

# ASSESSMENT OF DESERTIFICATION DYNAMICS USING NDVI TIME SERIES IN MARGINAL LAND AREAS OF JIGAWA STATE

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## ABSTRACT

This study examines the spatiotemporal trends in desertification in marginal land areas of Jigawa State, Nigeria, utilizing Normalized Difference Vegetation Index (NDVI) time-series analysis from 2015 to 2024. Landsat 8 satellite imagery was applied to derive NDVI values for both dry (February) and wet (June) seasons, and vegetation cover was classified into four categories: Very Low, Low, Moderate, and High. The Mann-Kendall test and Sen's Slope Estimator were used to assess the statistical significance and magnitude of NDVI trends over the study period. Findings reveal a sharp decline in the area covered by Low NDVI values during the dry season, with a 63% reduction between 2015 and 2024, indicating progressive vegetation degradation in arid months. Conversely, Moderate and High NDVI classes exhibited consistent increases in both February and June data, suggesting improved vegetation conditions and partial recovery in previously degraded zones. The results reflect an overall positive trend in vegetation health, particularly during the wet season. This study demonstrates the effectiveness of NDVI time-series analysis for monitoring land degradation and guiding sustainable land management practices. It stresses the need for the sustained use of remote sensing techniques in environmental assessment and policy planning to combat desertification in semi-arid regions.

**Keywords:** NDVI, Spatiotemporal, Desertification, Time Series, Sen's Slope, Mann-Kendall Test.

## INTRODUCTION

Desertification, characterized by the persistent degradation of drylands, is a major environmental issue in Northern Nigeria. It threatens food security, water resources, and ecological stability, particularly in ecologically fragile and agriculturally stressed marginal land areas (Adu & Adie, 2018). Jigawa State, in Nigeria's semi-arid region, is becoming increasingly vulnerable to desertification due to unsustainable land-use practices, population growth, and climatic variability.

Remote sensing has emerged as a powerful tool for monitoring vegetation dynamics over time. The Normalized Difference Vegetation Index (NDVI) is widely used to assess vegetation health and identify degradation trends. Time series analysis of NDVI data provides a reliable means of tracking desertification processes and evaluating the effectiveness of land management strategies (Chen et al., 2023).

This study utilizes NDVI (Normalized Difference Vegetation Index) time-series analysis to assess vegetation changes across the marginal lands of Jigawa State from 2015 to 2024. It aims to identify specific areas experiencing degradation, which is crucial for understanding the region's environmental challenges. The findings are intended to inform and strengthen sustainable environmental

management practices, thereby supporting the preservation and improvement of the area's ecological integrity.

## MATERIALS AND METHODS

### Study Area

Jigawa State lies in northwestern Nigeria and is predominantly classified as part of the country's semi-arid ecological zone. The state covers an area of approximately 23,000 km<sup>2</sup>, extending from latitude 10.901497°N to 12.997281°N and longitude 8.061218°E to 10.703718°E, and receives an average annual rainfall of 600–900 mm, concentrated mainly between June and September. The terrain is predominantly flat, with sandy and loamy soils susceptible to wind erosion and salinization.

This study focuses on the marginal land areas situated along the state's border with the Sahelian region, where desertification is most severe. The local government areas (LGAs) that are most prevalent in the region are Yankwashi, Roni, Kazaure, Babura, Sule Tankarkar, Gumel, Maigatari, Kaugama, and Birniwa. These areas are characterized by low vegetation cover, erratic rainfall, expanding dunes, and ongoing soil degradation (Figure 1).

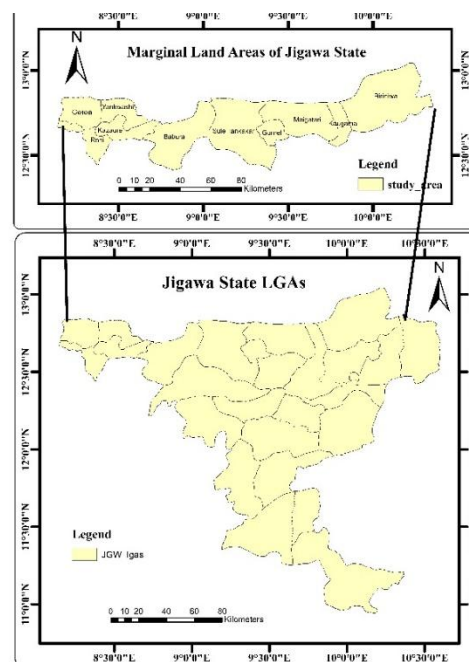


Figure 1. An Index Map of Jigawa State showing the Study Area.

### Data Collection

**Satellite Imagery:** The satellite data used in this study are Landsat

8 data and were obtained from the USGS Earth Explorer platform (earthexplorer.usgs.gov) on 6<sup>th</sup> December 2025. These datasets are open source for educational and research purposes, particularly for applications such as NDVI computation and vegetation monitoring. The Landsat 8 Operational Land Imager

improve data quality, a cloud mask was created in the Raster Calculator by applying a threshold to exclude NDVI values typically associated with cloud cover, thereby enhancing the reliability of the vegetation assessment.

**Table 1.** NDVI Standard Classification Scheme

NDVI Range	Vegetation Status / Land Cover
< 0.0	Water bodies, clouds, snow
0.0 – 0.1	Barren areas, rock, sand, urban surfaces
0.1 – 0.2	Sparse vegetation, shrubs, and dry grasslands
0.2 – 0.3	Moderate vegetation (e.g., grasslands, croplands)
0.3 – 0.5	Healthy vegetation (e.g., dense grass, crops)
> 0.5	Very dense vegetation (e.g., tropical forests)

**NDVI Calculation and Classification**

NDVI (Normalized Difference Vegetation Index) is a widely used remote sensing index for assessing and classifying vegetation cover. This index is derived from satellite images, using the red and near-infrared (NIR) bands. The formula for the Normalized Difference Vegetation Index (NDVI) is calculated as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Where:

*NIR* and *Red* are the reflectance values of the near-infrared and red bands, respectively.

NDVI values range from -1 to +1 and are commonly used to classify various land cover types and assess vegetation health. A standard classification scheme, frequently applied in environmental and remote sensing studies, includes the following categories (Table 1).

**Source:** Adopted from Lillesand et al. (2015).

(OLI) sensor provides multispectral data by capturing bands in the visible, near-infrared (NIR), and shortwave infrared (SWIR) portions of the electromagnetic spectrum (Lillesand et al., 2015). All the images were processed using ArcGIS 10.8 across six distinct periods, capturing both dry and wet seasons: February 2015, June 2015, February 2020, June 2020, February 2024, and June 2024.

The NDVI rasters for six time periods (Feb 2015, Jun 2015, Feb 2020, Jun 2020, Feb 2024, Jun 2024) for the study area were classified into four NDVI density classes, following the standard NDVI classification scheme (Figure 3.2.1).

**Data Processing and Analysis**

Pre-processing:

Standard cloud-masking techniques in ArcGIS were applied to improve data quality. Cloud masking involves removing or minimizing clouds and their shadows in satellite imagery, thereby enhancing the reliability of analyses, especially when computing indices such as NDVI for change detection (Esri, 2025). The NDVI data used in this study were pre-classified but contained cloud-contaminated areas that appeared as abnormally low values. To

**Trend Analysis of Desertification:**

Descriptive Statistics Analysis

Using the Spatial Analyst Tools in ArcGIS, the number of pixels per NDVI class for six time periods (February 2015, June 2015, February 2020, June 2020, February 2024, and June 2024) was calculated and converted into square kilometers (Table 1). This dataset facilitates the examination of desertification trends throughout the study period.

**Table 2.** NDVI\_Class\_Area\_Trend\_2015\_2024 in sq km

NDVI Class	15-Feb	15-Jun	20-Feb	20-Jun	24-Feb	24-Jun
Very Low	5443.38	172014.8	3982.77	228073.2	654.93	22731.84
Low	396271.5	318502.3	252874.8	272526.8	145682.3	320025.9
Moderate	252916.7	163137.4	389168.9	137455.6	489938.6	252292
High	12677.4	13654.44	21282.48	29253.33	31033.17	72259.2

**Mann-Kendall Test**

The Mann-Kendall test is a nonparametric statistical method commonly used to detect trends in time-series data (Yue & Wang, 2004), such as the Normalized Difference Vegetation Index (NDVI), without assuming a normal distribution. In this study, the Mann-Kendall test was employed to assess the statistical significance of NDVI trends over the study period, specifically to determine whether a monotonic trend, consistently increasing or decreasing, exists in the NDVI time series from 2015 to 2024. The test

computes the S statistic from pairwise comparisons of data points and then derives the Z statistic to assess the statistical significance of the detected trend. The computed Z value is then compared to critical values from the standard normal distribution (usually  $|Z| > 1.96$  is considered significant at the 95% confidence level).

**Sen's Slope Estimator**

In this study, after identifying significant trends with the Mann-Kendall test, Sen's

slope estimator was used to quantify the rate of change in NDVI from 2015 to 2024. Sen's slope estimator is a non-parametric statistical technique used to estimate both the magnitude and direction of a trend in time-series data, particularly when the data do not meet the assumptions of parametric tests. It computes the median of all possible pairwise slopes between data points, making it robust to outliers and non-normal data distributions (Helsel, D. R., & Hirsch, R. M., 2002). The resulting slope represents the rate of increase or decrease in NDVI over a specified time interval, typically expressed annually.

### Calculation of Percentage Change

Percentage change analysis is fundamental in NDVI-based studies, as it simplifies the precise assessment of increases or decreases in vegetation cover across different time periods. Expressing changes as percentages enables easier comparison of trends across different regions and temporal scales, thereby highlighting significant shifts in vegetation dynamics (Jensen, 2016).

The percentage change in NDVI class areas was computed using the standard formula widely applied in remote sensing and land use change analysis (Jensen, J. R., 2007; Lillesand, T. M. et al., 2015):

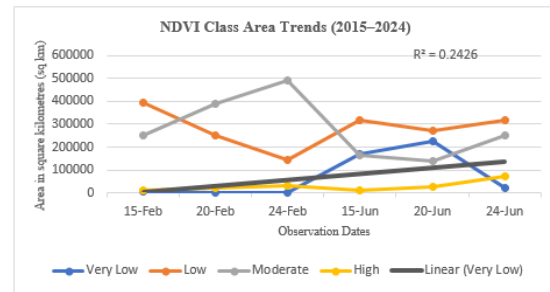
$$\text{Percentage Change} = \frac{A_{t2} - A_{t1}}{A_{t1}} \times 100$$

This formula quantifies the relative increase or decrease in the spatial extent of each NDVI class over time, where  $A_{t1}$  is the initial area, and  $A_{t2}$  is the final area. (e.g., in 2015)

## RESULTS AND DISCUSSION

### Temporal Trends in NDVI

The NDVI area values Table 2 and in figure 3, measured in square kilometers (km<sup>2</sup>) categorised into four classes: *Very Low*, *Low*, *Moderate*, and *High* illustrate the temporal area coverage of each NDVI class across six observation periods corresponding to the dry (February) and wet (June) seasons over three selected years (2015, 2020, and 2024). The graph (Figure 3) shows a great seasonal change in NDVI values, especially from February to June. Interestingly, the "Very Low"



**Figure 3.** A graph showing the NDVI Class Area Trends from 2015 to 2024

These changes are likely driven by a combination of increasing climatic variability (especially rainfall fluctuations), land-use/land-cover change such as urban expansion and agricultural intensification, and local vegetation recovery efforts, including improved vegetation growth during wetter seasons and possible afforestation or conservation practices in some areas.

However, the trendline analysis of the Normalized Difference Vegetation Index (NDVI) reveals significant insights into vegetation dynamics over the period. An upward-sloping line indicates an increase in NDVI, indicating a gain or recovery of vegetation in the area studied. Conversely, a downward-sloping line reflects a decrease in NDVI, suggesting a potential vegetation loss or desertification. These trends are necessary for understanding ecological changes and informing environmental management strategies.

### Spatial Patterns of Desertification (2015–2024)

The classification of NDVI maps (Figure 3.2.1) provides significant insights into the spatial distribution and extent of desertification processes within the study area. The expansion of "Very Low" and "Low" NDVI areas indicates a concerning trend of increased degradation, characterized by diminished vegetation cover and a consequent loss in land productivity. Conversely, a reduction in "Moderate" and "High" NDVI areas points to a decline in vegetation health, which may be due to overgrazing, deforestation, or climate-related stresses. Additionally, the spatial shift in NDVI zones highlights a dynamic landscape in which some previously degraded areas may show signs of recovery, while new regions are experiencing degradation. This highlights the serious role of monitoring NDVI classifications in understanding and effectively responding to the dynamics and challenges of desertification.

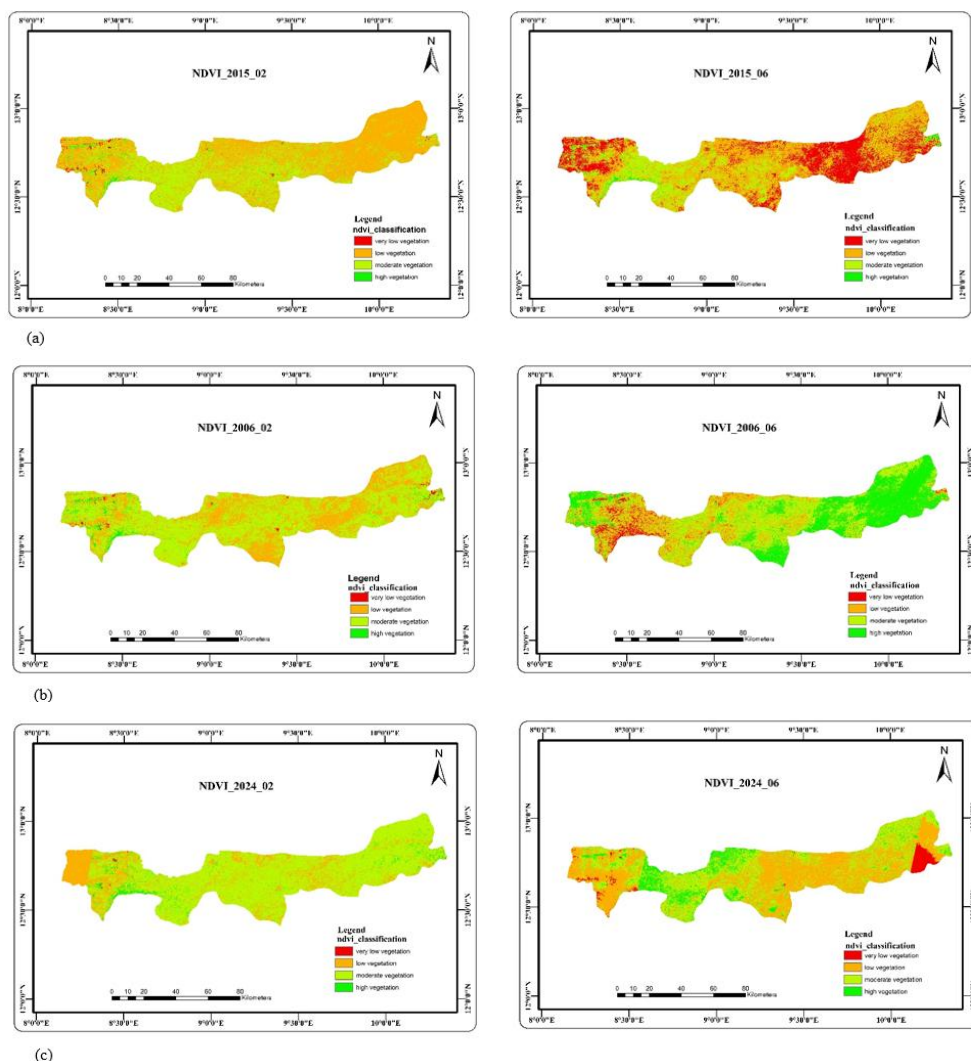


Figure 3 NDVI Density Classes; (a) NDVI\_2015 (b) NDVI\_2020 (c) NDVI\_2024

### Statistical Findings on NDVI Trends and Desertification (2015–2024)

Statistical analysis was conducted to examine the trends and the significance of changes in NDVI (Normalized Difference Vegetation Index) classes in the study area from 2015 to 2024. This was done using the Mann-Kendall trend test, Sen's Slope Estimator, and the calculation of the percentage change in NDVI classes.

#### Mann-Kendall Trend Test

The Mann-Kendall test was applied to each NDVI class to identify monotonic trends and their direction over the study period. The results showed:

Table 3. Mann-Kendall Test Result

NDVI Class	Z-Statistic	Trend Direction	Significance
Very Low	-1.77	Decreasing	Not significant
Low	-2.40	Decreasing	Significant
Moderate	1.84	Increasing	Not significant
High	2.58	Strongly Increasing	Significant

The statistical findings from the Kendall test, as presented in Table 3, indicate notable trends in vegetation classes based on NDVI (Normalized Difference Vegetation Index). The Low NDVI class shows a statistically significant declining trend, suggesting a reduction in degraded areas. Conversely, the High NDVI class exhibits a statistically significant positive trend, indicating a clear pattern of vegetation recovery or greening. In contrast, although the Very Low and Moderate NDVI classes show apparent trends, these are not statistically significant at the 95% confidence level, suggesting that the observed changes may not constitute robust indicators of vegetation dynamics.

#### Sen's Slope Estimator

To quantify the magnitude of NDVI changes over the study period, Sen's Slope estimator was applied to each NDVI class, with the results summarised in Table 4.

**Table 4.** Sen's Slope Estimator Result

NDVI Class	Sen's Slope (km/year)	(sq. km)	Trend
Very Low	-729.5		Decreasing
Low	-13801.7		Strongly Decreasing
Moderate	17143.4		Increasing
High	1683.7		Increasing

The Sen's slope result analysis (Table 4) reveals significant trends in vegetation cover as indicated by the NDVI (Normalized Difference Vegetation Index) classifications. The Low NDVI class has experienced a notable decline of approximately 13,802 km<sup>2</sup> per year, suggesting effective vegetation restoration in previously degraded areas. The Moderate NDVI class has increased by approximately 17,143 km<sup>2</sup> annually, indicating a positive transition toward healthier vegetation conditions. Moreover, the High NDVI class has increased, albeit at a slower rate, suggesting a gradual long-term improvement in overall vegetation cover. The consistent decline of the Very Low NDVI class is particularly encouraging, as it reflects progress in mitigating desertification. These findings collectively highlight a positive trend in vegetation health and restoration efforts.

**Calculating the Percentage Change in NDVI Classes**

Table 5 presents the calculated percentage change in area for each NDVI class between the start and end of the study period across three years: 2015 (15-Feb and 15-Jun), 2020 (20-Feb and 20-Jun), and 2024 (24-Feb and 24-Jun). The percentage change was computed using the following formula:

$$\text{Percentage Change (\%)} = (\text{Final Value} - \text{Initial Value}) / \text{Initial Value} \times 100$$

**Table 5.** Percentage change in NDVI classes from 2015 to 2024 (February data)

NDVI Class	2015 (15-Feb)	2024 (24-Feb)	Change (sq km)	% Change
Very Low	5,443.38	654.93	-4,788.45	-87.98%
Low	396,271.50	145,682.30	-250,589.2	-63.23%
Moderate	252,916.70	489,938.60	237,021.90	93.73%
High	12,677.40	31,033.17	18,355.77	144.75%

**Table 6.** Percentage change in NDVI classes from 2015 to 2024 (June data)

NDVI Class	2015 (15-Jun)	2024 (24-Jun)	Change (sq km)	% Change
Very Low	172.01 4.80	22,731.84	- 149,282.96	-86.82%
Low	318,502.30	320,025.90	1,523.60	0.48%
Moderate	163,137.40	252,292.00	89,154.60	54.66%
High	13,654.44	72,259.20	58,604.76	429.19%

The analysis of the percentage summary (Table 5) reveals significant changes in vegetation health as measured by NDVI (Normalized Difference Vegetation Index) across different categories. Very Low NDVI areas experienced a dramatic

decrease, with reductions of 88% in February and 87% in June, indicating a substantial decline in barren or severely degraded lands. In contrast, Low NDVI areas experienced an approximate significant decrease of 63% in February, while remaining relatively stable in June, with a marginal increase of 0.48%

In contrast, areas within the Moderate NDVI class expanded during both seasons, indicating a steady and sustained improvement in vegetation conditions. A remarkable increase was recorded in areas with high NDVI values, with 145% in February and 429% in June. This demonstrates a great improvement in dense vegetation cover. These results collectively indicate a general positive trend in vegetation recovery, especially in areas that transitioned from lower NDVI classes.

**Conclusion**

This research examined vegetation behavior across the marginal zones of Jigawa State from 2015 to 2024 by analyzing NDVI time-series patterns and applying the Mann-Kendall and Sen's slope statistical techniques. The results indicate notable shifts in vegetation condition over the decade, highlighting both increasing pressure on the landscape and evidence of gradual recovery.

Across the study period, areas with low NDVI values consistently contracted through February, pointing to declining dry-season vegetation and greater exposure to processes that promote land degradation. In contrast, moderate NDVI classes expanded in both February and June, suggesting a steady improvement in vegetation cover. Also, High NDVI regions displayed a slow but persistent increase, indicating that healthier vegetation is gradually re-establishing itself. Collectively, these outcomes suggest that many parts of the landscape are experiencing renewed vegetation growth, particularly zones that previously showed signs of stress.

The findings emphasize the importance of sustaining and strengthening ongoing land-restoration initiatives. Practices such as tree planting, integrating trees into agricultural systems, and adopting improved grazing and rangeland management strategies can support and further strengthen the positive vegetation trends observed. Locations that continue to exhibit declining NDVI, particularly during the dry season, should receive targeted interventions such as soil-stabilization measures, water-retention strategies, and the adoption of drought-tolerant crop varieties.

In addition, the study highlights the value of embedding satellite-based vegetation monitoring in state-level environmental management. Regular NDVI assessments can provide early indications of landscape degradation and generate evidence to inform effective decision-making. Enhancing public participation and local awareness will also be crucial, as community engagement typically increases the success and long-term viability of land-restoration programmes.

Future studies could enhance the understanding of vegetation dynamics by incorporating higher temporal resolutions, such as monthly or seasonal NDVI analyses. This approach would enable a more detailed capture of short-term variations in vegetation patterns and improve the detection of subtle changes over time. In addition, combining NDVI data with other environmental datasets, such as precipitation records, land-use/land-cover changes, and soil moisture measurements, would provide a more holistic framework for analyzing the climatic and ecological factors influencing vegetation dynamics and spatial patterns.

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