV – S	19,606	21,441	88.28
PV – S	5,300	5,463	93.94

Author, (2023)

Discussion

The findings of this study reveal a substantial decline in fractional vegetation cover across Zamfara State between 1985 and 2020, reflecting the cumulative impacts of anthropogenic activities and climatic variability in the Sudano–Sahelian ecological zone. The reduction of photosynthetic vegetation (PV) from 25,963 km² (65.3%) in 1985 to 13,847 km² (34.8%) in 2020 demonstrates an overall decline of approximately 46.7%, confirming an accelerated process of environmental degradation over the study period.

The most pronounced losses occurred after 2000, corresponding with rapid population growth, agricultural intensification, increased fuelwood extraction, and the expansion of artisanal mining activities. Similar trends have been reported in northern Nigeria, where agricultural encroachment and unsustainable exploitation of natural resources have contributed significantly to vegetation depletion and declining ecosystem services. The concentration of vegetation loss within Anka, Maru, Tsafe, Bungudu, and Talata Mafara Local Government Areas further supports the influence of human activities on landscape transformation.

Artisanal and small-scale gold mining has emerged as an important driver of environmental degradation in Zamfara State. Beyond direct vegetation clearance, mining activities have increased soil disturbance, accelerated erosion processes, and altered local hydrological systems. The observed reduction in dense vegetation patches within mining-dominated landscapes is therefore consistent with broader patterns of land degradation documented across semi-arid West Africa.

Climatic variability has also contributed to the observed vegetation dynamics. The Sudano–Sahelian region has experienced considerable fluctuations in rainfall distribution, increasing temperatures, and recurrent drought episodes over recent decades. These environmental stresses reduce vegetation productivity, inhibit natural regeneration, and intensify the impacts of anthropogenic disturbances. Consequently, vegetation change in Zamfara State reflects a complex interaction between human-induced pressures and climatic constraints.

The application of CLASlite proved particularly suitable for this investigation because fractional-cover approaches offer greater sensitivity in heterogeneous dryland environments than conventional categorical land-cover classifications. By estimating proportions of photosynthetic vegetation, non-photosynthetic vegetation, and bare substrate within individual pixels, the methodology reduced spectral confusion associated with mixed land-cover conditions. The overall classification accuracies (85–91%) and Kappa coefficients (0.78–0.86) indicate substantial agreement between classified outputs and validation data, demonstrating the robustness of the analytical framework.

The findings are consistent with regional studies conducted across northern Nigeria and the wider Sahel, which report widespread vegetation decline resulting from agricultural expansion, urban growth, overgrazing, and climate variability. However, the present study contributes a unique long-term perspective by providing a harmonized 35-year assessment of fractional vegetation dynamics for Zamfara State using a consistent methodological approach.

Implications for Environmental Management

The substantial reduction in vegetation cover has important implications for ecosystem sustainability, biodiversity conservation, and rural livelihoods. Declining vegetation resources increase susceptibility to soil erosion, reduce carbon sequestration capacity, diminish wildlife habitats, and weaken ecosystem resilience against climatic extremes. Consequently, environmental management strategies within Zamfara State should prioritize: Community-based afforestation and reforestation programmes; Sustainable fuelwood management practices; Regulation of artisanal mining activities; Promotion of climate-smart agricultural systems; Strengthening of protected-area management frameworks; and Continuous monitoring using geospatial technologies.

Such interventions are necessary to reverse ongoing degradation and support long-term ecological restoration across vulnerable landscapes.

Study Limitations

Despite providing valuable insights into long-term vegetation dynamics, this study possesses certain limitations. First, the analysis relied exclusively on remotely sensed observations and did not incorporate climatic variables, socio-economic indicators, or demographic information capable of explaining causal mechanisms underlying vegetation change. Second, only dry-season imagery was employed to maintain temporal consistency, which may not fully capture seasonal vegetation variability. Third, the study focused on fractional vegetation indicators without explicitly quantifying ecosystem service losses associated with observed land-cover changes.

Future Research Directions

Future investigations should integrate rainfall records, temperature trends, population data, agricultural statistics, and mining information to develop more comprehensive explanations of vegetation change processes. Machine-learning approaches and predictive modelling techniques may further improve the capacity to forecast future vegetation trajectories under different environmental and socio-economic scenarios. Additional research should also evaluate the implications of vegetation decline for ecosystem services, biodiversity conservation, and climate-change adaptation strategies within semi-arid Nigeria.

CONCLUSION

This study examined the spatio-temporal dynamics of fractional vegetation cover in Zamfara State, Nigeria, between 1985 and 2020 using multi-temporal Landsat imagery and the CLASlite analytical framework. The results revealed a substantial decline in photosynthetic vegetation cover, decreasing from 25,963 km² (65.3%) in 1985 to 13,847 km² (34.8%) in 2020. The findings indicate that vegetation degradation intensified after 2000, coinciding with increased agricultural activities, population growth, fuelwood extraction, and artisanal mining operations.

Spatial analyses demonstrated that central and northwestern parts of the state experienced the greatest vegetation losses, while isolated areas of regeneration occurred within parts of the northeastern region. The use of fractional-cover methodologies provided improved sensitivity for detecting subtle vegetation changes within heterogeneous semi-arid environments, thereby enhancing the reliability of long-term environmental assessments.

The study highlights the urgent need for sustainable land-management policies, strengthened environmental regulations, and large-scale ecological restoration programmes aimed at combating desertification and preserving ecosystem services. Particular emphasis should be placed on regulating mining activities, promoting afforestation initiatives, and encouraging climate-smart agricultural practices capable of reducing pressure on natural vegetation resources.

Notwithstanding its contributions, the study was limited by the absence of integrated climatic and socio-economic datasets necessary for detailed causal attribution. Future research should therefore combine remote-sensing approaches with environmental, demographic, and economic indicators to improve understanding of vegetation dynamics and support predictive modelling of land-cover change in semi-arid regions.

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