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RESEARCH ARTICLE

FOREST RESILIENCE AND COMMUNITY ADAPTATION TO CLIMATE VARIABILITY IN OKWANGWO, NIGERIA: A MULTI-DECADAL SOCIO-ECOLOGICAL ANALYSIS (2003–2024)

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ABSTRACT

This study explores forest change in the Okwangwo Division of Cross River National Park, Nigeria, by combining satellite based vegetation analysis with insights from indigenous communities. Using Normalized Difference Vegetation Index (NDVI) data from 2000 to 2022, we focused on vegetation health trends, especially between 2020 and 2024, with earlier years included when recent data was not available. The NDVI showed an unstable pattern with a significant decline between 2008 and 2014, slight recovery, and then another drop in 2022, indicating stress in forest cover. Net Primary Productivity (NPP) data, used to support carbon estimation, revealed similar declines particularly in 2016 and 2017, suggesting reduced forest productivity. To better understand environmental stressors, we analyzed Land Surface Temperature (LST), ERA5 air temperature, and CHIRPS rainfall data. Results showed a steady increase in both surface and air temperatures, with the hottest values recorded between 2020 and 2024. At the same time, rainfall steadily declined from 2014 to 2022, worsening moisture stress. This combination of heat and reduced rainfall points to climate pressure as a major factor in declining forest health. These satellite-based observations were supported by knowledge shared by indigenous community members who reported hotter dry seasons, irregular rainfall, and visible thinning of forest canopy over time. Their lived experiences added context to the data and helped confirm trends observed from space. By blending indigenous knowledge with remote sensing, this study offers a clearer picture of how climate variability is affecting protected tropical forests and highlights the value of local perspectives in guiding conservation efforts in places like Okwangwo.

Keywords: Forest change, indigenous knowledge, remote sensing, climate stress, ecosystem monitoring

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INTRODUCTION

Tropical forests are crucial ecosystems that play key roles in biodiversity conservation, climate regulation, and livelihoods (FAO, 2020). In Nigeria, forest degradation has been driven by land use changes, rising temperatures, and erratic rainfall patterns (Ayanlade et al., 2018). The Okwangwo Division of Cross River National Park (CRNP), a biodiversity hotspot in southeastern Nigeria, is particularly vulnerable to these pressures.

Understanding how forests respond to climate stress requires both scientific measurements and local observations. Remote sensing allows for long-term monitoring of vegetation health and climate variables across wide areas (Pettorelli et al., 2005). NDVI, derived from MODIS imagery, is widely used to track vegetation greenness and canopy health (Didan, 2015). NPP provides insight into how productive the vegetation is in terms of carbon accumulation (Running et al., 2004).

In addition, land surface and air temperature help detect heat stress, while rainfall data reveals moisture availability. MODIS LST, ERA5 temperature, and CHIRPS precipitation products are recognized for their reliability in tropical climate studies (Funk et al., 2015; Hersbach et al., 2020). However, technical assessments alone may miss on-the-ground experiences. Indigenous communities often detect subtle forest changes through direct interaction with the land. Integrating indigenous knowledge can therefore add depth and context to remote sensing data (Reed et al., 2008).

This study investigates how the forest in Okwangwo has changed over time in response to climate conditions. Using NDVI and NPP trends from MODIS products, along with CHIRPS, ERA5, and LST datasets from 2000 to 2024, we analyzed forest condition and productivity. Interviews with local community members also helped validate and interpret observed changes. By linking satellite observations with indigenous knowledge, this work aims to improve understanding of climate-related forest dynamics in Nigeria.

Aim and Objectives

The aim of this study is to assess how climate variability has affected forest health and productivity in Okwangwo Division of Cross River National Park, Nigeria, by integrating satellite-based observations with indigenous ecological knowledge.

Objectives:

1. To analyze long term trends in vegetation health using MODIS derived NDVI from 2000 to 2022.

2. To evaluate forest productivity changes using Net Primary Productivity (NPP) data.

3. To examine variations in temperature and rainfall using MODIS LST, ERA5 air temperature, and CHIRPS precipitation datasets.

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4. To map and visualize spatial patterns of NDVI, LST, precipitation, temperature, and NPP for selected years.
5. To incorporate indigenous knowledge on climate and forest changes for validating and enriching satellite-based findings.

Study Area

Okwangwo Division is one of two administrative divisions in Cross River National Park, located in southeastern Nigeria near the Cameroon border. It lies between latitudes 6.25°N and 6.45°N and longitudes 9.10°E and 9.40°E. The terrain is mountainous, with elevations ranging from 150 to over 1,700 meters. The area experiences a tropical monsoon climate, with a rainy season typically from March to October and a dry season from November to February.

The forest is part of the Guinean-Congolian rainforest zone and supports a high level of biodiversity, including rare and endemic species like the Nigeria-Cameroon chimpanzee. Human settlements around the park rely on the forest for farming, hunting, and collection of non-timber products. However, increased pressure from agricultural expansion, logging, and climate variability has raised concerns over long term forest stability (Oates et al., 2004; WWF, 2022; Orimoloye and Mazinyo, 2019).

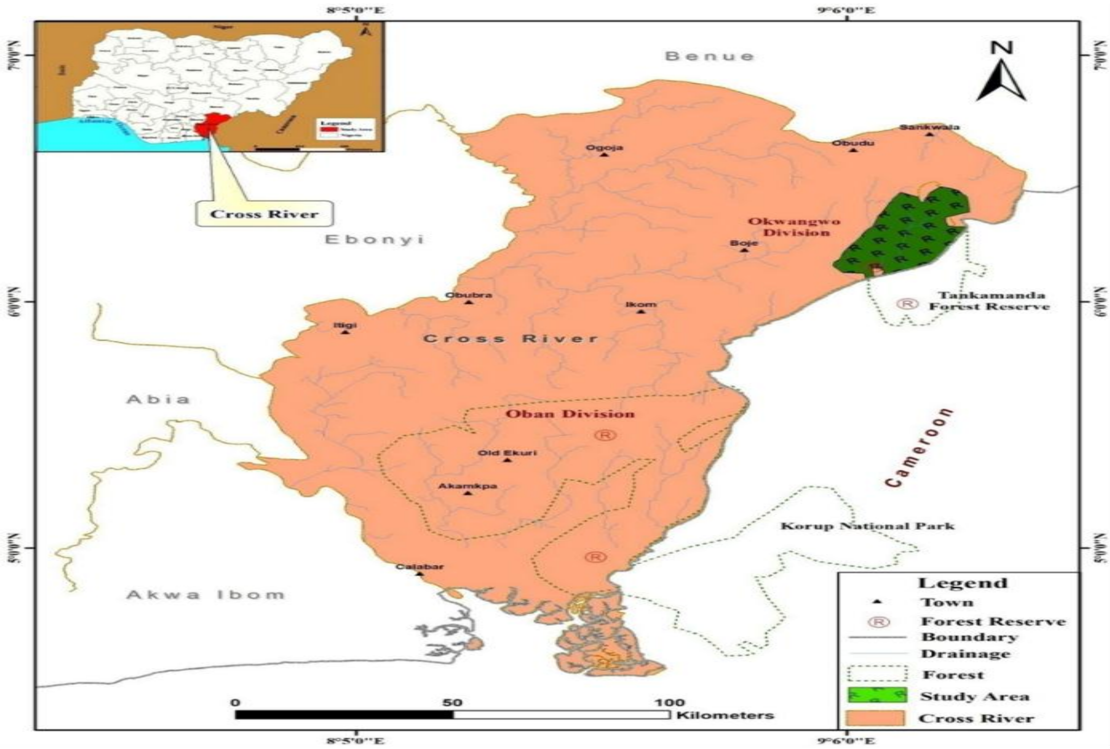

Figure 1.1: Location of Okwango Forest with the Cross River National Park, Cross River State Nigeria ***(Source: Cross River State Ministry of Agriculture, Calabar)***

LITERATURE REVIEW

Previous studies have established the effectiveness of satellite-based vegetation indices for forest monitoring. NDVI, as used in this study, has been widely applied in tropical forest contexts to assess canopy cover, vegetation stress, and land cover dynamics (Tucker, 1979; Pettorelli et al., 2005; Fensholt and Proud, 2012). MODIS NDVI products provide consistent temporal coverage and have been extensively validated in Nigerian forest ecosystems, particularly in evaluating forest degradation and regeneration cycles (Ayanlade et al., 2018; Omotosho et al., 2021).

Net Primary Productivity (NPP) is a valuable indicator for assessing carbon uptake and forest productivity. The MOD17A3HGF product used in this study has been validated for large-scale ecosystem productivity estimates (Running et al., 2004). Combining NPP with NDVI enhances the understanding of both structural and functional forest changes, providing insights into vegetation vigor and photosynthetic activity (Zhao and Running, 2010; Turner et al., 2006). Such integrative approaches have been employed in West and Central Africa to track deforestation, carbon flux, and ecosystem recovery (Saatchi et al., 2011).

Climate datasets such as CHIRPS and ERA5 are increasingly used in environmental research for their accuracy in data-sparse regions. CHIRPS in particular, has been shown to perform well in African rainfall monitoring and drought prediction models (Funk et al., 2015; Dinku et al., 2008). ERA5, developed by the European Centre for Medium-Range Weather Forecasts, provides high-resolution global reanalysis datasets that capture temperature, humidity, and other climate variables with high precision (Hersbach et al., 2020). MODIS Land Surface Temperature (LST) data have also been validated for detecting thermal anomalies and heat stress in forested regions across Africa (Wan et al., 2015; Hu and Brunsell, 2015). To Okoroafor et al (2024), advocate the promotion of AI tools in monitoring, protecting, and preserving the already endangered species from local to global context.

Incorporating indigenous knowledge in environmental assessment has received growing attention in recent decades. Reed et al. (2008) emphasized that local knowledge systems provide early warning signs of ecological change and offer socio-cultural context that satellite imagery may overlook. In West Africa, Nyong et al. (2007) showed how indigenous insights contribute to the interpretation of satellite-based findings, especially in climate adaptation and forest conservation. Ruheza et al. (2013), Augustino (2006), and Jimoh et al. (2012) have documented the value of traditional forest rules, sacred landscapes, and gendered resource-use patterns in explaining forest changes. For instance, in Okwangwo, practices such as taboo enforcement, sacred forest protection, and spiritual penalties were observed to influence conservation outcomes and biodiversity preservation. These findings align with broader studies in Ghana, Kenya, and Tanzania that emphasize the role of community belief systems and traditional ecological knowledge in sustainable resource management (Diawuo et al., 2015; Mwihomeke et al., 1998; Berkes et al., 2000; Kideghesho, 2008).

Indigenous knowledge also plays a vital role in enhancing resilience to climate variability. Studies have shown that local communities often possess detailed ecological calendars, species indicators, and behavioral adaptations that help buffer environmental stress (Klintenberg et al., 2003; Makondo and Thomas, 2018). These systems, when harmonized with remote sensing and GIS, enrich conservation planning and bridge the gap between empirical data and lived experience.

MATERIAL AND METHODS

Satellite Datasets: All satellite-based analysis was conducted using Google Earth Engine (Gorelick et al., 2017). The following datasets were used:

1. NDVI: MODIS MOD13A1 (Didan, 2015) at 500m resolution from 2000 to 2022. NDVI values were scaled and averaged annually.
2. Land Surface Temperature (LST): MODIS MOD11A1 product (Wan et al., 2015), corrected to degrees Celsius and averaged annually from 2000 to 2024.
3. Air Temperature: ERA5-Land hourly dataset (Hersbach et al., 2020), using temperature at 2 meters, converted to Celsius.
4. Rainfall: CHIRPS daily precipitation (Funk et al., 2015), summed annually from 2000 to 2024.
5. Net Primary Productivity (NPP): MODIS MOD17A3HGF (Running et al., 2004), annual estimates from 2000 to 2024.

Data Processing Custom JavaScript code was developed in Earth Engine to compute yearly averages (or sums, for rainfall) over the Area of Interest (AOI). NDVI, LST, temperature, rainfall, and NPP were each processed to produce time series trends. Each year was individually mapped for key indicators like NDVI in 2022, LST in 2024, and NPP in 2021, depending on latest reliable availability.

Indigenous Knowledge Collection Structured interviews were conducted with local community members in villages around the park. Respondents were selected based on length of residence and familiarity with forest use. They were asked to describe seasonal changes, rainfall patterns, forest use history, and observed changes in forest health. Their accounts were analyzed thematically to identify climate-related stressors and corroborate satellite trends.

RESULTS AND DISCUSSIONS

This section presents the temporal and spatial analysis of vegetation and climate variables in Okwangwo Division, using NDVI, NPP, Land Surface Temperature (LST), ERA5 air temperature, and CHIRPS rainfall. Results from 2000 to 2024 are discussed, with a specific focus on the recent period between 2020 and 2024. All data visualizations were derived from processed Google Earth Engine outputs and field-supplemented indigenous knowledge.

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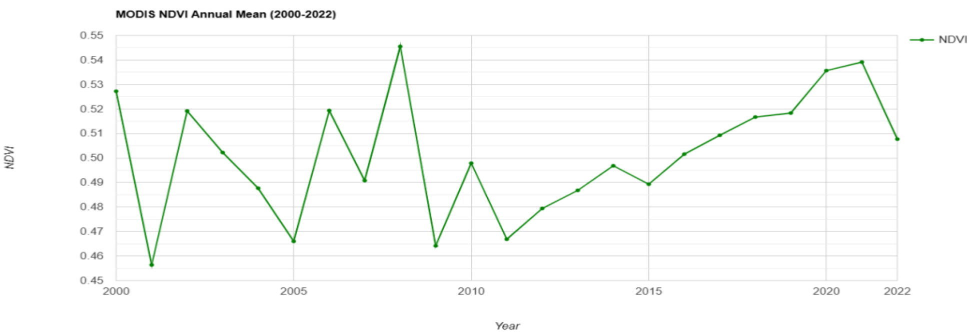
Vegetation Health (NDVI)

The NDVI trend from 2000 to 2022 in Figure 4.1 shows three distinct phases: a decline from 2008 to 2014, a period of slight recovery between 2015 and 2020, and another notable dip in 2022. The lowest NDVI value was recorded in 2014, suggesting significant vegetation stress.

Figure 4.1 Annual Mean NDVI



Source: Author's computation using GEE (MODIS NDVI, 2025).

The partial recovery post 2015 was short lived, as NDVI dropped again in 2022, aligning with community reports of unusual heat and canopy thinning. NDVI spatial maps also showed that areas near human settlements and buffer zones experienced the most vegetation loss.

These findings are consistent with similar studies conducted in other forested regions of West Africa. For instance, Adepoju and Adelabu (2020) examined NDVI trends in the Omo Forest Reserve in southwestern Nigeria and reported a comparable pattern of NDVI decline during the same period, attributing it to anthropogenic pressure and climate variability. Likewise, Justice et al. (2013) analyzed NDVI trends across Ghanaian forest reserves and found strong correlations between declining vegetation indices and proximity to settlements, particularly in buffer zones. These patterns reinforce the findings from Okwangwo and support the argument that vegetation health is significantly impacted by both climatic and anthropogenic factors.

Forest Productivity (NPP)

The Net Primary Productivity (NPP) trend in Figure 4.2 mirrors NDVI performance. While 2000 to 2010 showed relatively high productivity, a noticeable decline began in 2011 and worsened in 2016 and 2017. These years recorded the lowest productivity values, which corresponds with increased dry conditions observed in the climate datasets. Though there was a marginal rise between 2018 and 2020, the NPP began declining again toward 2022, indicating reduced carbon accumulation and vegetation vigor. These findings confirm that climate stress, especially reduced rainfall and rising heat, has weakened forest productivity.

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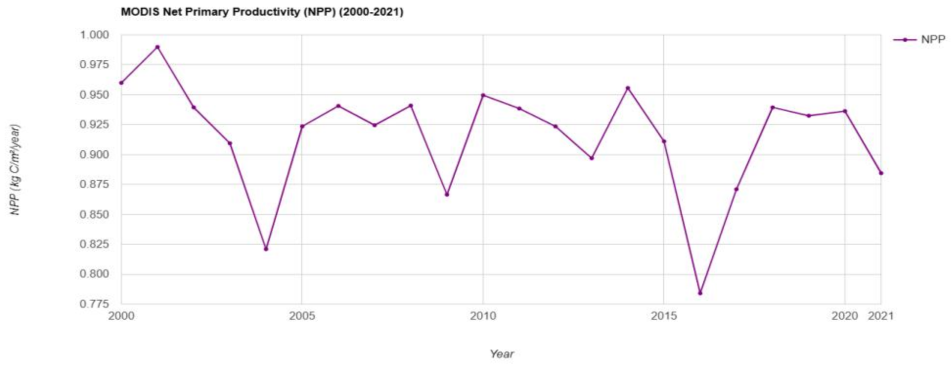
Figure 4.2 Annual Mean Net Primary Productivity



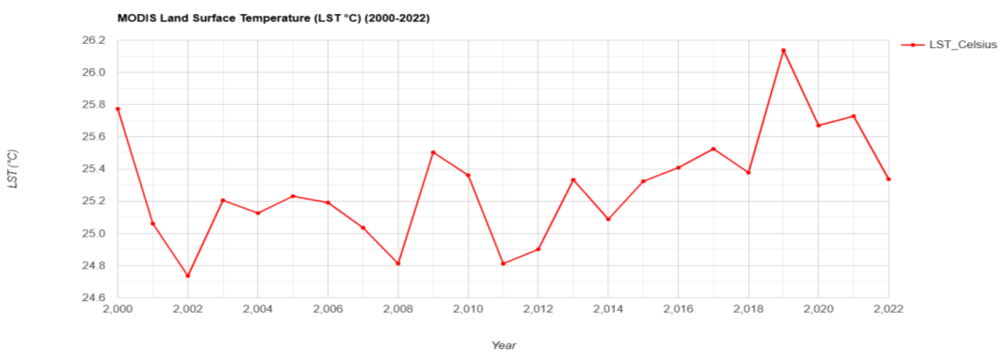
Source: Author's computation using GEE (MODIS NPP, 2024).

A study by Zhao and Running (2010) globally assessed NPP trends and highlighted that many tropical forests were showing reduced productivity due to climate-induced drought stress, particularly in Africa and Southeast Asia. In Nigeria, Ogunwusi and Jolaoso (2012) observed similar declines in forest biomass in the Cross River region, linking productivity losses to both deforestation and climatic extremes. These studies align with the observed NPP decline in Okwangwo, affirming that persistent rainfall reduction and elevated temperatures are key drivers of forest stress in the region.

Surface and Air Temperature Trends

MODIS LST data in Figure 4.3 shows a steady upward trend from 2000 to 2024. The hottest years were 2020 through 2024, with the 2024 LST reaching the highest average temperature of the entire 24-year period. ERA5 air temperature in Figure 4.4 also confirmed this rise in ambient conditions, especially during dry season months. Elevated temperature intensifies evapotranspiration and limits vegetation regeneration, contributing to the declining NDVI and NPP values.

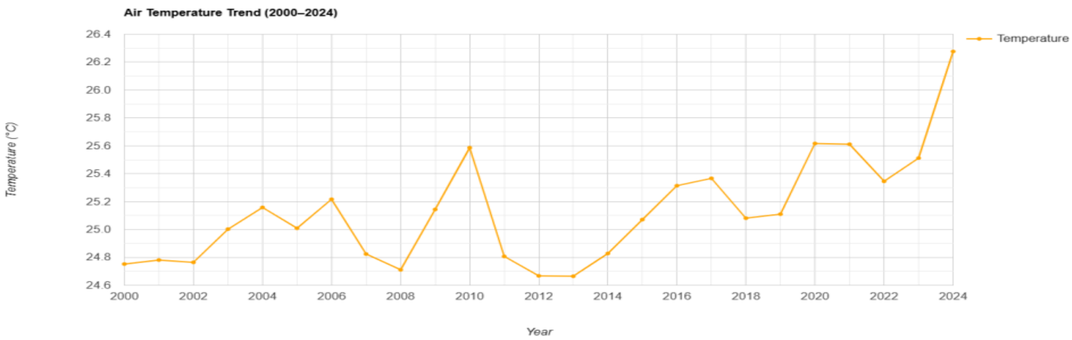
Figure 4.3 Annual Mean Land Surface Temperatures



Source: Author's computation using GEE (MODIS NPP, 2024).

Indigenous observations aligned with these findings, with many community members reporting hotter dry seasons and shorter rainy periods. These results are consistent with broader climate change assessments in Nigeria. NIMET (2022) reports indicate a 1.5°C rise in average annual temperatures over the last 30 years, particularly in forest-savanna ecotones. Olorunfemi et al. (2021) examined LST variations in Benue and Cross River States and observed similar patterns of rising temperature, with the highest increases occurring post 2018. Their study concluded that forest degradation is both a cause and a consequence of localized warming, as reduced canopy cover further enhances surface heating.

Figure 4.4 Annual Mean Air Temperatures



Source: Author's computation using GEE (MODIS NPP, 2024).

Rainfall Patterns (CHIRPS)

CHIRPS rainfall analysis revealed a steady decline in total annual rainfall after 2014. While rainfall volumes fluctuated in earlier years, there was a sharp reduction between 2015 and 2022. The lowest precipitation was observed in 2022, which coincided with the lowest NDVI value in the same year. Rainfall in the early 2000s supported higher vegetation productivity, but after 2014, persistent deficits led to increased moisture stress as shown in Figure 4.5. This rainfall trend was also mentioned by local farmers and forest users, who noted later arrival of rains and shorter growing seasons.

Figure 4.5 Annual Mean Precipitations

Source: Author's computation using GEE (MODIS NPP, 2024).

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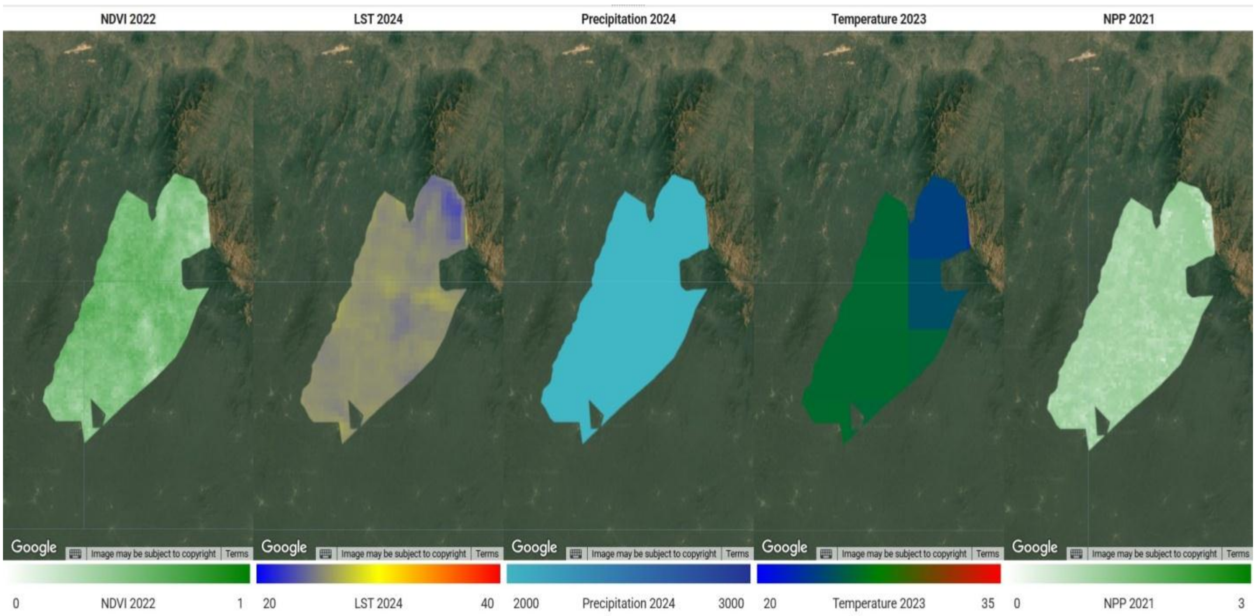
Comparable findings have been reported by Ayanlade et al. (2018), who used CHIRPS data to evaluate rainfall variability in southern Nigeria and identified a distinct drying trend after 2010. Their study attributed this to shifting rainfall onset and increased frequency of dry spells. Similarly, Oladele and Adeyemi (2021) reported declining rainfall in southeastern Nigeria and highlighted the implications for rainfed agriculture and forest health. These studies validate the observed CHIRPS trends in Okwangwo, strengthening the linkage between climate variability and forest stress.

Spatial Overlay and Hotspot Zones

Spatial analysis across the study area showed that the most significant forest loss and climate stress occurred in zones closer to the park boundaries in Figure 4.6. These areas also overlap with locations of high human activity, including farming, wood harvesting, and settlement expansion. Hotspot mapping indicated zones where NDVI was low and LST was high, identifying transition zones where forest degradation is most intense. These hotspots were confirmed by interviewees who identified places where previously dense canopy has become open and dry.

Figure 4.6 Okwangwo Forest showing NDVI, LST, NPP, CHIRPS, ERA5



Source: Generated by author using GEE datasets (NDVI, ERA5, LST, NPP, CHIRPS), 2024.

This pattern is widely documented in forest edge studies. Hansen et al. (2013), using global forest change data, observed that forest loss rates are significantly higher near roads and settlement edges. In Nigeria, Akinyemi et al. (2020) conducted a spatial hotspot analysis of forest reserves in Ondo State and identified similar edge degradation patterns due to encroachment. These parallels highlight the vulnerability of buffer zones, including those in Okwangwo, to synergistic effects of climate stress and human pressure.

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Indigenous Knowledge Confirmation

Community members' reports offered valuable ground truthing. Elders recalled more consistent rainfall in earlier decades and shaded paths that are now sun-exposed. Women, who farm near the forest and manage home gardens, noted changes in leaf coloration, fewer forest fruits, and greater plant mortality. Youths also recognized forest retreat and drying water sources. Cultural beliefs around sacred groves helped explain areas with better vegetation preservation, as these locations were protected by traditional taboos. These lived experiences gave context to the quantitative satellite data and reinforced the broader pattern of climate-driven forest decline.

Several studies have emphasized the role of indigenous ecological knowledge in complementing scientific findings. Berkes et al. (2000) showed that traditional knowledge systems can detect subtle ecological changes often missed by remote sensing. In Nigeria, Adekola and Mitchell (2011) used local insights to validate hydrological changes in the Niger Delta, confirming that community recollections align with hydrological data trends. These examples affirm the reliability of the indigenous narratives recorded in Okwangwo and their value in climate impact assessment.

SUMMARY AND CONCLUSION

This study reaffirms the critical vulnerability of Okwangwo's forest ecosystems to changing climate conditions, while spotlighting the indispensable value of indigenous knowledge in environmental monitoring. By weaving together scientific and traditional insights, the research provides not only a clearer picture of ecosystem stress but also a compelling case for inclusive conservation.

To chart a sustainable path, safeguarding Cross River National Park demands more than data, it requires dialogue, restoration, and resilience-building. Empowering local communities, embracing culturally rooted conservation practices, and institutionalizing collaborative strategies will be pivotal to sustaining the forest's ecological and socio-cultural legacy in an era of uncertainty.

Recommendations

Based on the findings of this study, the following recommendations are proposed to support sustainable forest management and climate resilience in Okwangwo Division of Cross River National Park:

Climate Smart Forest Management Strategies

Given the observed decline in vegetation health (NDVI), forest productivity (NPP), and rainfall (CHIRPS), while surface and air temperatures are rising, a shift towards climate smart forest interventions is necessary.

Agroforestry and buffer zone planting should be promoted to regenerate degraded areas and enhance ecological stability near human settlements.

Integrate early warning systems using satellite data (e.g., NDVI and LST monitoring) to predict periods of extreme dryness or vegetation stress, enabling timely conservation actions.

Community Led Conservation and Indigenous Knowledge Integration

The study confirmed the validity of community observations such as shrinking water sources, changes in forest fruit availability, and recollections of more stable climates decades ago.

Sacred groves and culturally protected zones should be officially recognized as conservation assets and included in management planning.

Enhanced Policy Support for Climate-Resilient Livelihoods

Declining forest productivity has direct consequences on the livelihoods of communities dependent on NTFPs (non-timber forest products), water, and farming.

Policy incentives (such as carbon credits or REDD+ programs) should be extended to communities who demonstrate sustainable land-use practices.

Cross Scale Monitoring Using Remote Sensing

Expand the use of Google Earth Engine, MODIS, CHIRPS, and ERA5 datasets for continuous vegetation and climate trend analysis.

Train park rangers and local researchers in basic remote sensing techniques to institutionalize real time environmental tracking.

Competing Interest

The authors have declared that no conflicting exist in this manuscript.

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