



Spatio-Temporal Assessment of Desertification Sensitivity in the Sudan Savannah Zone of Nigeria: A 25-Year MEDALUS-Based Analysis

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ABSTRACT

Aims: Desertification threatens the balance of dryland ecosystems across Nigeria's Sudan Savannah zone. This study applies the Mediterranean Desertification and Land-Use (MEDALUS) model to assess the spatio-temporal dynamics of desertification sensitivity in Jigawa and Yobe States over 25 years (2000-2025) at five-year intervals.

Materials & Methods: We integrated Landsat-derived Land-Use/Land-Cover (LU/LC) change detection with the MEDALUS quality index framework, an approach rarely applied at this temporal scale in the region. Soil (SQI), Vegetation (VQI), Management (MQI), and Climate (CQI) Quality Indices were combined to derive the Desertification Sensitivity Index (DSI); Mann-Kendall trend and Pearson/Spearman correlation analyses examined LU/LC-DSI relationships.

Findings: LU/LC classification accuracy exceeded 94% (Kappa >0.89) across all epochs. Over 54% of the study area was classified under High desertification sensitivity at every epoch, peaking with a Very High DSI share of 7.02% in 2015 - driven by soil quality decline and bareland expansion - before moderating to 2.98% by 2025. LU/LC recorded a net farmland loss of 5,571.71 km² and bareland expansion of 1,492.70 km² (2015-2025). These changes are consistent with anthropogenic pressure being associated with DSI intensification, rather than establishing it as the principal causal driver, alongside the climatic influences discussed below.

Conclusion: The findings highlight a persistently elevated but conditionally reversible desertification trajectory - the post-2015 amelioration being contingent on sustained land management and favorable climatic conditions rather than assured - emphasizing the need for land restoration policy and soil conservation strategies aligned with Nigeria's Land Degradation Neutrality commitments and the African Union's Great Green Wall Initiative.

Keywords: Desertification Sensitivity Index; Land-Use/Land-Cover Change; MEDALUS; Remote Sensing and GIS; Semi-Arid Region.

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Introduction

Land degradation and desertification are among the most persistent and economically costly environmental problems of the twenty-first century. Desertification is the loss of the natural or economic productivity of drylands due to Land-Use and related processes, affecting 33-39% of the global land surface and threatening 1.5-3.2 billion people worldwide^[1,2]. In Africa, where a large share of the population depends on rain-fed agriculture, severe land degradation has driven declining crop yields, accelerated soil erosion, biodiversity loss, and rising food insecurity^[3].

The MEDALUS model, developed by Kosmas et al.^[4] and refined through European Union research programs, provides a robust and internationally validated methodology for assessing desertification risk. The model computes a Desertification Sensitivity Index (DSI) by combining four environmental quality indices - Soil (SQI), Vegetation (VQI), Management (MQI), and Climate (CQI) - through a geometric mean formulation. This approach has been applied across the Mediterranean Basin^[5,6], sub-Saharan Africa^[7], and Nigeria^[8], demonstrating its regional adaptability.

Remote sensing and GIS have reduced the time required to monitor desertification and expanded the spatial scale at which land degradation can be assessed. Spatio-temporal analyses combining Landsat, Sentinel, and MODIS data with climate, soil, and vegetation indices can detect slow, progressive change over decadal scales^[9]. Despite this, MEDALUS applications remain sparse in West Africa; existing studies in sub-Saharan Africa are largely short-term and integrate limited long-term LU/LC dynamics and climate variability. Few studies^[8] have

applied MEDALUS in the Sudano-Sahelian zone of Nigeria - a country facing some of the most serious desertification pressures in sub-Saharan Africa - and none have conducted a continuous 25-year assessment capturing land degradation dynamics, including post-peak recovery.

This study addresses that gap through a spatio-temporal assessment of desertification sensitivity using the MEDALUS framework at five-year intervals between 2000 and 2025 across Jigawa and Yobe States, Nigeria. The specific objectives were to: (i) map the spatial distribution of SQI, VQI, MQI, CQI, and DSI for each epoch; (ii) quantify area-based changes in quality class distribution over time; (iii) integrate LU/LC change detection to contextualize land-cover drivers of DSI variability; and (iv) evaluate temporal trends and associations using the Mann-Kendall trend test and Pearson/Spearman correlation analyses. Despite the MEDALUS framework's demonstrated versatility, its application to Nigeria and the wider Sudano-Sahelian zone remains limited in three important respects. First, existing MEDALUS-based assessments in the region^[8] are largely single-epoch or short-interval snapshots, so they have not characterized the trajectory of desertification sensitivity over multi-decadal timeframes, including any post-peak recovery. Second, most prior applications treat the four quality indices in isolation from land-cover change processes, without explicitly linking LU/LC transitions to the drivers of DSI variability, limiting their diagnostic and policy value. Third, none of the available studies address the scale mismatch between coarse-resolution climate inputs and fine-resolution remote-sensing indices, a methodological gap

with direct implications for interpreting climate-driven quality classes. By providing a continuous 25-year, five-year assessment that integrates LU/LC change detection with the MEDALUS indices and explicitly interrogates this scale mismatch, the present study addresses these three gaps. It extends the MEDALUS framework to the Sudano-Sahelian context.

Materials & Methods

Study Area

Jigawa and Yobe States lie in northeastern Nigeria, with a combined extent of approximately 69,566 km² between 11°30'N–14°30'N and 9°00'E–13°30'E (Figure 1). This extent is the area enclosed by the GIS boundary layer used for the spatial analysis, and it differs slightly from the sum of the officially published administrative areas of Jigawa and Yobe States. Both states border the Republic of Niger to the north. The climate is semi-arid, with mean annual rainfall of 300–700 mm concentrated in June–September, mean temperatures of 27–35°C, potential evapotranspiration exceeding 2,000 mm.yr⁻¹, and recurrent drought. The region supports an estimated population exceeding 15 million (2023 projection), growing at 3.2–3.5% per annum, exerting intensifying pressure on land resources. Soils are predominantly coarse, shallow, and low in organic matter, making them vulnerable to wind and water erosion. Vegetation ranges from degraded Sudano-Sahelian savanna in the north to agropastoral mosaics and riparian corridors in the south, and population pressure has driven agricultural expansion, overgrazing, fuelwood extraction, and settlement encroachment onto previously vegetated land [10], all reflected in the observed LU/LC and DSI dynamics.

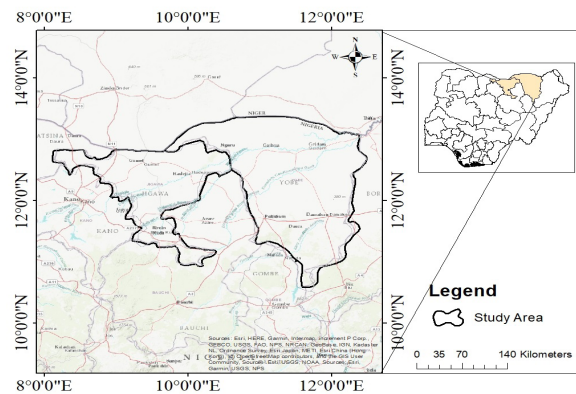


Figure 1) Location of the study area: Jigawa and Yobe States (bold outline) in the Sudan Savannah zone of northeastern Nigeria, bordering the Republic of Niger, shown on a reference basemap with graticule and scale bar; the inset shows the position of the two states (shaded) within Nigeria.

Data Sources

Multi-temporal Landsat imagery (Landsat 7 ETM+ and Landsat 8 OLI, 30 m resolution)^[11] was processed in Google Earth Engine (GEE)^[12] for 2000, 2005, 2010, 2015, 2020, and 2025 (dry season), with composites generated to minimize cloud cover (<10%). Auxiliary datasets included the SRTM DEM (30 m)^[13], ERA5 monthly precipitation and temperature reanalysis^[14], FAO Harmonized World Soil Database (HWSD v1.2) soil properties^[15], and LandScan/GPW population data^[16]. We derived NDVI^[17] composites from surface reflectance to characterize vegetation. We resampled all datasets to 30 m resolution (Table 1).

LU/LC Classification and MEDALUS Implementation

We used a Random Forest classifier^[18] in GEE for LU/LC classification, following radiometric calibration, atmospheric correction, cloud masking, and geometric alignment. We drew training samples from composite imagery and assessed classification accuracy using Overall Accuracy (OA) and the Kappa coefficient^[19,20] with a 70/30 train-validation split. OA ranged from 94.04–97.78% and Kappa from 0.8949–0.9605 across all epochs, confirming high

reliability. This is consistent with Kappa-based validation levels reported for comparable Landsat-based decision-tree and classification workflows in other semi-arid settings ^[21].

Table 1) Data sources, processing platforms, and derived outputs used to compute the MEDALUS quality indices (SQI, VQI, MQI, and CQI) and the Desertification Sensitivity Index (DSI) for Jigawa and Yobe States, Nigeria, 2000–2025.

Component	Data Source	Processing Platform	Output
Landsat Imagery	USGS (Landsat 7, 8)	Google Earth Engine	LU/LC maps, NDVI
DEM	SRTM (30 m)	Google Earth Engine	Slope, Aspect
Climate Data	ERA5 Reanalysis	Google Earth Engine	Rainfall, Aridity
Soil Data	FAO HWSD v1.2	Google Earth Engine	Soil Properties
Population Data	LandScan / GPW	Google Earth Engine	Human Pressure
MEDALUS Indices (SQI, VQI, MQI, CQI)	Derived Datasets	Google Earth Engine	Quality Index Maps
Desertification Sensitivity Index (DSI)	Computed (Geometric Mean)	Google Earth Engine	DSI Maps
Map Layout & Visualization	Exported GeoTIFFs	ArcGIS	Final Maps

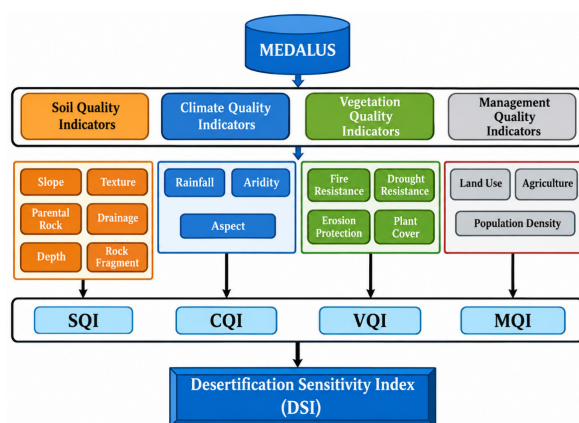


Figure 2) Methodological flowchart of the MEDALUS framework applied in this study, showing the indicators grouped under soil, climate, vegetation, and management quality, their aggregation into the Soil (SQI), Climate (CQI), Vegetation (VQI), and Management (MQI) Quality Indices, and the combination of the four indices into the Desertification Sensitivity Index (DSI).

The MEDALUS approach was implemented entirely in GEE (Figure 2). SQI, VQI, MQI, and CQI were derived from relevant variables (soil properties, NDVI, Land-Use, rainfall, slope), each reclassified from 1 (low sensitivity) to 2 (high sensitivity) and combined via geometric mean; DSI was then computed as the geometric mean of the four indices and classified into Low (1.00-1.22), Moderate (1.23-1.38), High (1.39-1.53), and Very High (1.54-2.00) sensitivity, following thresholds established by Kosmas et al. ^[4] and adopted in subsequent applications ^[22,23]. We classified individual quality indices as Weak (1.00-1.33), Moderate (1.34-1.66), or High (1.67-2.00) sensitivity. ERA5 monthly precipitation (0.25 degree resolution) was aggregated to mean annual totals over a 5-year window centered on each epoch and downscaled to the 30 m grid via bilinear interpolation. Because the study area lacks formal protected areas, MQI incorporated LandScan population density as a proxy for land-use intensity; despite this adjustment, MQI remained the weakest and least spatially discriminating component, consistent with other dryland applications lacking formal land-governance data ^[23].

The quality indices and the DSI were computed as geometric means of their constituent variable scores, following Kosmas et al. ^[4]:

$$SQI = \sqrt[5]{Pm \times T \times D \times S \times Rf} \quad \text{Eq. (1)}$$

where Pm is the parent material score, T is the soil texture score, D is the soil depth score, S is the slope gradient score, and Rf is the surface rock fragment (stoniness) score.

$$VQI = \sqrt[4]{VC \times DR \times EP \times FR} \quad \text{Eq. (2)}$$

where VC is the vegetation (plant) cover

score, DR is the drought resistance score, EP is the erosion protection score, and FR is the fire risk score.

$$MQI = \sqrt[3]{HP \times GP} \quad \text{Eq. (3)}$$

where HP is the human pressure score (derived from LandScan population density), and GP is the grazing pressure score.

$$CQI = \sqrt[3]{R \times AI} \quad \text{Eq. (4)}$$

where R is the rainfall score, and AI is the aridity index score.

$$DSI = \sqrt[4]{SQI \times VQI \times MQI \times CQI} \quad \text{Eq. (5)}$$

where SQI, VQI, MQI, and CQI are the Soil, Vegetation, Management, and Climate Quality Indices obtained from Eqs. (1)–(4), respectively, and DSI is the Desertification Sensitivity Index, ranging from 1 (least sensitive) to 2 (most sensitive).

Each variable within Eqs. (1)–(5) was scored on the standard MEDALUS 1–2 ordinal scale (1 = low sensitivity, 2 = high sensitivity) following the published class breakpoints of Kosmas et al. [4], then combined by geometric mean within each quality index before the four indices were themselves combined by geometric mean into DSI. This nested geometric mean structure was adopted, rather than an additive or weighted-sum structure, because it is the original and most widely replicated MEDALUS formulation and because a single very poor variable constrains the overall index score even where other variables are favorable, a behavior an additive formulation would not reproduce. We applied variable thresholds uniformly across epochs so the classification is directly comparable over time; Table 1 lists

the source dataset for each variable, and the variables are defined beneath Eqs. (1)–(4).

Statistical Analysis

Temporal trends in LU/LC class areas and in the share of each DSI class across the six epochs were evaluated with the nonparametric Mann-Kendall test [24,25], which detects monotonic trends without assuming normality and reports Kendall's tau (τ) as the measure of trend strength and direction. Associations between LU/LC class areas and MEDALUS index class shares were quantified with Pearson's product-moment correlation coefficient (r) [26] and, to accommodate non-linear monotonic relationships in the short series, Spearman's rank correlation coefficient (ρ) [27]. We assessed statistical significance at $\alpha = 0.05$ (two-tailed). Because each series comprises only six epochs ($n = 6$), test power is limited; therefore, interpret all coefficients as indicative of tendency and association rather than proof of causality.

Findings

Land-Use/Land-Cover Change (2000–2025)

LU/LC analysis reveals pronounced, spatially heterogeneous change over 2000–2025 (Table 2), characterized by a shift from productive to increasingly degraded and built-up surfaces. Farmland recorded a modest early gain before a substantial long-term decline, culminating in a net loss of 5,571.71 km² between 2015 and 2025. From 2000 to 2025, net farmland declined by a smaller amount (2,785.44 km²), since early-period gains (2000–2015) partially offset the later 2015–2025 decline. Vegetation cover initially increased due to reduced cultivation and secondary succession, then declined between 2015 and 2025 by 401.25 km². Grassland/wetland was highly dynamic:

Table 2) Area (km²) of the six land-use/land-cover (LU/LC) classes mapped in Jigawa and Yobe States by Random Forest classification of Landsat imagery at five-year intervals (2000–2025), with the net change over the most recent decade (2015–2025; positive values = gain, negative values = loss).

Land-Use/Land-Cover	2000	2005	2010	2015	2020	2025	Net change 2015–2025
Water	107.52	64.04	87.39	127.82	101.03	101.97	-25.85
Settlement	115.81	121.02	125.18	127.04	148.02	175.62	+48.58
Bareland	744.04	594.49	1,728.92	3,660.08	3,000.87	5,152.78	+1,492.70
Farmland	48,876.75	52,674.46	49,110.52	51,663.02	50,783.34	46,091.31	-5,571.71
Vegetation	1,887.38	3,581.22	3,663.70	2,949.10	2,128.72	2,547.85	-401.25
Grassland/Wetland	17,835.01	12,531.27	14,850.81	11,039.45	13,404.55	15,496.98	+4,457.53

an initial sharp decline followed by strong recovery yielded a net gain of 4,457.53 km² between 2015 and 2025, after a net decline of 6,795.56 km² over 2000–2015, likely reflecting land abandonment and reduced agricultural activity amid conflict. Bareland expanded noticeably over the study period, from 744.04 km² (2000) to 5,152.78 km² (2025), a net gain of 1,492.70 km² between 2015 and 2025 alone. Expansion was not monotonic - bareland fell in the 2000–2005 (744.04 to 594.49 km²) and 2015–2020 (3,660.08 to 3,000.87 km²) intervals before yielding an overall 2000–2025 net gain of 4,408.74 km², clearly indicating intensified degradation on balance despite these short-term interruptions. Settlement expanded steadily (+48.58 km², 2015–2025), reflecting persistent urban growth ^[10]. Water bodies remained relatively stable (-25.85 km² net). These dynamics underscore a critical shift toward degradation, declining agricultural capacity, and increasing anthropogenic pressure.

Soil Quality Index (SQI)

SQI showed the greatest temporal variability of the four indices (Table 3). In 2000, High sensitivity dominated (62.50%, 43,481.09 km²) with Moderate at 37.43%. Between

2000 and 2015, a progressive shift toward Moderate SQI occurred, peaking at 56.88% (39,570.19 km²) in 2015, as High contracted to 43.08% - likely reflecting agricultural intensification and conservation practices that improved topsoil cover^[3]. This agrees with rainfall-simulation evidence that land-use, slope, and surface cover are dominant controls on soil-erosion response in comparable drylands ^[28]. By 2020 and 2025, High SQI partially reverted (52.67%, 59.80%, respectively), consistent with renewed degradation pressure from expanding bareland and farmland abandonment ^[29]. Weak SQI remained negligible throughout (< or =0.07%).

Vegetation Quality Index (VQI)

The Moderate class dominated VQI throughout (87–99% of area), peaking at 98.39% in 2010, coinciding with maximum vegetation cover in the LU/LC record (Table 3). Weak VQI (better vegetation condition) ranged from 1.61% (2010) to 12.26% (2005), reflecting inter-annual rainfall variability ^[30]. High VQI (poor condition) remained effectively absent (< or =0.01%) at all epochs. By 2025, Weak VQI stood at 6.35% and Moderate at 93.63%, indicating persistent but moderate vegetative stress.

Management Quality Index (MQI)

MQI was overwhelmingly Moderate at every epoch, exceeding 99.90% of the area in most years (Table 3), reflecting a landscape of mixed agriculture, pastoralism, and limited formal land protection. High MQI was notable only in 2000 (0.73%) before declining to near zero, while Weak MQI remained minimal (< 0.11%) throughout, indicating management exerted a stable, moderate influence on desertification sensitivity rather than mitigating or amplifying it. Although MQI showed limited temporal discrimination, it is structurally required for computing the geometric mean as a DSI component, and its consistently Moderate value is informative: it indicates

that no part of the study area benefits from formal land management interventions that moderate degradation risk. The SQI, VQI, and bareland correlation analyses below (Table 4) address their relationship to the LU/LC record and capture the Land-Cover-mediated pathway by which management practices, or their absence, translate into observable degradation.

Climate Quality Index (CQI)

CQI was the most temporally stable index: Weak CQI (favorable climate) dominated 99.92-99.95% of the area at all epochs (Table 3). Within the MEDALUS scoring rubric, this reflects aridity and rainfall values that, while low by global standards, do not reach the extreme thresholds that trigger

Table 3) Share of the study area (%; Jigawa and Yobe States) in each sensitivity class of the Soil (SQI), Vegetation (VQI), Management (MQI), and Climate (CQI) Quality Indices and of the Desertification Sensitivity Index (DSI), 2000–2025. Quality index classes: Weak (1.00–1.33), Moderate (1.34–1.66), High (1.67–2.00); DSI classes: Low (1.00–1.22), Moderate (1.23–1.38), High (1.39–1.53), Very High (1.54–2.00).

Index	Class	2000	2005	2010	2015	2020	2025
SQI	Weak	0.06	0.04	0.03	0.04	0.07	0.06
SQI	Moderate	37.43	42.79	52.84	56.88	47.26	40.14
SQI	High	62.50	57.18	47.13	43.08	52.67	59.80
VQI	Weak	9.34	12.26	1.61	2.53	5.23	6.35
VQI	Moderate	90.65	87.74	98.39	97.47	94.76	93.63
VQI	High	0.01	0.00	0.00	0.01	0.01	0.01
MQI	Weak	0.11	0.08	0.04	0.04	0.05	0.06
MQI	Moderate	99.17	99.65	99.96	99.96	99.95	99.94
MQI	High	0.73	0.27	0.00	0.00	0.00	0.00
CQI	Weak	99.95	99.95	99.94	99.95	99.92	99.93
CQI	Moderate	0.02	0.01	0.02	0.02	0.04	0.03
CQI	High	0.00	0.00	0.00	0.00	0.00	0.00
DSI	Low	4.07	4.94	5.03	2.15	1.99	2.18
DSI	Moderate	22.49	18.63	20.78	36.20	30.56	34.82
DSI	High	72.04	75.33	71.42	54.63	61.78	60.03
DSI	Very High	1.39	1.10	2.77	7.02	5.66	2.98

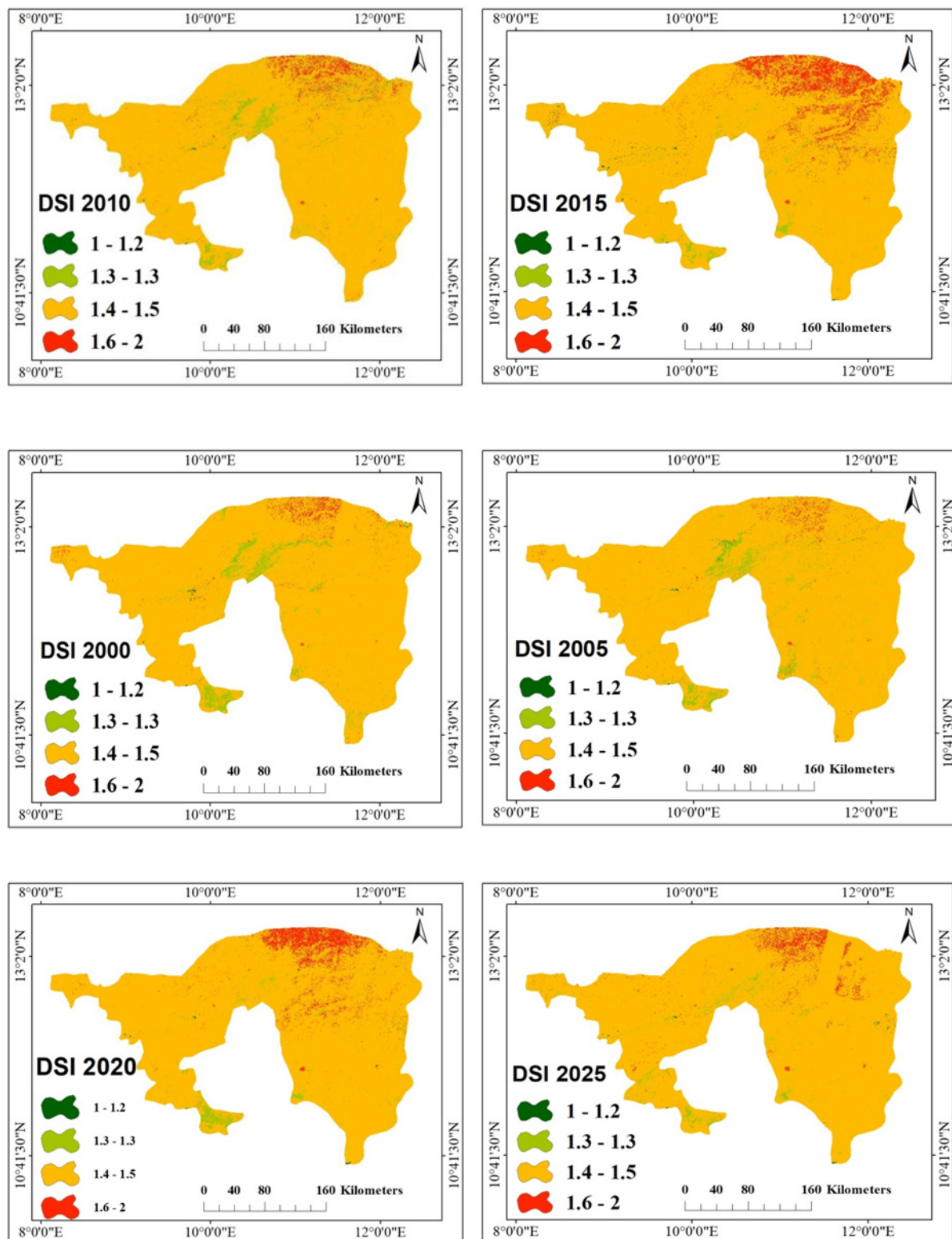


Figure 3) Spatial distribution of Desertification Sensitivity Index (DSI) classes in Jigawa and Yobe States, northeastern Nigeria, at five-year intervals from 2000 to 2025 (year labeled on each map; top row: 2010 and 2015; middle row: 2000 and 2005; bottom row: 2020 and 2025). DSI was computed as the geometric mean of SQI, VQI, MQI, and CQI (Eq. (5)). Legend values are rounded class limits corresponding to Low (1.00–1.22; dark green), Moderate (1.23–1.38; light green), High (1.39–1.53; orange), and Very High (1.54–2.00; red) sensitivity, following Kosmas et al. ^[4].

Table 4) Pearson correlation coefficients (r) between LU/LC class areas and MEDALUS index class shares in Jigawa and Yobe States across the six epochs, 2000–2025 (n = 6). VH DSI = Very High DSI share; H+VH DSI = combined High and Very High DSI share; SQI High = share of High SQI; VQI Weak = share of Weak VQI.

Variable	Bareland	Farmland	Settlement	Vegetation	Grassland	VH DSI	High DSI	H+VH DSI	SQI High	VQI Weak
Bareland	1									
Farmland	-0.50	1								
Settlement	0.86*	-0.63	1							
Vegetation	-0.21	0.35	-0.26	1						
Grassland	-0.20	-0.71	0.05	-0.49	1					
VH DSI	0.60	0.22	0.23	-0.16	-0.62	1				
High DSI	-0.87*	0.15	-0.55	0.30	0.42	-0.88*	1			
H+VH DSI	-0.92**	0.28	-0.64	0.34	0.32	-0.77	0.98**	1		
SQI High	-0.20	-0.42	0.20	-0.48	0.71	-0.73	0.45	0.32	1	
VQI Weak	-0.49	0.20	-0.17	-0.14	0.22	-0.69	0.58	0.50	0.78	1

Note: Pearson correlation matrix for LU/LC and DSI variables (2000–2025, n = 6). ** p < 0.01, and * p < 0.05.

Moderate/High classification. Moderate CQI never exceeded 0.04%, and High CQI was essentially absent, indicating that climate itself did not constitute a spatially differentiated driver of DSI at the resolution of the ERA5-derived inputs ^[31]; this is comparable to semi-arid drought-index monitoring using SPI/RDI under climate-change scenarios, which has similarly found climate quality to shift gradually rather than abruptly across epochs ^[32]. The MEDALUS framework treats all four quality indices as structurally necessary components of the geometric mean; a spatially uniform index still contributes multiplicatively to DSI and constrains the plausible range of the composite score, even where it does not itself differentiate sub-zones. As detailed in Scientific Limitations below, the coarse 0.25-degree resolution of the ERA5 climate inputs relative to the 30 m Landsat-derived

indices is the primary reason CQI shows limited spatial variability here, and this scale mismatch limits the study because CQI is one of the four quality indices that drive the MEDALUS model.

Desertification Sensitivity Index (DSI)

The composite DSI (Figure 3; Table 3) was dominated by the High class throughout the 25-year assessment, consistently exceeding 54% of the study area. In 2000, High DSI covered 72.04% (50,118.91 km²), Moderate 22.49%, and Very High only 1.39%. Between 2000 and 2015, High sensitivity contracted to 54.63% while Moderate expanded to 36.20% and Very High surged to its study-period maximum of 7.02% (4,884.14 km²) - the most critical desertification episode recorded, coinciding with a minimum in Low DSI (2.15%) and the major farmland loss/bareland expansion documented in the LU/LC record.

From 2015, partial amelioration occurred: by 2025, High stabilized at 60.03%, Very High fell to 2.98% (2,071.10 km²), and Moderate rose to 34.82%. The combined High+Very High share in 2025 (63.01%) nonetheless remained below the 2000 baseline (73.43%), indicating that while the most acute degradation phase has moderated, underlying desertification pressure has not reverted to baseline.

The description above is confined to the observed spatial and statistical pattern; its likely drivers require a fuller synthesis. This 2015-2025 improvement reflects a combination of climatic recovery and socio-ecological processes rather than a fundamental shift in land management. ERA5 data indicate increased rainfall across the Sahelian zone of Nigeria following the prolonged 2009-2015 dry period^[33]; because VQI derives from NDVI and SQI is strongly influenced by surface moisture, increased precipitation mechanically improves both indices even without intervention. The decline of insurgency after 2017 also enabled the resumption of agriculture in previously abandoned areas of Yobe State^[34], reducing bareland and improving MQI and vegetation cover; natural succession reinforced this as grassland/wetland expanded by 4,457 km², reducing wind-erosion susceptibility^[35]. These patterns align with the “green Sahel” phenomenon^[36], reflecting short-term ecoclimatic variability rather than necessarily a sustained structural improvement in land management.

Multi-Temporal DSI Change and Socioeconomic Drivers of the 2015 Peak

The merged DSI change pattern across 2015, 2020, and 2025 provides a direct spatial account of the transition between sensitivity classes over the most recent decade. Areas

that maintained or worsened to Very High DSI are concentrated in the north and northeast, where bareland expansion and farmland abandonment are most pronounced. At the same time, zones transitioning from High to Moderate DSI between 2020 and 2025 coincide with grassland/wetland expansion and partial vegetation recovery, suggesting that land resting from agriculture and natural succession can yield measurable amelioration within relatively short timeframes.

The 2015 peak in Very High DSI (7.02%) reflects climatic, security, and land-use pressures rather than a single driver. Prolonged below-average rainfall (2010-2015) intensified soil-moisture deficits and reduced vegetation cover; escalation of insurgency disrupted agriculture and land management, driving widespread farmland abandonment and bareland expansion. The post-2015 decline in DSI aligns with improved rainfall conditions, partial security restoration, and the effects of land-restoration programs.

Statistical Trend and Correlation

Analysis

Bareland extent expanded from 744 km² (2000) to 5,153 km² (2025), yielding a Kendall's tau^[24,25] = +0.733 (p = 0.056), a strong positive monotonic trend approaching significance despite the six-epoch series. The Very High DSI time series (1.39%-7.02%-2.98%) showed no significant monotonic trend (tau = +0.467, p = 0.272), correctly reflecting its non-monotonic peak-and-recovery pattern. Because the Mann-Kendall test is conventionally applied to longer time series, all tau and p-values reported here should be interpreted as indicative of monotonic tendency rather than as definitive confirmation of trend significance,

given the six-epoch ($n = 6$) series; this sample-size constraint applies equally to the correlation and rank-correlation coefficients reported below, whose confidence intervals are correspondingly wide.

Bareland expansion and Very High DSI were significantly and positively correlated (Spearman $\rho = +0.829$, $p = 0.042$; Pearson $r = +0.597$, $p = 0.211$), confirming land clearance as the immediate driver of extreme desertification sensitivity (Table 4). The relationship between bareland and combined High+Very High DSI share was stronger and negative ($r = -0.920$, $p = 0.009$). This negative sign reflects the study-period trajectory rather than a reversal of the degradation process: over 2000-2025, bareland trended upward while the combined High+Very High DSI share trended downward overall (from 73.43% in 2000 to 63.01% in 2025), because Sahel-wide climatic amelioration lifted a larger area of the landscape out of the High class into Moderate than bareland-driven intensification pushed into Very High. The two processes are therefore concurrent rather than contradictory: bareland expansion remains the dominant local driver of the Very High class specifically, evidenced by its significant positive association with Very High DSI alone ($\rho = +0.829$ above), while the region-wide High+Very High share is simultaneously being pulled down by climate-driven improvement elsewhere in the landscape. This also explains the apparent discrepancy between continued bareland expansion and partial DSI amelioration: the two indicators track different spatial processes operating at the same time rather than a single, uniform trend. Settlement expansion correlated strongly with bareland ($r = +0.859$, $p = 0.028$), confirming the demographic origin of degradation pressure.

DSI Moderate showed the strongest single association in the matrix ($r = -0.997$, $p < 0.001$, vs. High+Very High DSI). VQI Weak correlated positively with SQI High ($r = +0.785$, $p = 0.065$), indicating that the same bareland-driven process degrades both soil and vegetation quality simultaneously.

Discussion

The drivers of the 2015 Very High DSI peak and the subsequent 2015-2025 amelioration - climatic recovery, the decline of insurgency after 2017, and grassland/wetland expansion - were introduced descriptively in the Findings section above; this discussion synthesizes those drivers against the wider MEDALUS literature and evaluates their relative contribution.

Comparison with MEDALUS Studies in Sub-Saharan Africa and Semi-Arid Regions

The dominance of High DSI across the study area (>54% of total area at all epochs) is consistent with comparable MEDALUS applications across sub-Saharan Africa. Song et al. [7] applied the MEDALUS framework to identify land degradation patterns relevant to afforestation and reforestation planning in Ethiopia. Similarly, they found that vegetation and management quality dynamics were closely linked to degradation extent, reinforcing the framework's applicability across diverse African drylands. The observed partial recovery from 2015-2025 - contraction of Very High DSI from 7.02% to 2.98% - is broadly analogous to the "green Sahel" phenomenon documented in satellite-based studies^[36], which identified a Sahelian greening trend attributed to rainfall recovery following the severe droughts of the 1970s-1980s, while cautioning that greening does not necessarily imply full ecological

recovery. The Very High DSI peak of 7.02% in 2015 is broadly comparable to Very High DSI coverage reported in degraded agricultural zones of southern Italy (5.3-8.9%)^[23] and in southwestern Romania during drought years (6-10%)^[6], reinforcing the role of episodic climate anomalies in triggering temporary but spatially significant expansions of extreme desertification sensitivity.

Role of LU/LC Change in Modulating DSI

The LU/LC analysis reveals strong temporal coupling between bareland expansion, farmland loss, and elevated DSI, consistent with reported trajectories of cropland degradation and abandonment in semi-arid African drylands^[3,29]. Bareland, characterized by sparse vegetation cover, directly elevates VQI and SQI, thereby increasing DSI; this is evident in the spatial overlap between bareland-expansion zones in the north/northeast and persistent High/Very High DSI concentrations there. Conversely, grassland/wetland expansion (+4,457.53 km², 2015-2025) appears to have contributed to partial DSI amelioration, since even degraded grassland cover provides greater erosion protection and surface roughness than bare soil, consistent with evidence that land-cover type strongly controls surface susceptibility to wind erosion and dust emission in drylands^[21,35].

Climate and Soil Quality as Primary DSI Drivers

Despite the near-uniform dominance of Weak CQI (>99.9% at all epochs), climate variability remains a crucial indirect driver of DSI by modulating VQI, SQI, and MQI. Inter-annual rainfall variability directly affects NDVI-based vegetation scores, while prolonged drought accelerates soil moisture depletion and surface crusting (reflected in higher SQI). This aligns with

panel-regression findings from central Italy showing that while CQI itself has low spatial variance, its temporal covariation with SQI and VQI primarily drives DSI fluctuation^[37]. The soil quality oscillation presented here between High and Moderate SQI dominance is consistent with degradation trajectories described for sub-Saharan African smallholder systems, where continuous cultivation without inputs, combined with erosive rainfall, progressively depletes topsoil organic matter and structural stability^[3].

Management Implications

The consistently Moderate MQI and near absence of well-managed areas highlight the urgent need for improved land governance. Interventions such as participatory land-use planning, community-based natural resource management, soil and water conservation infrastructure (terracing, check dams, agroforestry), and policy frameworks incentivizing sustainable land management are critical priorities^[38]. The 4,884 km² identified as Very High DSI in 2015 provides a prioritization framework for targeting limited conservation resources. The measurable 2015-2025 improvement indicates that degradation is at least partially reversible on decadal timescales under favorable conditions, offering cautious optimism for restoration aligned with UNCCD Land Degradation Neutrality targets and the Great Green Wall Initiative^[38]. However, the persistence of High DSI across most of the landscape underscores that baseline susceptibility remains structurally elevated, requiring sustained commitment beyond short-term climate improvements.

Scientific Limitations

Several limitations should be acknowledged, foremost among them the scale mismatch

between the climate inputs and the remote-sensing data. First, the 0.25-degree (approximately 25 km) ERA5 reanalysis used for CQI is several orders of magnitude coarser than the 30 m Landsat-derived indices, and bilinear interpolation to the 30 m grid redistributes coarse-scale values across a fine grid without adding genuine sub-grid information; the fine-scale spatial pattern visible in the CQI/DSI outputs at 30 m should therefore be read as a resampling artifact of the underlying 25 km climate data rather than as evidence of fine-scale climate variation. The near-uniform CQI classification reported above (Weak class in >99.9% of the area at every epoch) is a direct, expected consequence of this scale mismatch, not a spurious result. This is treated here as a defined methodological limitation rather than something the present dataset can resolve; addressing it properly would require substituting a higher-resolution climate product (e.g., CHIRPS) or presenting CQI at its native 25 km resolution before resampling only for visualization, both of which fall outside the scope of the current 25-year Landsat-based analysis and are flagged as a priority for future work. Second, the MEDALUS framework assigns equal weight to all four quality indices in the geometric mean formulation, an assumption that may not reflect the relative importance of different degradation drivers across all sub-zones; sensitivity analyses of indicator weighting would strengthen DSI robustness^[23]. Third, NDVI-based vegetation assessment is susceptible to inter-annual rainfall variability, cloud-contamination artifacts, and dry-season acquisition timing, potentially conflating genuine degradation with seasonal greenness fluctuation. Fourth, this study lacks ground-truth field validation

- no in-situ soil sampling, vegetation transects, or community-based assessments were conducted, so the accuracy of MEDALUS-derived classifications relative to actual on-ground conditions cannot be independently verified. Fifth, MQI remains a weak discriminator here because land-management practices are homogeneous and it relies on LU/LC rather than direct governance data. Given these acknowledged uncertainties - particularly the climate-data scale mismatch and the absence of field validation - the policy recommendations below are offered as a prioritization evidence base rather than as a substitute for field-verified assessment before high-stakes land-degradation policy decisions.

Conclusion

This study presents a spatio-temporal assessment of desertification sensitivity using the MEDALUS framework over 25 years (2000-2025) at five-year intervals across Jigawa and Yobe States, Nigeria. High desertification sensitivity dominated the landscape throughout (54-75% of total area), confirming the region's structural susceptibility to land degradation. Very High DSI reached its maximum extent in 2015 (7.02%), representing the most critical desertification episode of the study period, before moderating to 2.98% by 2025.

Soil quality was the most temporally dynamic index, progressing from High-dominated (2000) to Moderate-dominated (2010-2015) before reverting toward High sensitivity, tightly coupled with LU/LC dynamics. Vegetation quality remained persistently Moderate; climate quality was stable and near-uniformly Weak, acting as an indirect rather than direct spatial driver of DSI variability. LU/LC analysis shows a net

farmland loss of 5,571.71 km² and bareland gain of 1,492.70 km² between 2015 and 2025, with grassland/wetland expansion spatially corresponding to DSI amelioration between 2020 and 2025.

These findings are consistent with MEDALUS-based studies across the Sahel, Mediterranean, and other semi-arid regions, confirming the model's cross-regional applicability. The spatial identification of persistent Very High and High DSI zones provides an evidence base for prioritizing land-restoration investment under UNCCD Land Degradation Neutrality commitments, SDG 15.3, and the Great Green Wall Initiative. On this basis: (a) Nigerian federal and state environment ministries should designate the persistently Very-High-DSI zones of northern/northeastern Yobe State as priority Land Degradation Neutrality intervention areas; (b) community-based early-warning systems integrating seasonal NDVI monitoring should be established to detect emerging bareland expansion before it reaches critical thresholds; (c) agricultural extension services should prioritise soil-conservation practices in areas where SQI has trended toward High sensitivity; and (d) the MEDALUS-derived DSI maps produced here should inform, as a prioritisation and screening tool, the national land-degradation assessment framework under the UNCCD National Action Programme. Given the acknowledged climate-data scale mismatch, equal indicator weighting, and absence of field validation, the maps are best used to target where field verification and finer-scale assessment should occur next, rather than as a stand-alone basis for high-stakes policy allocation. Future research should integrate finer-scale socioeconomic data, field soil sampling, higher-resolution climate products, and conflict-displacement

records to elucidate further the mechanisms driving observed DSI temporal dynamics.

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Ethical Permission

This study did not involve human participants, human data, or animals; it relied exclusively on publicly available satellite (Landsat), reanalysis (ERA5), and secondary soil/population datasets. No ethical approval was required.

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Conflict of Interest

The authors declare no conflicts of interest.

AI Use Declaration

The authors used Claude AI for language editing and proofread the entire manuscript for clarity and approval.

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