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Mapping Climate and Ecological Anomalies as a Veritable Tool for Planning Eco-Climate Resilience in Northern Nigeria

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Abstract

The Northern Nigeria savanna ecological zone is vulnerable to eco-climatic anomalies driven by climate change and land degradation. Despite previous studies on individual climate stressors, there are few studies on sub-national and spatial Eco-Climatic Resilience Index (ECRI) that integrate biophysical and social factors across the region, which limits targeted climate adaptation planning. This study applied Mann-Kendall rainfall trend analysis and the Sen slope test to rainfall data acquired from the Nigeria Meteorological Agency (NIMET) across 19 stations from 1971 to 2023. A four-stage cluster sampling design was employed to sample 2,400 farming households from 48 communities in the study regions. A Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data from 46 variables across climatic anomalies, ecological anomalies, exposure, sensitivity, adaptation capacity, and transformational adaptation capacity. Community PCA scores were interpolated and integrated into the composite ECRI, and the composite was classified into five resilience zones. The findings revealed a spatial mixed trend in rainfall as stations in the Sudan-Sahelian savanna showed both significant and insignificant upward trends, with the highest rate of change recorded in Kano (+17.89 mm/year), while stations in the Guinea Savanna indicate a significant and insignificant downward trend, with the highest rate of change recorded in Makurdi (−26.43 mm/year). Although the stations in Sudan-Sahelian showed upward rainfall trends, the ECRI map depicted a north-south resilience gradient, with very low resilience across the Sahelian savanna north and very high resilience across the Guinea Savanna south. Overall, the climate and ecological stressors were strongly related ($r = 0.82$). These findings imply that increased rainfall does not necessarily translate into improved climate resilience. The varying resilience levels depicted by ECRI signal the need for state/location-specific transformation/adaptation strategies to build individual, community, and state capacity for more resilient livelihoods across the study region and similar regions with similar socio-economic and climate characteristics.

Keywords: Eco-climatic resilience; climate anomalies; geospatial mapping; adaptive capacity; northern Nigeria; livelihood vulnerability

Introduction

Climate change represents one of the global challenges that affects sustainability and alters the environmental foundations upon which human livelihoods depend Fan et al. (2022). The upward rate of global warming, shifting precipitation patterns, and upward frequency of extreme weather events have created disruptions to socio-ecological systems worldwide (Lanlan et al., 2024; (Masson-Delmotte et al., 2022)) . These changes manifest as climate anomalies (departures from long-term means that include droughts, floods, heatwaves, erratic rainfall, and shifting seasonal boundaries) with effects on ecosystem integrity and human well-being (Banu & Fazal 2025; Wang et al. 2025). The consequences of climate anomalies extend beyond immediate environmental impacts. It threatens economic stability, social equity, and public health, particularly in developing countries with fragile infrastructure and limited adaptive capacity (Wang et al. 2025).

The global challenge of climate change is more acute in developing countries as rainfed agriculture remains the primary source of livelihood for millions of rural inhabitants. The Intergovernmental Panel on Climate Change (IPCC, 2022) confirms that climate change impacts have significantly affected livelihoods and living conditions, especially among the poorest and most vulnerable populations, and will continue to undermine development throughout the coming century. The imperative, therefore, is to understand these changes and develop effective adaptation strategies that enable communities to live with uncertainty while maintaining functional livelihoods.

Northern Nigeria experienced a unique climate vulnerability and ecological transformation. The region occupied three-quarters of Nigeria's land area. It has multiple savanna ecological zones, from the humid Derived and Guinea savannas in the south to the increasingly arid Sudan and Sahel savannas in the north (Abdulkadir et al., 2013; FORMECU, 1998). Research by AbdulKadir et al. (2015) documented a progressive southward shift in eco-climatic zone boundaries, with similar moisture stress identified beyond latitude 10°N, indicating advancement in aridity across the region. Agriculture dominates the northern Nigerian economy, as the bulk of the population relies more on agriculture for livelihood than in the other parts of the country (Oladunni et al., 2022). The dependence on rainfed agriculture and the existing ecological fragility have intensified anthropogenic pressures, which create vulnerability to climate variability and change (Samiullah & Khanum, 2024).

To adapt to climate variability, traditional adaptation practices, such as changing planting dates, applying manure, and crop rotation, remain important but are insufficient in the face of increased environmental change. This suggests a shift from increasing the area under cultivation to a transformative adaptation that encompasses collective action, institutional reform, and systemic change (Eriksen et al., 2021; UNFCCC, 2025). Similarly, effective adaptation requires spatial information that identifies where vulnerabilities are greatest and where interventions are most needed. Previous studies suggest geospatial technologies that enable the integration of diverse data types into coherent decision-support frameworks (Stock & Guesgen, 2016; Subiyanto et al., 2020). Furthermore, Principal Component Analysis (PCA) offers a robust statistical approach that reduces dimensionality in complex environmental datasets and reveals underlying structures (Jolliffe & Cadima, 2016).

Empirical evidence suggests that the relationship between climate and ecological dimensions is bidirectional and reinforcing, as Chuine et al. (2025) and Dervash et al. (2024) show: climate anomalies trigger ecological responses, while ecological degradation amplifies the impacts of climatic variability. Therefore, eco-climatic resilience is the capacity of socio-ecological systems to withstand, adapt to, cope with, and function effectively despite these disturbances (Grygorenko & Naydonova, 2023; Nath et al., 2025). Previous studies have examined climate trends and agricultural vulnerability in Nigeria (Akinwumiju et al., 2020; Makondo & Thomas, 2020; Mkpado et al., 2022; Nkrumah et al., 2019; Ntut et al., 2018; Ogunrinde et al., 2019; Sule et al., 2020). Despite growing knowledge on climate and its impacts in Nigeria, there is little effort in integrated assessments that consider climate anomalies, ecological responses, exposure, sensitivity, and adaptive capacity. Similarly, few studies have translated these multiple climate and ecological dimensions into spatial resilience maps that should guide policy and practice at sub-regional scales. This study addresses the research gap through mapping of climate and ecological anomalies across Northern Nigeria and developed a composite Eco-Climatic Resilience Index to identify priority zones for intervention. Therefore, the study aimed to examine the concept of eco-climatic anomalies, that is, departures from expected environmental conditions that disrupt the human-natural systems on which livelihoods depend. The specific objectives are to: (1) analyse spatiotemporal rainfall trends using long-term meteorological data (1971–2023); (2) assess the dimensions of eco-climatic anomalies, exposure, sensitivity, adaptive capacity, and transformative capacity; and (3) develop a geospatial database and map the distribution of resilience to guide

location-specific adaptation strategies. The findings could enable targeted and cost-effective interventions that aligned with Sustainable Development Goal 13 (climate action) and sustainable livelihood in Nigeria and other areas with shared socio-economic and climate characteristics.

Materials and Methods

Study Area

The study area encompasses northern Nigeria, spanning longitudes 2°43'44"E to 14°35'42"E and latitudes 5°36'45"N to 13°49'33"N (Figure 1). Covering more than three-quarters of Nigeria's total land area, the region constitutes the most spatially extensive ecological unit in the country. The study area is broadly characterised by Savanna vegetation, a mosaic of grasses and trees of varying species composition and structural density, in which canopy cover and grass biomass decrease progressively northward in response to a declining rainfall gradient (Abdulkadir *et al.*, 2013). Following the classification of FORMECU (1998), the Savanna is subdivided into four ecological zones arranged from south to north: Derived, Guinea, Sudan, and Sahel Savanna. Embedded within this latitudinal gradient are medium-to-high altitude ecological areas, principally the Jos Plateau in north-central Nigeria, which introduce orographic variation in both rainfall and temperature regimes (Figure 1).

The socioeconomic significance of the study area is considerable. Northern Nigeria is home to an estimated population of over 100 million people, the majority of whom depend on rainfed subsistence and smallholder agriculture for their livelihoods (NBS, 2022). A 2019 national survey cited by Oladunni et al. (2022) documented higher rates of dependence on agriculture in northern Nigeria than in any other geopolitical region of the country. The agricultural sector supports employment across cereal, legume, and tuber production systems and underpins food security, poverty reduction, and regional economic output. This pronounced dependence on climate-sensitive rainfed agriculture renders the study area particularly vulnerable to the eco-climatic anomalies examined in this study.

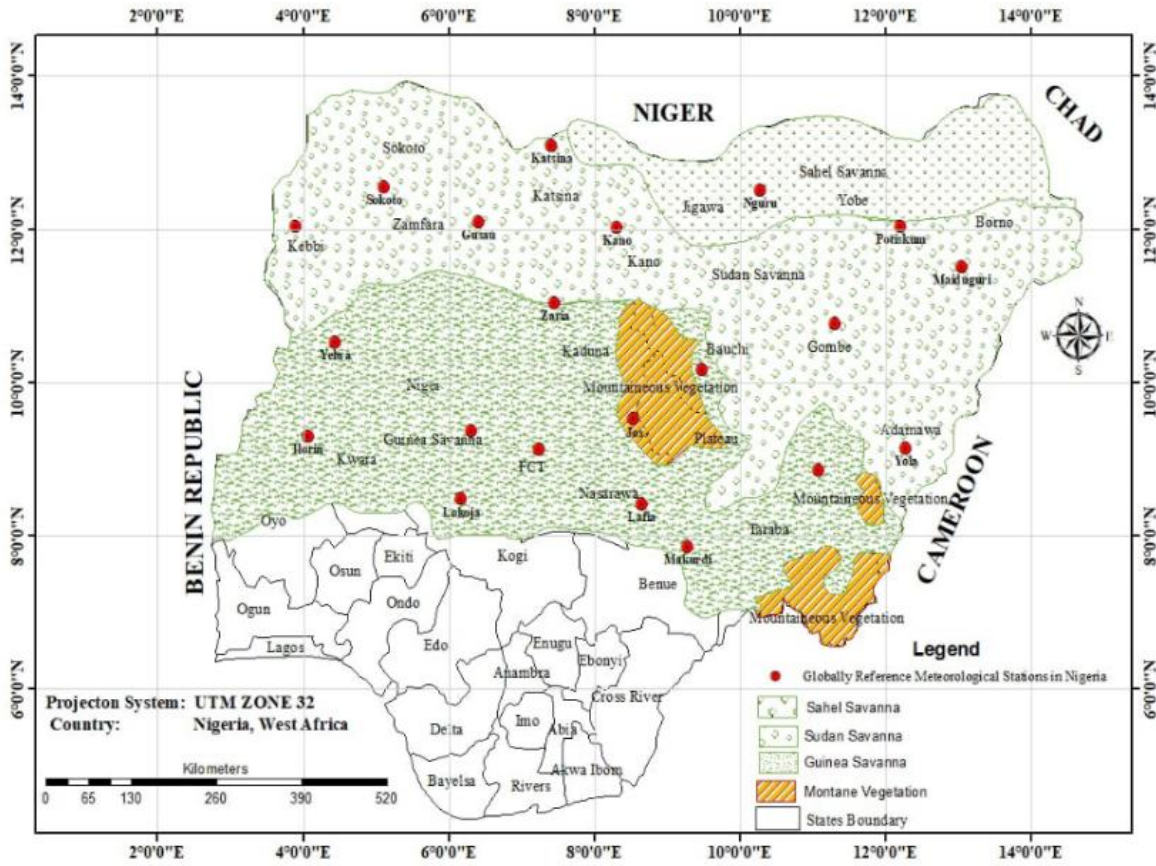


Figure 1: Digitized from the Savanna Ecological Zones
Source: FORMECU (1998)

Climate Data Acquisition and Quality Control

Daily rainfall data were obtained from the archives of the Nigerian Meteorological Agency (NIMET) for 19 globally referenced meteorological stations distributed across the study area, covering the period 1971–2023 (53 years). The geographic coordinates, elevation, and long-term rainfall coefficient of variation (CV) for each station are presented in Table 1. Generally, the Kano station in the Sudan-Sahelian savanna has the highest coefficient of variation (50.76%), while the Makurdi station in the Guinea savanna has the highest (42.75%). Station selection was guided by spatial coverage across the four ecological zones, data availability for the full study period, and conformity with WMO standards for synoptic station classification.

Data quality control and homogeneity assessment were performed using the RClimDex package in R RHtests V4 software (Zhang & Yang, 2004; Chen et al., 2017), which implements the standard quality control procedures recommended by the World Meteorological Organization (WMO)

Expert Team on Climate Change Detection and Indices (ETCCDI). Specifically, RClimDex was applied to: (i) identify and flag physically implausible values, including negative rainfall totals and daily values exceeding three standard deviations from the long-term station mean; (ii) detect and document gaps in the daily record; and (iii) apply automated correction of confirmed outliers where replacement values could be derived from neighbouring station records using inverse distance weighting interpolation. Stations with more than 10% missing data in any calendar decade were flagged for sensitivity analysis; no station exceeded this threshold in the final dataset. Annual totals were computed from the quality-controlled daily records and used as the basis for trend analysis.

Table 1: Data Points Rainfall Coefficient of Variation

Station	Latitude (°N)	Longitude (°E)	Elevation (m)	CV (%)
Sokoto	13.01	5.25	350	25.68
Katsina	13	7.53	517	33.68
Nguru	12.88	10.45	343	34.56
Gusau	12.17	6.67	450	23.14
Kano	12	8.52	472	50.76
Maiduguri	11.83	13.15	354	36.22
Zaria	11.07	7.7	641	21.93
Yelwa	10.88	4.75	244	26.05
Kaduna	10.6	7.43	642	20.19
Bauchi	10.31	9.84	621	30.73
Jos	9.92	8.89	1217	17.88
Minna	9.37	6.32	265	14.62
Yola	9.23	12.47	191	17.07
Bida	9.08	6.02	144	18.6
Abuja	9.07	7.48	536	14.85
Lafia	8.5	8.52	181	35.66
Lokoja	7.8	6.7	62	28.2
Makurdi	7.73	8.53	113	42.75
Ibadan	7.43	3.9	227	16.69

Field Survey Design and Sampling Framework

Sampling Strategy

A multi-stage sampling design was adopted to ensure representative coverage of the diverse ecological zones and farming systems across northern Nigeria. In the first stage, cluster sampling was employed to select two to three states from each of the three ecological zones under study:

Guinea Savanna, Sudan Savanna, and Sahel Savanna. In the second stage, two agricultural Local Government Areas (LGAs) were randomly selected from each chosen state. In the third stage, three farming communities were identified within each selected LGA, yielding a total of 48 farming communities stratified to represent the principal crop production systems of the region, including cereals, legumes, and tubers. This hierarchical design follows the multi-stage cluster sampling framework described by Sedgwick (2015), in which successive stages of random selection are structured around the natural geographic clustering of the population, thereby improving logistical efficiency without compromising representativeness (Sirwan, 2024). Field data were collected across the three principal ecological zones of the study area, namely the Guinea, Sudan, and Sahel Savanna zones, using a hierarchical multi-stage cluster sampling design. The sampling proceeded through four nested levels, as summarised in Table 2.

Table 2: Multi-Stage Sampling Framework

Stage	Unit	Selection Basis	Number Selected
1	Ecological zone	All three major zones are included	3
2	State	Purposive selection of agriculturally representative states; 2–3 per zone	8 states
3	Local Government Area (LGA)	Random selection of 2 agricultural LGAs per state	16 LGAs
4	Farming community	Identification of 3 farming communities per LGA based on the dominant crop system	48 communities

Instrument Design and Data Collection Procedures

Four complementary data collection instruments were employed: (i) a structured household questionnaire; (ii) an ecological field checklist; (iii) focus group discussion (FGD) guides administered at the community level; and (iv) direct field measurement protocols for vegetation and soil biophysical variables. This mixed-methods triangulation was adopted to cross-validate farmer perceptual data against biophysical field observations, thereby reducing response bias.

The household questionnaire was pre-tested in two communities not included in the final sample, and revisions were made based on piloting feedback before the main survey. Questionnaire administration was carried out by a trained field crew of 16 enumerators, two per state, who received a three-day standardised training workshop before the commencement of fieldwork. Inter-

enumerator reliability was assessed using the percentage agreement statistic across a 10% re-interview subsample; agreement exceeded 85% for all indicator items, indicating acceptable consistency in data collection.

Biophysical field data on vegetation and soil parameters were collected in accordance with the Standard Operating Procedures (SOPs) for savanna ecology monitoring established by Abdulkadir et al. (2013) . Ecological checklists documented observable changes in soil condition, vegetation structure, and species composition at each community location.

Ethical Approval

Generally, the data collection methods were conducted in accordance with the Directorate of Research, Innovation and Development (DRID), Federal University of Technology, Minna, ethical guidelines and regulations, which ensure that all participation remains voluntary, respondents' identities remain confidential, and the collected data are used strictly for academic purposes.

Indicator Framework and Variable Operationalisation

Eco-climatic resilience was assessed through six core indicator dimensions collectively encompassing 46 variables, as presented in Table 2. Farmer perception items for the climatic and ecological anomaly dimensions were scored on a five-point ordinal scale: 1 = Very Low, 2 = Low, 3 = Moderate, 4 = High, and 5 = Very High, representing each respondent's assessment of the severity or frequency of a given phenomenon relative to conditions prevailing 20–30 years prior. This retrospective comparative framing is consistent with established practice in community-based vulnerability assessment (Srinivasa Rao et al., 2019). Adaptation practice items were scored according to frequency of adoption: 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, and 5 = Always.

Table 2: List of Indicators Used to Collect Eco-climatic Variables

Indicator	Description	Key Parameters
Climatic Anomalies	Departures from long-term climatic norms	Drought, floods, heatwaves, heavy rainfall, early cessation, late onset, erratic rainfall, increased temperature, and shortening of the growing season

Ecological Anomalies	Ecological disturbances and degradation	Soil degradation, soil erosion, plant pests/diseases, species invasion/weed extension
Exposure	The degree to which systems are exposed to stresses	Soil fertility, surface water, groundwater, grassland, forest/woodland, species diversity, forage production, livestock carrying capacity
Sensitivity	The degree to which systems are affected by stresses	Vegetative cover, plant vigour, biomass production, soil moisture, ground cover by plant residues, soil type
Adaptive Capacity	Existing coping strategies	Changing planting dates, inorganic fertiliser application, animal manure application, mulching/cover crops, mixed farming, crop rotation, drought-resistant varieties, early maturing varieties, expansion of cultivated land, migration
Transformative Capacity	Systemic and institutional adaptation	Community intervention, government intervention, NGO/CBO support, restricted grazing, climate risk networks, small-scale dam construction, afforestation, agroforestry/alley cropping, high-yield varieties

Data Analysis

Climate Data Analysis: Mann-Kendall Trend Test

Long-term trends in annual rainfall were assessed using the non-parametric Mann-Kendall (MK) trend test (Kendall, 1975; Mann, 1945), with Sen's slope estimator (Sen, 1968) quantifying trend magnitude. The MK test was preferred for its distribution-free nature, robustness to outliers, and established application in African hydroclimatic trend detection (Marengo et al., 2021; Tabari & Nikbakht, 2012). Positive and negative Z values at $\alpha = 0.05$ indicate upward and downward trends, respectively. Sen's slope provides a non-parametric estimate of the rate of change (mm year^{-1}) as the median of all pairwise slopes across the time series.

Prior to trend testing, each station series was screened for serial autocorrelation using the lag-1 autocorrelation coefficient, given its well-documented tendency to inflate MK significance and

increase the probability of spurious trend detection (Yue et al., 2002). Where significant autocorrelation was detected ($p < 0.05$), the trend-free pre-whitening (TFPW) procedure of Yue *et al.* (2002) was applied to remove autocorrelation while preserving the trend signal. All analyses were performed in R (version 4.3.1) using the trend and Kendall packages.

Statistical Analysis: Principal Component Analysis (PCA)

Field data were coded using ordinal scales ranging from "very low" to "very high," with numerical identifiers assigned to each indicator to facilitate quantitative processing in SPSS (Version 26). Principal Component Analysis (PCA) was employed to reduce the dimensionality of the data and identify dominant patterns among the eco-climatic indicators. PCA transforms correlated variables into a set of linearly uncorrelated components, thereby simplifying complex datasets while minimising information loss and maximising interpretability (Jolliffe & Cadima, 2016; Greenacre *et al.*, 2022). Sampling adequacy was confirmed using the Kaiser-Meyer-Olkin (KMO) measure, and the suitability of the correlation structure was verified through Bartlett's test of sphericity (Field, 2024). Following the Kaiser criterion, only components with eigenvalues exceeding 1.0 were retained, and a Varimax rotation was applied to improve the interpretability (Hair et al., 2019). The first principal component (PC1) was selected for spatial analysis because it captured the greatest proportion of the total variance and provided a robust, non-redundant representation of the underlying eco-climatic signal (Mankovich *et al.*, 2025).

Spatial Analysis and Geospatial Database Construction

A geospatial database was developed by integrating field observations with geographic coordinates collected using handheld Global Positioning System (GPS) devices. Geospatial data combines location, attribute, and temporal information to represent phenomena distributed across space (Stock & Guesgen, 2016). To generate continuous surfaces of regional variability from the resulting point data, Inverse Distance Weighting (IDW) interpolation was applied with the following parameters: a power parameter of 2 (inverse square distance weighting), a variable search radius encompassing 12 nearest neighbours, and an output cell size of 250 m. Interpolation accuracy was evaluated through leave-one-out cross-validation by comparing predicted against observed values at each sample location. Before analysis, all raster datasets were standardised to a uniform spatial resolution, extent, and coordinate reference system (WGS 1984 UTM Zone 32N) to ensure spatial consistency across layers. Thematic surfaces were subsequently generated for

each indicator dimension: climatic anomalies, ecological anomalies, exposure, sensitivity, adaptive capacity, and transformative capacity.

Eco-Climatic Resilience Index (ECRI)

The thematic maps were integrated using the empirical relationship adapted from Subiyanto *et al.* (2020) to derive the Eco-Climatic Resilience Index (ECRI) as expressed in Equation (1):

$$ECRI = \frac{(ACI \times TCI)}{(EI \times SI)} \quad (1)$$

Where: ACI = Adaptive Capacity Index; TCI = Transformative Capacity Index; EI = Exposure Index and SI = Sensitivity Index

This composite index enables the identification of spatial gradients in resilience across Northern Nigeria, highlighting areas of high vulnerability and low adaptive capacity. By combining multivariate statistics with geospatial analysis, this framework illustrates the interaction between climatic variability, ecological conditions, and socio-institutional adaptation (Johanna, 2025).

Results

Rainfall Trends Across Northern Nigeria (1971–2023)

The Mann–Kendall trend test and Sen's slope estimator are represented in Table 3. The results revealed a mixed pattern of rainfall trends (upward, downward, significant increase, and non-significant trends) across the savanna region of northern Nigeria. The results indicated an insignificant upward or downward trend at the 5% significance level at the Sokoto, Maiduguri, Zaria, Yelwa, Bauchi, Minna, Yola, Bida, Lafia, Lokoja, and Ibadan stations. However, a significant upward trend was observed Katsina ($Z = 2.19, p = .03$), Nguru ($Z = 2.69, p = .01$), and Kano ($Z = 4.26, p < .01$) stations within the Sudan–Sahelian Savanna: . The positive Sen's slope values indicate consistent increases in annual rainfall over the study period, with Kano station recording the highest rate of increase (17.89 mm/year). In contrast, Kaduna ($Z = -2.05, p = .04$), Jos ($Z = -3.37, p < .01$), Abuja ($Z = -2.17, p = .03$), and Makurdi ($Z = -4.65, p < .01$) stations located in the Northern Guinea and Derived Savanna zones showed significant downward trends. Makurdi recorded the highest decline, with a Sen's slope of -26.43 mm/year.

269

Table 3: Mann-Kendall Trend Analysis of Annual Rainfall Totals (1971–2023)

Station	Z	P_value	Sen_Slope	significance
Sokoto	0.77	0.44	1.11	Upward
Katsina	2.19*	0.03	3.48	Upward
Nguru	2.69*	0.01	3.67	Upward
Gusau	-1.27	0.21	-2.49	Downward
Kano	4.26*	0.00	17.89	Upward
Maid	0.15	0.88	0.26	Upward
Zaria	0.57	0.57	1.19	Upward
Yelwa	0.73	0.47	1.09	Upward
Kaduna	-2.05*	0.04	-4.45	Downward
Bauchi	0.50	0.62	1.88	Upward
Jos	-3.37*	0.00	-5.18	Downward
Minna	-0.10	0.92	-0.40	Downward
Yola	-0.09	0.93	-0.18	Downward
Bida	-0.64	0.52	-0.88	Downward
Abuja	-2.17*	0.03	-5.40	Downward
Lafia	-1.73	0.08	-6.81	Downward
Lokoja	-1.40	0.16	-6.19	Downward
Makurdi	-4.65*	0.00	-26.43	Downward
Ibadan	1.01	0.31	2.46	Upward

270

*Significance $\alpha = 0.05$ **271 PCA of Eco-Climatic Resilience Dimensions**

272 PCA was applied separately to each of the six indicator datasets, with PC1 retained across all
 273 dimensions based on the Kaiser criterion (eigenvalue > 1) and scree plot inspection. The retained
 274 components explained variance ranging from 28.96% (transformational adaptation; eigenvalue =
 275 2.61) to 87.16% (sensitivity; eigenvalue = 3.49), with climatic anomalies yielding the highest
 276 eigenvalue of 9.62 (74.00% variance), followed by exposure at 60.83% (eigenvalue = 4.87),
 277 ecological anomalies at 35.74% (eigenvalue = 2.86), and adaptation practices at 34.52%
 278 (eigenvalue = 3.45). For the three dimensions where PC1 explains less than 40% of total variance
 279 (ecological anomalies, adaptation practices, and transformational adaptation), the retained
 280 component represents the dominant axis of co-variation rather than a full characterisation of the
 281 indicator space, a constraint acknowledged transparently in this analysis.

282 Climatic Anomalies

The climatic anomaly PCA (eigenvalue = 9.62; 74% variance) reflects a dominant and tightly integrated Climatic Stress and Aridification Axis, in which variables associated with seasonal compression and rainfall unpredictability (shorter growing seasons, late rain onset, early cessation, drought, false starts, erratic rainfall, and increased temperatures) all load strongly and positively on PC1. Heavy rainfall (−0.73) and flood events (−0.56) load negatively, indicating a structural separation between drought-driven and flood-associated anomalies within the study area. Spatially, the Climatic Anomaly Index (Figure 2) reveals very high anomaly scores concentrated across the extreme north (Sokoto, Zamfara, Katsina, Kano, Jigawa, Yobe, Gombe, and Borno), transitioning through moderate anomaly levels across Kebbi, Adamawa, Taraba, and parts of Nasarawa, Bauchi, Kaduna, Plateau, and Niger, to very low anomaly classification in the southern states of Oyo, Kwara, Kogi, Benue, and FCT.

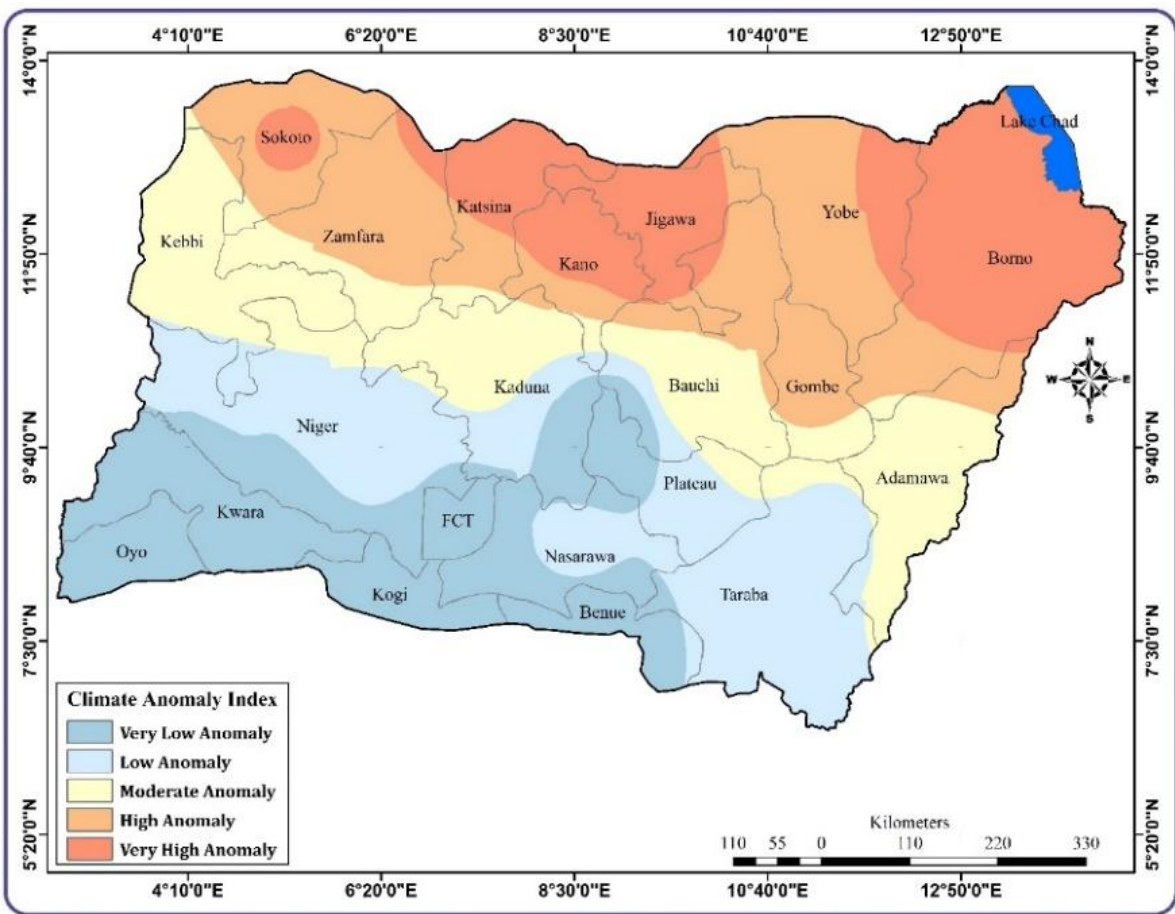


Fig. 2: Climatic Anomaly Map of Northern Nigeria

Ecological Anomalies

The ecological anomaly PCA (eigenvalue = 2.86; 35.74% variance) defines an Ecosystem Health Deterioration Axis driven primarily by invasive species proliferation, soil degradation, vector-borne disease, and plant disease and weed invasion, variables that together characterise cumulative biological and terrestrial stress under land use pressure and climate forcing. Soil erosion loads negatively (-0.66), reflecting its spatial dissociation from the biological invasion axis: active erosion is most severe in the more humid, topographically varied central zones, while degradation from compaction, salinisation, and biodiversity loss predominates in the arid north. A strong positive correlation of $r = 0.82$ between the Climatic Anomaly Index and Ecological Anomaly Index confirms that climatic stress is the primary, though not exclusive, driver of ecological deterioration across the study area. Spatially (Figure 3), very high ecological anomaly scores characterise Sokoto, Katsina, Kano, Jigawa, Yobe, and parts of Kaduna, Bauchi, and Borno, while very low scores across Oyo, Kwara, FCT, and southern Niger reflect relatively stable soils, denser vegetation, and enhanced biodiversity.

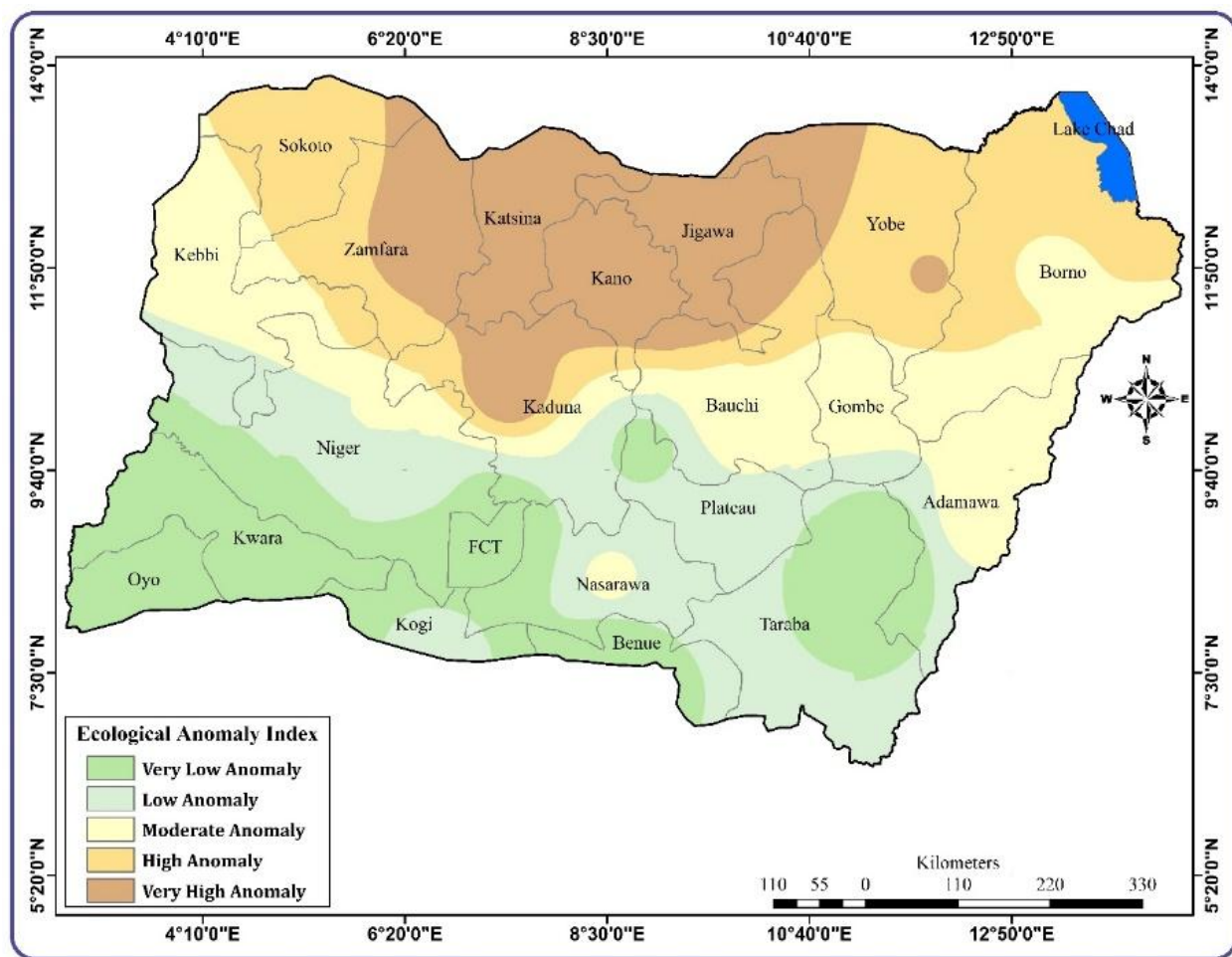


Fig. 3: Ecological Anomaly Map of Northern Nigeria

Exposure

The exposure PCA (eigenvalue = 4.87; 60.83% variance) constitutes an Ecological Resource Exposure Axis in which species diversity, surface water, forage production, forest land, grassland, composite change, and soil fertility co-vary strongly and positively, identifying regions simultaneously rich in natural resources and highly dependent on those resources for livelihoods, and therefore most exposed to climate-driven resource stress. The Exposure Index map (Figure 4) reveals two important spatial patterns: a broad north-south gradient of high to very high exposure across the Sahelian north (Katsina, Kano, Jigawa, Yobe, Gombe, and Borno), declining to very low exposure in the south; and a notable east-west differentiation within the Sudano-Sahelian zone itself, where Borno, Yobe, Katsina, Kano, and Jigawa exhibit distinctly higher resource exposure than comparable latitudes in the northwest, reflecting the eastward decline in Atlantic moisture flux documented across the wider Sahel.

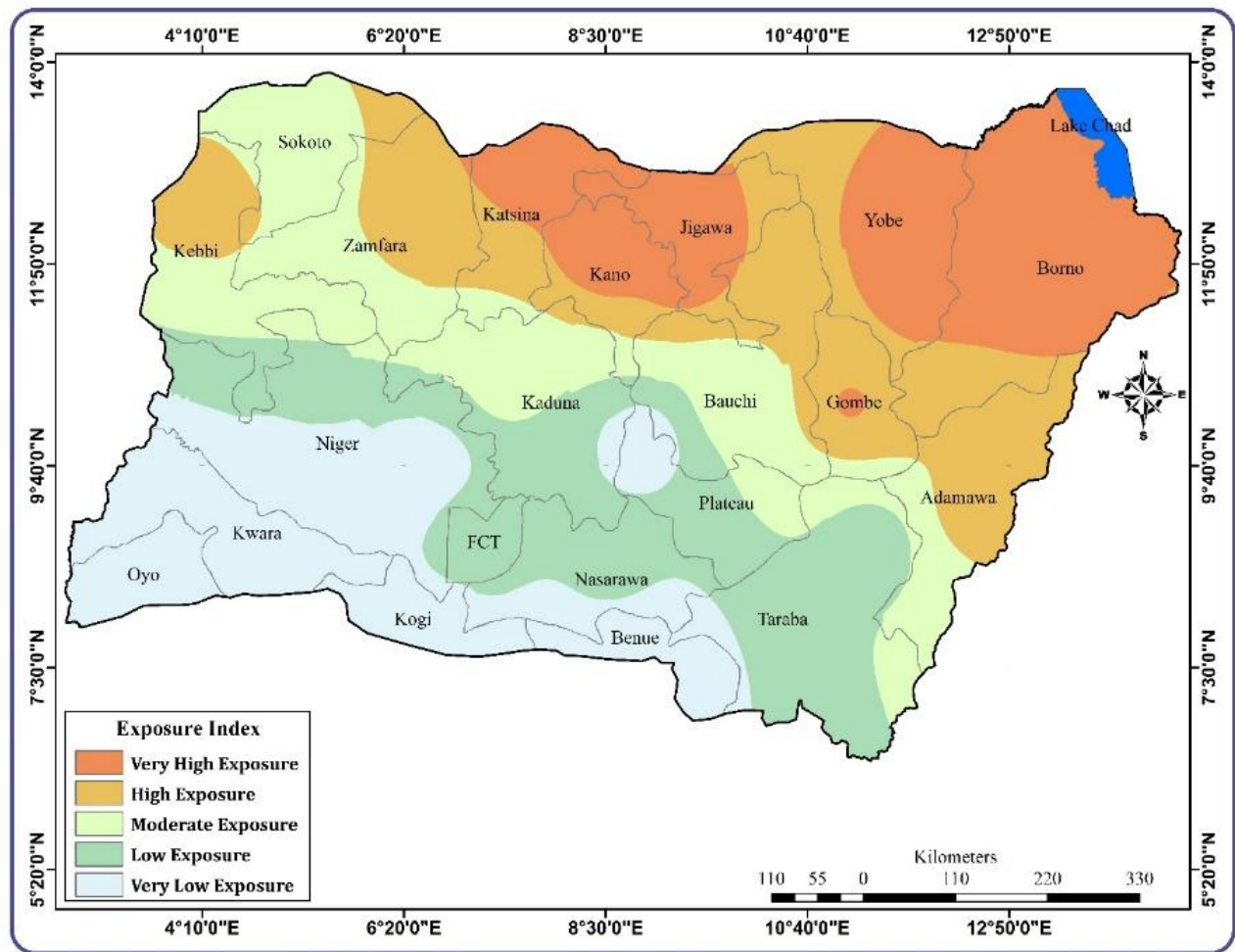


Fig. 4: Eco-climatic Exposure Map of Northern Nigeria

Sensitivity

The sensitivity PCA produced the most statistically coherent structure of any dimension (eigenvalue = 3.49; 87.16% variance), with plant vigour, soil moisture, vegetation cover, and ground cover all loading uniformly high and positively on PC1, defining a near-unidimensional Vegetation–Soil Moisture Sensitivity Axis. This tight coupling indicates that these biophysical variables respond to stress as a single integrated system: degradation in any one element rapidly propagates through the others, with important implications for intervention design. Improvements in soil moisture or vegetation cover are likely to generate co-benefits across the entire sensitivity axis. Spatially (Figure 5), very high sensitivity concentrates across the Sudano-Sahelian belt from Borno and Yobe westward through Jigawa, Kano, Katsina, Zamfara, Sokoto, and parts of Kebbi and Adamawa, with alternating longitudinal bands of intensity suggesting that climate dependence, while uniformly high across the belt, varies at the sub-state scale. Very low sensitivity characterises

the Guinea Savanna south (Oyo, Kwara, Kogi, Benue, FCT, and southern Niger), where higher rainfall and more productive soils provide biophysical buffering.

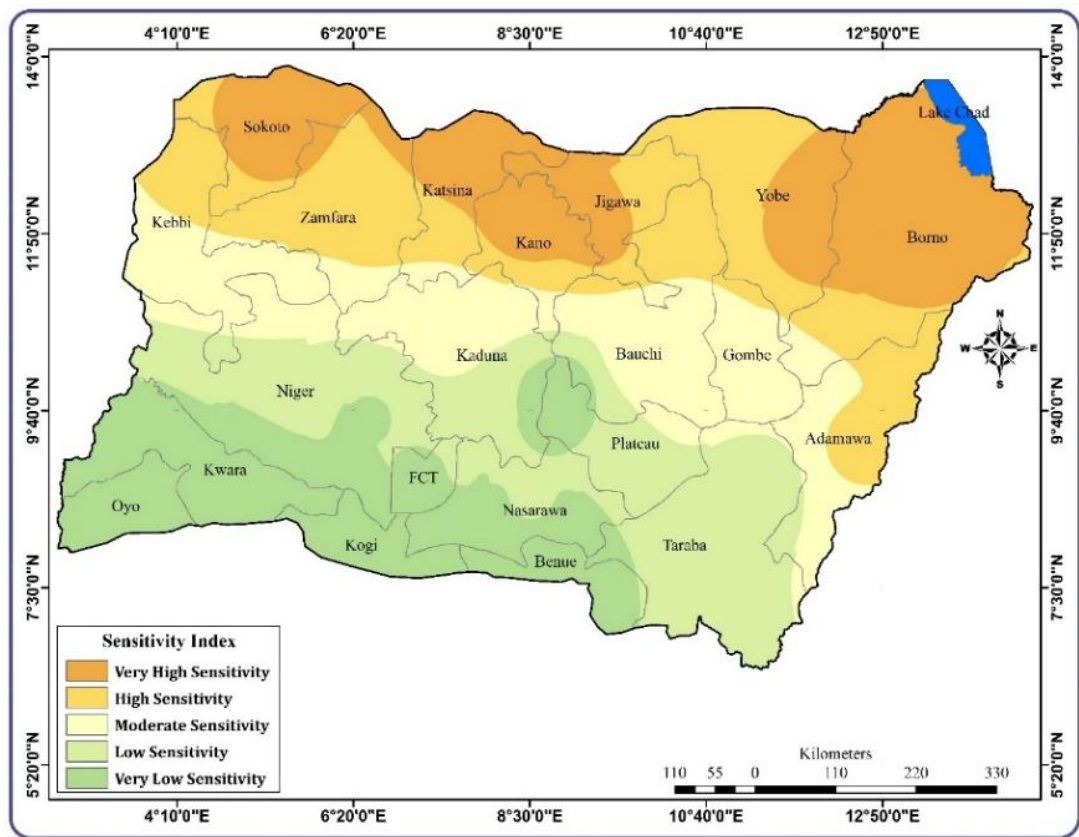


Fig. 5: Eco-climatic Sensitivity Map of Northern Nigeria

Adaptation Capacity

The adaptation practices PCA (eigenvalue = 3.45; 34.52% variance) defines a Livelihood-Based Adaptive Adjustment Axis in which migration, adjusted planting dates, manure application, drought-resistant crop varieties, and mulching constitute the core co-varying adaptive behaviours, while mixed farming, land expansion, and inorganic fertilizer use play supplemental roles. Critically, early crop planting and crop rotation load negatively, indicating that these traditional risk-spreading strategies are declining in adoption, representing an erosion of conventional agricultural knowledge that has not been adequately replaced. The Adaptation Practices Index (Figure 6) reveals a pattern spatially inverse to sensitivity: very high to high adaptation levels dominate the southern and central states (Oyo, Kwara, Kogi, Benue, Plateau, FCT, Niger, Nasarawa, Taraba, southern Kaduna, and Bauchi), while northern states including Sokoto,

Zamfara, Katsina, Jigawa, Yobe, and Borno exhibit the lowest adaptation scores. This spatial anti-correlation between ecological stress and adaptive capacity constitutes a critical adaptation deficit, whereby the communities most exposed to eco-climatic anomalies are simultaneously the least equipped to manage them.

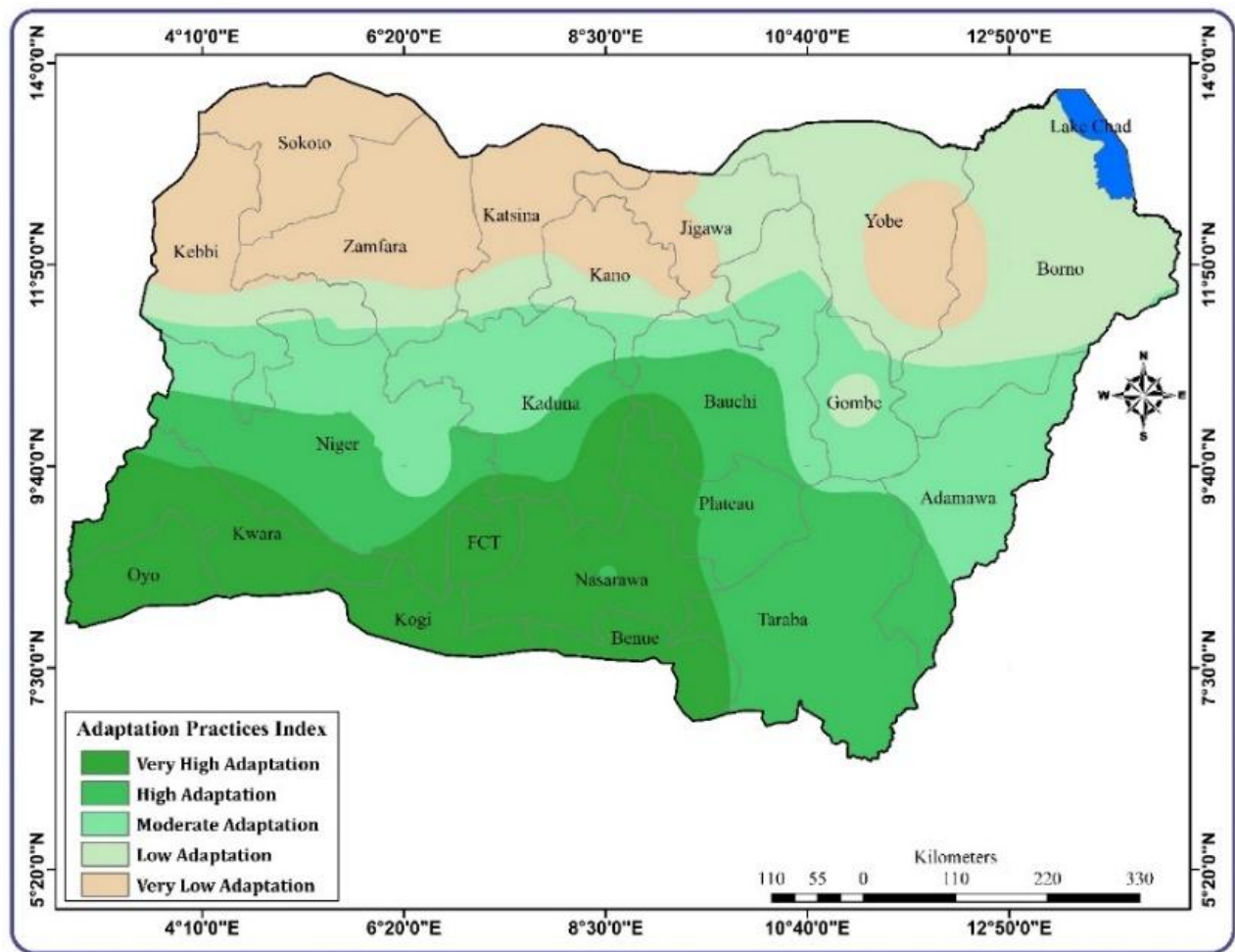


Fig.6: Eco-climatic Adaptation Map of Northern Nigeria

Transformational Adaptation Capacity

The transformational adaptation PCA (eigenvalue = 2.61; 28.96% variance) identifies an Institutional–Community Transformation Axis anchored by community participation, agroforestry, grazing control, government involvement, and climate network participation, confirming that systemic adaptation is driven by collaborative governance and participatory resource management rather than by technology transfer or external project delivery. High-yield

varieties and NGO support load weakly, while isolated infrastructure projects, such as small dams, load near-zero, indicating that singular technical interventions contribute minimally to the dominant transformation pattern. Spatially (Figure 7), high to very high transformational adaptation concentrates in the central and southwestern zones (Oyo, FCT, Benue, Kaduna, and parts of Kwara, Nasarawa, Plateau, Niger, Katsina, and Jigawa), while the northeastern and northwestern states of Borno, Yobe, Gombe, Adamawa, Sokoto, and Zamfara record the lowest institutional transformation capacity, compounding the adaptation deficit identified in the preceding dimension.

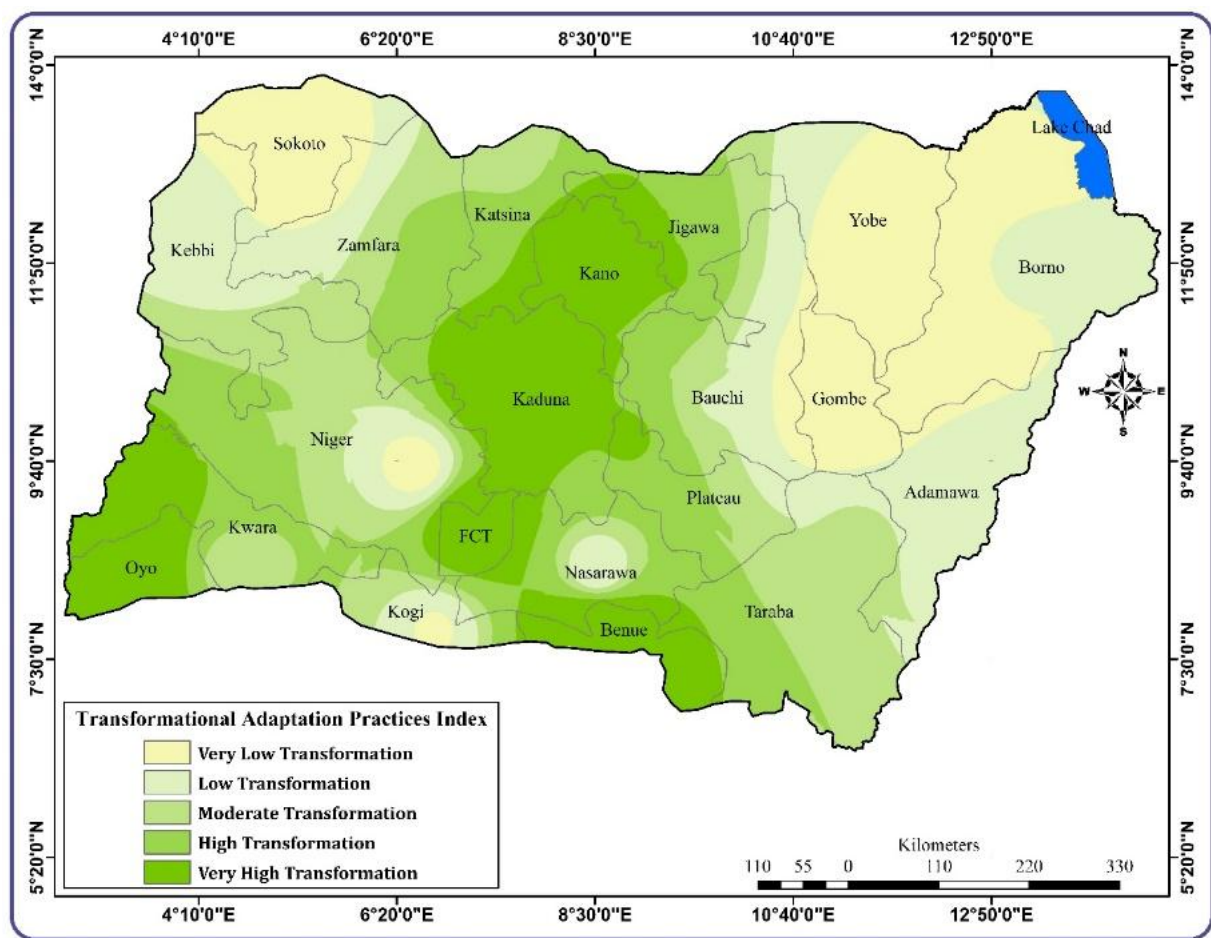


Fig. 7: Eco-climatic Transformational Adaptation Practices

Spatial Distribution of Eco-Climatic Resilience Index

The geospatial integration of the exposure, sensitivity, adaptive capacity, and transformational adaptation capacity indices reveals spatially differentiated levels of the Eco-Climatic Resilience Index (ECRI) across the study area, underscoring the imperative for targeted livelihood resilience-

building interventions. The spatial distribution of the ECRI shows a pronounced north-south gradient in resilience potential. Higher ECRI values characterise scenarios in which adaptive capacities effectively offset the combined effects of exposure and sensitivity, whereas lower values reflect a progressive erosion of resilience, in which these capacities are insufficient to counterbalance biophysical and climatic stressors.

The spatial distribution of the ECRI (Figure 8) reveals five identifiable resilience zones. The spatial pattern shows that very low resilience dominates the Sahelian and semi-arid north, where the compounding of very high exposure, very high sensitivity, low adaptive capacity, and weak institutional transformation produces the lowest ECRI values in the dataset. The low resilience zone extends this pattern southward into parts of Adamawa and Kebbi, indicating that resilience deficits are not confined to the ecological extreme of the Sahel but also penetrate into transitional zones. Moderate resilience across the central belt reflects an unstable equilibrium in which some adaptive gains are being undermined by continuing ecological stress. The very high resilience zones of Kwara, Oyo, southern Kogi, Benue, and the medium-altitude plateau states represent a structural contrast: lower ecological stress, higher and more diverse adaptive capacity, and stronger institutional and community-level governance combine to sustain livelihood resilience. These zones are not immune to eco-climatic stress but possess the biophysical and social capital to absorb and recover from it more effectively than the Sahelian north.

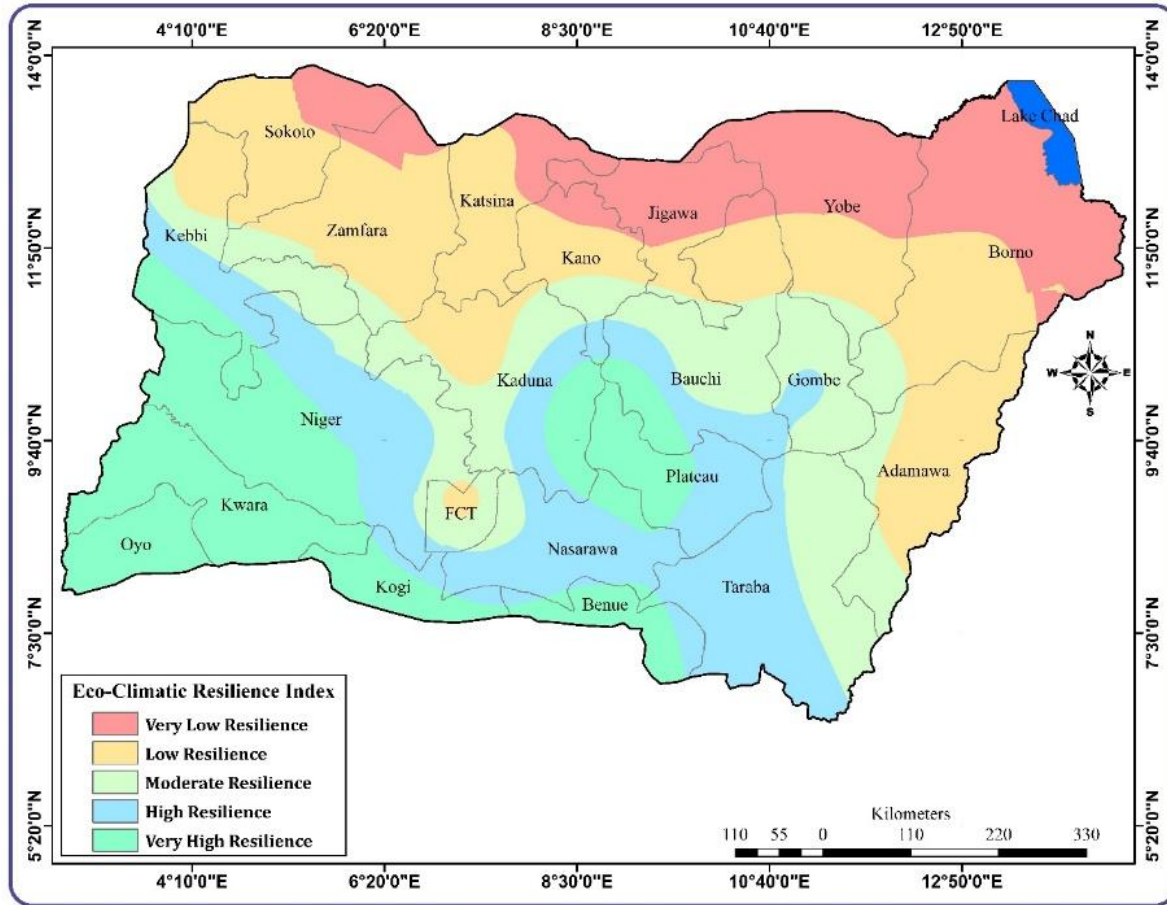


Fig. 8: Eco-climatic Resilience Index Map of Northern Nigeria

Overall, the six-dimensional PCA framework and composite ECRI mapping demonstrate that eco-climatic resilience in northern Nigeria is not a simple function of rainfall or vegetation zone. It emerges from the interaction of climatic stress, ecological resource availability, biophysical sensitivity, individual adaptive behaviour, and institutional capacity, dimensions that are spatially misaligned in ways that systematically disadvantage the most climatically stressed communities.

Discussion

Climatic Anomalies and the Intensification of Sahelian Aridity

The PCA of climatic variables, with PC1 accounting for 74% of the total variance, reveals a dominant, spatially coherent aridification regime across northern Nigeria, characterised by warming trends, shortened growing seasons, erratic rainfall onset and cessation, and an upward frequency of heat waves and drought events. This finding extends and corroborates the earlier

delineation of progressive southward shifts in eco-climatic zone boundaries reported for the region by AbdulKadir et al. (2015), indicating that the trajectory of aridification documented over preceding decades has continued and intensified. Piao (2025) confirmed that global warming substantially affects terrestrial aridity, particularly in dryland ecosystems, and the climatic pattern identified here is consistent with the broader Sahelian drying signal documented across West Africa.

The Mann-Kendall trend analysis reveals spatial heterogeneity within this overarching aridification narrative that the PCA alone does not capture. Stations in the Sudan-Sahelian zone, including Katsina ($Z = 2.19$, $p = 0.03$), Nguru ($Z = 2.69$, $p = 0.01$), and Kano ($Z = 4.26$, $p < 0.01$), showed statistically significant upward rainfall trends, while Guinea and Derived Savanna stations such as Makurdi ($Z = -4.65$, $p < 0.01$), Jos ($Z = -3.37$, $p < 0.01$), and Abuja ($Z = -2.17$, $p = 0.03$) showed significant downward trends. This divergence, where the drier north receives upward rainfall while the wetter south dries, is consistent with the empirical studies that established increase rainfall in west africa Sahel (Dogondaji & Isah, 2025; and Ibebuchi & Abu, 2023). It also aligns with projections from CMIP6 models, suggesting non-uniform redistribution of rainfall across West Africa under warming scenarios. In similar studies, Biasutti, (2019) and Saley & Salack (2023) observed an increased rainfall in the northern part of the Sahel and a downward rainfall in the southern part. These results, when compared with the least resilient pattern in the Sudano-Sahelian zone, implied that upward rainfall trends in the Sahelian zone do not affect the ecological or socio-economic resilience of the inhabitants. Yang et al. (2025), identify extreme rainfall and soil degradation as other variables that could still expose areas to climate shocks. Furthermore, studies indicate that increased rainfall may coincide with greater rainfall variability, false onset events, and shortened effective growing seasons, which can exacerbate vulnerability and reduce resilience in fragile dryland ecosystems (Wang et al., 2022; Chinasho et al., 2026).

The strong positive correlation ($r = 0.82$) between climatic and ecological anomaly indices further confirms that climatic stress functions as the primary driver of ecological deterioration across the study area. This bidirectional relationship, whereby climatic anomalies degrade ecological function, which in turn reduces the buffering capacity of ecosystems against future climate shocks, represents a compounding vulnerability dynamic that is particularly acute in the Sudano-Sahelian zone (Chuine et al., 2025).

Ecological Exposure and Sensitivity: A Biophysical Vulnerability Axis

The ecological anomaly PCA (eigenvalue = 2.86; 35.74% variance) and sensitivity PCA (eigenvalue = 3.49; 87.16% variance) together define what may be termed a Biophysical Vulnerability Axis along the north-south gradient of the study area. The moderate variance explained by the ecological anomaly component reflects the inherently multidimensional character of ecological stress, a finding consistent with Dervash et al. (2024), who demonstrated that soil biota disruption, biodiversity loss, and pest dynamics do not co-vary as tightly as purely climatic variables. Conversely, the exceptionally high variance explained by the sensitivity component (87.16%) indicates that vegetation cover, plant vigour, soil moisture, and ground cover operate as a tightly coupled biophysical system in which any perturbation cascades rapidly through the ecosystem, a finding reinforced by Yang et al., (2023) and Faiz et al. (2025), who showed that soil moisture deficits trigger non-linear transitions in vegetation states that are difficult to reverse.

The spatial pattern of exposure diverges from a simple north-south gradient in one important respect: the eastern sub-region (Borno and Yobe states) and parts of the central Sahelian belt (Katsina, Kano, and Jigawa) indicate a higher exposure than comparable latitudes to the west. This longitudinal differentiation in exposure has not been previously mapped at this spatial resolution for northern Nigeria and represents a substantive empirical contribution of the present study. It likely reflects the declining Atlantic moisture flux eastward across the Sahel, documented by Adigun et al. (2024) and Obossou et al. (2025) , which reduces the ecological buffering provided by surface water and grassland resources in eastern states. Pascual et al. (2022) demonstrated that simultaneous multiple stressors produce disproportionate declines in ecosystem health relative to single-stressor impacts, and the convergence of high climatic anomalies, elevated exposure, and high sensitivity in the Sahelian northeast therefore represents a systemic risk hotspot that warrants prioritised intervention.

The Adaptation Deficit: Where Vulnerability is Greatest, Adaptive Capacity is Lowest

Perhaps the most policy-consequential finding of this study is the spatial inversion between sensitivity and adaptation capacity. The Adaptation Practices Index reveals that the states exhibiting the highest eco-climatic sensitivity (Sokoto, Zamfara, Katsina, Jigawa, Yobe, and Borno) consistently show the lowest levels of adaptive practice adoption. This maladaptation geography, where need and capacity are spatially anti-correlated, is not unique to northern Nigeria:

Eriksen et al. (2021) identified an analogous adaptation deficit across Sub-Saharan drylands and argued that incremental, technically focused adaptation approaches systematically fail in contexts of structural socioeconomic marginalisation. The negative PCA loadings for early crop planting (−0.35) and crop rotation (−0.03) suggest that traditional risk-spreading strategies are declining in relevance or are inconsistently applied, signalling a transition in adaptive behaviour that has not yet been replaced by adequately resourced modern alternatives. This erosion of traditional knowledge, combined with the absence of sufficient institutional support, creates a dangerous adaptive vacuum in the most climatically stressed zones (Pret et al., 2025).

The Transformational Adaptation Index compounds this picture. Although community participation, agroforestry, and grazing control load strongly on the institutional-community transformation axis, these practices are most prevalent in the central and southwestern zones, where ecological stress is comparatively lower. In the most vulnerable northeastern and northwestern states, transformational adaptation scores are lowest, precisely where systemic change is most urgently required. This finding aligns with UNFCCC (2025) assessments, indicating that inclusive governance and coordinated community action are the primary determinants of effective adaptation, yet these governance mechanisms are weakest in contexts of pre-existing fragility.

Eco-Climatic Resilience: Spatial Patterns and Structural Determinants

The composite Eco-Climatic Resilience Index (ECRI) map reveals a pronounced north-south gradient in resilience potential, with very low resilience concentrated in the Sahelian states of Sokoto, Zamfara, Katsina, Kano, Jigawa, Yobe, and Borno, and very high resilience extending across Southern Kebbi, Niger, Kwara, Oyo, and the medium-high altitude areas of Plateau and Kaduna. This spatial pattern is not merely a reflection of rainfall gradients but rather emerges from the compounding interactions among four structurally distinct dimensions: biophysical exposure, ecosystem sensitivity, individual-level adaptive behaviour, and institutional capacity for transformation. Zhai & Lee (2024) and Beck et al. (2025) demonstrated that reducing vulnerability requires simultaneous progress across all these dimensions, and the ECRI map reveals that no single dimension is being adequately addressed in the most resilience-deficient zones.

Compared with comparable regional resilience assessments, including FEWS NET livelihood zone mapping and CILSS agro-climatic vulnerability indices for the West African Sahel, the spatial

configuration identified in this study is broadly consistent, but provides substantially finer sub-national resolution (state and LGA level) that enables location-specific intervention design. The identification of moderate-to-high resilience in the medium-altitude zones of Plateau, Kaduna, Bauchi, and Nasarawa states is particularly noteworthy, as these areas are frequently overlooked in regional analyses that emphasise the extreme north. Pakhira et al. (2024) stressed that understanding the linkages between climate variability and ecosystem resilience at fine spatial scales is essential for effective conservation and adaptive management, and the present ECRI framework directly addresses this need.

The North-Eastern Exception: Security, Governance, and Ecological Fragility

A noteworthy departure from the latitudinal pattern of resilience occurs in north-eastern Nigeria, where resilience is lower than would be predicted by the ecological zone alone. Borno and Yobe states exhibit very low ECRI scores that reflect not only climatic and ecological stress, but also the compounding effects of nearly two decades of Boko Haram insurgency, which has systematically dismantled the institutional, social, and governance infrastructure upon which adaptive capacity depends (Abubakar et al., 2025; Oluwagbemi, 2023). Moran et al. (2019) described this dynamic as a cycle of ecological fragility, wherein conflict disrupts land management, accelerates degradation, reduces food security, and generates the conditions for renewed instability, a feedback loop that donor interventions alone are unable to break. The finding that substantial NGO and international donor presence in the northeast has not translated into measurable improvements in community eco-climatic resilience is a sobering empirical result that challenges the prevailing humanitarian model of externally driven resilience-building. Shrivastava & Agrawal (2025) similarly argued that resilience in post-conflict environments requires holistic, locally anchored interventions that address structural vulnerabilities rather than delivering discrete project-based responses. The present study quantifies, for the first time, the gap between donor investment and resilience outcomes in this specific north-eastern context, a contribution that carries direct implications for how international climate finance should be targeted and evaluated in conflict-affected dryland environments.

Implications for Location-Specific Eco-Climatic Resilience Policy

Collectively, the ECRI spatial framework developed here provides an empirical basis for differentiated, location-specific resilience policy across five distinct intervention zones. In very

low resilience zones (Sahelian states: Sokoto, Zamfara, Katsina, Kano, Jigawa, Yobe, Borno), the fundamental challenge is the simultaneous deficit in both adaptive capacity and institutional transformation. Interventions must prioritise structural change over incremental adaptation: large-scale agroforestry restoration, community-led early warning systems linked to NIMET seasonal forecasts, targeted social protection for climate-displaced households, and strengthened sub-national governance of rangelands and water resources. In low-resilience zones (parts of Kebbi, Adamawa, and Gombe), the transition from very low to low resilience indicates some institutional presence but insufficient reach. Scaling existing NGO and government programmes, particularly those addressing soil restoration and the adoption of drought-tolerant crops, offers a viable entry point. In moderate resilience zones (Bauchi, Nasarawa, Taraba, and central Kaduna), the emphasis should shift to consolidating gains and preventing erosion of existing adaptive practices under upward climatic stress. In high- and very-high-resilience zones (Niger, Kwara, Oyo, and the plateau areas), the priority is to maintain ecosystem integrity while transferring technical and institutional knowledge, including agroforestry models and community governance frameworks, to lower-resilience neighbouring zones. This spatial differentiation directly responds to the call by Eriksen et al. (2021) and Zhai & Lee (2024) for adaptation strategies that move beyond generic national frameworks toward place-based transformational planning.

Conclusion

A favourable climate is vital for sustainable livelihoods in Northern Nigeria, where a large proportion of the population depends on rainfed agriculture. The uncertainty and magnitude of environmental change across the region are intensifying climate and ecological anomalies, as well as the resultant multidimensional poverty among the inhabitants. These constitute natural hazards that have been threatening the natural environment and human livelihoods across the study region. By implication, it intensifies food insecurity, famine, loss of biodiversity, poverty, socio-economic instability and southward migration. This study produced a sub-national empirical Eco-Climatic Resilience Index for northern Nigeria that integrates PCA-derived community-level indices across six biophysical and social dimensions. The findings established that though the stations in Sudan-Sahelian showed upward rainfall trends, the ECRI map depicted a north-south resilience gradient, with very low resilience across the Sahelian savanna north and very high resilience across the Guinea Savanna south. Similarly, it has been established that the areas under the greatest climatic

and ecological pressure (Sokoto, Zamfara, Katsina, Kano, Jigawa, Yobe, and Borno) also show the lowest adoption of adaptive practices and the weakest capacity for institutional transformation. This implies that increased rainfall does not necessarily translate into improved climate resilience. The results of PCA illustrate climatic anomalies: cumulative percentage of variance is 74%, sensitivity is 87.16%, and exposure is 60.83%, which reveal the strong explanatory influence of the highly interrelated variables typical of the indicators. The moderate proportion includes ecological indicators at 35.74%, adaptation practices at 34.53%, and transformed adaptation practices at 28.96% of the variables, reflecting the complex and multidimensional nature of the indicators. Overall, the climate and ecological stressors are strongly related ($r = 0.82$). Generally, the variability that characterises the eco-climatically resilient zones provides the basis for building resilience across the vulnerable and hazard-prone zone, faced with increasing eco-climatic anomalies and their attendant crop failure, famine, insecurity, and southward migration, which is aggravating crime across the country. Thus, there is an urgent need to develop strategies that enable individuals, communities, and states to adapt, cope, and function effectively in the face of ecoclimate-related shocks and to mitigate their negative impacts, thereby building ecoclimate resilience for enhanced livelihoods in Northern Nigeria and other regions with shared socio-economic and climate characteristics.

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Funding Declaration

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Author Contributions

AA conceptualised the study, designed the research framework, drafted the initial manuscript, supervised the research process, and edited the final manuscript. AJ and II collected and processed the climate and ecological datasets and conducted data analysis and interpretation. MTU provided supervision and administrative support, contributed to the interpretation of results, and reviewed

and revised the manuscript for intellectual content. AA and HBA performed advanced data analysis, mapping, and visualisation of climate and ecological anomalies. SAC contributed to methodological refinement and interpretation of results. All authors read and approved the final manuscript.

Clinical trial number: Not applicable.

Ethics, Consent to Participate, and Consent to Publish: Informed consent was obtained from all participants prior to completing the questionnaire. Consent to publish is not applicable, as no identifiable personal information is included in this study.

Data Availability: All data supporting the findings of this study are available and can be obtained from the corresponding Author upon request.

Ethical Approval

This study was approved by the ethics committee of the Directorate of Research, Innovation and Development (DRID), Federal University of Technology, Minna, in accordance with ethical guidelines and regulations, ensuring that all participation remains voluntary, respondents' identities remain confidential, and the collected data are used strictly for academic purposes.

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