

Research Article

Drivers of Vegetation Cover Loss in Zamfara State: Disentangling Climatic Variability and Anthropogenic Pressures (1985–2020)

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ABSTRACT

Understanding the drivers of vegetation cover change in semiarid regions is critical for sustainable land management and climate adaptation. In this paper, the relative influence of climatic variability and anthropogenic pressures on long-term vegetation cover loss across Zamfara State, Nigeria, from 1985 to 2020 was investigated. Fractional vegetation cover maps derived from CLASlite-processed Landsat imagery were integrated with climatic datasets (rainfall and temperature) and human activity proxies (population density, artisanal mining, and agricultural expansion). Statistical and spatial analyses, including correlation, multiple regression, and random forest modelling, were used to quantify the contribution of each driver to vegetation change. The results reveal that both climate and anthropogenic activities significantly influence vegetation dynamics, with anthropogenic pressures explaining approximately 60% of the observed variability. Mining and settlement density emerged as dominant local drivers, whereas rainfall variability accounted for large-scale temporal fluctuations. The findings emphasize the need for integrated land use and climate policies that address both human and environmental factors that drive vegetation degradation in northern Nigeria.

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1 Introduction

Vegetation degradation is a pervasive environmental challenge across the Sudano-Sahelian region of West Africa, where fragile ecosystems are exposed to both climatic stressors and increasing anthropogenic pressures (Nicholson, 2013). Understanding the relative contributions of these drivers is essential for designing effective mitigation and adaptation strategies. In Nigeria's Zamfara State, recurring droughts, unsustainable agricultural practices, and artisanal mining have transformed the landscape over the past four decades (Abubakar et al., 2009). While some previous studies have documented general vegetation decline in northern Nigeria, few have disentangled the combined influence of climate and human pressures at the regional scale (Allnutt et al., 2013).

In this paper, long-term vegetation cover change analysis derived from CLASlite-processed Landsat data (1985–2020) is performed. It integrates multisource datasets to assess how rainfall variability, temperature trends, population growth, and mining activity collectively drive vegetation dynamics. The objectives of this study are to identify the dominant drivers of vegetation loss across Zamfara State, quantify the magnitude of their influence, and map the spatial distribution of climate- and human-dominated degradation zones.

The primary concern was to examine the temporal fluctuations in vegetation cover within the Zamfara State region and its surrounding areas. It is important to note

that while other factors may also contribute to the decline in vegetation, this research focuses specifically on the temporal changes in the classified vegetation cover categories. These findings contribute to an enhanced scientific understanding of the depletion of vegetation cover in northern Nigeria. Policymakers are anticipated to find this knowledge valuable in addressing the multifaceted nature of the situation. Furthermore, it is anticipated that the outcomes will assist the government in its efforts to combat the issue of deforestation in northern Nigeria.

Consequently, the findings illustrate the spatial discrepancies and arrangements in the distribution of various categories of vegetation cover. This is particularly relevant considering the preexisting knowledge regarding the insufficient availability of vegetation monitoring data in the region (Adhikari et al., 2016). Therefore, it is possible to perform relevant site-specific re-examinations and/or determinations and include them in the development of effective policies needed to run the framework for managing natural resources in the region. This includes finding alternatives quickly when they are needed.

2 Materials and Methods

2.1 Study Area

Zamfara State lies between latitudes 10°15'N and 13°45'N and longitudes 5°00'E and 7°15'E, covering an estimated area of 39,762 km² (Figure 1). The state experiences a

tropical continental climate with distinct wet (May–October) and dry (November–April) seasons. The vegetation ranges from the Sudan savanna in the south to the Sahel savanna in the north. The soils are mainly sandy loam with moderate fertility, supporting both rain-fed agriculture and grazing. Population growth, artisanal mining, and agricultural encroachment have intensified land degradation.

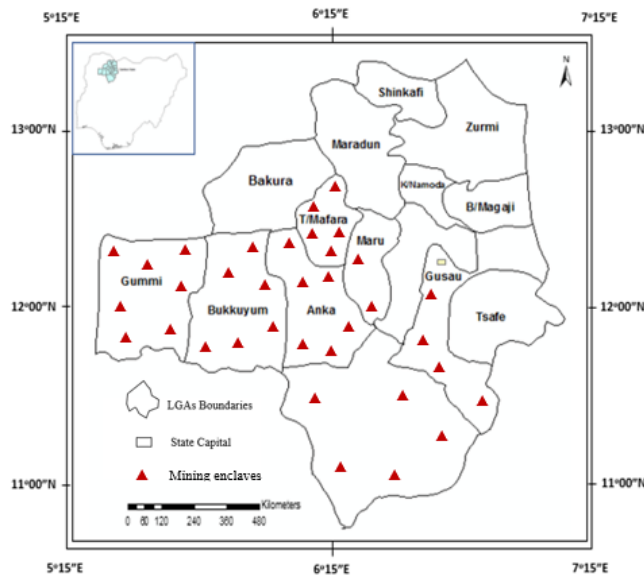


Figure 1: Zamfara State showing mining enclaves

2.2 Data Sources

Fractional vegetation cover maps for eight epochs (1985, 1990, 1995, 2000, 2005, 2010, 2015, and 2020) were derived using CLASlite from atmospherically corrected Landsat TM, ETM+, and OLI imagery (Table 1). Climatic data, including mean annual rainfall and mean temperature, were obtained from the Nigerian Meteorological Agency (NiMet) and corroborated with the CHIRPS and MODIS datasets. Human activity proxies were compiled from population census data, mining site inventories, and land use maps derived from high-resolution imagery. Each dataset was harmonized to a 30 m spatial resolution and projected to UTM Zone 32 N. All the data were clipped to the Zamfara state boundary for consistency.

Landsat offers medium-resolution data that are appropriate for regional-scale land cover and land use mapping. Facilitates a seasonal or annual assessment of alterations (vegetation growth, urban development, deforestation) (Ayele et al., 2018). Multispectral capabilities facilitate several analyses, including vegetation indices (NDVIs), water body identification, and urban area delineation. Enhanced radiometric resolution augments the ability to discern minute variations in reflectance, hence enhancing classification precision (Asner et al., 2009). This facilitates extensive temporal examination of alterations in land surfaces. Data can be utilized immediately in GIS and remote

sensing tools for subsequent analysis. (Bunyanga et al., 2021).

Table 1: Technical specifications of the images used

Landsat Satellite	Imaging Instrument (Sensor)		Band	Spectral Range (nm)	Resolution (m)	Dynamic Range (bit)
Landsat 5	TM	1	Blue	0.45-0.52	30	8
		2	Green	0.52-0.60	30	8
		3	Red	0.63-0.69	30	8
		4	IR	0.76-0.90	30	8
		5	SWIR 1	1.55-1.75	30	8
		6	Thermal	10.40-12.50	120	8
		7	SWIR 2	2.08-2.35	30	8
Landsat 7	ETM+	1	Blue	0.45-0.52	30	8
		2	Green	0.52-0.60	30	8
		3	Red	0.63-0.69	30	8
		4	IR	0.77-0.90	30	8
		5	SWIR 1	1.55-1.75	30	8
		6	Thermal	10.40-12.50	60	8
		7	SWIR 2	2.09-2.35	30	8
Landsat 8	OLI	8	P-Chrome	0.52-0.90	15	8
		1	Ultra-Blue	0.435 - 0.451	30	8
		2	Blue	0.452 - 0.512	30	8
		3	Green	0.533 - 0.590	30	8
		4	Red	0.636 - 0.673	30	8
		5	NIR	0.851 - 0.879	30	8
		6	SWIR 1	1.566 - 1.651	30	8
		7	SWIR 2	2.107 - 2.294	30	8
		8	P-Chrome	0.503 - 0.676	30	8
		9	Cirrus	1.363 - 1.384	15	8
		10	TIR 1	10.60 - 11.19	30	8
11	TIR 2	11.50 - 12.51	100	8		

Source: United States Geological Survey (2021).

2.3 Data Analysis

2.3.1 Climatic Variability Analysis

Rainfall and temperature trends were analysed using the Mann–Kendall test and Sen’s slope estimator to determine significant temporal changes. Anomalies were computed relative to the 1985–2020 mean, and standardized indices were created to capture interannual variability. Spatial interpolation (inverse distance weighting) was applied to generate continuous climate surfaces for correlation with vegetation change maps (Nicholson, 2013).

2.3.2 Anthropogenic Pressure Metrics

Population density maps were derived for 1991, 2006, and 2016 using census data and projected to 2020. Mining activities were mapped using a combination of field GPS coordinates and visual interpretation of Landsat and Sentinel-2 imagery. Agricultural expansion was quantified from the land use/land cover classification of the same epochs. Each variable was normalized to a 0–1 scale to allow comparative modelling (Begue et al., 2011).

2.3.3 Statistical modelling

To quantify driver importance, multiple linear regression and random forest models were applied using vegetation cover loss as the dependent variable. The predictors included rainfall anomalies, temperature trends, population density, mining site density, and agricultural expansion. Model performance was assessed using R^2 , RMSE, and variable importance metrics. Spatial overlays were created to visualize dominant driver zones (Thapa et al., 2023).

2.3.4 Validation and Uncertainty

Validation was achieved by cross-checking the predicted vegetation cover change against the observed fractional cover differences and field verification points. Uncertainty analysis included leave-one-out cross-validation and sensitivity testing to assess model robustness (Thapa et al., 2023).

2.3.5 NDVI Output

The normalized difference vegetation index (NDVI) generates a distinct image file or layer as its resulting output. The normalized difference vegetation index (NDVI) is a measure that can vary between -1.0 and +1.0. However, it is typically observed that values less than zero do not have significant ecological implications. Therefore, the range of the NDVI index is typically adjusted to span from 0.0 to +1.0. Elevated values are indicative of an increased disparity between the red and near-infrared wavelengths captured by the sensor, thereby suggesting the presence of plants that exhibit heightened photosynthetic activity. Low normalized difference vegetation index (NDVI) values suggest a minimal disparity between red and near-infrared (NIR) signals. This phenomenon manifests when the level of photosynthetic activity is diminished or when there is a minimal amount of near-infrared (NIR) light reflection, such as in the case of water exhibiting low NIR reflectance. The NDVI is widely used in rangeland ecosystems because of its simplicity of application and correlation with numerous environmental indicators.

3 Results

3.1 Climatic Variability Trends

Analysis of climatic records between 1985 and 2020 revealed substantial interannual variability in rainfall and temperature across Zamfara State. The rainfall gradually decreased, as estimated at approximately -1.2 mm yr^{-1} , whereas the mean annual temperature increased at an average rate of $0.03 \text{ }^{\circ}\text{C yr}^{-1}$ over the study period. Pronounced drought episodes observed in approximately 1990, 2005, and 2010 coincided with marked reductions in vegetation cover, indicating the sensitivity of vegetation dynamics to climatic fluctuations.

The summarized climatic data (Table 2) grouped into five-year intervals further demonstrate increasing temperature conditions across the study period. The mean annual temperature increased from $29.39 \text{ }^{\circ}\text{C}$ during 1985–1990 to $29.63 \text{ }^{\circ}\text{C}$ during 2016–2020, whereas the rainfall fluctuated considerably, ranging from 77.44 mm in 1991–1995 to 90.34 mm in 2016–2020. Relative humidity exhibited only slight variations throughout the period.

These findings suggest that although rainfall variability contributed to vegetation stress, the persistent increase in temperature may have intensified evapotranspiration rates, thereby reducing soil moisture availability and accelerating vegetation degradation processes in the semiarid environment of Zamfara State.

Table 2: Summarized Climatic Data for Zamfara State Grouped by 5-year Intervals for 1985 to 2020

Period	MeanTemp ($^{\circ}\text{C}$)	Rainfall (mm)	MaxTemp ($^{\circ}\text{C}$)	Min Temp ($^{\circ}\text{C}$)	Humidity (%)
1985-1990	29.39	82.19	33.53	25.44	33.02
1991-1995	29.46	77.44	33.42	25.36	32.6
1996-2000	29.58	89.71	33.72	25.48	32.93
2001-2005	29.59	81.15	33.61	25.52	33.5
2006-2010	29.52	82.03	33.63	25.59	32.78
2011-2015	29.55	87.91	33.54	25.45	32.58
2016-2020	29.63	90.34	33.62	25.54	32.84

3.2 Anthropogenic Influence on Vegetation Cover Changes

Anthropogenic activities were identified as major contributors to vegetation cover loss within the study area. Population density increased significantly from approximately $65 \text{ persons km}^{-2}$ in 1985 to $172 \text{ persons km}^{-2}$ in 2020, reflecting rapid demographic expansion and increasing pressure on land resources.

Similarly, artisanal mining activities expanded rapidly after 2000, particularly within the Local Government Area of Anka, Maru, and Talata Mafara. The proliferation of mining sites resulted in extensive land clearing, the removal of natural vegetation, and

landscape fragmentation. Agricultural expansion also increased substantially, with cultivated land estimated to have expanded by nearly 45% between 1985 and 2020. This expansion was largely driven by increasing food demand, rural livelihood dependence on agriculture, and continuous encroachment into previously vegetated areas.

The combined effects of mining, agricultural intensification, fuelwood exploitation, and settlement growth contributed significantly to long-term vegetation degradation across the state.

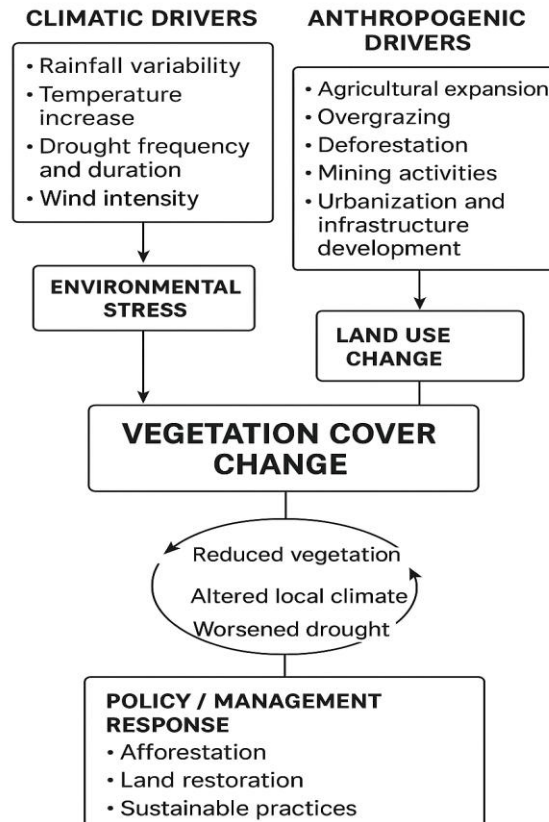


Figure 2: Conceptual Illustration of Climatic and Anthropogenic Drivers' Influence

3.3 Statistical Modelling and Accuracy Assessment

The regression analysis in the software revealed that anthropogenic variables exerted a stronger influence on vegetation cover loss than climatic factors did. Anthropogenic drivers explained approximately 58.6% of the total observed vegetation degradation ($p < 0.01$), whereas climatic variables accounted for approximately 33.2%.

The random forest model produced strong predictive performance, with a coefficient of determination (R^2) of 0.81 and a root mean square error (RMSE) of 0.07, indicating high model reliability in explaining vegetation cover dynamics. Variable importance analysis revealed that mining density was the most influential factor, contributing 34% to vegetation loss, followed by

population density (26%), rainfall anomalies (22%), temperature variation (11%), and agricultural expansion (7%).

The accuracy assessment conducted for vegetation classification between 1985 and 2020 demonstrated satisfactory model performance throughout the study years (Table 3). The correlation coefficients (R^2) ranged from 0.780 in 1985 to 0.980 in 2010 and 2015, whereas the RMSE values consistently decreased over time, indicating a progressive improvement in classification accuracy. The classification outputs for 2010 and 2015 were rated as "excellent," confirming the robustness of the applied modelling and classification techniques.

Table 3: Analysis of Accuracy Assessment from 1985 to 2020

Vegetation Class cover (year)	Total Area (ha)	Correlation (R)	P- value	Accuracy Assessment RMSE	Remark
1985	3561430	0.78	0.005	± 0.910	Moderate accuracy
1990	3561430	0.857	0.001	± 0.880	Good accuracy
1995	3561430	0.819	0.001	± 0.830	Good accuracy
2000	3561430	0.901	0.001	± 0.858	Very good accuracy
2005	3561430	0.911	0.001	± 0.820	Very good accuracy
2010	3561430	0.98	0.001	± 0.810	Excellent accuracy
2015	3561430	0.98	0.001	± 0.800	Excellent accuracy
2020	3561430	0.9	0.001	± 0.820	Very good accuracy

3.4 Spatial distribution of vegetation cover change

Spatial analysis revealed considerable heterogeneity in vegetation cover dynamics across Zamfara State. The northern parts of the state were predominantly climate-driven degradation zones, where low rainfall and prolonged dry conditions strongly influenced vegetation decline. In contrast, the central and western regions exhibited human-dominated degradation patterns associated with artisanal mining, agricultural encroachment, urban expansion, and increased settlement activities (Figure 4).

The analysis of fractional vegetation cover further indicated substantial reductions in photosynthetic vegetation (PV) over the study period (Table 4). PV declined dramatically from 65.37% in 1985 to 21.55% in 2020. Conversely, bare soil (S) increased from 15.21% in 1985 to 70.24% in 2020, indicating severe land degradation and exposure of soil surfaces. The

percentage of nonphotosynthetic vegetation (NPV) also decreased gradually from 19.42% to 8.21% during the same period.

The observed increase in bare surfaces reflects accelerated vegetation depletion and declining ecosystem resilience within the study area.

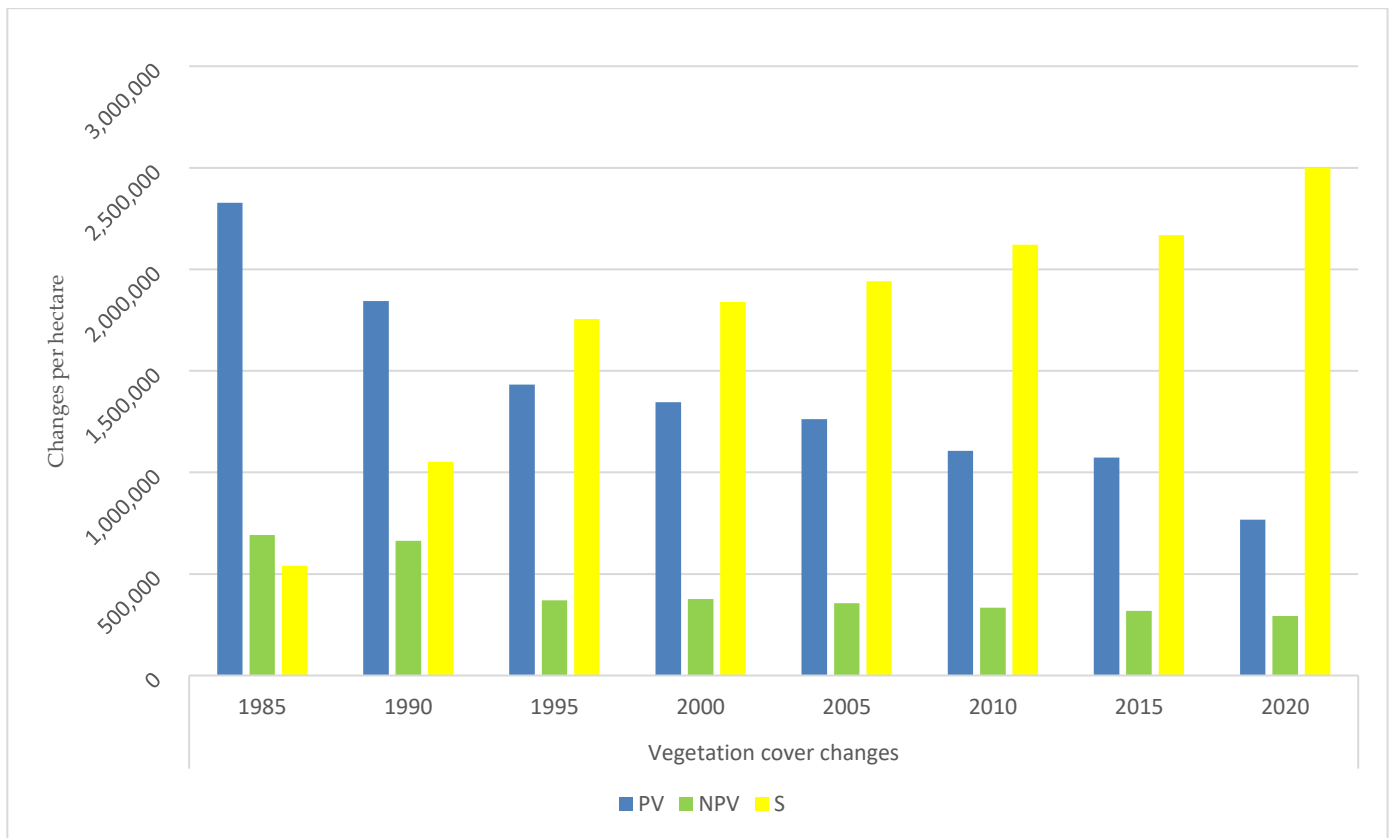


Figure 3: Histogram Depicting the Variations in Vegetation Cover Classes over the Study Period

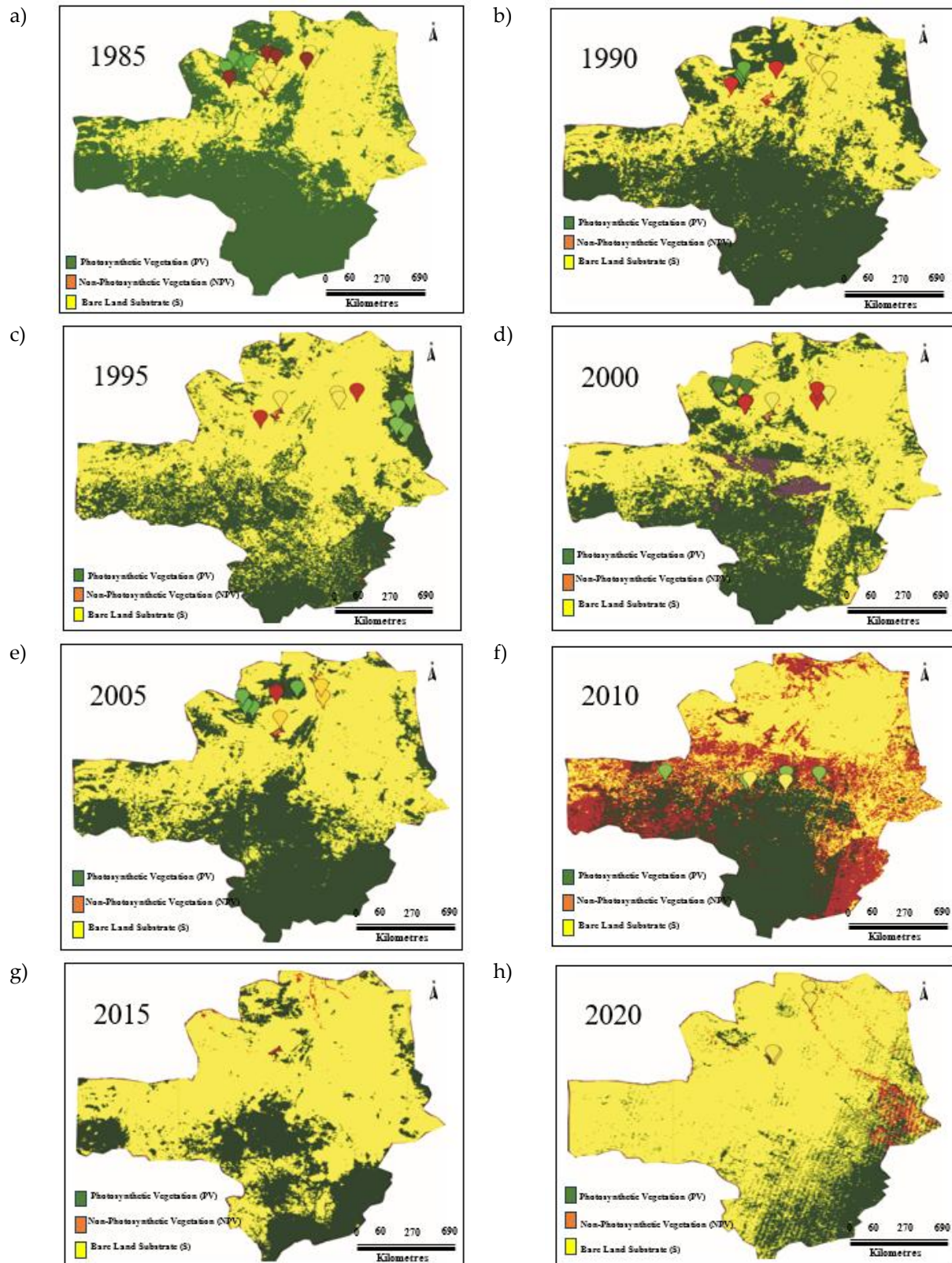


Figure 4: Spatial variation of vegetation cover dynamics in Zamfara State

Table 4: Analysis of vegetation cover changes based on total area extent per hectare

Year	PV (%)	NPV (%)	S (%)
1985	65.37	19.42	15.21
1990	51.78	18.65	29.57
1995	40.21	10.38	49.30
2000	37.78	10.56	51.65
2005	35.45	10.00	54.55
2010	31.05	9.38	59.57
2015	30.13	8.93	60.94
2020	21.55	8.21	70.24

3.5 NDVI result output

Analysis of the Landsat-derived NDVI data in CLASLite between 1985 and 2020 revealed a consistent downward

trend in vegetation health, with the NDVI values declining from dense vegetation (0.3–0.32) in 1985 to sparsely vegetated or degraded land (NDVI < 0.2) by 2020 (Figure 5).

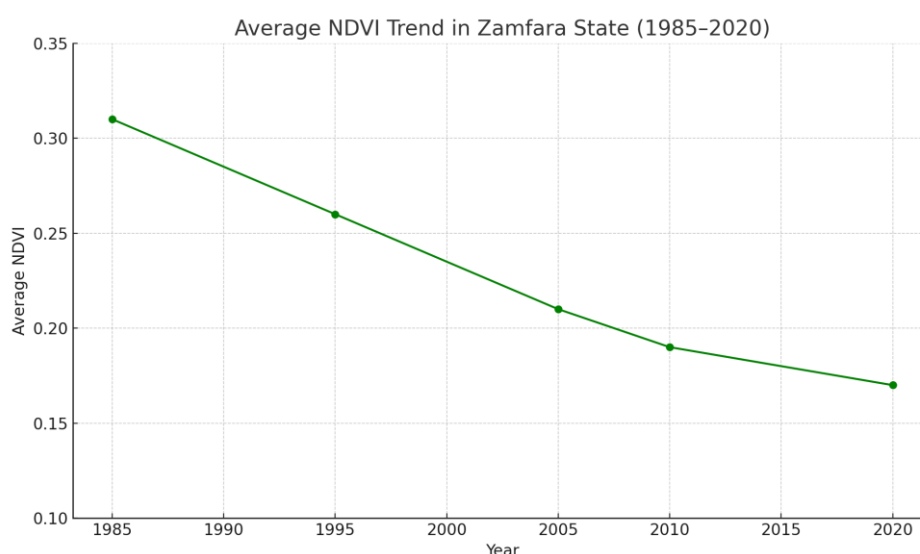


Figure 5: Average NDVI Trend in Zamfara State (1985 = 2020)

3.6 NDVI Analysis

Landsat-derived NDVI analysis generated through CLASLite revealed a persistent decline in vegetation health between 1985 and 2020. The NDVI values decreased from approximately 0.30–0.32 in 1985, indicating relatively dense and healthy vegetation cover, to values below 0.20 in 2020, indicating sparse vegetation and severely degraded land conditions.

The downwards trend in the NDVI corresponds strongly with increasing anthropogenic disturbances and recurrent climatic stress events observed during the study period. These results therefore confirm that vegetation degradation has progressed and ecological productivity has decreased across Zamfara State.

4 Discussion

The findings of this study demonstrate that vegetation cover change in Zamfara state is controlled by the combined effects of climate variability and anthropogenic disturbances. However, the stronger contribution of anthropogenic variables indicates that anthropogenic

activities constitute the dominant driver of vegetation degradation within the study area.

The observed decline in vegetation cover corresponds to increasing population pressure, agricultural expansion, and rapid proliferation of artisanal mining activities. Similar findings have been reported by studies conducted across the West African Sahel, where human-induced land degradation has increasingly surpassed climatic influences in determining vegetation dynamics. Studies by Herrmann *et al.* and Anyamba and Tucker demonstrated that prolonged land use pressure combined with recurrent drought conditions significantly reduces vegetation productivity in semiarid ecosystems.

The decline in the NDVI values observed in this study is also consistent with findings from northern Nigeria and other Sahelian environments where vegetation degradation has been linked to unsustainable agricultural practices, deforestation, and fuelwood extraction. Previous studies conducted in Katsina State and Sokoto State similarly reported increasing bare land surfaces associated with rapid demographic growth and agricultural intensification.

Furthermore, the significant contribution of artisanal mining identified in this study aligns with research undertaken in mining regions of Ghana and northwestern Nigeria, where uncontrolled mining activities were found to accelerate deforestation, soil erosion, and landscape fragmentation. The concentration of severe vegetation loss within the Anka, Maru, and Talata Mafara LGAs supports previous observations that mining hotspots often correspond with intense ecological degradation.

The climatic findings also corroborate earlier studies across the Sahel region, which reported increasing temperatures and irregular rainfall patterns as critical stressors affecting vegetation recovery and ecosystem productivity. The recurrent drought years identified in this study correspond with documented Sahelian drought episodes that significantly impacted vegetation conditions across West Africa.

A major strength and synergy of this research with previous studies lies in its integration of CLASlite fractional cover analysis, NDVI modelling, random forest prediction, and long-term Landsat datasets to provide a comprehensive assessment of vegetation dynamics. While many previous studies have relied solely on NDVI or land use classification techniques, the present study combines machine learning approaches with spatial modelling to establish hierarchical relationships between climatic and anthropogenic drivers. This integrated approach improves the understanding of vegetation degradation processes and enhances the reliability of predictive assessments.

Additionally, the spatial differentiation between climate-dominated and human-dominated degradation

zones represents an important contribution to vegetation change studies in semiarid regions. This spatially explicit approach provides valuable information for designing location-specific environmental management and restoration strategies.

The results of this study confirm that sustainable vegetation management in Zamfara State requires integrated interventions targeting both environmental and socioeconomic drivers. The effective regulation of artisanal mining, the promotion of sustainable agricultural practices, afforestation programs, and climate adaptation measures are essential for reducing vegetation degradation and improving ecosystem resilience.

5 Conclusion

In this study, the climatic and anthropogenic drivers of vegetation loss in Zamfara state were disentangled using multidecadal remote sensing and statistical modelling. Anthropogenic factors, especially mining and population growth, accounted for most of the observed degradation, while climate variability modulated interannual fluctuations. These findings underscore the urgency of integrated land management and climate adaptation policies. Future work should incorporate socioeconomic datasets and finer-resolution satellite imagery to improve the predictive accuracy and policy relevance.

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