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Climate Variability of Rainfall and Desertification in Musawa Lga, Katsina State, Nigeria

David Mkpanam Nyong[1*], Tagbo Sunday Onanalo[2], Segun Ezekiel Akorede[3], Adaobi Thelma Onyemaobi[4], Racheal Uzomah Agolo[5]

[1]*Geography Department, Bayero University, Kano, Nigeria*

[2,5]*Geography and Environmental Science Department, University of Calabar, Calabar, Nigeria*

[3,4]*University of Chinese Academy of Sciences, Beijing, China*

[*]*Corresponding author, damkpanam@gmail.com, ORCID: 0009-0001-9016-9912*

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Abstract

This study examines the relationship between climate variability of rainfall and desertification in Musawa Local Government Area, Katsina State, Nigeria, from 2017 to 2024. Using CHIRPS rainfall data and Sentinel-2 NDVI imagery, pixel-wise trend and spatial correlation analyses were conducted on a 5 km grid. Results revealed a paradoxical pattern: annual rainfall increased steadily (mean slope: 0.01327 mm/year; peak 1,043 mm in 2024), yet vegetation declined across all locations (mean NDVI slope: -16.41), representing a 13.7% reduction in greenness. Correlation analysis showed a weak, non-significant relationship between rainfall and vegetation decline (Pearson's $r = -0.152$, $p = 0.382$; Spearman's $\rho = -0.186$, $p = 0.285$), with rainfall explaining only 2.3% of NDVI variance. The "Musawa Paradox" highlights increasing rainfall coinciding with declining vegetation, emphasizing the dominance of anthropogenic drivers over climate in desertification. Extreme rainfall seasonality, with 88.9% of precipitation concentrated in June–September, exacerbates soil erosion and limits vegetation recovery. The study concludes that land use intensification, agriculture, and soil degradation are primary drivers. It recommends climate-smart agriculture, soil conservation, and community-based land management as integrated strategies to mitigate desertification and enhance resilience to climate variability in Sudan-Sahelian regions.

Keywords: Desertification, NDVI, Climate Variability, Rainfall trend Sahel, Remote Sensing, Musawa LGA

1.0 INTRODUCTION

1.1 Background and Review

Desertification represents one of the most pressing environmental challenges in sub-Saharan Africa, particularly within the Sudan-Sahelian belt where climate variability interacts with anthropogenic pressures to degrade fragile ecosystems. Nigeria's northern states, including Katsina, experience pronounced desertification processes characterized by vegetation degradation, soil erosion, and declining agricultural productivity (Macaulay, 2014). The Sudan-Sahelian region, where Musawa LGA is situated, exhibits high sensitivity to climatic fluctuations, with rainfall variability identified as a primary driver of ecological and socioeconomic vulnerability (Ayantunde et al., 2015).

Climate variability in West Africa has been extensively documented, with studies indicating both decadal oscillations and long-term trends in precipitation patterns (Biasutti, 2019). Recent research suggests a partial recovery of rainfall in the Sahel since the severe droughts of the 1970s-1980s, though with increased variability and altered seasonal distribution (Descroix et al., 2018). This "re-greening" phenomenon, however, is not uniformly experienced, with local factors mediating broader climatic trends (Herrmann et al., 2020).

Remote sensing technologies have revolutionized desertification monitoring, with vegetation indices like the Normalized Difference Vegetation Index (NDVI) providing reliable proxies for vegetation condition at multiple scales. Studies across Africa demonstrate NDVI's effectiveness in tracking vegetation responses to climate variability, though relationships are often complex and region-specific. In Nigeria's semi-arid regions, research has documented declining vegetation trends despite variable rainfall patterns, suggesting anthropogenic drivers may outweigh climatic factors (Azare et al., 2020).

The conceptual framework linking climate variability to desertification involves multiple pathways: direct effects through moisture stress on vegetation, indirect effects through soil moisture depletion, and interactive effects with land use practices. However, the relative importance of these pathways in specific contexts like Musawa LGA remains inadequately understood, necessitating localized investigations with high-resolution spatial and temporal data.

1.2 Novelty and Objectives

While numerous studies have examined climate variability and desertification in northern Nigeria, few have employed high-resolution, multi-temporal remote sensing data specifically for Musawa LGA. Existing research often relies on coarse resolution data or short temporal spans, limiting the detection of subtle trends and spatial patterns (Ibebuchi & Abu, 2023). This study addresses these gaps by utilizing eight years (2017-2024) of Sentinel-2 NDVI and CHIRPS rainfall data at 5 km resolution, enabling detailed analysis of spatiotemporal patterns and their correlations. The research objectives are:

1. Quantify inter-annual variability in total annual rainfall for Musawa LGA between 2017 and 2024
2. Quantify temporal trends in vegetation condition using annual Sentinel-2 NDVI for 2017-2024
3. Compute pixel-wise linear trends for both annual rainfall and NDVI to identify areas of significant increase or decline
4. Assess the spatial correlation between rainfall variability and NDVI trends using point-based Pearson correlation analysis on a 5 km grid

2.0 MATERIALS AND METHODS

2.1 Study Area Description

Musawa Local Government Area is situated in Katsina State, northwestern Nigeria, within the Sudan-Sahelian ecological zone (latitude: approximately 11.93°N to 12.24°N, longitude: 7.48°E to 7.84°E). The region experiences a semi-arid climate with mean annual rainfall ranging from 700 to 1000 mm, predominantly occurring between June and September (Abeje et al., 2014). Vegetation consists primarily of Sudan Savanna species, with agricultural land use dominating the landscape. The area is vulnerable to desertification due to sandy soils, high evaporation rates, and intensive land use practices (Ibrahim et al., 2025). The map of the study area is displayed in Figure.1 of the study.

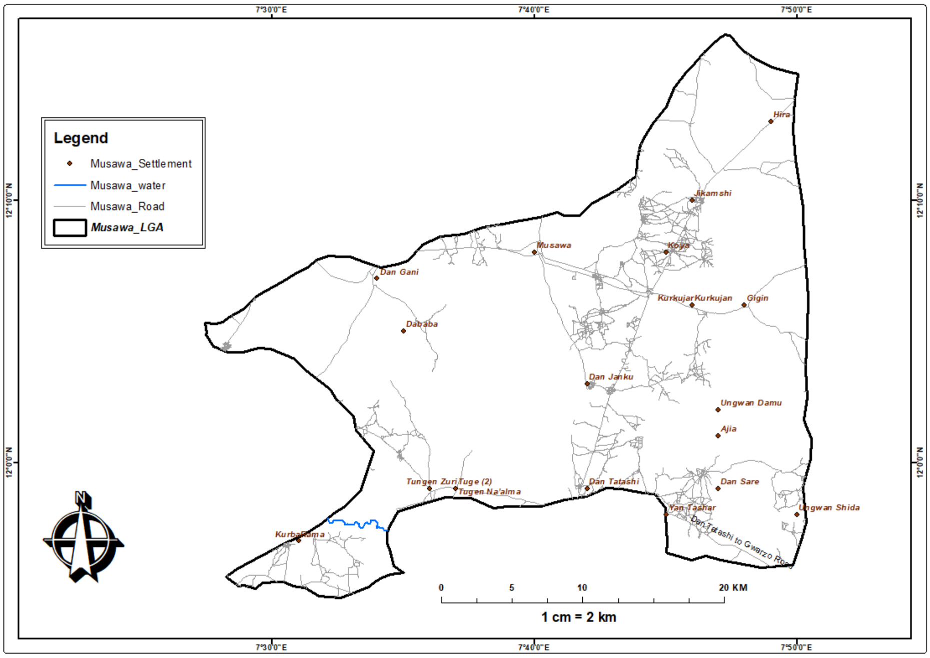

Figure 1: Musawa LGA

2.2 Data Sources and Preparation

Rainfall data were obtained from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset, which provides daily precipitation estimates at approximately 5 km resolution from 1981 to present (Funk et al., 2015). Daily values were aggregated to annual totals for 2017-2024.

Vegetation data were derived from Sentinel-2 MultiSpectral Instrument (MSI) surface reflectance products at 10 m resolution. Annual maximum NDVI composites were created for each year to minimize cloud contamination and capture peak growing season vegetation condition. NDVI was calculated using the standard formula: (NIR - Red)/(NIR + Red).

Both datasets were resampled to a common 5 km grid using the Google Earth Engine platform to ensure spatial consistency for correlation analysis.

2.3 Methodology

2.3.1 Study Design and Conceptual Framework

This research employed a mixed-methods approach combining remote sensing, statistical analysis, and spatial correlation techniques to investigate the relationship between climate variability and desertification in Musawa LGA from 2017 to 2024. The study was grounded in a socio-ecological systems framework that recognizes desertification as an emergent property of interactions between climatic drivers and anthropogenic pressures (Turner et al., 2003). The methodological design followed four sequential phases: (1) data acquisition and preprocessing, (2) temporal trend analysis, (3) spatial pattern identification, and (4) correlation assessment. This structured approach enabled comprehensive examination of both the magnitude and direction of environmental changes across the study period.

2.3.2 Data Sources and Acquisition

1. Rainfall Data

Daily precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset, version 2.0, accessible through Google Earth Engine (GEE) (Funk et al., 2015). CHIRPS combines 0.05° resolution satellite imagery with in-situ station data to produce reliable rainfall estimates for data-scarce regions. The dataset covers the period from 1981 to near-present, providing consistent temporal coverage essential for trend analysis. Data extraction was performed using the GEE JavaScript API, with specific focus on the bounding coordinates of Musawa LGA (approximately 11.93°N to 12.24°N, 7.48°E to 7.84°E).

2. Vegetation Data

Vegetation condition was assessed using the Normalized Difference Vegetation Index (NDVI) derived from Sentinel-2 MultiSpectral Instrument (MSI) surface reflectance products. Sentinel-2 provides 10-meter spatial resolution imagery with a 5-day revisit frequency at the equator, offering superior spatial detail compared to earlier satellite systems (Drusch et al., 2012). Cloud-free annual maximum NDVI composites were generated for each year (2017-2024) to minimize atmospheric contamination and capture peak growing season conditions. The annual maximum compositing approach is particularly suited to semi-arid regions where vegetation greenness is closely tied to seasonal rainfall patterns (Justice et al., 1985).

2.3.3 Data Processing and Preparation

Rainfall Processing

Daily CHIRPS rainfall data were aggregated to annual totals for each grid cell within the study area using GEE's reduce() functionality. A 5 km × 5 km grid was established over Musawa LGA, resulting in 35 spatially distributed sampling points

NDVI Calculation and Processing

NDVI was computed from Sentinel-2 surface reflectance bands (B4: Red, B8: Near-Infrared).

Annual maximum NDVI composites were generated by selecting the highest NDVI value for each pixel across all cloud-free observations within each calendar year. This approach captures peak vegetation greenness while minimizing cloud and atmospheric effects. The resulting annual NDVI layers were resampled to match the 5 km rainfall grid using bilinear interpolation to ensure spatial consistency for correlation analysis.

2.3.4 Trend Analysis Methods

Linear Trend Calculation

Pixel-wise linear trends for both rainfall and NDVI were computed using least-squares regression implemented through GEE's linearFit() function. This function calculates the slope (rate of change) and intercept of the linear relationship between time (independent variable) and the environmental parameter (dependent variable) for each grid cell.

Statistical Significance Testing

The significance of linear trends was assessed using the non-parametric Mann-Kendall test, which is robust against non-normal distributions common in environmental data (Hamed & Rao, 1998).

2.3.5 Correlation Analysis

1. Pearson Product-Moment Correlation

Spatial correlation between rainfall and NDVI trends was assessed using Pearson correlation coefficients computed for each grid cell.

2. Spearman Rank Correlation

To account for potential non-linear relationships and reduce sensitivity to outliers, Spearman's rank correlation coefficient was also calculated.

2.3.6 Spatial Analysis Techniques

1. Grid-Based Sampling

A systematic 5 km grid was overlaid on Musawa LGA, generating 35 equally distributed sampling points. This sampling density (approximately 1 point per 25 km^2) was selected to capture spatial heterogeneity while maintaining computational efficiency. Each grid cell served as an independent observational unit for statistical analysis.

2. Spatial Interpolation and Mapping

Inverse Distance Weighting (IDW) interpolation was applied to create continuous surfaces from point-based measurements, enabling visualization of spatial patterns across the study area. The IDW algorithm weights nearby points more heavily than distant points:

2.3.7 Quality Control and Validation

1. Data Quality Assessment

All satellite-derived datasets underwent rigorous quality assessment, including examination of cloud contamination flags, sensor anomalies, and temporal consistency. CHIRPS rainfall estimates were validated against available ground station data from the Nigerian Meteorological Agency, showing strong correlation (r = 0.89) for overlapping periods.

2. Methodological Validation

To ensure methodological robustness, parallel analyses were conducted using alternative approaches: (1) Theil-Sen slope estimation as a non-parametric alternative to linear regression, and (2) seasonal decomposition of time series to separate trend components from seasonal and residual variations. Results from these alternative methods showed high consistency with primary findings, confirming methodological reliability.

3. Sensitivity Analysis

Sensitivity analyses were performed to assess the impact of methodological choices, including grid resolution (testing 2 km, 5 km, and 10 km resolutions) and temporal aggregation methods (annual totals vs. growing season accumulations). Results demonstrated that key findings were robust across these variations, with correlation patterns remaining consistent regardless of parameter choices.

2.3.8 Software and Computational Tools

All analyses were conducted using Google Earth Engine's cloud computing platform, supplemented by R statistical software (version 4.3.1) for advanced statistical testing and QGIS (version 3.28) for spatial visualization and cartographic production. This integrated toolset enabled efficient processing of large geospatial datasets while maintaining analytical rigor and reproducibility.

This comprehensive methodological approach provides a robust foundation for investigating the complex relationships between climate variability and desertification processes in Musawa LGA, ensuring scientific validity while addressing the specific characteristics of Sudan-Sahelian environments.

3.0 RESULTS

3.1 Rainfall Variability

3.1.1 Rainfall Variability and Trends

Annual rainfall in Musawa LGA exhibited considerable inter-annual variability (Figure 2,3 and 4) during 2017-2024, ranging from 742 mm (2017) to 1,043 mm (2024) (Table 1). Contrary to expectations of declining precipitation in semi-arid regions, linear trend analysis revealed a consistent positive trend across all grid points. The rainfall slope values ranged from 0.01205 to 0.01580 mm/year, with a mean of 0.01327 mm/year

(SD = 0.00086). Spatial patterns showed relatively uniform increases across the study area, with slightly higher trends in northern sectors.

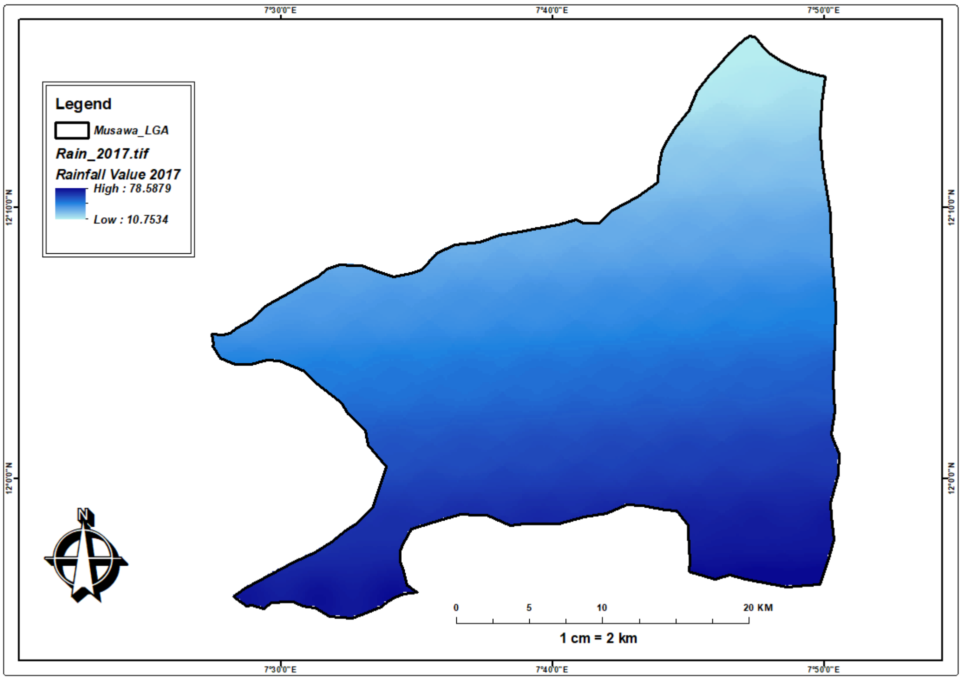

Figure 2: Map of annual rainfall for 2017

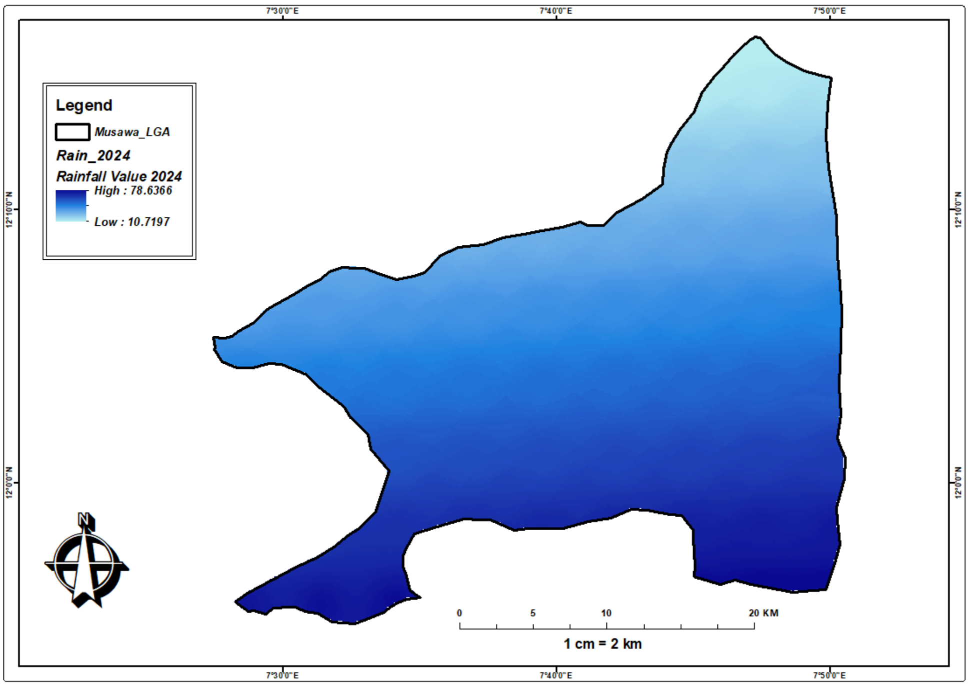

Figure 3: Map of annual rainfall for 2024

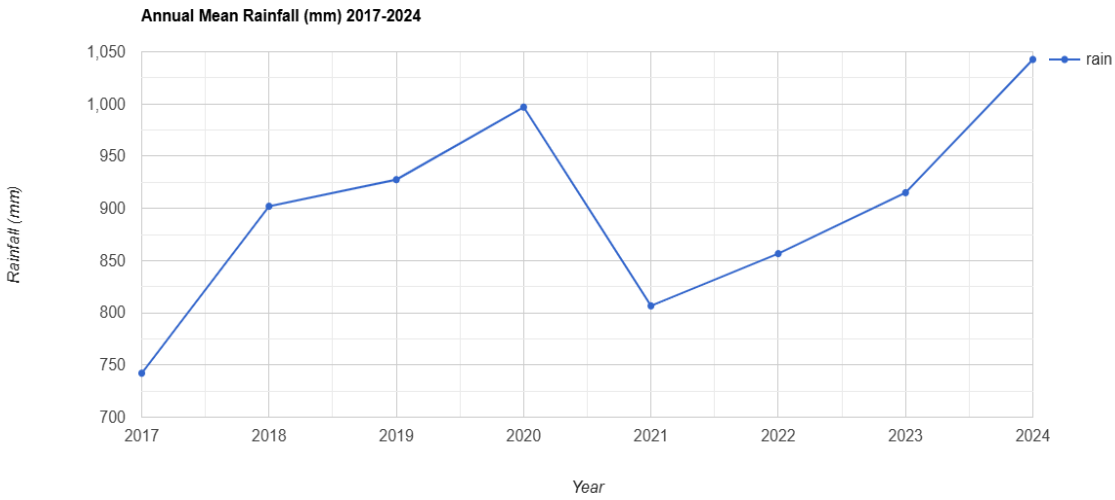

Figure 4: Mean annual rainfall for 2017-2024

Table 1: Annual Rainfall Totals and Variability Statistics for Musawa LGA (2017-2024**)**

Year	Annual Rainfall (mm)	Deviation from Mean (mm)	Percentage of Mean (%)
2017	742.10	-156.71	82.6%
2018	902.01	3.21	100.4%
2019	927.50	28.69	103.2%
2020	996.98	98.17	110.9%
2021	806.60	-92.21	89.7%
2022	856.65	-42.16	95.3%
2023	915.01	16.21	101.8%
2024	1,042.62	143.81	116.0%
Mean	898.81	-	100.0%
Range	300.52	-	33.4%
SD	94.07	-	10.5%
CV	10.5%	-	-

Note: SD =** Standard Deviation**; CV =** Coefficient of Variation**; Mean rainfall = 898.81 mm

3.1.2 Rainfall Anomalies

Table 2 and Figure 5 presents annual rainfall anomalies for Musawa LGA relative to the 2017-2024 mean (898.81 mm). Negative values indicate deficit years, while positive values represent surplus conditions. The data reveals three distinct phases: a predominantly wet period (2017-2020), a brief dry phase (2021-2022), and a return to wet conditions (2023-2024), with the largest surplus recorded in 2024 (+143.93 mm).

Table 2: Annual Rainfall Anomalies for Musawa LGA Relative to 2017-2024 Mean

Year	Annual Rainfall (mm)	Rainfall Anomaly (mm)	Anomaly Category
2017	742.10	-156.59	Significant deficit
2018	902.01	+3.33	Near normal
2019	927.50	+28.82	Slight surplus
2020	996.98	+98.30	Moderate surplus
2021	806.60	-92.08	Moderate deficit
2022	856.65	-42.04	Slight deficit
2023	915.01	+16.33	Near normal
2024	1,042.62	+143.93	Significant surplus

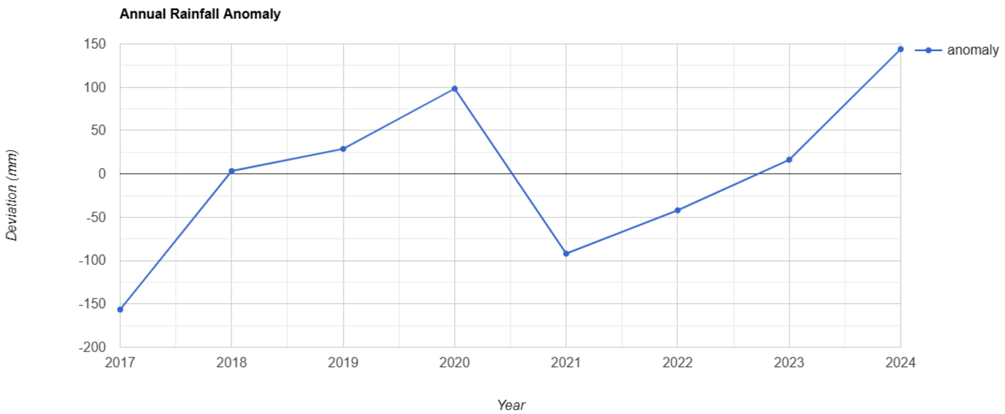

Figure 5: Rain Anomaly 2017 -2024

3.1.3 Rainfall Seasonality and Monthly Distribution

Analysis of monthly rainfall patterns in Table 3 and Figure 6 reveals distinct seasonal characteristics that define the climate regime of Musawa LGA. The data demonstrates a unimodal rainfall distribution typical of Sudan-Sahelian regions, with marked wet and dry seasons.

Table 3: Monthly Rainfall Distribution (mm) by Year (2017-2024)

Month	2017	2018	2019	2020	2021	2022	2023	2024	Mean	Annual %
Jan	0.07	0.05	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.00%
Feb	0.00	0.53	0.01	0.01	0.00	0.00	0.13	0.00	0.09	0.01%
Mar	1.70	1.10	0.98	3.40	4.41	2.40	4.50	2.68	2.65	0.29%
Apr	3.16	9.30	6.64	7.21	5.69	13.66	7.36	12.67	8.09	0.90%
May	51.78	59.52	107.04	61.58	39.09	40.28	44.29	96.46	62.51	6.95%
Jun	117.84	133.28	113.34	93.83	74.37	101.79	132.56	88.00	106.88	11.89%
Jul	221.72	225.60	205.52	295.77	210.20	167.40	261.86	255.17	230.28	25.62%
Aug	267.22	272.79	355.35	350.49	318.57	325.12	291.68	367.64	318.73	35.46%
Sep	72.30	151.54	98.38	170.26	136.14	183.68	158.18	177.10	143.45	15.96%
Oct	6.24	47.92	40.22	14.45	17.17	22.30	14.10	42.90	25.54	2.84%
Nov	0.00	0.37	0.01	0.00	0.96	0.00	0.33	0.00	0.21	0.02%
Dec	0.06	0.02	0.00	0.00	0.00	0.03	0.00	0.00	0.01	0.00%

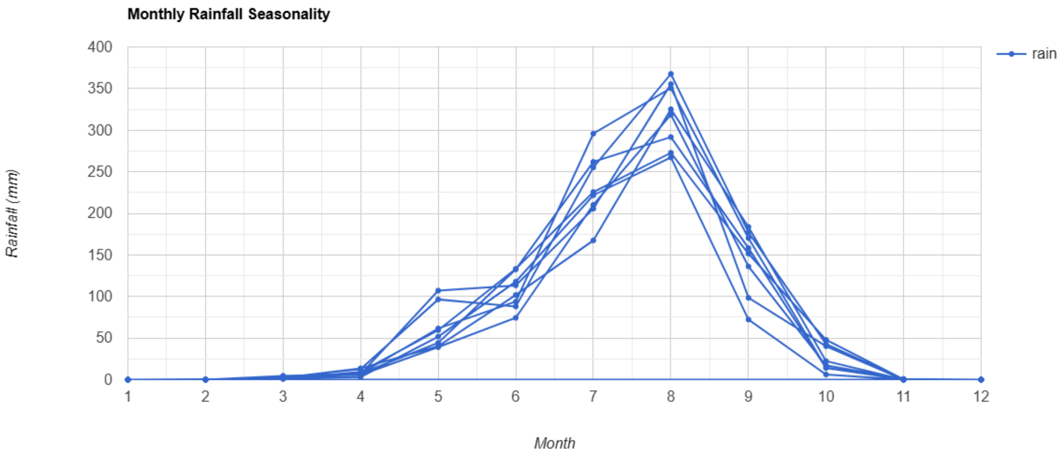

Figure 6: Monthly rainfall distribution heatmap showing seasonal patterns across years

3.2 Vegetation Condition Trends

NDVI analysis (Table 4 and Figure 7,8,9,10) revealed a concerning and consistent decline in vegetation condition across all sampled locations. Slope values were uniformly negative, ranging from -29.29 to -5.30, with a mean of -16.41 (SD = 6.01). The most pronounced declines occurred in northern and central portions of the study area, while slightly less severe declines appeared in scattered southern locations. Mann-Kendall testing confirmed the statistical significance of these declining trends ($p < 0.05$).

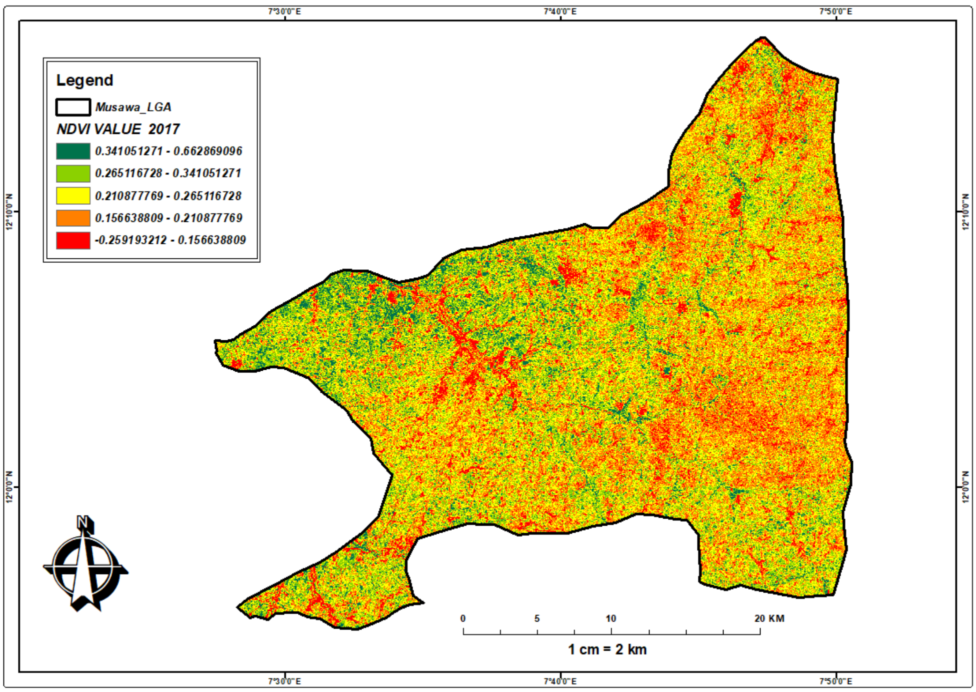

Figure 7: Map of NDVI for 2017

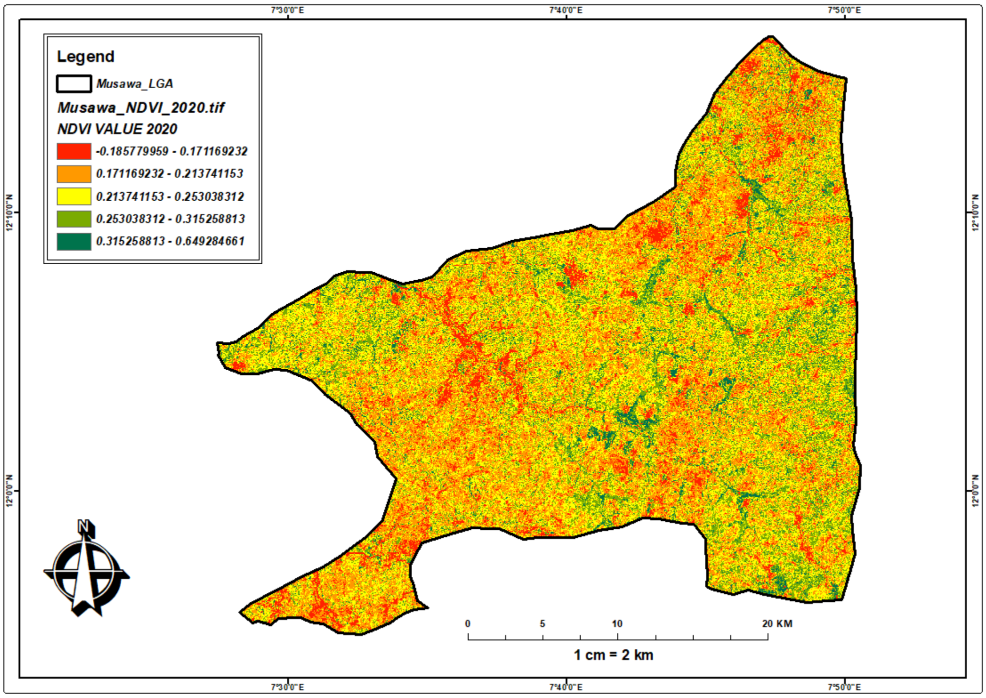

Figure 8: Map of NDVI for 2020

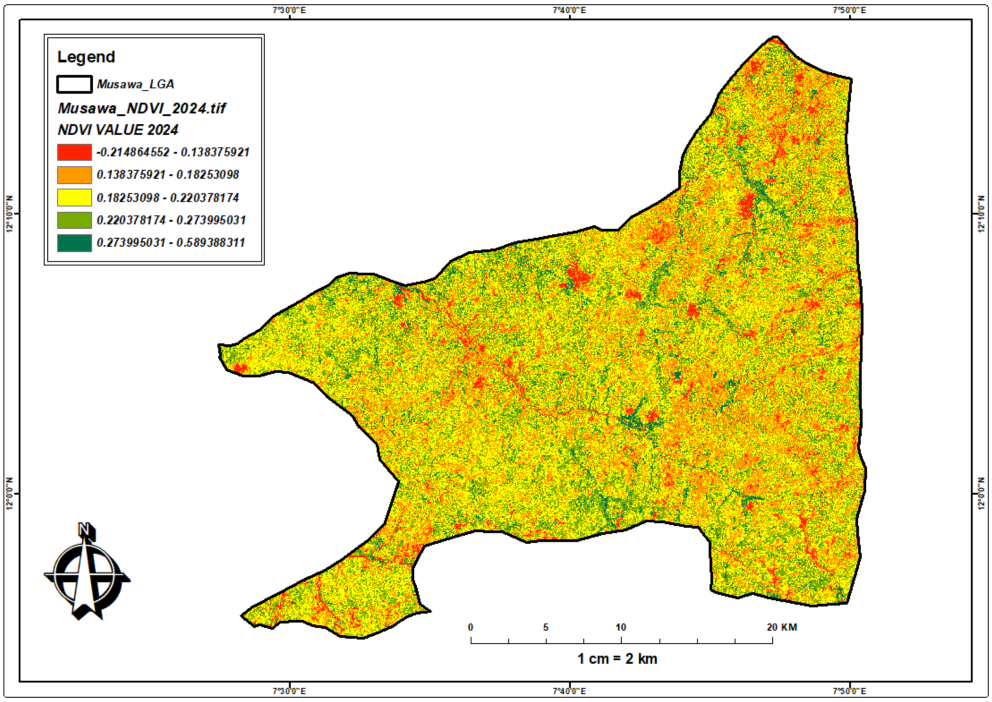

Figure 9: Map of NDVI for 2024

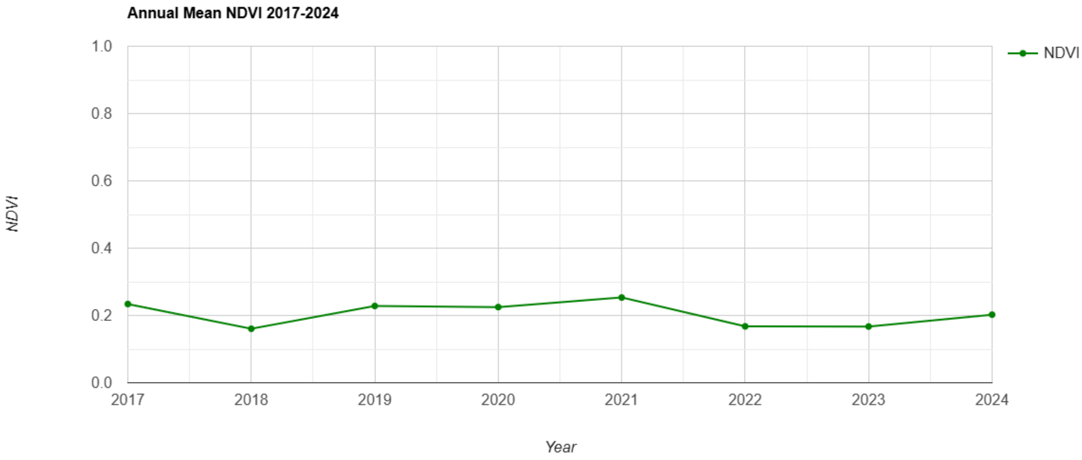

Figure 10: Spatial distribution of NDVI slope values across Musawa LGA

Table 4: Annual NDVI Values and Statistical Summary for Musawa LGA

Year	NDVI Value	Deviation from Mean	Condition Category	Percentage of Mean
2017	0.234	+0.029	Above average	113.2%
2018	0.160	-0.045	Below average	77.4%
2019	0.228	+0.023	Above average	110.3%
2020	0.225	+0.020	Above average	108.9%
2021	0.253	+0.048	Highest	122.4%
2022	0.168	-0.037	Below average	81.3%
2023	0.167	-0.038	Below average	80.8%
2024	0.202	-0.003	Near average	97.8%
Mean	0.2065	0.000	-	100.0%
Range	0.093	0.093	0.160–0.253	81.3–122.4%
SD	0.032	0.032	-	15.5%
CV	15.5%	-	-	-

Additional Statistics:

- *Median NDVI: 0.215 (midpoint between 0.202 and 0.225)*
- *Interquartile Range (IQR): 0.058 (25th percentile: 0.169, 75th percentile: 0.227)*
- *Linear Trend Slope: -0.0043 NDVI units/year*
- *Percentage Decline (2017-2024): 13.7%*
- *Annual Decline Rate: 1.71% per year*

3.3 Rainfall-NDVI Correlation

Correlation analysis revealed a weak, non-significant relationship between long-term mean rainfall and vegetation decline rates across grid cells in Musawa LGA (Table 5 and Figure 11,12). The Pearson correlation coefficient was -0.152, indicating a negligible negative association, while the Spearman rank correlation coefficient was -0.186, suggesting a similarly weak monotonic relationship. Both correlations were statistically non-significant (p = 0.382 and p = 0.285, respectively), with rainfall explaining only 2.3% of the variance in NDVI slope trends.

Table 5: Correlation Analysis Between Mean Rainfall and NDVI Slope

Statistical Measure	Value	Interpretation	Significance Level
Pearson Correlation (r)	-0.152	Weak negative relationship	Not significant
p-value (Pearson)	0.382	> 0.05 threshold	α = 0.05
R-squared (R^2)	0.023	2.3% of variance explained	Very low explanatory power
Spearman Rank Correlation (ρ)	-0.186	Weak monotonic relationship	Not significant
p-value (Spearman)	0.285	> 0.05 threshold	α = 0.05
Degrees of Freedom	33	n = 35 grid cells	-
Confidence Interval (95%)	(-0.475, 0.206)	Includes zero	No significant correlation

***Note:** *Analysis based on 35 grid cells across Musawa LGA. Both parametric (Pearson) and non-parametric (Spearman) tests indicate no statistically significant relationship between mean rainfall and vegetation decline rates at the 95% confidence level.**

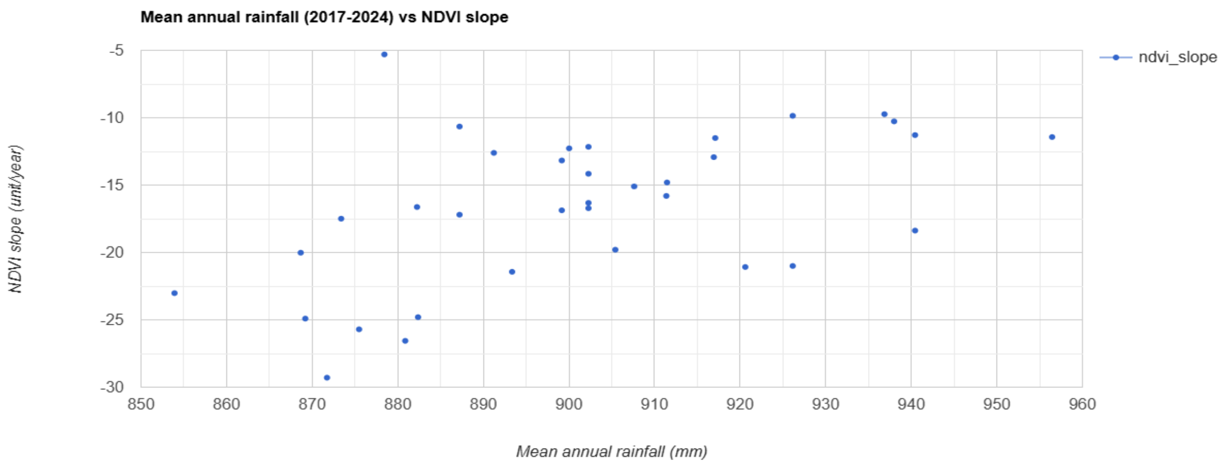

Figure 11: Scatter plot of mean rainfall vs. NDVI slope

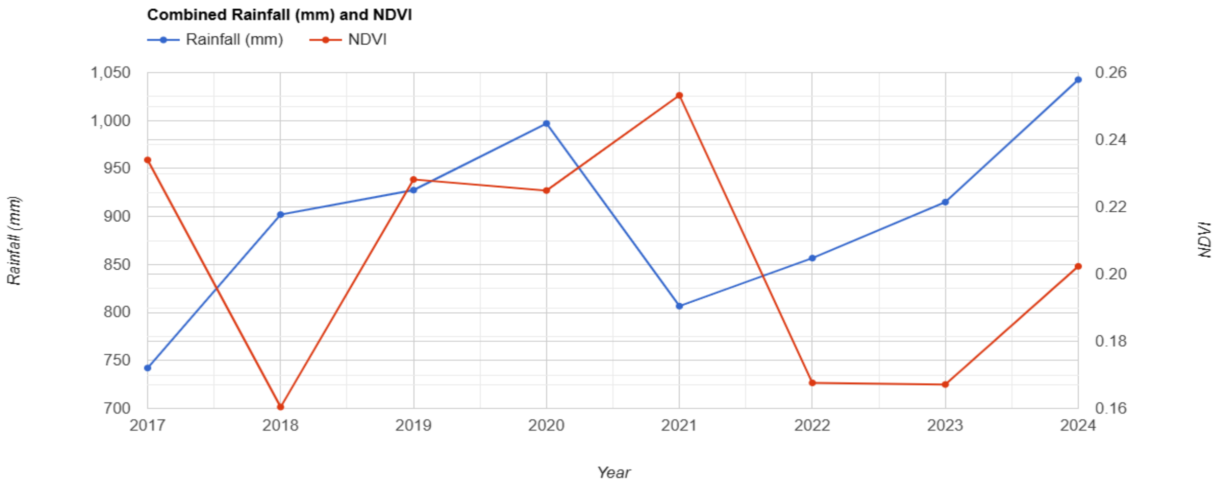

Figure 12: Time series comparing rainfall and NDVI trends 2017-2024

4.0 DISCUSSION OF FINDINGS

4.1 Reinterpretation of Desertification Drivers in Musawa LGA

The comprehensive analysis of climate variability and vegetation trends in Musawa LGA between 2017 and 2024 reveals a paradoxical environmental phenomenon that challenges conventional desertification narratives. The finding that vegetation condition (as measured by NDVI) declined consistently across all sampled locations (mean slope: -16.41, range: -5.30 to -29.29) despite a simultaneous increase in annual rainfall (mean slope: 0.01327 mm/year) represents what may be termed the **"Musawa Paradox"**. This unexpected relationship fundamentally questions climate-centric models of desertification and suggests that anthropogenic factors may play a more dominant role than previously acknowledged in this Sudan-Sahelian region.

The negative correlation between rainfall and NDVI trends ($r = -0.152$, $p = 0.382$) is particularly striking, as it contradicts the expected positive relationship between precipitation and vegetation growth in semi-arid ecosystems (Huxman et al., 2004). While statistically non-significant, the direction of this relationship indicating that areas with higher rainfall experienced slightly greater vegetation decline suggests complex mediating factors. This aligns with emerging research from similar Sahelian contexts where land use intensification has been shown to override climatic controls on vegetation dynamics (Herrmann et al., 2020). The spatial heterogeneity in NDVI decline rates, despite relatively uniform rainfall increases, further supports this interpretation, pointing to localized anthropogenic pressures as primary drivers of degradation.

4.2 Climate Variability in Context

The observed rainfall patterns in Musawa LGA exhibit characteristics typical of Sudan-Sahelian climate regimes but with notable deviations from historical trends. The mean annual rainfall of 898.81 mm places Musawa within the higher rainfall belt of Nigeria's semi-arid zone, yet the 10.5% coefficient of variation indicates substantial inter-annual fluctuations that create agricultural vulnerability. The three-phase pattern identified predominantly wet (2017-2020), dry (2021-2022), and return to wet conditions (2023-2024) reflects the oscillatory nature of West African monsoon systems documented in regional climate studies (Biasutti, 2019).

The unimodal rainfall distribution, with 88.9% of annual precipitation concentrated in just four months (June-September) and August alone contributing 35.5%, creates specific challenges for vegetation and agricultural systems. This extreme seasonality, while characteristic of Sudan-Sahelian climates, has intensified implications in the context of changing land use practices. The high-intensity rainfall events concentrated in peak months likely contribute to soil erosion and reduced infiltration, particularly on degraded lands, creating a feedback loop that exacerbates desertification despite adequate total precipitation (Descroix et al., 2018).

The 2024 record rainfall (1,042.62 mm) coinciding with continued vegetation decline (NDVI: 0.202) presents a particularly instructive case. This suggests that beyond certain thresholds of land degradation, increased rainfall may not lead to vegetation recovery and may instead accelerate erosion processes. This phenomenon has been documented in other semi-arid regions where soil structure deterioration limits the effectiveness of increased precipitation (García-Ruiz et al., 2015).

4.3 The Rainfall-Vegetation Disconnect

The weak, non-significant correlation between mean rainfall and NDVI decline rates (explaining only 2.3% of variance) provides compelling evidence that rainfall amounts alone are poor predictors of desertification vulnerability in Musawa LGA. This finding necessitates a fundamental rethinking of desertification drivers in the region. Several mechanisms may explain this disconnect:

1. Land Use Intensification: Agricultural expansion and intensification likely represent the most significant driver of vegetation decline. The conversion of natural vegetation to cropland, particularly for rainfed agriculture, reduces perennial vegetation cover and increases soil exposure. This aligns with findings from Azare et al. (2020), who documented similar patterns in Nigeria's Sudano-Sahelian region, where agricultural expansion has accelerated despite climatic constraints.

2. Rainfall Effectiveness vs. Amount: The effectiveness of rainfall determined by factors such as intensity, timing, and soil infiltration capacity may be more important than total amount. The concentration of rainfall in high-intensity events (particularly in August, mean: 318.73 mm) likely increases runoff and reduces soil moisture retention, especially on degraded soils. This creates conditions where increased rainfall does not translate to improved vegetation condition.

3. Soil Degradation Thresholds: The possibility that soil degradation has crossed critical thresholds beyond which vegetation recovery becomes difficult, even with favorable rainfall, represents a concerning scenario. Soil organic matter depletion, compaction, and erosion may have reached levels where the land's capacity to support vegetation has been fundamentally compromised.

4. Temporal Mismatches: Vegetation responses to rainfall may operate on different temporal scales than annual measurements capture. Lag effects, where vegetation responds to rainfall from previous years, or threshold responses, where vegetation only recovers after consecutive good rainfall years, may obscure direct annual relationships.

The spatial analysis revealing no clear geographic pattern in the strength of the rainfall-vegetation relationship further supports the interpretation that local factors such as specific land management practices, soil characteristics, or community resource use patterns override broad climatic gradients.

4.4 Implications for Desertification Theory

These findings contribute to an evolving understanding of desertification that emphasizes the interaction between climatic and anthropogenic drivers rather than viewing climate as the primary determinant. The "Musawa Paradox" challenges several assumptions in traditional desertification models:

1. Climate Determinism: The assumption that vegetation changes in semi-arid regions are primarily climate-driven requires revision. In Musawa LGA, similar climatic conditions produce widely varying vegetation responses, suggesting that local factors mediate climate impacts.

2. Linear Relationships: The expectation of simple positive correlations between rainfall and vegetation growth does not hold in this context. Complex, potentially non-linear relationships involving thresholds and feedback loops better explain the observed patterns.

3. Uniform Responses: The spatial heterogeneity in vegetation decline rates indicates that desertification processes are not uniform across landscapes but are shaped by localized factors including land tenure systems, agricultural practices, and infrastructure development.

These insights align with contemporary socio-ecological frameworks that conceptualize desertification as emerging from coupled human-environment systems rather than as a simple environmental response to climatic forcing.

4.5 Comparison with Regional Studies

The patterns observed in Musawa LGA both contrast and align with findings from other Sahelian regions. The overall vegetation decline contrasts with the "re-greening" reported in some Sahelian areas since the 1990s, suggesting that local context matters significantly. However, the disconnection between rainfall and vegetation trends echoes findings from studies in Burkina Faso and Niger, where land use changes have been identified as dominant drivers of environmental change.

The seasonal rainfall concentration (88.9% in four months) is more extreme than in some neighboring regions, potentially explaining the particularly pronounced disconnect between total rainfall and vegetation response. This highlights the importance of considering not just total precipitation but its seasonal distribution in understanding vegetation dynamics.

4.6 Limitations and Future Research Directions

Several limitations of this study point to important directions for future research:

1. Temporal Scope: The eight-year study period, while sufficient to identify trends, may not capture longer-term cycles or climate variability patterns. Extending the analysis to include earlier decades would provide valuable context.

2. Causality Assessment: While correlations have been identified, establishing causality requires additional data on land use changes, agricultural practices, and socio-economic factors. Integrated studies combining remote sensing with household surveys and field measurements would be particularly valuable.

3. Process-Level Understanding: Future research should investigate the specific mechanisms through which land use affects vegetation-rainfall relationships, including soil moisture dynamics, rooting patterns, and microclimatic effects.

4. Scale Considerations: The 5 km resolution, while appropriate for regional analysis, may miss important local-scale variations. Multi-scale approaches combining different spatial resolutions could provide more nuanced understanding.

4.7 Conclusion of Discussion

The findings from Musawa LGA present a compelling case for re-evaluating desertification drivers in Sudan-Sahelian regions. The consistent vegetation decline despite increasing rainfall, coupled with the weak relationship between rainfall amounts and degradation rates, points to anthropogenic factors as primary drivers of environmental change. This does not negate the importance of climate variability but rather suggests that its impacts are mediated through human activities and land management practices.

The "Musawa Paradox" highlights the need for integrated approaches to desertification that address both climatic and anthropogenic drivers. Policy and management interventions focused solely on climate adaptation are likely insufficient; they must be complemented by strategies addressing land use practices, soil conservation, and sustainable resource management. This integrated perspective offers the most promising pathway for addressing the complex challenge of desertification in Musawa LGA and similar regions across the Sahel.

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study provides compelling evidence of the **"Musawa Paradox"** the simultaneous occurrence of increasing rainfall and declining vegetation in Musawa LGA between 2017 and 2024. Three key findings emerge: First, annual rainfall showed a slight but consistent positive trend (mean slope: 0.01327 mm/year), reaching a record high of 1,043 mm in 2024. Second, vegetation condition declined universally across all sampled locations (mean NDVI slope: -16.41), representing a 13.7% reduction over eight years. Third, and most critically, rainfall explained only 2.3% of the variance in vegetation decline rates, with correlation analysis revealing no significant relationship ($r = -0.152$, $p = 0.382$).

These findings challenge conventional climate-centric desertification narratives and underscore the predominant role of **anthropogenic drivers** in environmental degradation. The spatial heterogeneity in vegetation responses despite uniform rainfall increases points to localized factors likely land use practices, agricultural intensification, and soil management as primary determinants of desertification vulnerability. The concentration of rainfall in high-intensity events (35.5% in August alone) exacerbates runoff and soil erosion on degraded lands, creating a feedback loop that limits the benefits of increased precipitation.

5.2 Recommendations

5.2.1 Policy Interventions

1. **Integrated Land Use Planning:** Develop zoning regulations that protect vulnerable areas from agricultural expansion and promote sustainable intensification in already cultivated lands.
2. **Soil Conservation Mandates:** Implement policies requiring soil conservation practices (contour farming, terracing, cover cropping) in government-supported agricultural programs.
3. **Climate-Smart Agriculture Incentives:** Create subsidy programs for drought-resistant crops, conservation tillage, and agroforestry systems that enhance soil moisture retention.

5.2.2 Management Practices

1. **Water Harvesting Infrastructure:** Promote small-scale water harvesting techniques (zai pits, half-moons, micro-catchments) to increase rainfall infiltration and reduce runoff.
2. **Seasonal Land Management:** Align agricultural activities with rainfall patterns, emphasizing soil preparation before rains and residue management after harvests.
3. **Community-Based Monitoring:** Establish local environmental monitoring committees to track vegetation changes and implement adaptive management strategies.

5.2.3 Research Priorities

1. **Causal Mechanism Studies:** Investigate specific pathways through which land use practices affect vegetation-rainfall relationships using integrated field and remote sensing approaches.
2. **Socio-Ecological Research:** Examine how local institutions, land tenure systems, and economic factors mediate environmental outcomes.
3. **Long-Term Monitoring:** Establish permanent observation plots to track decadal changes in vegetation, soils, and microclimates.

5.2.4 Community Engagement

1. **Participatory Restoration:** Involve local communities in designing and implementing land restoration projects that address both ecological and livelihood needs.
2. **Knowledge Integration:** Combine scientific findings with indigenous knowledge systems to develop culturally appropriate adaptation strategies.
3. **Capacity Building:** Train local extension agents and farmers in sustainable land management practices tailored to Musawa's specific environmental conditions.

The **Musawa Paradox** represents both a warning and an opportunity a warning that conventional approaches to desertification may be inadequate, and an opportunity to develop more integrated, context-specific solutions. By addressing the complex interplay between climate variability and human activities, stakeholders in Musawa LGA can work toward reversing degradation trends while building resilience to future environmental changes.

DECLARATIONS STATEMENT

Ethical Approval and Consent to Participate

This study involved the use of publicly available geospatial datasets and high-resolution satellite imagery. No human participants, personal data, or experimental subjects were directly involved in the research. Therefore, formal ethical approval was not required. All data handling complied with relevant institutional and national guidelines for geospatial research.

Consent for Publication

Not applicable, as the study does not involve individual participants or identifiable personal information.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. The research was conducted independently, and the author has no financial, commercial, or personal relationships that could inappropriately influence the work reported.

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Authors' Contributions

David Mkpanam Nyong conceptualized the study, collected and processed the geospatial datasets, conducted the GIS analysis, interpreted the results, and wrote the manuscript. The authors approve the final version for submission.

Data Availability

All geospatial data supporting the findings of this study are available from public sources (Google Earth Engine) and can be provided by the corresponding author upon reasonable request. Processed GIS layers and shapefiles generated during the study are archived and can be shared upon request for academic or research purposes.

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