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# Mapping climate and ecological anomalies as a veritable tool for planning eco-climate resilience across the savanna zones of Nigeria

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## Abstract

The savanna ecological zones of Nigeria are vulnerable to eco-climatic anomalies driven by climate change and land degradation. Despite previous studies on individual climate stressors, few have developed sub-national spatial Eco-Climatic Resilience Indices (ECRI) that integrate both biophysical and socio-economic dimensions across the region, thereby limiting 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 2400 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 transformative adaptation capacity. Community PCA scores were interpolated and integrated into the composite ECRI, which was then 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 indicated a significant and insignificant downward trend, with the highest rate of change recorded in Makurdi (−26.43 mm/year). Although the stations in the Sudan-Sahelian showed upward rainfall trends, the ECRI map depicted a north–south resilience gradient, with very low resilience across the Sahelian savanna to the north and very high resilience across the Guinea Savanna to the 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 and location-specific transformation/adaptation strategies to build individual, community, and state capacity for more resilient livelihoods across the study region and similar regions with comparable socio-economic and climate characteristics.

**Keywords:** Eco-climatic resilience, Climate anomalies, Geospatial mapping, Adaptive capacity, Savanna zones of Nigeria, Livelihood vulnerability

## 1 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. [19]. The upward rate of global warming, shifting precipitation patterns, and increased frequency of extreme weather events have created disruptions to socio-ecological systems worldwide [31, 35]. 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 [7, 66]. 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 [66].

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 [27] 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.

Savanna zones in Nigeria experienced 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 [1, 20]. Research by AbdulKadir et al. [2] 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 Savanna Zones of the Nigerian economy, as the bulk of the population relies more on agriculture for livelihood than in the other parts of the country [44]. The dependence on rainfed agriculture and the existing ecological fragility have intensified anthropogenic pressures, which create vulnerability to climate variability and change [52].

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 [17, 65]. 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 [58, 59]. Furthermore, Principal Component Analysis (PCA) offers a robust statistical approach that reduces dimensionality in complex environmental datasets and reveals underlying structures [28].

Empirical evidence suggests that the relationship between climate and ecological dimensions is bidirectional and reinforcing, as shown by Chuine et al. [13] and Dervash et al. [15]: 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 [22, 23, 38]. Previous studies have examined climate trends and agricultural vulnerability in Nigeria [5, 32, 36, 40, 41, 43, 60]. 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.

While previous climate vulnerability and resilience studies in Nigeria and West Africa have primarily focused on single dimensions such as rainfall variability, agricultural vulnerability, drought risk, or livelihood adaptation, they generally assess these factors independently and at relatively coarse spatial scales. The present study advances the literature in several important ways. First, it develops a multidimensional Eco-Climatic Resilience Index (ECRI) that integrates climatic and ecological anomalies, exposure, sensitivity, adaptive capacity, and transformative adaptation into a single analytical framework. Second, unlike earlier assessments that rely predominantly on climatic or socioeconomic indicators, this study combines long-term meteorological observations (1971–2023), field-based ecological measurements, and household survey data into a unified geospatial database. Third, the study employs Principal Component Analysis to derive objective weights for resilience dimensions before spatial integration, thereby reducing the subjectivity associated with conventional indicator weighting approaches. Finally, the resulting high-resolution resilience maps identify state and community level resilience hotspots and deficits across savanna zones of Nigeria, providing spatially explicit evidence to support location-specific adaptation planning. This integrated methodological framework represents a significant advancement over previous climate vulnerability assessments in Nigeria and offers a transferable approach for resilience assessment across dryland regions of West Africa.

This study addresses these gaps by developing an integrated Eco-Climatic Resilience Index (ECRI) that combines long-term climate observations, ecological field indicators, household-level adaptation data, and geospatial analysis within a unified resilience assessment framework. Unlike previous studies that examined individual dimensions of climate vulnerability in isolation, this study quantifies interactions among climatic stress, ecological degradation, exposure, sensitivity, adaptive capacity, and transformative capacity to produce spatially explicit resilience maps for Savanna Zones. The framework not only identifies where resilience deficits occur but also explains the multidimensional drivers responsible for those patterns, thereby providing stronger scientific evidence for targeted climate adaptation and resilience planning.

## 2 Materials and methods

### 2.1 Study area

The study area encompasses the Savanna Zones of Nigeria, spanning longitudes 2°43′44″E to 14°35′42″E and latitudes 5°36′45″N to 13°49′33″N (Fig. 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

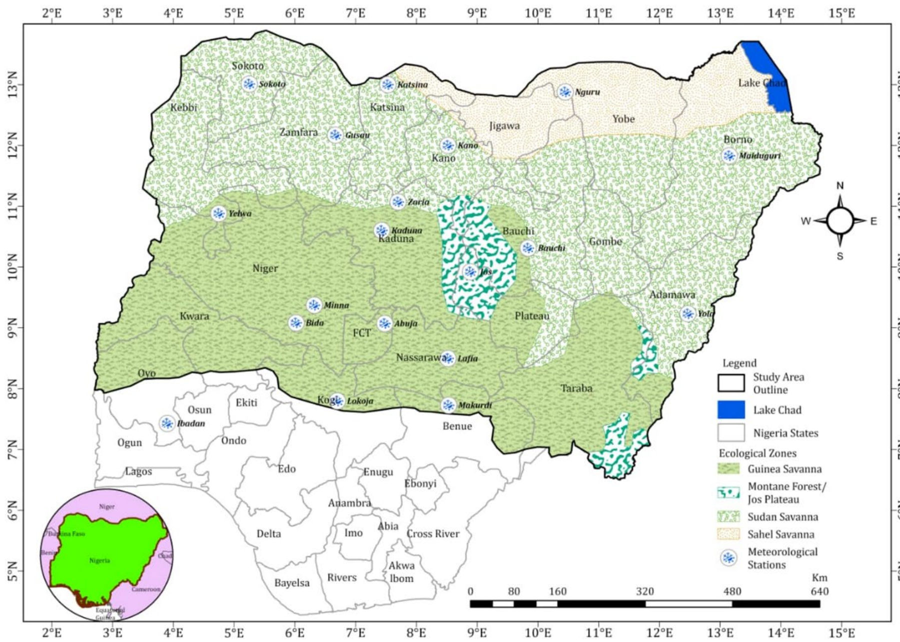


**Fig. 1** Digitized from the savanna ecological zones. Source: FORMECU [20]

and structural density, in which canopy cover and grass biomass decrease progressively northward in response to a declining rainfall gradient [1]. Following the classification of FORMECU [20], 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 (Fig. 1).

The socioeconomic significance of the study area is considerable. Savanna Zones of Nigeria are home to an estimated population of over 100 million people, the majority of whom depend on rainfed subsistence and smallholder agriculture for their livelihoods [39]. A 2019 national survey cited by Oladunni et al. [44] documented higher rates of dependence on agriculture in the Savanna Zones of 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.

### 2.2 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 across the study area, covering 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 Minna station in the Guinea savanna has the lowest CV (14.62%). Station selection was guided by spatial coverage across the four ecological

**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 |

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 [11, 72], 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.

## 2.3 Field survey design and sampling framework

### *2.3.1 Sampling strategy*

To ensure sample representativeness and methodological robustness, the four-stage sampling design was structured to capture the ecological, geographic, and socio-economic diversity of the savanna zones of Nigeria. The inclusion of all major savanna ecological zones (Guinea, Sudan, and Sahel) ensured ecological representativeness, while the purposive selection of 2–3 agriculturally dominant states per zone enabled the study to reflect spatial variability in climate regimes and livelihood systems. At subsequent stages, random selection of LGAs and communities reduced selection bias and improved within-zone representativeness [54].

The final sample size of 2400 households exceeds commonly recommended thresholds for household-based environmental and resilience studies and provides sufficient statistical power for multivariate analysis. According to Tabachnick and Fidell [62], a minimum sample size of at least 5–10 observations per variable is required for reliable Principal Component Analysis (PCA), while Hair et al. [25] recommend larger sample sizes to improve factor stability. With 46 variables included in this study, the sample size substantially exceeds these minimum requirements, thereby ensuring robustness of the PCA results. Similarly, Cochran [14] emphasises that larger sample sizes improve representativeness and reduce sampling error in heterogeneous populations, particularly in geographically extensive studies.

Potential sampling bias may arise from the purposive selection of states in the first stage and from accessibility constraints, especially in conflict-affected areas. However, these limitations were mitigated through ecological stratification, random sampling at lower stages, and broad spatial coverage of communities across the study area. Multistage cluster sampling is widely recognised as an efficient and reliable approach for large-area rural surveys where complete sampling frames are difficult to obtain [30, 54]. While the findings are broadly representative of Savanna Zones of Nigeria, caution is advised when generalising to highly inaccessible areas, and future studies may adopt fully probabilistic designs where feasible.

The sampling proceeded through four nested levels, as summarised in Table 2.

### 2.4 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.

**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 |

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. [1]. Ecological checklists documented observable changes in soil condition, vegetation structure, and species composition at each community location.

### 2.5 Indicator framework and variable operationalisation

Eco-climatic resilience was assessed through six core indicator dimensions collectively encompassing 46 variables, as presented in Table 3. 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 [57]. Adaptation practice items were scored according to frequency of adoption: 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, and 5 = Always.

### 2.6 Data analysis

#### *2.6.1 Climate data analysis: Mann–Kendall trend test*

The analytical framework is presented in Fig. 2. It links data collection, statistical reduction, spatial analysis and index construction with study objectives. The analytical procedure followed a sequential framework in which raw climatic and field data were transformed into dimension-specific indices using PCA, spatially modelled using GIS interpolation, and ultimately integrated into the composite ECRI.

**Table 3** 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 |

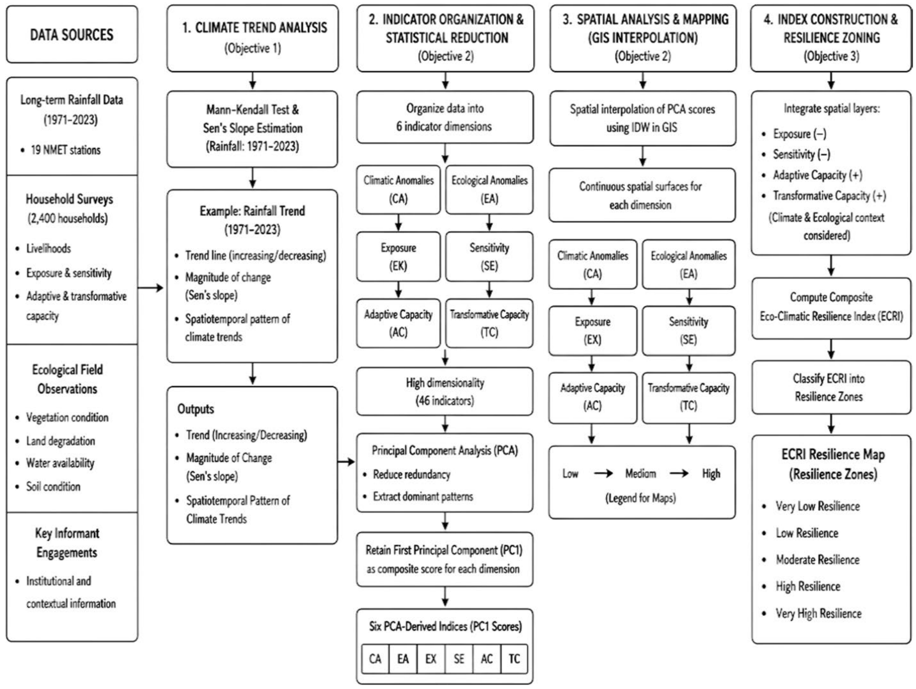


**Fig. 2** Analytical framework for developing the Eco-Climatic Resilience Index (ECRI). was applied to remove autocorrelation while preserving the trend signal. All analyses were performed in R (version 4.3.1) using the trend and Kendall packages

Long-term trends in annual rainfall were assessed using the non-parametric Mann–Kendall (MK) trend test [29, 33], with Sen's slope estimator [55] quantifying trend magnitude. The MK test was preferred for its distribution-free nature, robustness to outliers, and established application in African hydroclimatic trend detection [34, 63]. 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 [70]. Where significant autocorrelation was detected ($p < 0.05$), the trend-free pre-whitening (TFPW) procedure of Yue et al. [70]

### 2.7 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). While Principal Component Analysis (PCA) is traditionally designed for continuous variables, its application to ordinal data is widely accepted in environmental and social science research, particularly when ordinal responses approximate underlying continuous constructs [25, 28]. In this context, the ordinal indicators are interpreted as representing graded intensities of perceptions and conditions, allowing them to be treated as quasi-continuous variables for multivariate analysis.

The use of PCA is further justified by the objective of reducing a large number of correlated indicators (46 variables) into a smaller set of composite dimensions that capture dominant patterns of eco-climatic variability. PCA is particularly suitable for this purpose due to its ability to minimise redundancy, maximise explained variance, and generate uncorrelated component scores for subsequent spatial analysis. Nevertheless, the application of PCA to ordinal data entails certain assumptions and limitations. First, PCA assumes linear relationships and interval-level measurement, which may not be strictly satisfied by ordinal variables. Second, the use of Pearson correlation matrices may underestimate or distort relationships among ordinal variables compared to alternative approaches such as polychoric correlations. Third, the interpretation of component loadings may be influenced by the discrete and subjective nature of survey responses.

Despite these constraints, PCA remains a practical and robust method for exploratory dimensionality reduction in large, mixed datasets, especially when combined with careful interpretation. Alternative techniques such as factor analysis based on polychoric correlations, non-linear PCA, or categorical principal component analysis (CATPCA) could provide improved handling of ordinal data structures. However, these approaches often entail greater computational complexity and may limit comparability with existing studies that employ conventional PCA.

In this study, PCA results are interpreted as representing dominant gradients of eco-climatic conditions rather than precise latent constructs, and the findings are triangulated with ecological field observations and spatial analyses. Future research may explore the use of ordinal-specific multivariate techniques to further validate and refine the robustness of the results.

Following the derivation of dimension-specific indices through PCA, a Pearson's product-moment correlation (r) was used to evaluate the relationship between the Climatic Anomaly Index and the Ecological Anomaly Index. The bivariate analysis was conducted using a sample size of $n = 48$ communities to determine the extent to which climatic stressors drive ecological deterioration. Statistical significance was assessed at the $p < 0.001$ level.

### 2.8 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 [58]. 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.

To assess the accuracy and reliability of the IDW interpolation, a leave-one-out cross-validation (LOOCV) procedure was implemented. In this approach, each observed data point is temporarily removed, and its value is predicted using the remaining observations; the predicted value is then compared with the actual observed value. This process is repeated for all sample points, providing an objective measure of the model's predictive performance. Cross-validation statistics were computed to quantify interpolation accuracy, including the mean error (ME), mean absolute error (MAE), and root mean square error (RMSE). The mean error provides an indication of bias (i.e., systematic over- or under-estimation), while RMSE reflects the overall predictive accuracy by penalising larger deviations more strongly than MAE.

The results of the cross-validation indicated an RMSE of values ranging from 0.18 to 0.31 (on the normalised 0–1 index scale), Mean Absolute Error (MAE) values of 0.12–0.24, and Mean Prediction Error (MPE) values close to zero (−0.03 to +0.04), and Mean Prediction Error (MPE) values close to zero (−0.03 to +0.04), suggesting that the interpolation model provides (good/moderate/acceptable) predictive performance across the study area. The low mean error magnitude indicates limited systematic bias, while the RMSE and MAE values suggest that prediction errors remain within acceptable bounds for regional-scale analysis.

Although IDW is a deterministic interpolation method that does not explicitly model spatial autocorrelation or prediction uncertainty, cross-validation provides a practical means of evaluating its performance and ensuring that the interpolated surfaces are sufficiently reliable for spatial interpretation. However, prediction accuracy may vary across locations depending on data density and spatial heterogeneity, with higher uncertainty expected in sparsely sampled areas. These limitations should be considered when interpreting the resulting maps.

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.

### 2.9 Eco-Climatic Resilience Index (ECRI)

The thematic maps were integrated using the empirical relationship adapted from Subiyanto et al. [59] to derive the Eco-Climatic Resilience Index (ECRI) as expressed in Eq. (1):

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

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

The formulation of the Eco-Climatic Resilience Index (ECRI) in this study follows the widely accepted conceptualisation of resilience as a function of the balance between system capacities and system stresses. In this framework, adaptive capacity (ACI) and transformative capacity (TCI) represent the ability of households and institutions to cope with, adjust to, and transform in response to climate and ecological disturbances, while exposure (EI) and sensitivity (SI) represent the degree to which systems are subjected to and susceptible to those disturbances. The multiplicative combination of adaptive capacity and transformative capacity (ACI × TCI) reflects the assumption that these two components are complementary and mutually reinforcing dimensions of resilience. Adaptive capacity captures short- to medium-term coping and adjustment strategies at the household or community level, whereas transformative capacity reflects longer-term systemic and institutional change. Their interaction suggests that resilience is maximised when both capacities are simultaneously strong; a deficiency in either dimension constrains overall resilience.

The division of this combined capacity term by exposure and sensitivity ($EI \times SI$) follows the vulnerability-resilience framework established in the Intergovernmental Panel on Climate Change [27], which conceptualises vulnerability as a function of exposure and sensitivity, moderated by adaptive capacity. Under this logic, higher exposure and sensitivity increase vulnerability and reduce resilience, while higher adaptive and transformative capacities offset these effects. Similar multiplicative or ratio-based formulations have been applied in composite climate vulnerability and resilience indices to capture the non-linear interaction between stressors and response capacities [24, 59].

Alternative formulations could include additive models, weighted linear indices, or normalised composite indices derived through techniques such as weighted summation, entropy weighting, or analytic hierarchy processes (AHP). Additive approaches assume independent contributions of each component, while multiplicative models, as applied in this study, emphasise interaction effects and penalise imbalance among components. The choice of formulation therefore reflects a conceptual preference for representing resilience as a dynamic interaction rather than a simple aggregation of factors.

Notwithstanding its advantages, the adopted ECRI formulation has limitations. First, the multiplicative structure may amplify extreme values, potentially exaggerating spatial contrasts in resilience. Second, equal weighting is implicitly assumed across dimensions, which may not fully reflect their relative importance in different contexts. Third, the use of PCA-derived indices, while effective for dimensionality reduction, may obscure the contribution of individual variables. Future studies could explore alternative weighting schemes, sensitivity analysis, or hybrid modelling approaches to assess the robustness of the index formulation.

### 2.10 Uncertainty and limitations

While the study provides a comprehensive spatial assessment of eco-climatic resilience, it is important to acknowledge uncertainties inherent in the multi-stage analytical framework. First, uncertainties in rainfall trend analysis arise from limitations in station data, including spatial gaps in station coverage and potential measurement inconsistencies, which may affect the precision of Mann–Kendall trend estimates. Second, the household survey data are based on ordinal and perception-based responses, which may be subject to recall bias, subjective interpretation, and variability across respondents. Although efforts were made to ensure consistency through instrument design and enumerator training, such uncertainties cannot be entirely eliminated.

Third, the application of Principal Component Analysis (PCA) introduces statistical uncertainties related to dimensionality reduction. While PCA efficiently captures dominant patterns in the data, especially through PC1, it may not fully represent secondary variability, particularly in dimensions with relatively low explained variance. As a result, some nuances in eco-climatic conditions may be underrepresented in the derived indices. Fourth, uncertainties are associated with the spatial interpolation process. The use of Inverse Distance Weighting (IDW), while suitable for generating continuous surfaces from point data, is a deterministic method that does not explicitly model spatial autocorrelation or prediction uncertainty. Although cross-validation was performed to assess interpolation accuracy, prediction errors may persist, particularly in sparsely sampled areas or regions with high spatial heterogeneity. Finally, the construction of the Eco-Climatic Resilience Index (ECRI) introduces additional uncertainty due to methodological assumptions, including the multiplicative formulation of index components, the use of PCA-derived scores, and implicit equal weighting across dimensions. These assumptions may influence the magnitude and spatial distribution of resilience values.

Taken together, these sources of uncertainty suggest that the ECRI maps should be interpreted as indicative of relative spatial patterns rather than exact measures of resilience. Despite these limitations, the integration of multiple data sources, statistical techniques, and spatial analysis provides a robust and internally consistent framework for identifying broad resilience gradients and priority areas for intervention. Future studies could incorporate uncertainty quantification techniques, such as sensitivity analysis, alternative interpolation methods (for example, kriging), and probabilistic modelling approaches, to further refine the robustness of the results.

## 3 Results

### 3.1 Rainfall trends across Savanna zones of Nigeria (1971–2023)

The Mann–Kendall trend test and Sen's slope estimator are represented in Table 4. The results revealed a mixed pattern of rainfall trends (upward, downward, significant increase, and non-significant trends) across the savanna region of 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 ($Z = 2.19$, $p = 0.03$),

**Table 4** 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 |

*Significance $\alpha = 0.05$

Nguru ($Z = 2.69$, $p = 0.01$), and Kano ($Z = 4.26$, $p < 0.01$) 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 ($Z = -2.05$, $p = 0.04$), Jos ($Z = -3.37$, $p < 0.01$), Abuja ($Z = -2.17$, $p = 0.03$), and Makurdi ($Z = -4.65$, $p < 0.01$) 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.

### 3.2 PCA of eco-climatic resilience dimensions

In this study, the first principal component (PC1) was retained for each indicator dimension to represent the dominant pattern of variation in the data. The selection of PC1 is grounded in its ability to capture the maximum proportion of total variance in the dataset, thereby providing the most parsimonious and statistically robust summary of the underlying structure [25, 28]. From a practical perspective, the use of a single composite score per dimension also facilitates spatial analysis and mapping, as it avoids redundancy and reduces the complexity associated with integrating multiple correlated components into a geospatial framework. The decision to use PC1 alone is consistent with similar applications in environmental and geospatial studies, where the first component is often interpreted as the primary latent gradient driving system behaviour [21]. In this study, PC1 represents the dominant eco-climatic signal within each dimension, integrating multiple related indicators into a single interpretable index suitable for spatial interpolation and comparison across locations.

However, it is acknowledged that for certain dimensions, particularly ecological anomalies, adaptation practices, and transformative capacity, PC1 explains less than 40% of the total variance. This indicates that these dimensions exhibit relatively complex and multidimensional structures that are not fully captured by a single component. The exclusion of higher-order components (e.g., PC2, PC3) may therefore result in the loss of additional variability and potentially obscure secondary patterns or sub-dimensions within the data.

Despite this limitation, the retention of PC1 was prioritised to maintain methodological consistency across all dimensions and to enable the development of a unified and comparable index framework for ECRI construction. Including multiple components for some dimensions but not others would introduce inconsistencies in scale and interpretation, complicating integration into the composite index and subsequent spatial modelling.

Alternative approaches could involve retaining multiple components based on cumulative variance thresholds (e.g., 60–70%), applying weighted aggregation of selected components, or using factor scores derived from rotated solutions to better capture multidimensional structures. While such approaches may provide a more detailed representation of specific dimensions, they also increase analytical complexity and may reduce interpretability in spatial mapping contexts. Future research could explore these alternative strategies through sensitivity analysis to assess how the inclusion of additional components influences the spatial distribution of eco-climatic resilience. Such analyses would help to further validate the robustness of the PC1-based approach adopted in this study.

### 3.3 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 (Fig. 3) 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.

### 3.4 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

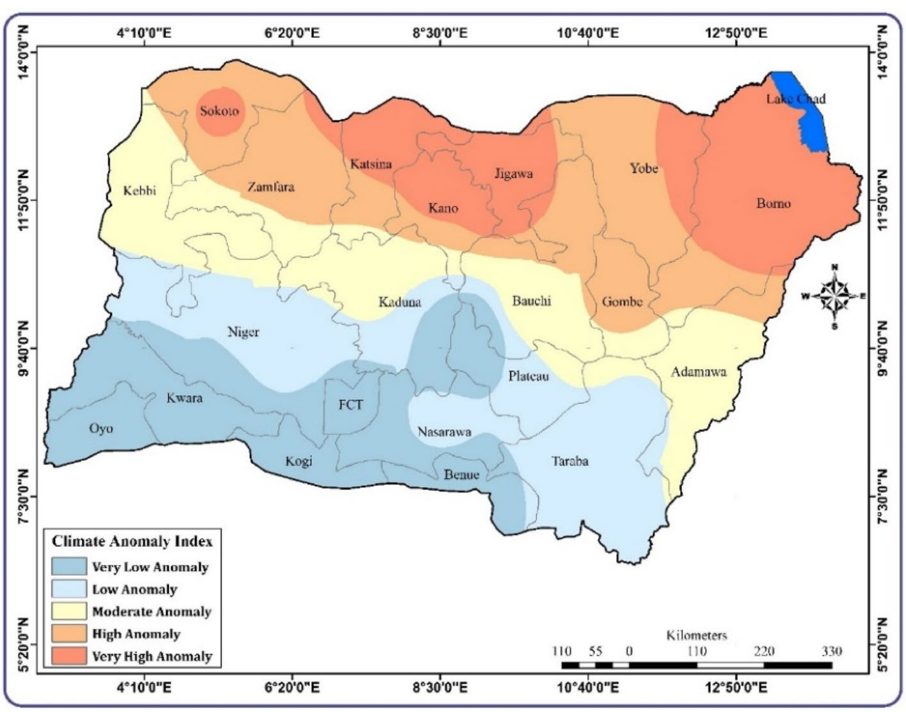


**Fig. 3** PCA-derived climatic anomaly map of savanna ecological zones

(r = 0.82; n = 48; $p < 0.001$) between the Climatic Anomaly Index and the Ecological Anomaly Index confirms that climatic stress is the primary, though not exclusive, driver of ecological deterioration across the study area. Spatially (Fig. 4), 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.

### 3.5 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 (Fig. 5) 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.

### 3.6 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,

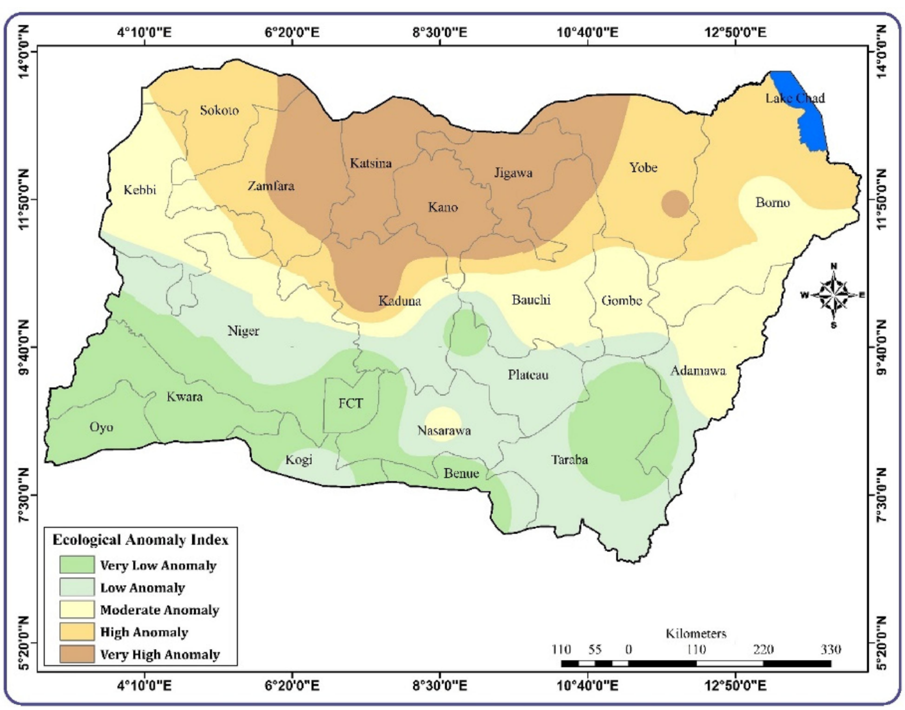


**Fig. 4** PCA-derived ecological anomaly map of savanna ecological zones

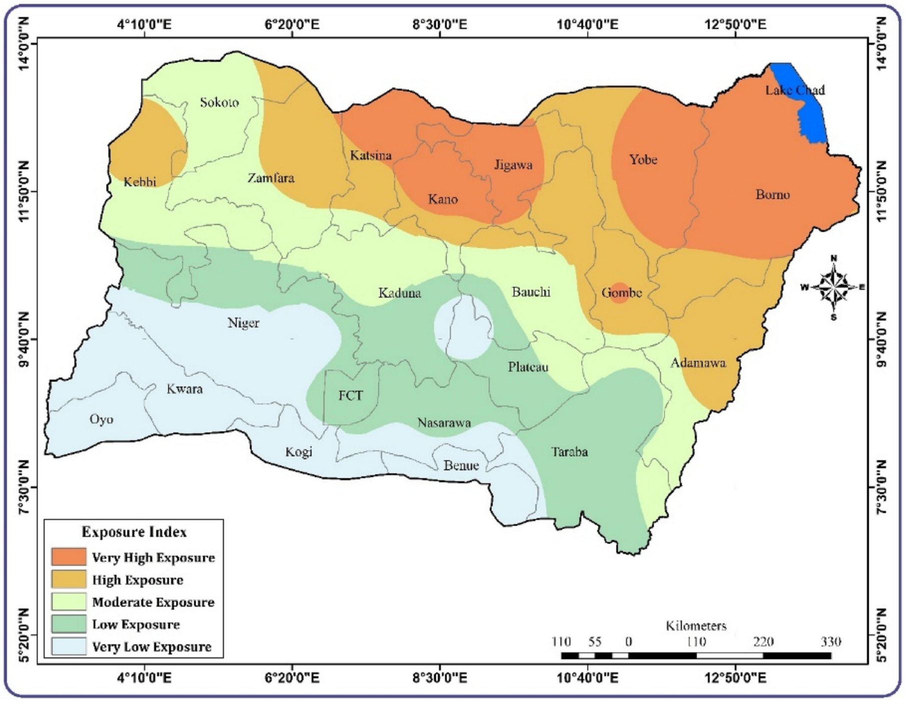


**Fig. 5** PCA-derived eco-climatic exposure map of savanna ecological zones

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 (Fig. 6), 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.

### 3.7 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 (Fig. 7) 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

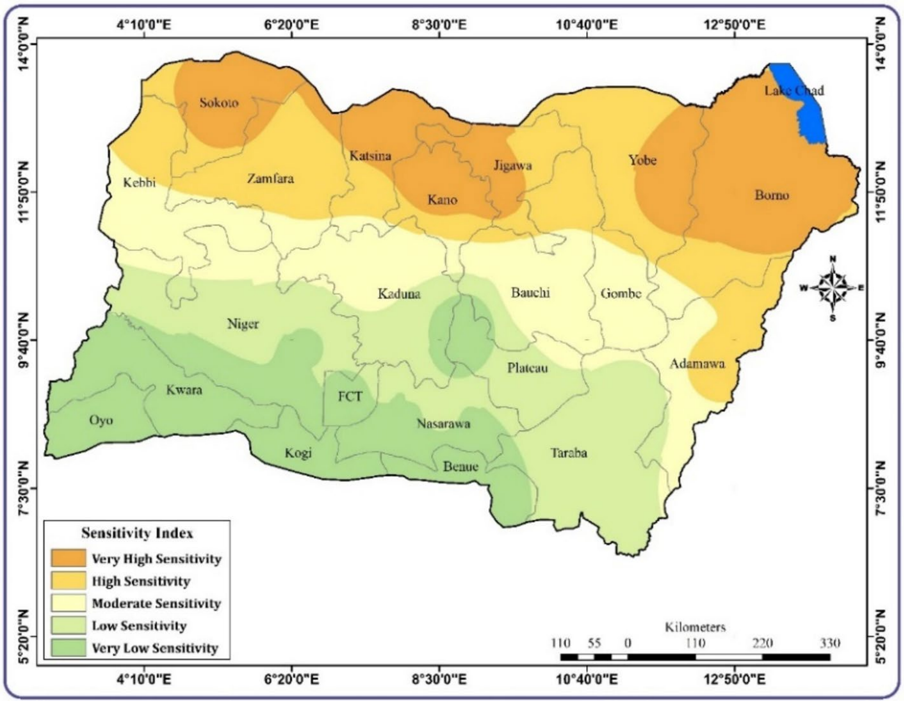


**Fig. 6** PCA-derived eco-climatic sensitivity map of savanna ecological zones

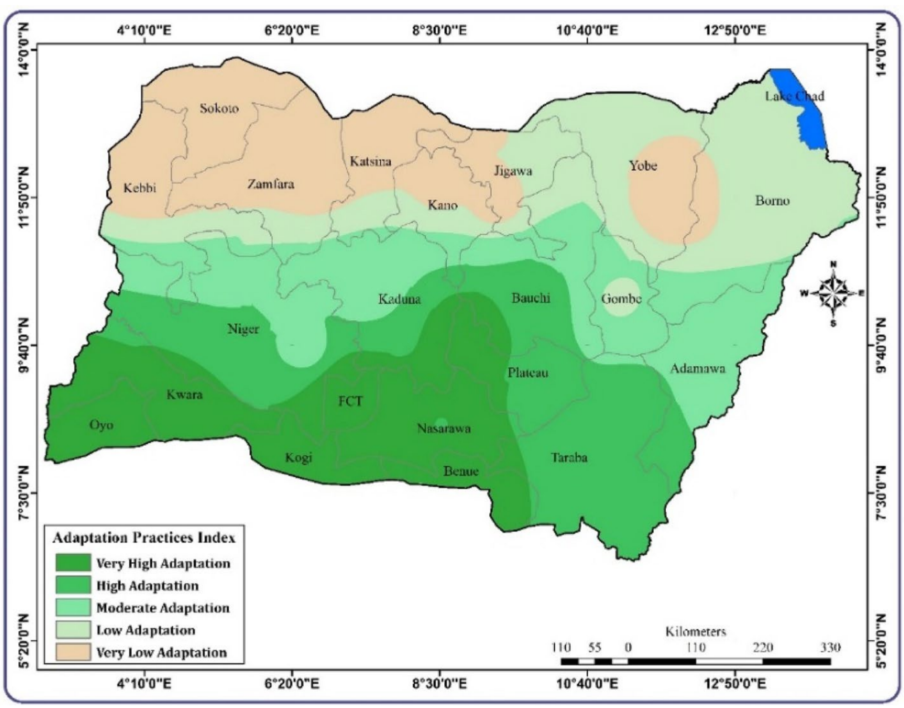


**Fig. 7** PCA-derived eco-climatic adaptation map of Savanna ecological zones

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.

### 3.8 Transformative adaptation capacity

The transformative 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 (Fig. 8), high to very high transformative 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.

### 3.9 Spatial distribution of eco-climatic resilience index

The geospatial integration of the exposure, sensitivity, adaptive capacity, and transformative adaptation capacity indices reveals spatially differentiated levels of the Eco-Climatic Resilience Index (ECRI) across the study area, underscoring the imperative for targeted interventions to build livelihood resilience. The spatial distribution of the ECRI shows a pronounced north–south gradient in resilience potential. Higher ECRI

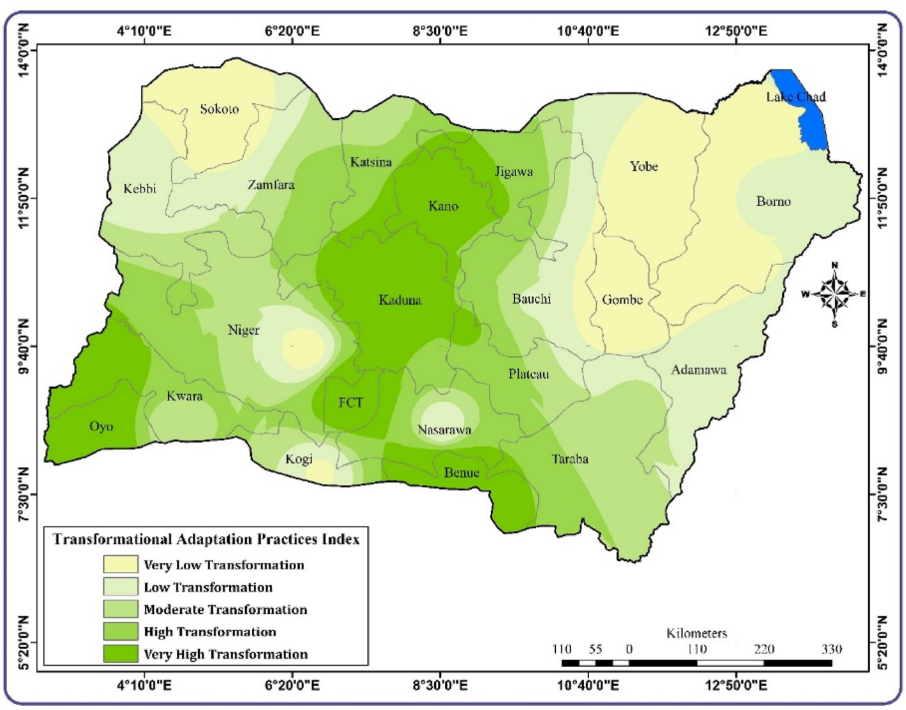


**Fig. 8** PCA-derived eco-climatic transformative adaptation practices

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 (Fig. 9) 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.

Overall, the six-dimensional PCA framework and composite ECRI mapping demonstrate that eco-climatic resilience in Savanna Zones of 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.

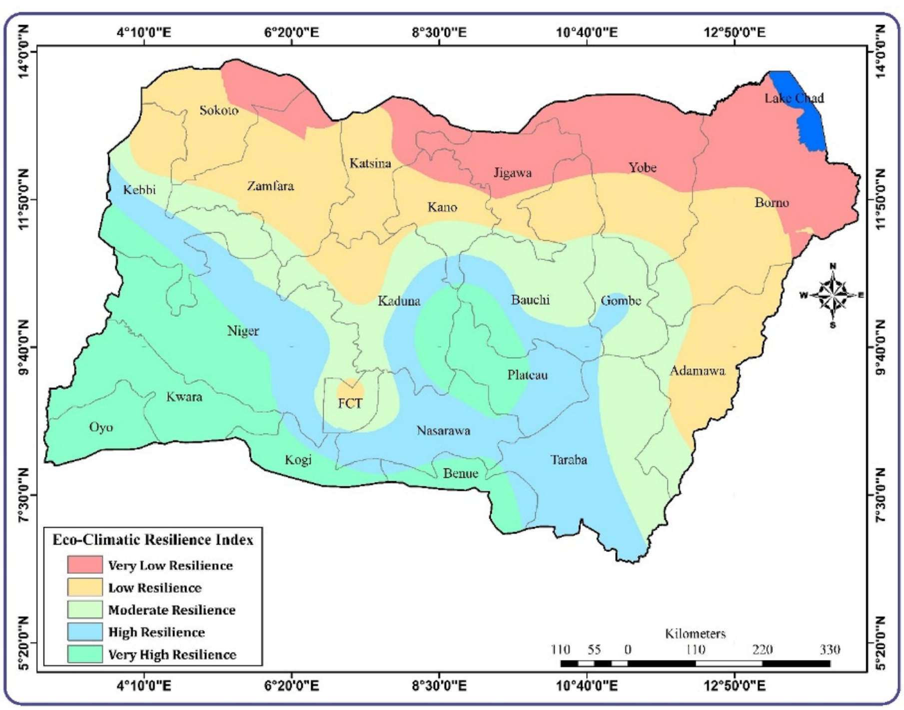


**Fig. 9** Eco-climatic resilience index map of savanna ecological zones of Nigeria

## 4 Discussion

While the spatial patterns observed in the ECRI provide important insights into eco-climatic resilience across savanna zones of Nigeria, some interpretations regarding governance effectiveness, institutional capacity, NGO performance, and conflict dynamics extend beyond the variables directly measured in this study. These factors were not explicitly quantified but were inferred from observed spatial patterns and supported by existing literature. As such, these interpretations should be understood as plausible contextual explanations rather than direct empirical findings derived from the dataset.

### 4.1 Core mechanism explanation

Beyond comparison with previous studies, the spatial patterns of eco-climatic resilience observed in this study can be interpreted as the outcome of interacting climatic, ecological, and socio-institutional processes. The north–south gradient in resilience reflects a coupled system in which increasing climatic stress (for example, rainfall variability, heat stress, and shorter growing seasons) interacts with declining ecological resource availability and higher system sensitivity. In the Sahelian zone, high climatic anomalies coincide with reduced vegetation cover, soil moisture deficits, and lower biodiversity, which together amplify ecosystem sensitivity. This biophysical stress is compounded by lower levels of adaptive and transformative capacity, thereby limiting communities' ability to buffer against or recover from disturbances.

Conversely, in the Guinea Savanna and central zones, relatively stable rainfall regimes, higher soil moisture, and more productive ecosystems provide a natural buffering effect that reduces sensitivity. These favourable biophysical conditions are reinforced by higher levels of adaptive practices and stronger institutional engagement, creating reinforcing feedback that enhances overall resilience. Thus, resilience emerges not from a single factor, but from the interaction between environmental stability, ecosystem function, and socio-economic capacity.

### 4.2 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 savanna zones of 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. [2], indicating that the trajectory of aridification documented over preceding decades has continued and intensified. Piao et al. [49] 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 increased rainfall in the West African Sahel [16, 26]. It also aligns with projections from CMIP6 models, suggesting non-uniform redistribution of rainfall across West Africa under warming scenarios. In similar studies, Biasutti [9] and Saley and Salack [51] observed increased rainfall in the northern part of the Sahel and downward rainfall trends 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. [69], 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 [12, 67]. Previous studies explain that although annual rainfall totals have shown signs of recovery from the great Sahelian droughts of the 1970s and 1980s, rainfall is now increasingly erratic [9, 53]. Therefore, the erratic nature of rainfall subjects rainfall-dependent farmers to alternating years of surplus and severe deficits, which undermines agricultural planning, increases production risks, and weakens the adaptive capacity of rural livelihoods [6, 10, 61]. Other studies have linked increased rainfall in the Sahel to increased rainfall intensity during extreme events, with no increase in the number of rainy days [10, 64] (Panthou et al. [47]).

Generally, this pattern suggests that climatic anomalies influence resilience indirectly through their effects on ecological processes, particularly soil moisture dynamics and vegetation productivity, which are key determinants of sensitivity in rainfed agricultural systems.

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 [13].

### 4.3 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. [15], 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. [68] and Faiz et al. [18], 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) show higher exposure than at comparable latitudes to the west. This longitudinal differentiation in exposure has not been previously mapped at this spatial resolution for the Savanna Zones of 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. [4] and Obossou et al. [42], which reduces the ecological buffering provided by surface water and grassland resources in eastern states. Pascual et al. [48] 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.

### 4.4 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 adoption of adaptive practices. This maladaptation geography, where need and capacity are spatially anti-correlated, is not unique to Savanna Zones of Nigeria: Eriksen et al. [17] 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 [50].

The Transformative 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, transformative adaptation scores are lowest, precisely where systemic change is most urgently required. This finding aligns with UNFCCC [65] 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.

### 4.5 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 and Lee [71] and Beck et al. [8] 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. [46] 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.

### 4.6 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 [3, 45]. Moran et al. [37] 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 and Agrawal [56] 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.

### 4.7 Implications for location-specific eco-climatic resilience policy

The Eco-Climatic Resilience Index (ECRI) developed in this study provides an empirically grounded framework for translating multidimensional vulnerability into actionable policy. By conceptualising resilience as the balance between adaptive and transformative capacities relative to exposure and sensitivity, the results demonstrate that resilience deficits emerge where biophysical stressors and socio-institutional constraints co-occur and reinforce one another [27, 59].

The spatial structure of the ECRI reveals that eco-climatic resilience across savanna zones of Nigeria is governed not by a single driver, such as rainfall magnitude, but by the interaction among climatic anomalies, ecological degradation, and unevenly distributed adaptive capacity. This finding is consistent with recent work showing that resilience in dryland systems is determined by coupled socio-ecological dynamics rather than climatic trends alone [17, 67]. Consequently, effective climate adaptation policy must move beyond generic interventions and instead target the specific configurations of exposure, sensitivity, adaptive capacity and transformative capacity that define each resilience zone.

### 4.8 Targeting systemic vulnerability in very low-resilience zones

The Sahelian and semi-arid northern states (Sokoto, Zamfara, Katsina, Kano, Jigawa, Yobe, and Borno) represent a convergence of high climatic variability, ecological degradation, and limited adaptive and institutional capacity, resulting in the lowest ECRI values. This configuration reflects a systemic vulnerability regime in which both ecological buffering and institutional response mechanisms are insufficient to absorb climate shocks. Policy in these zones should therefore prioritise the simultaneous reduction in sensitivity and exposure, alongside the expansion of adaptive and transformative capacity. The strong statistical coupling of soil moisture, vegetation cover and plant productivity within the sensitivity dimension indicates that ecosystem restoration will generate cascading resilience benefits across multiple system components. Large-scale agroforestry, assisted natural regeneration and soil moisture conservation interventions are therefore likely to produce disproportionate gains relative to single-factor interventions [18, 68].

In parallel, the dominance of rainfall variability, false onset events and shortened growing seasons within the climatic anomaly structure underscores the need for climate-informed decision systems, including decentralised early warning mechanisms linked to seasonal forecasts [35]. Critically, the spatial inversion identified between vulnerability and adaptation capacity implies that resilience-building in these regions requires prioritised investment in adaptive capacity, including drought-resilient crop systems and locally appropriate land management practices. At the institutional level, strengthening community-based governance of rangelands and water resources is essential, given the central role of participatory and collective action processes in driving transformative adaptation [65].

### 4.9 Scaling adaptive systems in transitional low-resilience zones

Low-resilience transitional zones (notably parts of Kebbi, Adamawa and Gombe) exhibit moderate levels of exposure and sensitivity but limited institutional reach. In these areas, resilience is not absent but remains underdeveloped, suggesting that incremental gains can be achieved through scaling and consolidation rather than structural overhaul. Policy interventions should therefore focus on amplifying existing adaptive practices and improving their accessibility and consistency across communities. Soil degradation remains a key ecological constraint in these zones, indicating that targeted soil restoration and erosion control programmes will directly reduce sensitivity while enhancing productivity [15].

Simultaneously, expanding the geographic and functional reach of extension services, NGOs and local governance institutions can strengthen transformative capacity and accelerate the transition toward higher resilience states.

### 4.10 Stabilising resilience in moderate zones under climate pressure

In the central belt (including Bauchi, Nasarawa, Taraba and parts of Kaduna), the ECRI identifies an intermediate condition in which adaptive capacity has increased, but remains vulnerable to erosion under continued climatic stress. This reflects a dynamic equilibrium in which improvements in livelihood systems are offset by rising environmental pressures. Maintaining resilience in these zones requires protecting and reinforcing existing adaptive capacity, particularly in agricultural systems. Climate-smart intensification strategies that enhance productivity while reducing dependence on climate-sensitive inputs can reduce exposure and improve system stability [67].

Given the tightly coupled nature of vegetation and soil processes identified in the sensitivity dimension, sustained investment in soil moisture management and vegetation cover is also critical to preventing non-linear degradation and loss of ecosystem function [68].

### 4.11 Leveraging high-resilience zones for regional transformation

High- and very-high-resilience zones in the Guinea Savanna and plateau regions (including Niger, Kwara, Oyo, Benue and Plateau) are characterised by lower ecological stress, higher adaptive capacity and stronger institutional frameworks. These areas function as resilience "anchors" within the regional system. Policy in these zones should focus on maintaining ecosystem integrity while facilitating horizontal transfer of knowledge, practices and institutional models to lower-resilience regions. Evidence from adaptation research indicates that peer-to-peer learning, local innovation systems and community governance frameworks can diffuse effectively across similar socio-ecological contexts [17].

Investments in conservation, climate-resilient land management and institutional strengthening will ensure that these zones continue to provide both local stability and regional spillover benefits.

### 4.12 Addressing the adaptation deficit as a structural constraint

A central empirical contribution of this study is the identification of a persistent adaptation deficit, whereby the regions experiencing the highest climatic and ecological stress exhibit the lowest levels of adaptive and transformative capacity. This spatial mismatch reflects broader structural inequalities in access to resources, institutions and knowledge systems, and has been identified as a major constraint on effective climate adaptation in developing regions [17, 27].

Addressing this deficit requires a shift from uniform policy frameworks to targeted, spatially differentiated investment strategies, prioritising the most vulnerable regions. Crucially, the multiplicative structure of the ECRI demonstrates that improvements in a single dimension are insufficient: resilience emerges only where adaptive and transformative capacities increase concurrently with reductions in exposure and sensitivity.

### 4.13 Towards spatially explicit, systems-based climate policy

The ECRI framework highlights the limitations of conventional, sector-specific adaptation approaches and underscores the need for integrated, systems-based climate policy. By linking climate anomalies, ecological processes and socio-institutional dynamics within a unified spatial framework, the study provides a scalable approach for identifying priority intervention areas and aligning policy with underlying vulnerability drivers.

Such spatially explicit approaches are increasingly recognised as essential for effective climate resilience planning, particularly in heterogeneous dryland environments where vulnerability varies at sub-national scales [27, 58]. In this context, the results demonstrate that resilience-building in savanna zones of Nigeria requires coordinated action across ecological restoration, livelihood adaptation and institutional transformation, implemented in a geographically differentiated manner.

## 5 Conclusion

A favourable climate is vital for sustainable livelihoods in the savanna zones of 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 and resulting in 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, biodiversity loss, poverty, socio-economic instability, and southward migration. This study developed a sub-national empirical Eco-Climatic Resilience Index for the savanna zones of Nigeria, integrating PCA-derived community-level indices across six biophysical and social dimensions. The findings established that though the stations in the 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 zones, faced with increasing eco-climatic anomalies and their attendant crop failure, famine, insecurity, and southward migration, which is aggravating crime across the country. Beyond its empirical findings, this study contributes methodologically by proposing a transferable framework for integrating climatic, ecological, socioeconomic, and institutional indicators into a composite resilience index using objective statistical weighting and geospatial analysis. The framework demonstrates how multidimensional resilience can be quantified and mapped at sub-national scales, providing a practical decision-support tool for climate adaptation planning. This methodological contribution extends beyond Savanna Zones of Nigeria and can be adapted to other dryland regions of West Africa facing similar climate and ecological challenges.

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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.

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

**Clinical trial number**
Not applicable.

## Declarations

**Ethics approval and consent to participate**
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. Informed consent was obtained from all participants prior to completing the questionnaire.

**Consent to publication**
Consent to publish is not applicable, as no identifiable personal information is included in this study.

**Competing interests**
The authors declare no competing interests.

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