FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 22, November, 2026, pp 109 – 117
DOI : https://doi.org/10.33003/fjs-2026-1022-6068

Spatial Assessment of Dry-Season Vegetation Condition using Sentinel-2 NDVI in the Guinea Savanna Landscape of Elaite, North-Central Nigeria

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Received: 30 Sep. 2026
Accepted: 19 Oct. 2026
Published: 24 Oct. 2026

ABSTRACT
Despite increasing dry-season vegetation stress in Guinea savanna communities in North-Central Nigeria under the combined pressures of climatic seasonality and anthropogenic land-use change, fine-scale, community-level spatial evidence remains limited. This study presents dry-season vegetation conditions in Elaite using Sentinel-2 Level-2A imagery acquired on 15th February 2026. We calculated the normalised difference vegetation index (NDVI) in QGIS and classified it into four vegetation-stress categories using thresholds calibrated against known Guinea savanna benchmarks. The NDVI values ranged from 0.0 to 0.44, indicating high spatial variability in vegetation condition. Built-up and sparsely vegetated surfaces dominated the landscape (87.85%; 1,113 ha; mean NDVI = 0.15), indicating high physiological stress under peak dry-season conditions. Cultivated and fallow lands covered 10.42% (132 ha; mean NDVI = 0.23) and showed moderate stress. Dense shrubland (3 ha; mean NDVI = 0.38) was limited to riparian corridors and covered 0.24% of the area. Wetland and open-water surfaces (19 ha; 1.5%) had negative NDVI values. The lowest NDVI values are concentrated in human-modified zones, and the highest NDVI values are restricted to hydrologically buffered riparian zones, consistent with drought response theory, which predicts that residual soil moisture availability mediates vegetation resilience under moisture deficits. The results provide a baseline for monitoring land degradation, assessing drought, and planning climate-change adaptation in Guinea savanna environments.

Keywords: NDVI, Vegetation stress, Guinea savanna, Sentinel-2, Dry season, Elaite, land degradation

INTRODUCTION

Vegetation is important for the health and stability of terrestrial ecosystems. It supports biodiversity and regulates biogeochemical and energy exchange processes. It is also reported to be important for soils and for the provision of vital ecosystem services on which many rural communities in sub-Saharan Africa depend for farming, fuelwood, grazing, and other livelihood activities (Frank et al., 2015; IPCC, 2013; Wang et al., 2006; Wen et al., 2017).In Guinea savanna zones, vegetation growth is strongly seasonal, with rapid regeneration during the rainy season and a distinct decay phase in the dry season, when moisture becomes limiting. However, scholars confirmed that these natural cycles are increasingly affected by anthropogenic activities such as agricultural expansion, overgrazing, bush burning, and fuelwood harvesting (Adenle, 2020; Brandt et al., 2016; Vicente-Serrano et al., 2013). As pressure on land resources increases, understanding local-scale vegetation dynamics during the dry season is becoming more important. This knowledge is highly relevant for monitoring land degradation, environmental management, and guiding climate adaptation policies in Guinea savanna landscapes (Chu et al., 2019; Guan et al., 2021).

Remote sensing techniques, especially satellite-based vegetation monitoring, have emerged as one of the most efficient methods for assessing vegetation condition over large spatial and temporal scales (Pettorelli et al., 2005; Huete, 2016). The NDVI (Normalized Difference Vegetation Index) is one of the most popular techniques. It reliably indicates vegetation health, greenness, and photosynthetic activity using the red and near-infrared portions of the electromagnetic spectrum (Pettorelli et al., 2005; Tucker, 1979; Rouse et al., 1973). NDVI is particularly useful in savanna environments, where vegetation conditions change rapidly between the wet and dry seasons. As soil moisture falls and water stress increases during the dry season, plant photosynthesis decreases, chlorophyll content declines, and vegetation cover thins, scholars say. These changes reduce NDVI values, often before visible signs of vegetation decline appear on the ground (McDowell et al., 2011; Vicente-Serrano et al., 2013; Zeppel et al., 2015). NDVI is widely used to monitor vegetation stress, identify areas prone to degradation, and support land management and environmental planning at local and regional scales (Scanlon et al., 2005; Xu et al., 2017).

According to Drusch et al. (2012), the availability of European Space Agency (ESA) Sentinel-2 satellite imagery at a spatial resolution of 10–20 meters has greatly enhanced the practical utility of NDVI for vegetation stress. This provision helps detect fine-scale land-cover variations that coarser-resolution sensors (e.g., MODIS at 250 m to 1 km) often obscure or mix. Adamu et al. (2021) demonstrate that Sentinel-2 data are much more useful for identifying localized vegetation stress, changes in seasonal plant growth patterns, and signs of human-induced disturbances in fragmented rural landscapes in the Guinea savanna region of West Africa. Furthermore, several studies found that NDVI values obtained during the dry season show stronger physiological and human-related stress signals in Guinea savanna environments than those acquired during the wet season.

Scholars have argued that wet-season images usually represent maximum plant growth driven by rainfall. Dry-season data better reflect the residual stress conditions that often affect the long-term health of these biomes (Adenle, 2020; Fensholt et al., 2009; Anyamba & Tucker, 2005).

Despite these advances, high-resolution NDVI studies focused specifically on the dry season at the community level remain rare in the rural Guinea savanna areas of Kogi State and the wider Middle Belt region of Nigeria. Most previous research has been carried out at much larger regional or state-wide scales and often using multi-year image composites that smooth out important local differences and mask the true intensity of vegetation stress during the peak dry season (Adenle, 2020; Osunmadewa et al., 2015). Elaite is a typical rural settlement in the Ajaokuta Local Government Area of Kogi State. It represents many communities in the Guinea savanna, which are located near floodplains, depend heavily on subsistence farming, and are near industrial developments. To date, no detailed, high-resolution remote sensing assessment of dry-season vegetation stress has been conducted in this type of setting. Scholars have argued that this lack of evidence makes it difficult for local authorities to design more targeted interventions and limits understanding of the spatial drivers of vegetation decline at the community scale (König et al., 2018; Li et al., 2013).

This study aims to address this critical gap by providing the first high-resolution and detailed assessment of dry-season vegetation stress in Elaite using Sentinel-2 Level-2A imagery and NDVI threshold classification based on established benchmarks for Guinea savanna environments (Hmimina et al., 2013; Pettorelli et al., 2005). The study makes three major contributions. First, it establishes a robust baseline community-level NDVI for this previously unstudied rural settlement in North-Central Nigeria. Second, it offers a practical, open-source methodological framework for fine-scale dry-season vegetation monitoring in similar data-poor rural areas across West Africa. And lastly, it provides clear, spatially explicit information that can directly support local efforts in land degradation management, drought monitoring, and climate adaptation planning at the community and local government levels.

MATERIALS AND METHODS

Study Area

Elaite is a rural town in North-Central Nigeria, located in the Ajaokuta Local Government Area of Kogi State, between latitudes 7°33′N and 7°34′N and longitudes 6°39′E and 6°40′E. Its geographical setting is presented in Figure 1, which comprises three map panels: the top-left panel shows the map of Nigeria with Kogi State highlighted; the bottom-left panel illustrates Ajaokuta Local Government Area within Kogi State and the location of Elaite; and the right-hand panel presents a detailed map of the study area, showing the spatial extent and location of Elaite.

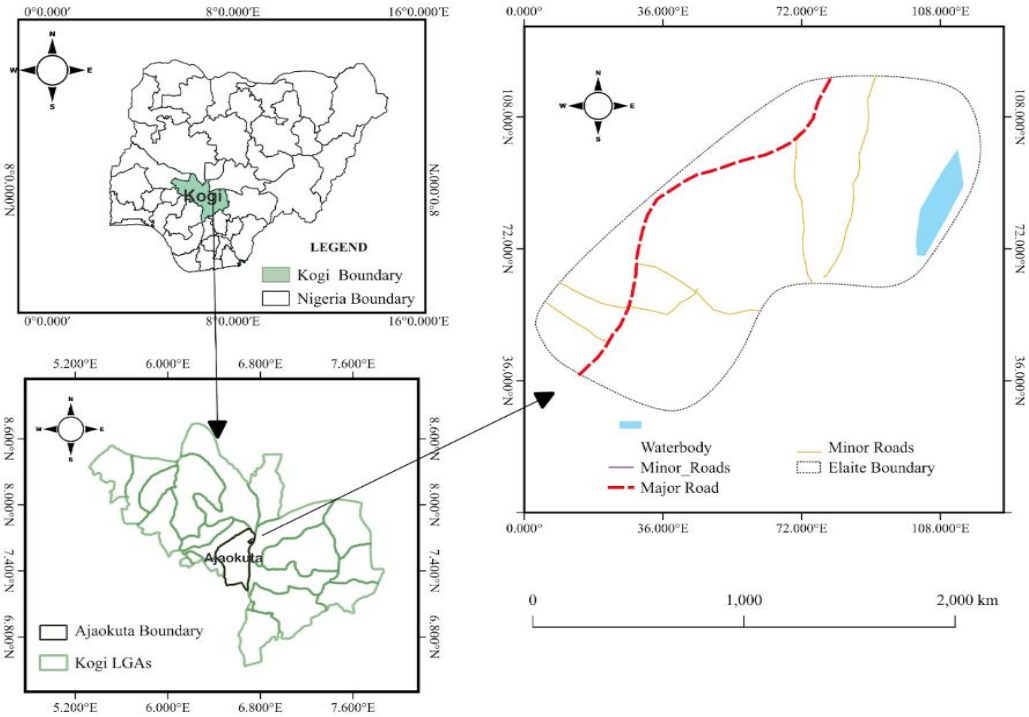

Figure 1: Map of Elaite Community in Ajaokuta Local Government Area, Kogi State
Source: Laboratory Analysis by the authors, 2026

Elaite is within the Guinea savanna ecological zone, characterized by a mixture of tall grasses, scattered deciduous trees, and seasonal vegetation. Common tree species are Isoberlinia spp. and Vitellaria paradoxa (shea tree). Riparian gallery forest patches occur along streams and drainage channels (Areola, 1982; White, 1983). The landscape is predominantly rural, with a mixture of agricultural activities, natural vegetation, and scattered settlements, covering about 1,267ha of mixed agricultural and savanna environments.

Elaite is situated in the tropical wet-and-dry climate zone (Köppen–Geiger classification: Aw). The wet season is from April or May to October, with a mean annual rainfall of 1,100–1,500 mm. Rainfall start and end dates vary from year to year, significantly affecting farming planning and vegetation phenology (Olaniran, 2002). The dry season runs from November to March or early April. Northeast Harmattan winds characterize it, reducing humidity and increasing moisture loss from soils and plant tissues (Olaniran, 2002).

Daytime temperatures are always above 33°C and can reach 41°C during the peak months of Harmattan (Animashaun et al., 2020; Ayanlade, 2023).

Temperatures during these periods create vapor pressure deficits that quickly deplete soil moisture and induce visible vegetation senescence long before the rains return. The strong contrast between wet-season productivity and dry-season physiological stress thus offers an ideal opportunity to study the spectral expression of moisture deficit across a Guinea savanna landscape (Fensholt et al., 2009; Pettorelli et al., 2005).

The terrain is gently undulating, with broad interfluves separated by shallow drainage channels that carry surface runoff westward to the Niger River floodplain. This proximity to the floodplain is relevant to understanding spatial patterns of vegetation condition: plants in low-lying areas along drainage lines can access residual soil moisture long after upland soils have dried out, creating sharp NDVI contrasts between riparian and non-riparian surfaces (McDowell et al., 2013). The soils are predominantly ferruginous, tropical weathered soils derived from Precambrian Basement Complex rocks and are moderately fertile under natural vegetation cover but prone to erosion and nutrient depletion under intensive tillage and repeated burning (Areola, 1982). The major economic activity is subsistence farming of yams, cassava, maize, and sorghum, with some grazing and fuelwood collection. The assessment focuses on the natural savanna woodland, which has been fragmented into a heterogeneous, patchy land-use mosaic due to expanding agriculture and selective tree removal (Adenle, 2020; Osunmadewa et al., 2015).

The Ajaokuta Steel Company, although located within the same Local Government Area as Elaite, has exerted only limited direct influence on land-use transformation within the community. This is because large-scale industrial complexes in Nigeria typically generate pronounced spatial and environmental impacts within their immediate operational zones, while peripheral rural settlements experience weaker land-conversion pressures, particularly where industrial–rural linkages and transport-driven urban expansion are minimal (Mabogunje, 1980). Consequently, Elaite has largely maintained its predominantly rural ecological structure, with minimal direct industrial-induced land-use change.

Data Collection

The satellite data used in the present study were a single Sentinel-2A Level-2A multispectral image downloaded from the Copernicus Open Access Hub (scihub.copernicus.eu) for the acquisition date of 15 February 2026. Sentinel-2 Level-2A products deliver surface reflectance values corrected to the bottom of the atmosphere by the Sen2Cor processor, removing the confounding effects of atmospheric scattering and absorption before delivery to the user (Drusch et al., 2012; Main-Knorn et al., 2017). This eliminates the need for additional atmospheric correction before index calculation and makes Level-2A data especially suitable for studies without access to specialized radiometric processing software.

The authors deliberately chose February as the acquisition month. This Period falls roughly in the middle of the dry season in the Guinea savanna zone of North-Central Nigeria, when the Harmattan conditions are well established, soil moisture has been exhausted across most of the landscape, and vegetation photosynthetic activity is close to its seasonal minimum (Olaniran, 2002; Animashaun et al., 2020). This is the time of year when NDVI is most sensitive to physiological stress signals, because green, actively photosynthesizing canopy is minimal, and the spectral contrast between stressed and relatively healthier vegetation surfaces is greatest (Tucker, 1979; Pettorelli et al., 2005; Fensholt et al., 2009).

If the picture had been taken in October, it would have been very different. The Guinea savanna landscape at that time is at or near a productive peak, with soils still moist from months of wet-season rainfall and woody canopy fully leafed out. In Guinea savanna environments, wet-season NDVI reliably reflects this burst of photosynthesis rather than the vegetation's basic structural and physiological conditions (Anyamba & Tucker, 2005; Fensholt et al., 2009). Thus, an October NDVI map would mostly capture seasonal greenness rather than the stress conditions that this study is designed to document. A uniform signal of late wet-season canopy fullness (Tucker, 1979; Pettorelli et al., 2005) would conceal the stress signals that differentiate moderately healthy riparian shrubland from severely depleted upland savanna. The seasonal sensitivity of NDVI to physiological stress has been observed in dryland and savanna environments worldwide, with dry-season acquisitions consistently demonstrating stronger discrimination between degraded and intact vegetation surfaces (Vicente-Serrano et al., 2013; Adenle, 2020).

Cloud cover was not a major issue for the analysis. Scene metadata indicated 7% cloud cover across the entire tile, and a visual inspection of the true-colour composite showed the study boundary was cloud-free. The Sentinel-2 Level-2A products include a Scene Classification Layer (SCL) to characterize cloud and cloud-shadow pixels for an easy-to-interpret quality control before index calculation (Drusch et al., 2012; Main-Knorn et al., 2017). As the affected pixels were entirely outside the study boundary, no cloud-masking or pixel-exclusion procedures were required.

NDVI was calculated using the red (665 nm) and near-infrared (842 nm) spectral bands of Sentinel-2 (Bands 4 and 8, respectively) (Rouse et al., 1973; Tucker, 1979). Both bands are provided at a native 10 m spatial resolution, which is preserved throughout the analysis to maintain spatial integrity. A single MODIS pixel at 250 m resolution encompasses an area equivalent to 625 Sentinel-2 pixels, increasing the likelihood of spectral mixing and masking fine-scale landscape variability. In contrast, Sentinel-2 images better resolve smallholder farm plots and fragmented vegetation patches, improving accuracy in heterogeneous rural environments. Previous studies have demonstrated the suitability of Sentinel-2 data for detailed vegetation and land use analysis in savanna ecosystems due to its high spatial and radiometric resolution (Drusch et al., 2012; Adamu et al., 2021; Xue & Su, 2017). Table 1 summarizes the dataset's main characteristics.

Table 1: Data Characteristics used for this Study

Parameter	Details
Satellite / Sensor	Sentinel-2A MSI (Multispectral Instrument)
Processing Level	Level-2A (Bottom-of-Atmosphere Reflectance; Sen2Cor)
Acquisition Date	15 February 2026
Spatial Resolution	10 m (Bands 4 and 8)

Parameter	Details
Cloud Cover (%)	7%
Spectral Bands Used	Band 4 – Red (665 nm); Band 8 – NIR (842 nm)
Data Source	Copernicus Open Access Hub (scihub.copernicus.eu)

Image Pre-Processing and NDVI Calculation

The Sentinel-2 Level-2A products were already atmospherically corrected (Main-Knorn et al., 2017), so no further radiometric correction was needed. Pre-processing was limited to spatial subsetting and quality checks. We clipped the image to the Elaite study boundary (7°33′-7°34′N; 6°39′-6°40′E), digitized it in QGIS using high-quality basemaps as reference, and projected it to WGS 84. We visually checked cloud cover within the study area using image metadata. Cloud contamination was minimal, so no further masking was needed.

NDVI was calculated using the standard formulation:

$$NDVI = (NIR - Red) / (NIR + Red) = (Band\ 8 - Band\ 4) / (Band\ 8 + Band\ 4)$$

Rouse et al. (1973) and Tucker (1979) developed the formulation.

The NDVI raster was produced using QGIS Raster Calculator (QGIS Development Team, 2024) and the spatial resolution was kept constant at 10 m; the resulting continuous NDVI surface was clipped to the study boundary to create a spatially explicit map of the vegetation index for the Elaite community.

Classification using NDVI Threshold

The continuous NDVI raster was then reclassified into four vegetation stress categories using the Reclassify by Table tool in QGIS. We derived threshold values from previous studies in semi-arid and sub-humid savanna environments during the dry season (Hmimina et al., 2013; Vicente-Serrano et al., 2013; Adenle, 2020). The thresholds used in analogous ecological settings ensure that the derived stress categories align with plausible vegetation responses to moisture limitation. We selected a threshold-driven NDVI classification method rather than supervised image classification because the main objective was to assess vegetation stress trends, not to produce a detailed land-cover map, and because extensive field-based training samples were unavailable (Pettorelli et al., 2005; Xue & Su, 2017). Under these conditions, NDVI thresholding provided a more practical, consistent way to identify different levels of vegetation stress (Huete et al., 1985). Table 2 shows the classification scheme.

Table 2: Classification Scheme of NDVI for Vegetation Stress Assessment

NDVI Range	Vegetation Condition	Ecological Interpretation
< 0.00	Very Severe Stress	Bare soil, built-up surfaces, or open water bodies; no photosynthetically active vegetation
0.00–0.15	Severe Stress	Sparse vegetation with strong moisture deficit; dormant grass, degraded savanna, exposed soil surface
0.16–0.30	Moderate Stress	Partially stressed vegetation or actively cultivated fields; mixed canopy with variable moisture access
0.31–0.44	Relatively Healthy / Low Stress	Dense vegetation retaining residual soil moisture; riparian shrubland and woodland patches

Source: Thresholds adapted from Hmimina et al., 2013, Vicente-Serrano et al., 2013, and Adenle, 2020.

Zonal Statistics and Spatial Analysis

This research was conducted with spatial analysis using a multi-stage workflow in QGIS 3.x. First, we derived a continuous NDVI surface from the Sentinel-2 imagery to capture spatial variability in vegetation condition. Subsequently, the NDVI raster was classified into vegetation stress categories using the threshold method based on the NDVI interpretation frameworks for savanna environments (Pettorelli et al., 2005; Xue & Su, 2017; Hmimina et al., 2013). To improve thematic interpretation, we produced a hybrid land-cover map by integrating the reclassified NDVI output with visual interpretation of Sentinel-2 true-color composites (Bands 4, 3, and 2; Drusch et al., 2012), then dissolved polygons and combined adjacent pixels of the same thematic category to derive spatially coherent land-cover units.

A zonal statistical analysis to quantify the spatial characteristics of each vegetation stress class was conducted, including pixel count, area coverage (ha), % distribution, mean NDVI, minimum and maximum values, and standard deviation. We identified four dominant land cover categories: wetlands and open water surfaces; bare and sparsely vegetated land; cultivated and fallow land; and dense shrubland. All analysis was operationalized using open-source geospatial tools, ensuring methodological transparency and replicability (Adamu et al., 2021; Osunmadewa et al., 2015).

Limitations of the Approach

Several limitations should be considered when interpreting this study's findings. First, the analysis used a single-date Sentinel-2 image acquired during the peak dry season, providing only a temporal snapshot of vegetation condition. As a result, the study does not account for seasonal vegetation dynamics, inter-annual variability, or long-term degradation trajectories. Multi-temporal observations would better enable evaluation of vegetation responses to climatic variability and land-use change (Fensholt et al., 2009; Chu et al., 2019). Second, no systematic field-based validation data were available during the study Period. The classification outputs were validated using high-definition basemaps, Sentinel-2 true-color composites, and local knowledge.

Moreover, NDVI is influenced by soil background reflectance and mixed-pixel effects, particularly in heterogeneous savanna environments characterized by sparse canopy cover and fragmented land-use patterns (Huete et al., 1985; Pettorelli et al., 2005). Therefore, the resulting classes should be interpreted as indicators of relative vegetation stress rather than as direct measures of ecological degradation

intensity. However, considering the above limitations, the approach adopted provides a feasible and cost-effective means to assess dry-season vegetation stress in data-limited rural environments (Adamu et al., 2021), and the 10 m spatial resolution of Sentinel-2 significantly cuts down on mixed-pixel uncertainty compared to coarser sensors like MODIS (Drusch et al., 2012).

RESULTS AND DISCUSSION

Continuous NDVI Spatial Distribution

The NDVI continuous surface for Elaite during the peak of the 2025/2026 dry season ranged from 0.15 to 0.44, indicating substantial spatial variation in vegetation condition across the study area. Most pixels fell within the lower range of the scale (0.00–0.20), suggesting that much of the landscape was characterized by bare soil, sparsely vegetated surfaces, or vegetation under considerable physiological stress. The maximum NDVI value recorded (0.44) is typical of moisture-limited environments in the Guinea savanna, where small patches of denser vegetation in hydrologically favorable areas retain relatively higher levels of greenness during the dry season. Figure 2 illustrates the spatial distribution of NDVI values across the study area and shows the NDVI map of Elaite for the 2025/2026 dry season.

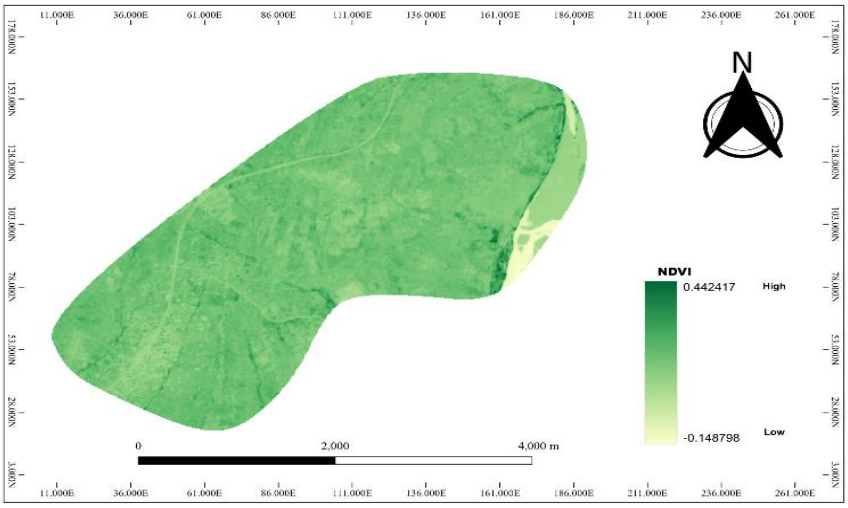

Figure 2: Normalized Difference Vegetation Index (NDVI) map of Elaite during the 2025/2026 dry season
Source: Laboratory analysis by the authors, 2026.

Higher values as seen in this case are more typical of dense tropical forests than of dry-season savanna landscapes (Tucker, 1979; Anyamba & Tucker, 2005; Prince & Justice, 1991). Negative NDVI values (0.15 to 0.00) were generally confined to scattered patches corresponding to seasonal water bodies, drainage channels, and wetland areas in the community's lower-elevation areas.

The spatial distribution of NDVI values reflects the combined effects of topography, soil moisture availability, and land-use history across the study area (Areola, 1982; Adenle, 2020). Consistently, relatively higher NDVI values were observed along drainage channels, low-lying riparian zones and remnant woodland patches, indicating localized areas of moisture retention and lessened physiological stress. This pattern aligns with drought-response theory, which suggests that vegetation's access to residual soil moisture buffers physiological stress during seasonal water deficits, sustaining higher productivity than surrounding uplands (McDowell et al., 2011; McDowell et al., 2013). Conversely, the lowest NDVI values were recorded in highly cultivated and grazed areas, where anthropogenic pressure, combined with seasonal moisture limitations, results in vegetation conditions approaching those of bare soil. This spatial contrast highlights the feedback effects of climate stress and land-use intensity on dry-season vegetation in savanna environments (Adenle, 2020; Brandt et al., 2016).

Classification of the Vegetation Stress

We applied a four-class threshold classification to the continuous NDVI surface to produce a vegetation stress map of Elaite. The resulting classification, shown in Figure 3, reveals that the largest category was the sparsely vegetated and built-up surfaces class, which accounted for 87.85% of the study area (approximately 1,113 ha; mean NDVI = 0.15; Table 3). This class comprises bare and degraded soils, dried grass remnants, compacted ground, and built-up areas distributed throughout Elaite, all with NDVI values indicating severe physiological stress or virtually no active photosynthesis. The dominance of this extreme stress class is consistent with plant physiological stress theory. Although grass species exhibit different drought-response strategies—with isohydric species closing their stomata early to conserve water and anisohydric species maintaining stomatal conductance for longer periods—both strategies tend to converge towards very low NDVI values under the prolonged and intense moisture deficits characteristic of the peak Harmattan season (Attia et al., 2015; McDowell et al., 2011). Figure 3 illustrates the spatial distribution of the four vegetation stress classes across the study area, highlighting the predominance of sparsely vegetated and built-up surfaces and the limited extent of areas exhibiting healthier vegetation conditions.

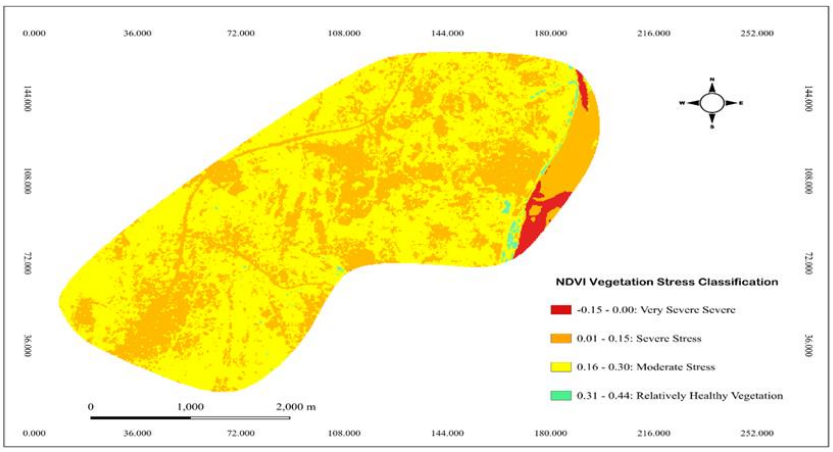

Figure 3: Elaite NDVI Vegetation Stress Classifications.
Source: Laboratory analysis by the authors, 2026.

The second largest class was cultivated and fallow lands (ca. 10.42% (≈132 ha; mean NDVI = 0.23) of the study area), indicative of moderate vegetation stress, as would be expected for a landscape with reduced soil moisture and incomplete canopy cover typical of agricultural fields during the peak dry season (Osunmadewa et al., 2015). These areas are dispersed in a pattern that closely resembles the fragmented structure of smallholder agricultural plots interspersed with residential areas throughout the community. Dense shrubland represented only 0.24% of the total area (≈3 ha) but had the highest mean NDVI (0.38) among all vegetated classes. These patches were widely distributed along riparian corridors and topographic depressions, where subsurface moisture mitigates the full impact of dry-season stress (McDowell et al., 2013; Fensholt et al., 2009). Wetland and open-water surfaces accounted for about 1.5% (≈19 ha) and exhibited negative mean NDVI values (around −0.09), typical of standing water and saturated soils (Tucker, 1979; Anyamba & Tucker, 2005).

The dispersed distribution of these areas closely parallels the fragmented nature of smallholder farming plots interspersed with residential zones across the community. Dense shrubland was uncommon (0.24% of the total area, approximately 3 ha) but had the highest mean NDVI (0.38) of all vegetated classes. Most of these patches occurred in riparian corridors and in topographic depressions, where subsurface moisture helps buffer the full impact of dry-season stress. Wetland and open water surfaces accounted for about 1.5% of the area (about 19 ha) and had negative mean NDVI values (approximately 0.09), typical of standing water and saturated soils.

NDVI Statistics for Land Cover Type

A distinct gradient in mean NDVI values across land-cover classes (Table 3) supports the hypothesis that vegetation stress increases with decreasing soil moisture and increasing human disturbance (Adenle, 2020; Pettorelli et al., 2005). The SD values provide additional information on class level variability. Dense shrubland had the lowest variability (SD = 0.022), suggesting a relatively consistent and stable canopy, as these areas are buffered by consistent moisture (McDowell et al., 2013). The built-up and sparsely vegetated class had a moderate SD (0.031), indicating variability from completely bare soil to patches of dormant grass at different stages of dry-season dieback (Tucker, 1979; Huete et al., 1985). Table 3 provides complete descriptive statistics for NDVI values for the four land-cover classes.

Table 3: Summary statistics of NDVI values per land-cover class

Land Cover Class	Pixel Count	Mean NDVI	Min NDVI	Max NDVI	Std Dev	Area (ha)	Coverage (%)
Wetland /open Water	1,915	-0.093	-0.149	-0.000	0.039	19	1.50
Sparsely Vegetated/Built -up	65,097	0.151	0.000	0.200	0.031	1,113	87.85
Cultivated /Fallow land	7,497	0.227	0.200	0.350	0.029	132	10.42
Dense Shrubland	259	0.380	0.350	0.442	0.022	3	0.24
TOTAL	74, 768	-	-	-	-	1,267	100.00

Cultivated and fallow lands also showed moderate variability (SD = 0.029), attributed to differences in crop growth stages, fallow-field age, and management intensity (Osunmadewa et al., 2015). The highest SD (0.039) was observed in wetland and open-water surfaces, mainly due to the mixed pixels at water-land boundaries and the degree of waterlogging (Anyamba & Tucker, 2005).

Spatial Pattern of Vegetation Stresses

The spatial distribution of vegetation stress classes shows a landscape with prevalent severe and very severe stress in its central and elevated parts. Vegetation condition is relatively better near the drainage channels and lower-lying terrain. Overall, more than 85% of the study area experienced severe to very severe stress during the peak dry season, indicating the severity of seasonal moisture deficit in this Guinea savanna environment (Olaniran, 2002; Animashaun et al., 2020). Relatively healthier vegetation was largely confined to narrow riparian corridors and small isolated patches of shrubland, which stand out as important dry-season refugia, demonstrating the key role that hydrological buffering plays in helping vegetation survive the most stressful Period of the

year (McDowell et al., 2013; Fensholt et al., 2009).

The lowest NDVI values were mainly located in areas with the highest agricultural activity and settlement density. This strong spatial overlap indicates that human land-use pressure exacerbates the effects of seasonal drought on vegetation, causing NDVI levels to fall below those expected based on rainfall alone (Adenle, 2020; Brandt et al., 2016). This finding aligns with disturbance ecology theory, which posits that human activities often interact with climatic stresses to exacerbate vegetation decline (Adenle, 2020; Pettorelli et al., 2005). On the other hand, the high NDVI values concentrated in riparian zones – even though the same regional dry-season climate extended over the entire study area – highlight the important buffering role of local hydrological conditions in maintaining vegetation resilience (McDowell et al., 2011; Anyamba & Tucker, 2005).

Discussion

The NDVI values in Elaite ranged from 0.15 to 0.44 during the 2025/2026 dry season, within the normal range for the Guinea savanna landscape during the peak dry season, as seen in other parts of West Africa. In semi-arid and sub-humid savannas, dry-season NDVI values typically range from 0.1 to 0.4 (Anyamba and Tucker, 2005; Prince and Justice, 1991), with values > 0.5 largely confined to riparian forests or areas with permanent water. Hence, the maximum value observed in Elaite (0.44) is consistent with the expected range for a moisture-limited savanna environment and does not indicate an anomalous degree of degradation (Tucker, 1979; Hmimina et al., 2013). Even in the densest patches of riparian shrubland, NDVI values did not exceed 0.44. From a plant physiological stress perspective, this indicates that even the better-protected woody vegetation operated under suboptimal moisture conditions, consistent with the isohydric stomatal closure strategy commonly observed in Guinea savanna tree species (Attia et al., 2015).

The severe stress class dominates the study area (87.85%), indicating that both seasonal dryness and human activities put the area under pressure. Based on the spectral reflectance theory, during drought, chlorophyll degradation and reduction in leaf area cause a reduction in the NIR reflectance and an increase in the absorption of red light, which shifts the NDVI values towards those of bare soil (Tucker, 1979; Drusch et al., 2012; Rouse et al., 1973). This expectation is consistent with the mean NDVI of 0.15 in the dominant sparsely vegetated class. However, disturbance ecology theory provides additional insight. In heavily human-modified landscapes, activities such as fuelwood collection, overgrazing, and land clearing reduce canopy cover and increase exposed bare ground, pushing NDVI even lower than climate alone would predict (Adenle, 2020; Brandt et al., 2016). This interaction was theoretically predicted, and the spatial concentration of the lowest NDVI values in zones of intensive agricultural activity confirms this prediction in the Elaite landscape.

The highest NDVI values (mean = 0.38) were almost exclusively located in riparian corridors and topographic depressions, although they comprised only ca. 3 ha. Drought response theory suggests that vegetation with access to subsurface moisture via capillary rise from shallow water tables can maintain higher photosynthetic activity and better canopy structure even during the peak of the dry season (McDowell et al., 2011; McDowell et al., 2013). This explains why these small patches had NDVI values significantly higher than those of the surrounding upland areas. Comparable patterns have been documented across Nigeria and West Africa, where riparian vegetation generally has NDVI values 0.1 to 0.2 units higher than adjacent upland savanna during the dry season (Adenle, 2020; Fensholt et al., 2009; Anyamba & Tucker, 2005).

The 3 hectares, in addition to their academic value, are the community's most important ecological refugia, representing critical sites for dry-season biodiversity and soil carbon storage (Brandt et al., 2016; Pettorelli et al., 2005). Their very low internal variability (SD = 0.022) indicates a structurally stable and well-buffered system – but also a potentially fragile one. Further encroachment, driven by agricultural expansion or fuelwood harvesting, may disproportionately reduce the community's overall vegetation resilience. These areas are important sources of moisture and seeds, allowing the broader savanna to regenerate after the dry season (McDowell et al., 2013; Adenle, 2020). Thus, protecting them should be a high priority for land management in Elaite and similar Guinea savanna communities (König et al., 2018).

This work shows that Sentinel-2 Level-2A images processed completely in the open-source QGIS environment can deliver a fine-scale, management-relevant assessment of dry-season vegetation stress at the community scale for data-scarce Guinea savanna landscapes (Drusch et al., 2012; Adamu et al., 2021). The 10 m spatial resolution was especially useful for capturing fine-scale heterogeneity, such as riparian patches, field boundaries, and fallow plots, features that are ecologically and agronomically important but often undetectable with coarser sensors such as MODIS (Xue & Su, 2017; Huete et al., 1985). A major limitation is its single-date design, which captures only a snapshot of peak dry-season conditions and ignores interannual variability and seasonal dynamics (Fensholt et al., 2009; Chu et al., 2019). Future research can include wet-season imagery to calculate NDVI amplitude and field validation, such as soil moisture and biomass estimation, to improve accuracy assessment and local threshold calibration (Hmimina et al., 2013; Pettorelli et al., 2005).

Conclusion

This work is the first high-resolution, spatially detailed assessment of dry-season vegetation stress in Elaite, Ajaokuta Local Government Area, Kogi State, Nigeria. Using Sentinel-2 Level-2A imagery and a process-informed NDVI classification (Drusch et al., 2012; Rouse et al., 1973; Tucker, 1979), results show NDVI values ranging from −0.15 to 0.44, reflecting the intense moisture limitation typical of the Guinea savanna dry season (Olaniran, 2002; Animashaun et al., 2020) as well as the combined pressure of seasonal climate and human activities on vegetation (Adenle, 2020; Brandt et al., 2016). About 85% of the study area experienced severe to very severe vegetation stress, particularly in agricultural and settlement-modified areas. Dense shrubland, totaling 3 ha and restricted to riparian corridors, had a much higher mean NDVI of 0.38, highlighting the importance of hydrological buffering for vegetation survival during the height of the dry season (McDowell et al. 2011; McDowell et al. 2013).

These findings are interpreted using an integrated theoretical framework: spectral reflectance theory explains the visibility of stress in NDVI (Tucker, 1979; Drusch et al., 2012); plant physiological stress theory explains species differences (Attia et al., 2015; Zeppel et al., 2015); disturbance ecology theory explains the greater decline in human-modified areas (Adenle, 2020); and drought response theory explains the role of riparian zones as dry-season refugia (McDowell et al., 2013). Our study has three key contributions. First, it establishes a high-resolution NDVI baseline for a class of Guinea savanna communities not reported in the literature.

Second, it presents a replicable, open-source methodological framework applicable to data-poor rural communities across West Africa (Adamu et al., 2021). Third, it delivers spatially explicit information for land degradation management, drought monitoring, and climate adaptation planning (König et al., 2018; Osunmadewa et al., 2015).

The study recommends protecting riparian vegetation through buffer conservation and native species restoration; promoting agroforestry and community-based soil and water conservation practices in areas under significant stress; and institutionalising annual wet- and dry-season Sentinel-2 monitoring to detect vegetation degradation. Future research should include field measurements of soil moisture and biomass to validate NDVI results and to refine vegetation stress classification thresholds tailored to local conditions.

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