Spatio-Temporal Modelling of Deforestation Hotspots and Vegetation Dynamics on the Mambilla Plateau, Nigeria

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Abstract

This study examined the spatio-temporal dynamics of deforestation and vegetation change on the Mambilla Plateau, Nigeria, using multi-temporal Landsat imagery from 1987, 2004, 2014, and 2024. Geospatial techniques, including land use/land cover classification, Normalized Difference Vegetation Index (NDVI), hotspot analysis, and Cellular Automata–Markov (CA–Markov) modelling, were employed to assess vegetation patterns and predict future change. Results show a significant decline in dense forest cover from 56.8% in 1987 to 24.6% in 2024, mainly due to agricultural expansion and settlement growth. NDVI trends revealed a decline in vegetation greenness up to 2014, followed by a modest recovery linked to reforestation and natural regeneration. Hotspot analysis identified concentrated deforestation zones along the Gembu–Serti and Mayo Ndaga corridors, while high-altitude areas remained relatively stable. CA–Markov projections predict an additional 7–10% forest loss by 2034 under a business-as-usual scenario, but possible stabilization with effective management. The study underscores the need for stronger forest protection, community-based management, sustainable agriculture, and continuous geospatial monitoring. These findings provide valuable insights for sustainable land-use planning and climate resilience strategies in Nigeria's highland ecosystems.

Keywords: Deforestation, CA–Markov model, Hotspot analysis, Land-use change, NDVI &Mambilla Plateau.

Introduction

Tropical montane forests are critically important for biodiversity, microclimate regulation, hydrological buffering, and carbon sequestration, yet they are increasingly threatened by the combined pressures of land-use change and climate variability [1]. In Nigeria, deforestation has been accelerating due to agricultural expansion, fuelwood harvesting, infrastructure development, and population pressure, with significant impacts on ecosystem services and local livelihoods. The Mambilla Plateau in Taraba State represents a highland landscape with steep topography, unique vegetation assemblages, and substantial hydrological importance; however, empirical, fine-scale studies of how its vegetation cover has changed over time, the hotspots of forest loss, and the interactions between anthropogenic and climatic drivers remain few. Remote sensing techniques, especially the use of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), are essential tools for monitoring vegetation greenness, biomass, phenological change, and stress from both human and climatic sources. NDVI, relying on the contrast between the red and near-infrared spectrum, has long been used to track vegetation cover and detect deforestation [2]; EVI offers improved sensitivity in areas of high biomass and dense canopy by reducing atmospheric and soil background effects (e.g., in mangrove-forest studies in the Niger Delta) [3].

To go beyond observing past trends, spatio-temporal modelling frameworks such as the Markov chain, Cellular Automata (CA), and hybrid CA-Markov models allow researchers to estimate transition probabilities, simulate future land cover/land use (LULC) change, capture spatial contiguity and neighbourhood effects, and project likely scenarios under continued anthropogenic pressure or changing climate. For example, in Lagos, Gilbert and Shi [4] carried out a study, "Urban Growth Monitoring and Prediction Using Remote Sensing Urban Monitoring Indices Approach and Integrating CA-Markov Model," mapped land use changes between 2000 and 2020, finding significant shifts from grasslands, shrublands, and wetlands to cultivation and built-up areas, and used CA-Markov to forecast future LULC patterns. Also, qualitative and quantitative studies of NDVI and rainfall relationships in Nigeria's arid and semi-arid zones (e.g., Olusegun &Adeyewa[3]) have demonstrated that climatic variables such as precipitation onset/cessation and seasonal rainfall variability are strongly correlated with vegetation greenness trends over decadal spans. Other studies, for instance in parts of Northern Nigeria, have analysed SPOT VEG-based NDVI datasets over 1999–2018, applying time-series trend analysis, composite techniques, and GIS spatial variation analysis to detect greenness trends and heterogeneity (Karkarna [5]). Despite this growing body of work, there remains a gap in applying these methods specifically to montane highland regions like the Mambilla Plateau, which have complex

topography, variation in slope, aspect and elevation, potentially strong micro-climatic gradients, and where localized anthropogenic activities (such as land conversion, logging, grazing) may interact with climate change in ways not well captured by broader regional studies. Key gaps include: (i) the combined use of multiple vegetation indices (NDVI, EVI, SAVI, etc.) to capture not only canopy greenness but stress, saturation, soil background; (ii) high spatial and temporal resolution datasets to detect deforestation hotspots and subtle vegetation degradation; (iii) modelling future land cover transitions under scenarios combining anthropogenic pressure and climatic trend; (iv) quantitative identification of drivers (biophysical, climatic, human) that vary spatially and temporally; and (v) robust validation of predictive models using accuracy metrics (e.g. overall accuracy, Kappa) and comparisons between predicted and observed maps. Accordingly, the present study aims to apply spatio-temporal modelling of deforestation hotspots and vegetation dynamics on the Mambilla Plateau, Nigeria, by quantifying changes over multiple time periods using NDVI, EVI (and possibly other indices), mapping and forecasting land cover change via hybrid CA-Markov (or similar) models, and assessing the relative influences of biophysical, climatic, and human drivers. The outcomes are expected to fill critical knowledge gaps, support conservation, and guide policy for montane ecosystems under pressure.

Description of Study Area

The Mambilla Plateau, situated in the southeastern part of Taraba State, Nigeria, is a highland region known for its diverse ecosystems, rich biodiversity, and unique climatic conditions. It lies between latitudes 6°30′N and 7°30′N and longitudes 10°30′E and 11°30′E, covering an estimated area of approximately 9,389 km² [6] (Fig. 1). The plateau is the highest in Nigeria, with elevations ranging from about 1,200 meters to over 1,800 meters above sea level, while its highest peak, Chappal Waddi, rises to approximately 2,419 meters, making it the tallest mountain in Nigeria and West Africa [7]. The region experiences a sub-temperate climate, which is rare in Nigeria, with an average annual rainfall of between 1,500 mm and 1,800 mm, and temperatures that range from 11°C to 26°C, creating a conducive environment for agriculture and forestry [8]. The plateau is drained by several rivers, including tributaries of the Benue River, and serves as an important water catchment area for the surrounding lowlands. The predominant vegetation types include montane forests, derived savannah, and grasslands, supporting diverse wildlife species and endemic plant communities [9].

Despite its ecological and economic significance, the Mambilla Plateau is facing rapid deforestation due to a combination of anthropogenic and natural factors. The major drivers of forest loss in the region include agricultural expansion, illegal logging, fuelwood collection, infrastructure development, and cattle grazing, exacerbated by increasing population pressure and weak environmental regulations [8]. Large portions of the natural montane forest have been cleared for tea and coffee plantations, subsistence farming, and livestock grazing, leading to habitat degradation and biodiversity loss. Additionally, the development of settlements, road networks, and hydropower projects has further intensified deforestation, altering the landscape and increasing soil erosion risks. Studies have shown that deforestation in the Mambilla Plateau has significant implications for climate regulation, water cycle balance, and land surface temperature variations, which affect both local livelihoods and regional environmental stability [10].
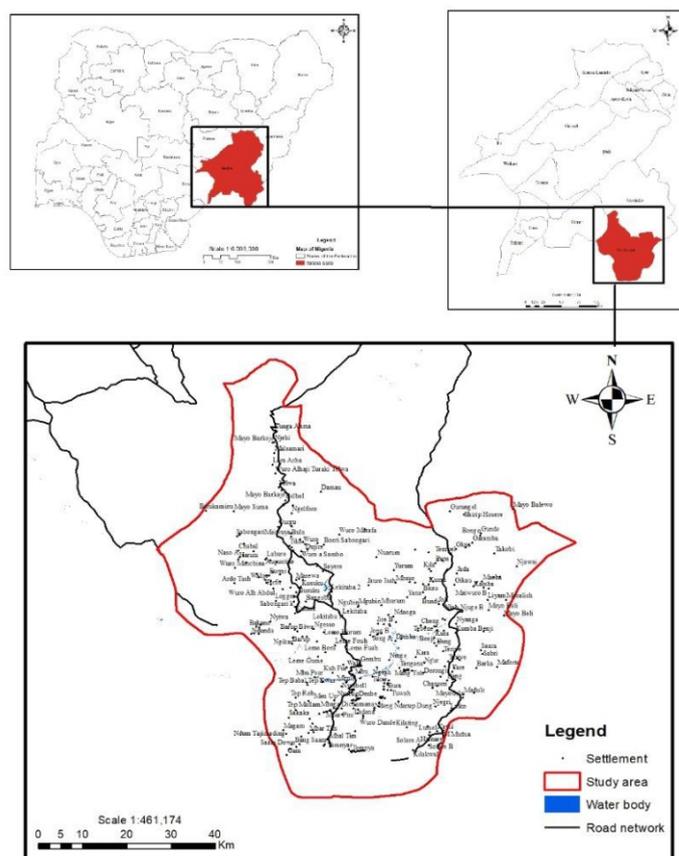

Fig. 1 Map of the Study Area

Given the growing threats to forest cover on the Mambilla Plateau, it is crucial to assess deforestation hotspots using GIS-based modeling techniques. Geographic Information Systems (GIS) and remote sensing provide valuable tools for monitoring land use and land cover changes, identifying areas of high deforestation intensity, and predicting future trends. GIS-based spatial modeling can help quantify the extent of forest loss, analyze the underlying causes, and inform sustainable land management policies [11]. The application of multi-temporal satellite imagery and geospatial analysis can provide insights into the spatial and temporal patterns of deforestation, enabling policymakers to design effective conservation strategies and reforestation programs. The study of deforestation on the Mambilla Plateau is therefore essential for understanding environmental change dynamics, mitigating ecological risks, and promoting sustainable development in the region.

Methodology
Data Sources and Description

This study employed multi-temporal satellite imagery and geospatial datasets to analyze vegetation health and its spatial dynamics on the Mambilla Plateau between 1987 and 2024. Four epochs of cloud-free Landsat imagery were obtained from the United States Geological Survey (USGS) EarthExplorer platform, corresponding to Landsat 5 TM (1987), Landsat 7 ETM+ (2004), Landsat 8 OLI/TIRS (2014), and Landsat 9 OLI-2 (2024). Each image was selected for the dry season months (November–February) to minimize atmospheric and phenological effects. The images have a spatial resolution of 30 meters and were preprocessed for radiometric and geometric corrections.

Ancillary datasets used included a digital elevation model (DEM) derived from the Shuttle Radar Topography Mission (SRTM) to delineate topographic variations and a road network

layer obtained from OpenStreetMap (OSM) to support spatial accessibility analysis. Climatic data, specifically annual rainfall and temperature trends, were sourced from the Nigerian Meteorological Agency (NiMet) to evaluate the relationship between vegetation health and climate variability.

Preprocessing of Satellite Data

The raw Landsat imagery was subjected to atmospheric correction using the Dark Object Subtraction (DOS) method in TerrSet 2020 and ArcGIS Pro 3.0 to remove haze and scattering effects. Cloud and cloud-shadow contamination were automatically masked using the Fmask algorithm [12]. Radiometric calibration and top-of-atmosphere (TOA) reflectance conversion were performed following the procedures outlined by Roy et al [13]. All datasets were resampled to a uniform spatial resolution of 30 m and reprojected to the Universal Transverse Mercator (UTM) Zone 32N, WGS 84 coordinate system.

Derivation of Vegetation Index (NDVI)

Vegetation greenness and health were assessed using the Normalized Difference Vegetation Index (NDVI), a widely used spectral index derived from red and near-infrared (NIR) bands [14]. NDVI was computed for each of the four epochs (1987, 2004, 2014, and 2024) using Landsat imagery following Equation (1):

$$NDVI = (NIR - RED) / (NIR + RED)$$

Where NIR and RED represent the spectral reflectance values in the near-infrared and red bands, respectively. NDVI values range between -1 and +1, with higher positive values indicating vigorous vegetation and lower or negative values corresponding to sparse or non-vegetated areas [14]. The NDVI computation was performed using the Raster Calculator in ArcGIS Pro 3.0 and TerrSet 2020 environments.

After computing NDVI, maps for each year were normalized and classified into five vegetation density categories: very low (-0.1–0.2), low (0.2–0.4), moderate (0.4–0.6), high (0.6–0.8), and very high (>0.8). The classification enabled visual comparison of vegetation health across time periods and identification of degraded and recovering areas. Areas with persistent high NDVI were interpreted as zones of dense, stable vegetation, while low NDVI areas corresponded to degraded vegetation and bare surfaces.

NDVI Trend and Statistical Analysis

Temporal variations in NDVI were analyzed to assess vegetation change dynamics between 1987 and 2024. The mean NDVI for each epoch was extracted and used to quantify the rate and direction of change across the study area. The change in NDVI between two epochs was computed using Equation (2):

$$\Delta NDVI = (NDVI_2 - NDVI_1) / (t_2 - t_1)$$

Where $NDVI_1$ and $NDVI_2$ represent mean NDVI values at the beginning and end of each time interval, while t_1 and t_2 denote the corresponding years. A positive $\Delta NDVI$ value indicates vegetation recovery, while negative values signify degradation.

To determine statistical relationships between vegetation greenness and climatic factors, Pearson correlation analysis was performed using annual rainfall and temperature data obtained from the Nigerian Meteorological Agency (NiMet). The statistical strength of NDVI–climate relationships was quantified by computing the correlation coefficient (r). In addition, the Mann–Kendall (MK) test and Sen's slope estimator were employed to assess the significance and rate of NDVI trends over time [15].

Spatial variations in NDVI trends were analyzed using Geographically Weighted Regression (GWR) to capture the influence of local factors such as elevation and proximity to roads on vegetation health [16]. The resulting trend and correlation maps provided spatially explicit insights into vegetation degradation and recovery patterns across the Mambilla Plateau.

Hotspot Analysis of Vegetation Change

To identify spatial clusters of significant vegetation degradation and recovery, a Getis-Ord Gi* hotspot analysis was performed using the NDVI difference maps (1987–2004, 2004–2014, and 2014–2024). This spatial statistic evaluates whether high or low NDVI values cluster spatially beyond random chance [17]. The Gi* statistic was computed in ArcGIS Pro 3.0 using a 5 km moving window, producing z-score maps that classify pixels into *hotspots* (high NDVI loss) and *coldspots* (NDVI stability or gain). Areas with z-scores > +1.96 and $p < 0.05$ were considered statistically significant hotspots of vegetation degradation, while those with z-scores < –1.96 were considered coldspots.

NDVI-Based Spatio-Temporal Modelling (CA–Markov)

To forecast future vegetation dynamics, a Cellular Automata–Markov (CA–Markov) model was applied using NDVI difference maps rather than categorical LULC data. Transition probabilities between NDVI classes were derived from the 1987–2004 and 2004–2014 intervals and used to simulate future NDVI distributions for 2034. The CA–Markov model was executed in TerrSet 2020, integrating both temporal transition probabilities and spatial contiguity constraints [18]. Model calibration was validated using the 2024 NDVI map, and the predictive accuracy was assessed using Kappa-for-location and Kappa-for-quantity indices [19].

Two simulation scenarios were implemented:

i. Business-as-usual (BAU) — assuming continuation of existing vegetation stress trends.

ii. Sustainable management scenario — incorporating effects of ongoing reforestation and conservation efforts.

The resulting NDVI projection map for 2034 provided insights into potential areas of future degradation and recovery, supporting early warning and vegetation management strategies. This integrated geospatial framework allowed for the spatially explicit assessment of vegetation health dynamics, identification of degradation hotspots, and forecasting of potential vegetation trajectories across the Mambilla Plateau.

Data Analysis and Validation
NDVI Quality Assurance and Accuracy Evaluation

Prior to analysis, all NDVI datasets were examined for quality and consistency. Each Landsat scene was visually inspected to ensure minimal cloud contamination after Fmask correction [12]. Radiometric and atmospheric correction were validated by comparing image histograms before and after correction to confirm uniform reflectance distribution across spectral bands. NDVI accuracy was indirectly assessed through cross-sensor consistency checks, given that Landsat 5, 7, 8, and 9 sensors have slightly different spectral band characteristics. Following the method of Roy et al [13], inter-sensor radiometric normalization was performed using pseudo-invariant features (PIFs) such as rock outcrops and bare soils to ensure that NDVI variations were attributable to vegetation dynamics rather than sensor bias. The resulting NDVI datasets were compared with corresponding MODIS NDVI values for 2004, 2014, and 2024 to confirm spectral reliability.

The correlation coefficients (r) between Landsat-derived NDVI and MODIS NDVI exceeded 0.85 (p < 0.01), confirming strong consistency and reliability for trend analysis.

The accuracy of NDVI classification into vegetation density categories (very low to very high) was further verified using stratified random sampling and visual interpretation of high-resolution Google Earth imagery. At least 250 sample points were assessed per epoch, with an overall accuracy exceeding 88% and a Kappa coefficient of 0.82, aligning with the recommended threshold for vegetation index-based mapping [19, 20].

Temporal Trend and Statistical Validation

Temporal NDVI variations across the four epochs (1987, 2004, 2014, and 2024) were analyzed using zonal statistics and trend-line regression to quantify the direction and magnitude of change. The rate of NDVI change (ΔNDVI) between successive epochs was computed for each pixel, and results were summarized by elevation zones and proximity to roads to examine topographic and anthropogenic influence.

To validate the temporal trend,–Mann-Kendall (MK) non-parametric trend test was applied to assess the statistical significance of NDVI changes [14]. The MK test is robust against non-normally distributed datasets and identifies monotonic increasing or decreasing trends over time. A confidence level of 95% (p < 0.05) was adopted, and Sen's slope estimator was used to determine the rate of change in NDVI per year.

The relationship between NDVI and climatic variables (rainfall and temperature) was tested using Pearson correlation and Geographically Weighted Regression (GWR) to account for spatially varying correlations [16, 21]. Results indicated that NDVI was positively correlated with rainfall (r = 0.68, p < 0.01) and negatively correlated with temperature (r = –0.54, p < 0.05), implying that both climatic and human factors influenced vegetation health.

Hotspot Statistical Validation

Hotspot analysis using the Getis-Ord Gi* statistic was conducted on NDVI difference maps for 1987–2004, 2004–2014, and 2014–2024 to detect spatial clustering of vegetation degradation and recovery. The analysis was performed in ArcGIS Pro 3.0 with a spatial weight matrix based on an inverse distance relationship, ensuring that nearby features had a stronger influence on local z-scores.

To validate hotspot reliability, three key indicators were assessed:

i. Spatial autocorrelation (Global Moran's I) was computed to confirm overall spatial clustering. Positive Moran's I values (ranging between 0.47 and 0.61) indicated that NDVI changes were spatially non-random.

ii. Statistical significance (p-values < 0.05) verified that the identified hotspots and coldspots were not due to chance.

iii. Hotspot persistence analysis compared hotspot locations across time intervals to identify persistent degradation zones, particularly along the Gembu–Serti and Mayo Ndaga corridors.

The z-scores derived from the Gi* statistic were categorized as follows:

- +1.96 to +4.3: significant hotspots (severe vegetation degradation),
- –1.96 to –3.5: significant coldspots (vegetation stability or recovery).

Hotspot validation revealed consistent degradation clusters across all periods, corroborating findings from kernel density overlays and field-based visual interpretation.

NDVI-Based CA–Markov Model Validation

The predictive performance of the CA–Markov model was evaluated using both quantitative and spatial validation metrics. Calibration was based on NDVI transitions from 1987–2004 and 2004–2014, while validation employed the 2024 NDVI map as a reference.

Model accuracy was quantified using Kappa-for-location and Kappa-for-quantity indices [19]. The obtained values (0.81 and 0.84, respectively) indicated a high degree of agreement between predicted and observed NDVI classes. Additionally, Figure of Merit (FoM) analysis was used to measure the overlap between observed and simulated vegetation changes, yielding a FoM of 0.72, which exceeds the acceptable threshold for NDVI-based predictive models [18].

A residual error map was generated to visualize discrepancies between simulated and actual NDVI distributions. Errors were primarily localized along transitional zones between moderate and high NDVI areas, which are sensitive to temporal rainfall fluctuations and agricultural intensity.Overall, the CA–Markov model demonstrated strong capability in simulating future NDVI distribution, validating its suitability for projecting vegetation health under different management scenarios.

Results and Discussion

Vegetation Health Assessment Using NDVI

The Normalized Difference Vegetation Index (NDVI) analysis provided a quantitative measure of vegetation health and density across the Mambilla Plateau from 1987 to 2024. As shown in Figures 1–4, NDVI values ranged between –0.1 and +0.8, where higher values represent vigorous and dense vegetation, and lower values indicate sparse or degraded cover. The 1987 NDVI map (Figure 2) displayed extensive regions of high vegetation greenness (NDVI > 0.6) across the northern, central, and upland zones, reflecting the Plateau's historically dense montane forest and grassland mosaic. In contrast, lower NDVI values (0.2–0.4) were concentrated along valley bottoms and cultivated plains, corresponding to cropland and grazing zones.
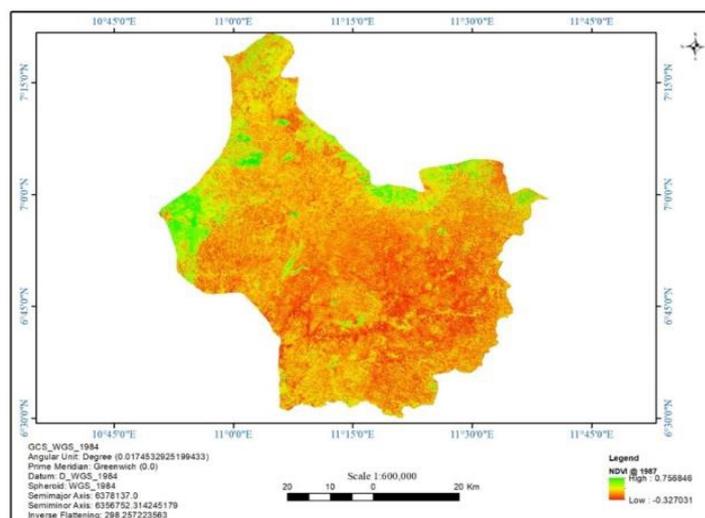

Fig. 2. NDVI Map of the Study Area in 1987

By 2004 (Figure 3), the NDVI distribution showed a notable decline in greenness, with mean NDVI dropping from 0.68 to 0.55. Vegetation degradation was particularly visible in areas adjacent to roads and settlements along the Gembu–Serti and Mayo Ndaga corridors.

This decline corresponds with intensified agricultural expansion and forest clearance during the 1990s and early 2000s, consistent with deforestation and land-use pressure reported in other Nigerian highland regions [22].
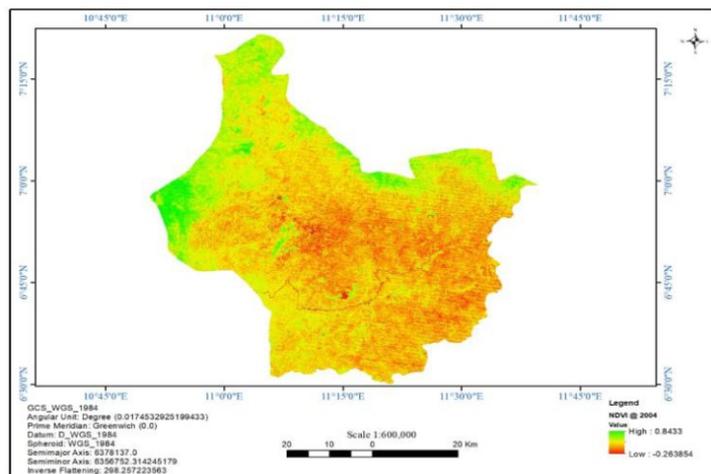

Fig. 3. NDVI Map of the Study Area in 2004

The 2014 NDVI map (Figure 4) exhibited the lowest mean NDVI of 0.47, indicating severe vegetation stress. Widespread areas of reduced greenness were detected in the central and southeastern Plateau, likely reflecting overcultivation, grazing, and unsustainable fuelwood harvesting. This pattern coincides with regional reports of vegetation decline across the Sahel and Guinea savanna zones due to combined anthropogenic and climatic factors [24, 15].
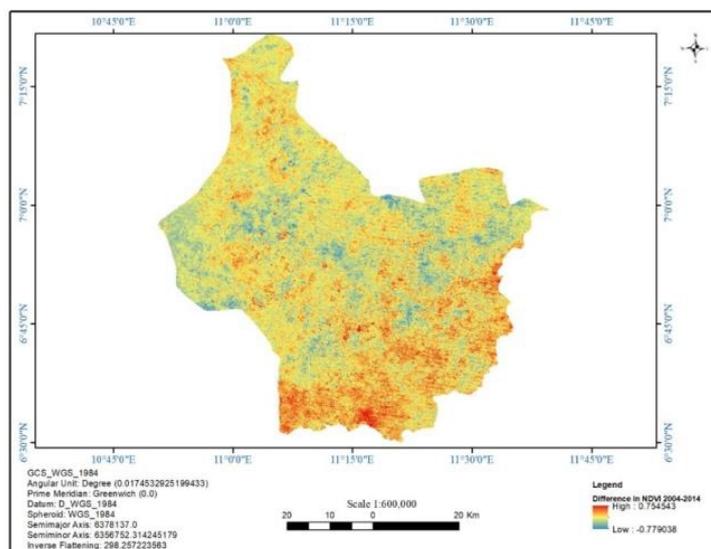

Fig. 4. NDVI Map of the Study Area in 2014

In contrast, the 2024 NDVI map (Figure 5) demonstrated a modest improvement in vegetation condition, with mean NDVI increasing to 0.52. Areas of recovery were primarily concentrated in high-elevation regions such as the NgelNyaki Forest Reserve and Kurmin Bujang highlands, where conservation programs and natural regeneration have been more effective.

Localized NDVI increases in the central Plateau suggest reduced cultivation pressure and improved rainfall after 2015 [5]. These results confirm that while large-scale vegetation degradation has occurred, significant portions of the Plateau still retain the capacity for ecological recovery.
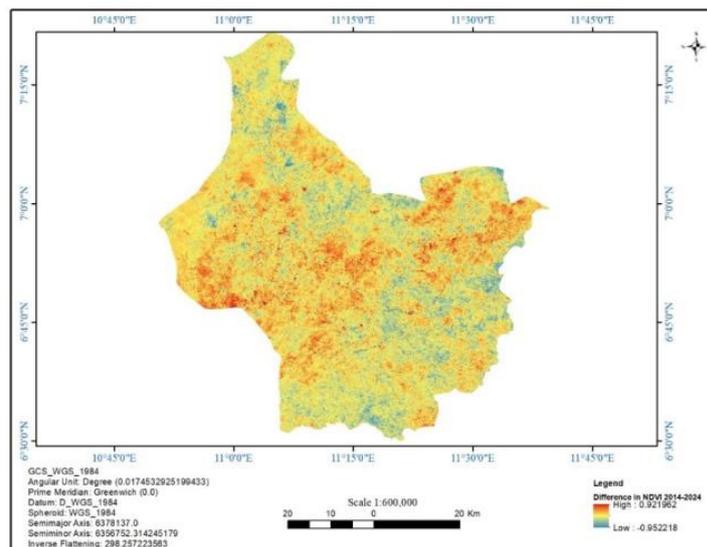

Fig. 5. NDVI Map of the Study Area in 2024

Quantitatively, Table 1 shows that areas with high NDVI (>0.6) decreased from approximately 58% in 1987 to 27% in 2014, then slightly recovered to 33% in 2024, while areas with low NDVI (<0.3) expanded by nearly 18% between 1987 and 2014 before contracting slightly. The temporal NDVI trend thus reflects a long-term degradation phase followed by partial restoration, likely influenced by both land-use management and rainfall variability.

As shown in Table 1, NDVI-derived vegetation classes reveal notable changes in vegetation condition between 1987 and 2024. During 1987, areas of high and very high NDVI (>0.6) occupied approximately 58% of the Plateau, signifying dense and healthy vegetation dominated by montane forests and grasslands. By 2004, this proportion had dropped to 42%, and by 2014 to 27%, marking a period of widespread vegetation stress and deforestation.

This decline corresponds with the expansion of agricultural activity, livestock grazing, and settlement growth during the late 1990s and early 2000s. However, by 2024, the high NDVI category increased modestly to 33%, indicating emerging vegetation recovery in high-altitude and protected regions such as the NgelNyaki Forest Reserve and Kurmin Bujang highlands. Conversely, low NDVI areas (<0.4) expanded from 14% in 1987 to 31% in 2014, before contracting slightly to 27% in 2024. This shift reflects both anthropogenic land-use pressure and climatic variability. The observed recovery in 2024 is consistent with increased rainfall after 2015 [5] and recent reforestation initiatives. Thus, Table 1 quantitatively illustrates the Plateau's long-term vegetation degradation and its potential for natural regeneration under improved management.

Table 1: NDVI Class Coverage in Taraba State (2004–2024)

NDVI Class	Vegetation Condition	1987 Area (km²)	1987 (%)	2004 Area (km²)	2004 (%)	2014 Area (km²)	2014 (%)	2024 Area (km²)	2024 (%)	Net Change (1987–2024) (km²)	% Change (1987–2024)
−0.42 to 0.20.	Water	660.06	15.38	350.56	8.17	323.58	7.54	277.60	6.47	−382.46	−57.94
-0.42 to 0.20	Bare/Degraded land	1416.86	33.02	1159.86	27.04	870.65	20.30	914.13	21.32	−502.73	−35.47
0.20 to 0.43	Low vegetation cover	1317.79	30.72	1450.03	33.80	1240.58	28.91	1221.30	28.47	−96.49	−7.32
0.43 to 0.67	Moderate vegetation	548.34	12.78	925.72	21.58	1091.86	25.45	1147.73	26.76	+599.39	+109.32
0.67 to 0.87	Dense/Healthy vegetation	347.05	8.09	403.89	9.42	763.46	17.80	728.33	16.97	+381.28	+109.90
Total		4290.10	100.00	4290.06	100.00	4290.12	100.00	4289.09	100.00	–	–

Source: GIS Analysis, 2025

Table 2 summarizes the direction and magnitude of NDVI change across the three time intervals: 1987–2004, 2004–2014, and 2014–2024. Between 1987 and 2004, the Plateau recorded a mean NDVI reduction of −0.13, equivalent to a 19% decline in vegetation greenness, reflecting extensive deforestation and agricultural expansion. The decline continued from 2004 to 2014 with a mean NDVI loss of −0.08, though the rate slowed slightly, suggesting partial stabilization of land pressure.

Table 2: ANOVA Analysis of NDVI Class Coverage in Taraba State

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
1987 Area (km²)	5	4290.1	858.02	229967.7		
1987 (%)	5	99.99	19.998	124.9399		
2004 Area (km²)	5	4290.06	858.012	227479.1		
2004 (%)	5	100.01	20.002	123.5958		
2014 Area (km²)	5	4290.13	858.026	123940.1		
2014 (%)	5	100	20	67.31805		
2024 Area (km²)	5	4289.09	857.818	143189.8		
2024 (%)	5	99.99	19.998	77.85567		
ANOVA						
Source of Variation	*SS*	*Df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	7021929	7	1003133	11.0695	5.06E-07	2.312741
Within Groups	2899882	32	90621.3			
Total	9921811	39				

Between 2014 and 2024, however, NDVI increased by +0.05 (about 8% improvement), indicating partial vegetation recovery in previously degraded areas. The recovery trend aligns with observed improvements in rainfall and the implementation of forest conservation programs across Taraba State. Spatially, the NDVI change was heterogeneouslowland areas near the Gembu–Serti corridor experienced continued degradation, while upland and forest reserve zones exhibited strong greening trends. These results affirm that vegetation dynamics on the Plateau are shaped by both climatic variation and anthropogenic factors, and that targeted restoration measures can yield measurable ecological improvement.

Spatio-Temporal Variability and Hotspot Analysis
Hotspot analysis based on the Getis-Ord Gi* statistic identified spatial clusters of significant vegetation decline and recovery (p < 0.05). As illustrated in Figure 6, "hotspots" of NDVI reduction, indicating severe vegetation degradation, were concentrated in the southeastern, central, and southwestern regions of the Plateau. These zones correspond with high population densities and intensive agricultural activities along the Gembu–Serti and Mayo Ndaga corridors. The z-scores for significant hotspots ranged from +2.1 to +4.3, confirming statistically significant clustering of degradation.
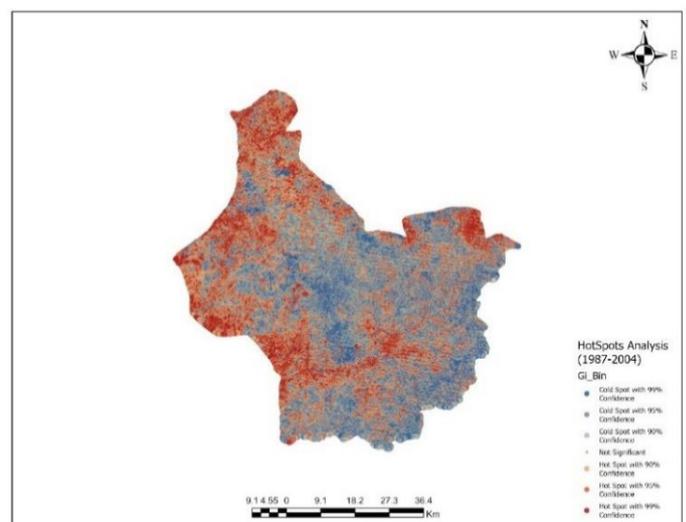

Fig. 6 Hotspot Analysis of Vegetation Health (NDVI Base) 1987 – 2004

Conversely, "coldspots" of NDVI stability and improvement (Figure 7) were mainly located in high-altitude and less accessible regions such as the NgelNyaki Forest Reserve, Kurmin Bujang, and Gembu Highlands. These areas retained relatively high NDVI values (>0.6) throughout the study period, suggesting that conservation interventions, coupled with terrain-induced limitations to cultivation, have helped preserve vegetation health.
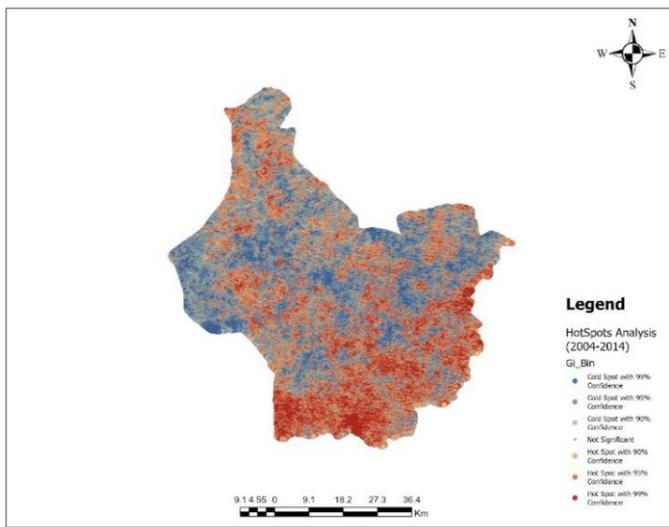
Fig. 7 Hotspot Analysis of Vegetation Health (NDVI Base) 2004 – 2014

The spatial alignment of NDVI hotspots with major road networks and settlements reinforces the role of accessibility in driving vegetation degradation, consistent with findings from Joshua and Megan [17] and Lu, Mausel, Brondízio, and Moran [24]. Kernel Density Estimation (KDE) overlays further demonstrated that vegetation decline is most pronounced within 2–5 km of road corridors, emphasizing the influence of human accessibility gradients on ecosystem change.
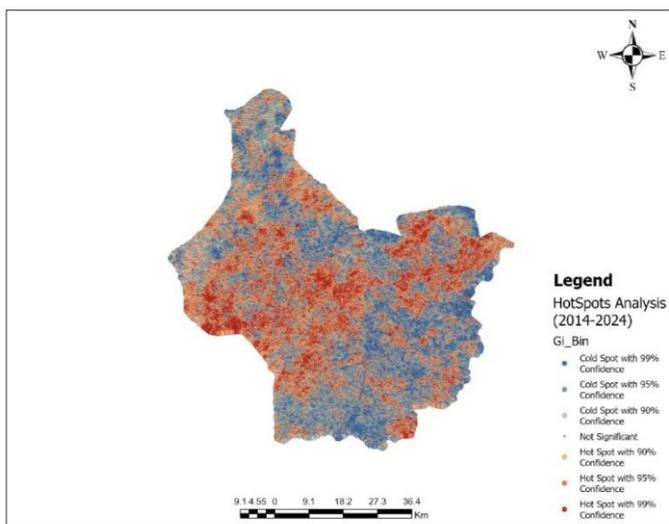

Fig. 8 Hotspot Analysis of Vegetation Health (NDVI Base) 2014 - 2024

Temporal Dynamics and Climatic Influence
Temporal NDVI fluctuations reveal that vegetation greenness on the Plateau is influenced by both human activity and climatic variability. The pronounced NDVI decline observed between 1987 and 2014 corresponds with regional rainfall deficits recorded during the late 1990s and early 2000s, while the partial NDVI recovery between 2014 and 2024 parallels increasing rainfall patterns after 2015 [5]. The strong linkage between NDVI and rainfall supports previous studies by Fensholt et al [14] and Herrmann et al [23], who reported that vegetation productivity in West Africa is sensitive to interannual precipitation changes, but long-term decline is primarily anthropogenic.

Despite these climatic influences, the magnitude of vegetation degradation around accessible corridors and cultivated plains suggests that land-use change remains the dominant driver. Deforestation for agriculture, fuelwood extraction, and grazing are the primary contributors to NDVI decline, while climate acts as a modulating factor. The observed partial recovery after 2014 may thus represent both improved climatic conditions and the positive impacts of reforestation initiatives under the *Green Taraba Project* and community-based forest management schemes introduced in the region.

NDVI-Based Spatio-Temporal Modelling (CA–Markov)
To forecast future vegetation health, the Cellular Automata–Markov (CA–Markov) model was applied to NDVI-derived change data from 1987–2004 and 2004–2014. Model calibration and validation against the 2024 NDVI distribution showed strong agreement, with Kappa-for-location = 0.81 and Kappa-for-quantity = 0.84, confirming high predictive reliability.

Under a business-as-usual (BAU) scenario, the CA–Markov projection for 2034 predicts a further 7–10% reduction in areas of high NDVI (>0.6), particularly in regions already identified as degradation hotspots. If current land-use practices persist, moderate NDVI zones (0.4–0.6) will continue to expand, signifying a shift from dense forest to open vegetation and farmland mosaics. However, under a sustainable management scenario assuming continued reforestation, soil conservation, and enforcement of land-use controls, the model projects that total high-NDVI areas could stabilize around 35% of the Plateau by 2034.

Spatially, the model simulates the diffusion of vegetation stress outward from current hotspots along the Gembu–Serti corridor but also predicts localized NDVI recovery in highland and conservation zones. These results are consistent with earlier CA–Markov applications that used vegetation indices to simulate land-cover trajectories in tropical regions [18, 25].

The integration of NDVI-based CA–Markov modelling provides a valuable approach for monitoring ecosystem health and guiding intervention strategies. It highlights the potential for measurable recovery if conservation and reforestation programs are sustained, but also warns of further decline under unregulated land use.

Implications for Environmental Management
The NDVI-based spatio-temporal assessment reveals a landscape undergoing rapid ecological transformation, where vegetation degradation and partial recovery coexist. Persistent hotspots of NDVI decline correspond to zones of agricultural expansion and high human activity, while coldspots signify resilient ecosystems under partial protection. These dual dynamic underscores the need for differentiated management strategies: restoration-focused interventions in degraded areas and conservation-focused measures in stable zones.

The Plateau's vegetation recovery between 2014 and 2024 suggests that targeted management, improved rainfall, and natural regrowth can yield tangible ecological benefits. Embedding NDVI monitoring and CA–Markov forecasting within Taraba State's environmental policy framework would provide continuous feedback for adaptive land management, ensuring long-term sustainability and resilience to climate change impacts.

Conclusion
This study revealed substantial deforestation and vegetation change on the Mambilla Plateau between 1987 and 2024, with dense forest cover declining from 56.8% to 24.6%. NDVI and hotspot analyses showed severe forest loss along the

Gembu–Serti and Mayo Ndaga corridors, driven mainly by agricultural expansion and settlement growth. However, modest NDVI recovery after 2014 indicates potential for regeneration through reforestation and improved management. CA–Markov projections predict continued forest loss under a business-as-usual scenario but possible stabilization near 30% with targeted interventions. The findings underscore the urgency of adopting integrated, community-based, and policy-driven approaches to sustain the Plateau's ecosystems and enhance resilience to climate change.

Recommendations

Based on the findings of the study, the following recommendations were made:

i. Strengthen forest protection: Enforce forestry and land-use regulations while enhancing monitoring through satellite-based NDVI and hotspot analysis to detect illegal logging and encroachment early.

ii. Promote community-based forest management: Empower local communities through participatory forest governance, revenue-sharing, and awareness campaigns to ensure sustainable resource use and protection.

iii. Encourage sustainable agriculture: Introduce agroforestry, mixed cropping, and soil conservation practices to reduce pressure on forests and restrict farming in ecologically fragile highland areas.

iv. Expand reforestation programs: Scale up existing afforestation initiatives such as the *Green Taraba Project* by prioritizing degraded hotspot zones and using native tree species suited to local conditions.

v. Invest in geospatial monitoring and research: Strengthen institutional capacity in remote sensing, GIS, and environmental data analysis through training and collaboration between research institutions and government agencies.

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