Assessing Carbon Sequestration and Land Productivity Dynamics in Namibia Using Multi-Sensor EO Data and a GeoAI Framework

Ryan Theodore BENADE, Namibia and Oluibukun Gbenga AJAYI, Namibia

Key words: Carbon Sequestration, Degradation Attribution, Google Earth Engine, Land Productivity Dynamics, MODIS, Namibia, Net Primary Productivity

SUMMARY

Land degradation and climate variability constrain carbon sequestration in African drylands, yet national-scale, spatially explicit evidence to guide Land Degradation Neutrality (LDN) and climate reporting remains limited. This study applies a GeoAI-enabled monitoring framework to quantify carbon sequestration dynamics and attribute degradation drivers across Namibia from 2000 to 2024. Implemented entirely in Google Earth Engine, the workflow integrates MODIS annual net primary productivity (MOD17A3HGF, 500 m), MODIS vegetation indices (MOD13A1, NDVI composites) and CHIRPS precipitation (v2.0; ~5 km).

Temporal trends are quantified using pixel-wise linear regression, and carbon density is estimated via a simplified residence-time conversion of Net Primary Productivity (NPP). Land Productivity Dynamics (LPD) is operationalised through trajectory, state and performance components, with a complementary rule-based attribution separating climate-driven productivity decline (co-occurring rainfall decline) from anthropogenic signals (declining vegetation under stable/improving rainfall). Results reveal pronounced north–south gradients in carbon density consistent with rainfall controls: national mean carbon density is 2.1 ± 1.5 kg C/m², with northern, central and southern regions averaging 5.2, 3.6 and 1.2 kg C/m², respectively and peak stocks (5–7 kg C/m²) concentrated in the northeastern corridor. Positive carbon trends dominate ~81% of the country, but drought intensification (notably 2015, 2019 and 2023) exposes threshold vulnerability, particularly in Central Namibia.

Attribution mapping indicates 670,232 km² (81.3%) as stable or recovering, while climate-driven degradation affects 69,270 km² (8.4%) and anthropogenic degradation 84,419 km² (10.3%), with distinct spatial clustering that supports targeted intervention. The framework demonstrates a transparent, scalable approach for operational dryland carbon monitoring and restoration prioritisation, directly supporting Namibia's UNCCD LDN implementation and Paris Agreement mitigation planning.

Assessing Carbon Sequestration and Land Productivity Dynamics in Namibia Using Multi-Sensor EO Data and a GeoAI Framework

Ryan Theodore BENADE, Namibia and Oluibukun Gbenga AJAYI, Namibia

1. INTRODUCTION

According to Olsson et al. (2019), land degradation represents one of the most critical environmental challenges of the 21st century, affecting approximately 3.2 billion people globally and threatening the sustainability of ecosystem services essential for human well-being. Drylands, comprising arid, semi-arid, and dry sub-humid regions that cover 47% of the Earth's land surface, are disproportionately vulnerable to degradation processes driven by climate variability, unsustainable land management practices, and socioeconomic pressures (Yan et al., 2024). In sub-Saharan Africa, where drylands constitute over 43% of the land area and support more than 325 million people, land degradation undermines food security, intensifies poverty and accelerates rural-urban migration (Global Center on Adaptation, 2021, p. 312). The carbon sequestration potential of dryland ecosystems, while historically underappreciated compared to tropical forests, has emerged as critical for climate change mitigation (Siyum, 2020). Despite moisture constraints, drylands store approximately 30% of the global soil organic carbon pool (Hanan et al., 2021). Understanding the spatial and temporal dynamics of carbon sequestration across dryland terrain is, therefore, essential for achieving both the Paris Agreement's climate stabilisation goals and the United Nations Convention to Combat Desertification's (UNCCD) Land Degradation Neutrality (LDN) targets (Sahara and Sahel Observatory, 2024).

Accurate, spatially explicit monitoring of land degradation and carbon dynamics across extensive drylands remains methodologically difficult. National-scale field surveys are prohibitively costly, and the strong natural variability in dryland productivity driven by stochastic rainfall makes it hard to separate climate-driven fluctuations from human-induced degradation (Hallman & Robinson, 2024; Wu et al., 2024). However, open-access Earth Observation datasets such as MODIS and CHIRPS, together with cloud platforms such as Google Earth Engine, have removed many computational barriers that once limited large-scale analysis in developing-country contexts (Gorelick et al., 2017). Within this scope, the UNCCD Land Productivity Dynamics (LPD) framework strengthens operational monitoring by combining trajectory, state and performance dimensions of change (Sims et al., 2021). Its performance indicator, using residual trend analysis to compare observed productivity with climate-predicted expectations, helps isolate management effects from climate variability, improving degradation attribution (Mechiche-Alami & Abdi, 2020).

The integration of artificial intelligence and machine learning techniques with Earth Observation data has catalysed a new generation of environmental monitoring capabilities, termed "GeoAI" for its fusion of geospatial analytics with computational intelligence (Esri, n.d.). Machine learning algorithms enable automated differentiation of degradation types, integration of multi-source data streams and spatially adaptive regression models that provide more accurate climate normalisation than global linear relationships (Osman et al., 2025). However, the application of GeoAI approaches to carbon monitoring in drylands remains relatively promising, as noted by Shen et al. (2023), compared to tropical forest applications, with most dryland carbon assessments employing static allometric equations inadequate for capturing fine-scale spatial heterogeneity and rapid temporal dynamics characteristic of semi-arid ecosystems.

In Namibia, these methodological gaps intersect with urgent policy and reporting needs. Under the UNCCD, the country set voluntary Land Degradation Neutrality (LDN) targets in 2018, aiming for neutral or positive change in land-based natural capital by 2030, including restoring 15% of degraded land and enhancing carbon stocks in drylands (MEFT, 2018). Under the Paris Agreement, Namibia's NDC includes conditional land-use mitigation pledges, with terrestrial carbon sequestration identified as a cost-effective route to national emission reductions (MEFT, 2021). Delivering these goals requires spatially explicit baselines of carbon stocks, identification of high-potential restoration areas and monitoring systems that can verify sequestration outcomes for climate finance. Yet, robust evidence on conservancy impacts on productivity and carbon dynamics remains limited, weakening policy guidance on where to invest to scale restoration beyond existing conservancies.

This study addresses knowledge gaps through development and implementation of an integrated GeoAI-driven monitoring framework that fuses multi-sensor Earth Observation data (MODIS NPP, CHIRPS rainfall and MODIS NDVI) with machine learning-based degradation attribution and spatially adaptive regression for climate normalisation. The objectives are to quantify spatial patterns and temporal trends in carbon density across Namibia's climatic and land use gradients from 2000 to 2024, to assess Land Productivity Dynamics through integrated trajectory, state and performance indicators, as well as to differentiate climate-driven degradation from anthropogenic impacts through residual analysis, enabling targeted attribution to specific drivers. This supports the evaluation of regional variations in carbon sequestration trajectories across Northern, Central and Southern Namibia's divergent rainfall regimes. The analytical workflow, implemented entirely within Google Earth Engine's cloud computing environment, demonstrates its scalability for resource-constrained national environmental agencies requiring operational monitoring capabilities without substantial computational infrastructure investments.

2. METHODOLOGY

2.1 Study area and data integration

Covering an area of about 824,292 km², Namibia has significant climatic gradients caused by cold Benguela Current upwelling, subtropical high-pressure systems and continental interior heating (Geodatos, 2025; Ruppel-Schlichting, 2022, p. 65). The hyperarid Namib Desert has a mean annual rainfall of < 50 mm, while the northeastern Kavango-Zambezi region has a mean annual rainfall of > 600 mm (World Bank Group, 2021). Interannual variability is extremely high, with coefficients of variation surpassing 40–80% (FAO, n.d.). The study area (Figure 1) was divided into three climate zones, northern Namibia (north of 20°S, 400-600 mm rainfall), central Namibia (21°S-24°S, 200-400 mm rainfall) and southern Namibia (south of 23°S, < 200 mm rainfall) (Atlas of Namibia Team, 2022).

Using the methodology presented in Figure 2, Google Earth Engine (Gorelick et al., 2017) was employed for all data collection and processing over the study period (January 1, 2000 – December 31, 2024), which spanned 25 years of continuous monitoring. MODIS MOD17A3HGF Version 6 (Running & Zhao, 2019) at 500m resolution (2000-2021, 22 observations) was used to calculate annual NPP estimations. Annual totals (2000-2024, 25 observations) were calculated by aggregating daily precipitation estimates at ~5km resolution from CHIRPS Version 2.0 (Funk et al., 2015). The 16-day NDVI composite at 500m resolution were obtained by MODIS MOD13A1 Version 6.1 (Didan, 2015), with annual median composites calculated to lower atmospheric contamination. In large-scale rangeland systems, the 500m resolution demonstrated computing efficiency while preserving enough spatial detail for terrain-scale pattern detection.

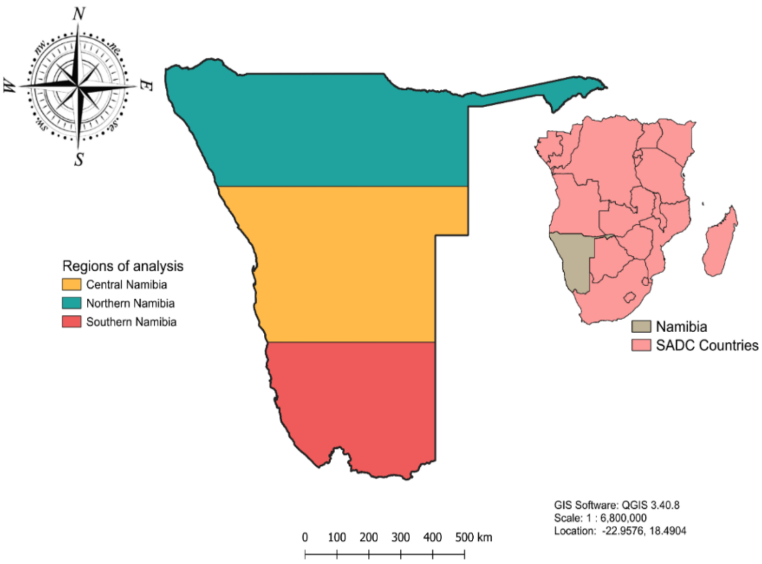

Figure 1. Study area (Namibia) and regional climate zones used for analysis (Northern, Central, Southern)

2.2 Temporal trend analysis and carbon estimation

Pixel-wise ordinary least squares regression was used in linear regression to quantify directional trends between time (since 2000) and the variable of interest. The slope (rate of change each year) and intercept bands were returned by the ee.Reducer.linearFit() function. Simplified allometric conversion was used to estimate carbon density as presented in equation (1):

$$\text{Carbon Density (kg C/m}^2\text{)} = \text{NPP (kg C/m}^2\text{/year)} \times 10 \text{ years} \tag{1}$$

While this approach simplifies vegetation type heterogeneity, it provides spatially consistent and temporally complete coverage, which is appropriate for restoration prioritisation and broad-scale monitoring (dos Santos et al., 2025).

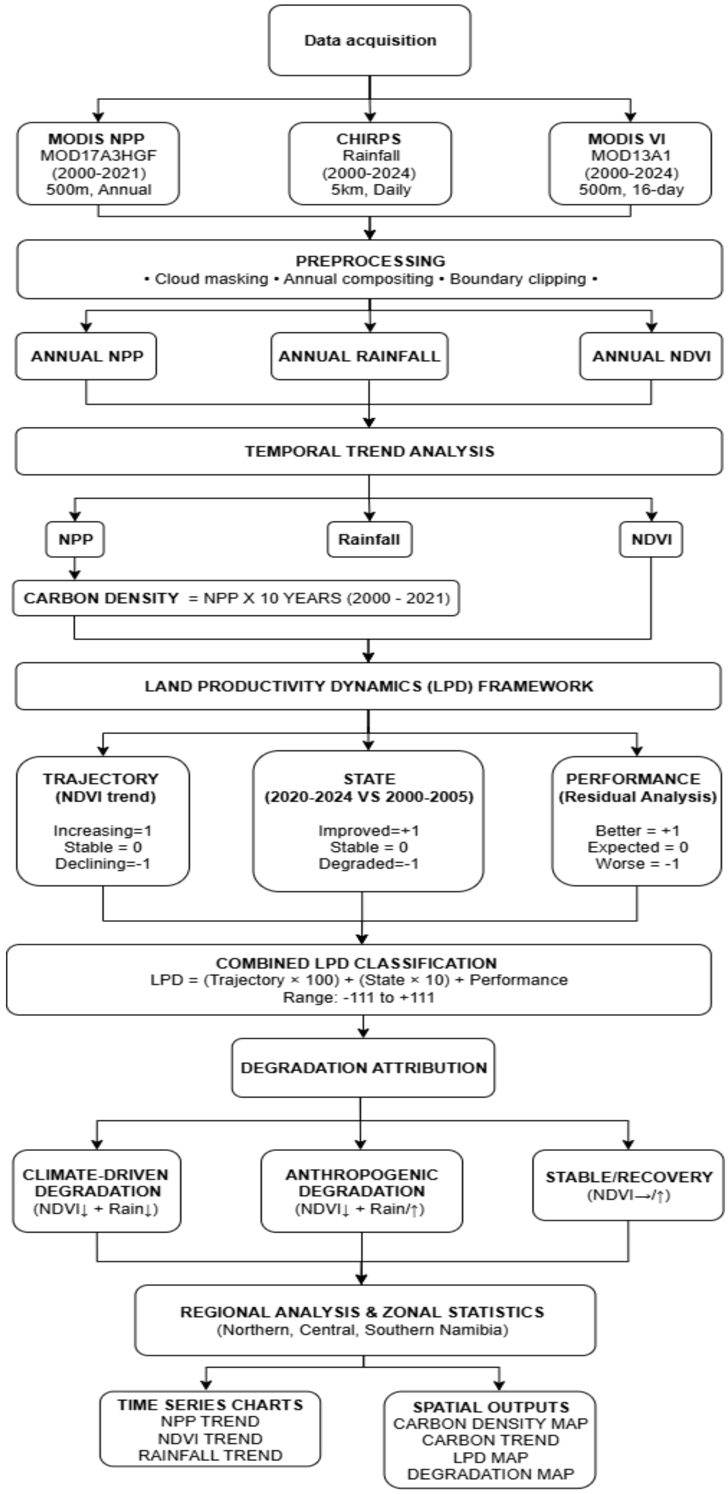

Figure 2. GeoAI framework implemented in Google Earth Engine (2000–2024): inputs, processing steps and outputs

2.3 Land productivity dynamics framework

The LPD methodology (Shen et al., 2023) was implemented through three complementary indicators:

i. **Trajectory indicator:** Quantified long-term NDVI trend direction using regression slopes increasing productivity (slope > +0.001 units/year), stable (± 0.001), declining (< -0.001), representing ±2.5% change over 25 years.

ii. **State indicator:** Compared recent (2020-2024) versus baseline (2000-2005) mean NDVI: improved (difference > +0.10 units), stable (± 0.10) or degraded (< -0.10), representing substantial change (25 - 66% of typical Namibian NDVI range).

iii. **Performance indicator:** Employed residual analysis isolating human management effects from climate variability (Equation 2):

$$\text{Performance Residual} = \text{NDVI Trend Slope} - (\text{Rainfall Trend Slope} \times 0.0001) \qquad (2)$$

Pixels were classified as better-than-expected (residual > +0.002), as-expected (±0.002) or worse-than-expected (< -0.002), with positive residuals indicating beneficial management and negative residuals suggesting degradation beyond climate drivers.

Combined classification: The three indicators were integrated as (Equation 3):

$$\text{LPD Class} = (\text{Trajectory} \times 100) + (\text{State} \times 10) + \text{Performance} \qquad (3)$$

Producing values from -111 (declining, degraded, worse-than-expected) to +111 (increasing, improved, better-than-expected).

2.4 Degradation attribution

A rule-based classification differentiated climate-driven degradation from anthropogenic impacts, where Climate-driven is indicated by a declining NDVI unit (slope < -0.001) and a declining rainfall unit (slope < -5 mm/year). Anthropogenic degradation is indicated by a declining NDVI but stable or improving rainfall (slope ≥ -5 mm/year), while stable/recovery is hinted at when there is stabilisation or an increasing NDVI (slope ≥ -0.001). In comparison to rule-based methods, Random Forest classifiers are often linked to higher model complexity and longer processing times, but frequently achieving superior predictive accuracy (Berhane et al., 2018). Due to computer memory constraints and the requirement for transparent decision logic independent of training data, a rule-based classification, which is ideal for attribution analysis of land productivity dynamics, was chosen. Spatial concordance with LPD performance characteristics was used to validate the classification outcomes.

2.5 Regional analysis and computational implementation

Zonal statistics were used in quantitative regional comparisons to calculate the mean and standard deviation for the Northern, Central and Southern regions. Area statistics produced extent estimates in km² by multiplying categorised images by pixel area and adding up the results countrywide. Using regional time series charts that extracted mean values over a 25-year period, temporal dynamics were visualised. There were no local processing limitations as the full analytical workflow was carried out on Google Earth Engine's cloud environment. Pre-processed MODIS products, annual aggregation, boundary filtering and optimised reducers all contributed to computational efficiency. For integration into the country's spatial infrastructure, the final deliverables were exported at a resolution of 500 meters.

3. RESULTS

3.1 Carbon density patterns and spatial heterogeneity

The GeoAI framework successfully processed 22 annual MODIS NPP images (2000-2021), 25 annual MODIS vegetation index composites (2000-2024) and 25 annual CHIRPS rainfall datasets (2000-2024) across Namibia's 824,292 km² (FAO, n.d.), bounding three climatic regions, northern Namibia (mean annual rainfall 491 mm), central Namibia (340 mm) and southern Namibia (113 mm).

Mean carbon density presents strong spatial heterogeneity aligned with climatic gradients (Figure 3). The northeastern corridor displayed the highest carbon accumulation with 5-7 kg C/m², while south-western hyperarid zones show minimal stocks below 1 kg C/m². National carbon density averaged 2.1 kg C/m² (±1.5 kg C/m² SD), with regional values following the rainfall gradient such as northern Namibia with 5.2 kg C/m², Central Namibia with 3.6 kg C/m² and southern Namibia with 1.2 kg C/m². Showing a four-fold difference, underscoring moisture availability's dominant control on ecosystem productivity across Namibia's semi-arid to arid terrain.

3.2 Temporal trends and regional dynamics

The 25-year temporal analysis revealed predominantly positive carbon sequestration trends across approximately 81% of Namibia's territory (Figure 4), with accumulation rates between 0.05 and 0.34 kg C/m²/yr. The strongest positive trends were concentrated in the northeastern corridor and north-central regions (>0.2 kg C/m²/yr), while the southwestern arid regions showed near-zero or slightly negative trends.

Net Primary Productivity trends revealed distinct regional dynamics (Figure 5). With northern Namibia indicating high interannual variability, ranging from 0.101 kg C/m²/yr (2002 drought) to 0.564 kg C/m²/yr (2021), demonstrating strong recovery capacity (165% rebound from 2019 drought to 2021 peak). Central Namibia fluctuated between 0.111 kg C/m²/yr (2015 drought) and 0.436 kg C/m²/yr (2021 recovery), achieving a 199% recovery rate between 2019-2021. Southern Namibia maintained consistently low productivity (0.066-0.159 kg C/m²/yr, mean ~0.11 kg C/m²/yr). All three regions achieved their highest or near-highest NPP values in 2021, indicating synchronised ecosystem recovery despite increasing climate stress.

NDVI trends corroborated NPP patterns (Figure 6), displaying widespread positive greening with darker concentrations in northern/northeastern regions (+0.010 to +0.014 units/yr). northern Namibia maintained high vegetation greenness (0.311-0.428), though 2024 values declined to 0.338 reflecting recent drought impacts. Central Namibia presented greater vulnerability, declining from 0.259 (2000) to 0.239 (2024), including a severe 2019 drop to

0.229. Southern Namibia remained stable within a narrow 0.134-0.178 range throughout 25 years, indicating adaptation to chronic aridity.

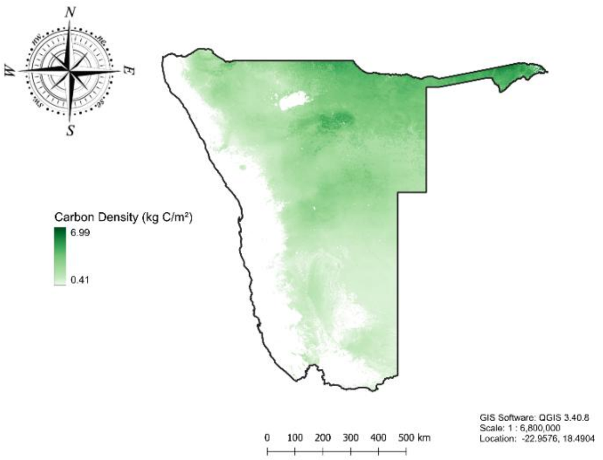

Figure 3. Spatial distribution of mean carbon density (kg C/m²) across Namibia

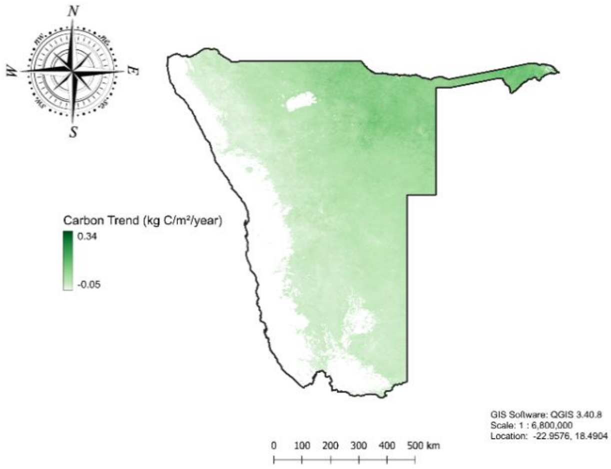

Figure 4. Spatial distribution of carbon trend (kg C/m² year) across Namibia

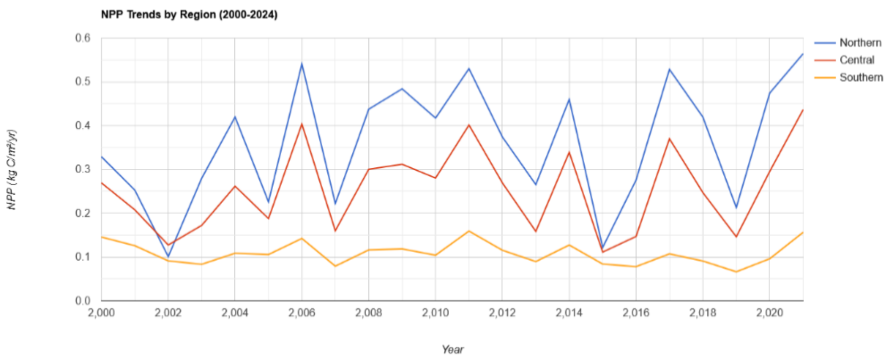

Figure 5. Annual mean NPP by region (Northern, Central, Southern Namibia)

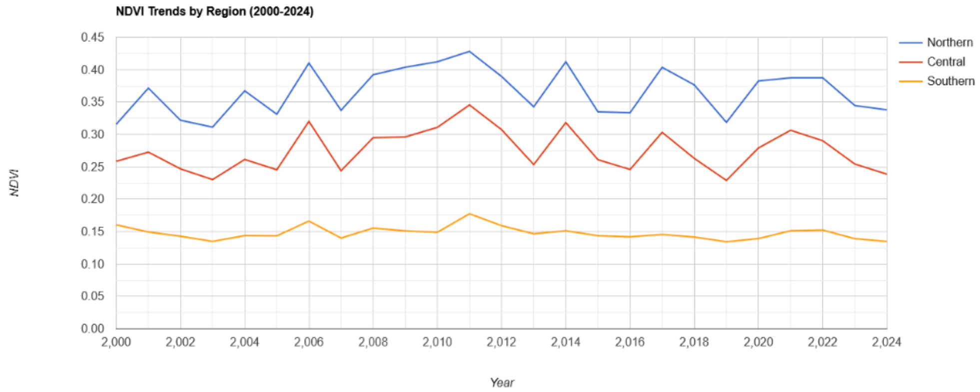

Figure 6. Annual mean NDVI by region (Northern, Central, Southern Namibia), 2000–2024

3.3 Rainfall variability and drought intensification

The rainfall analysis revealed pronounced interannual variability and an intensification of drought frequency (Figure 7). Northern Namibia's mean rainfall (491 mm) ranged from 241 mm (2019 catastrophic drought) to 798 mm (2011 exceptional year), 3.3-fold variability. Central Namibia averaged 340 mm, spanning 160 mm (2023) to 599 mm (2006), highest relative variability (3.8-fold range). Southern Namibia's chronically low rainfall averaged 113 mm/yr, fluctuating between 50 mm (2023) and 192 mm (2011).

Five major drought events were documented: 2002 (moderate), 2007 (severe in South), 2015 (major tri-regional, Northern 307 mm, Central 203 mm, Southern 84 mm), 2019 (catastrophic as the worst on record) and 2023 being extreme, (Central 159 mm and Southern 50 mm setting new records). Post-2015 period demonstrated accelerating drought frequency such as in 2015, 2019, 2023 compared to sporadic pre-2015 droughts. The 2023-2024 crisis particularly impacted Central Namibia, where in 2023 rainfall represented only 47% of long-term mean, resulting in severe NDVI decline to 0.239 by 2024.

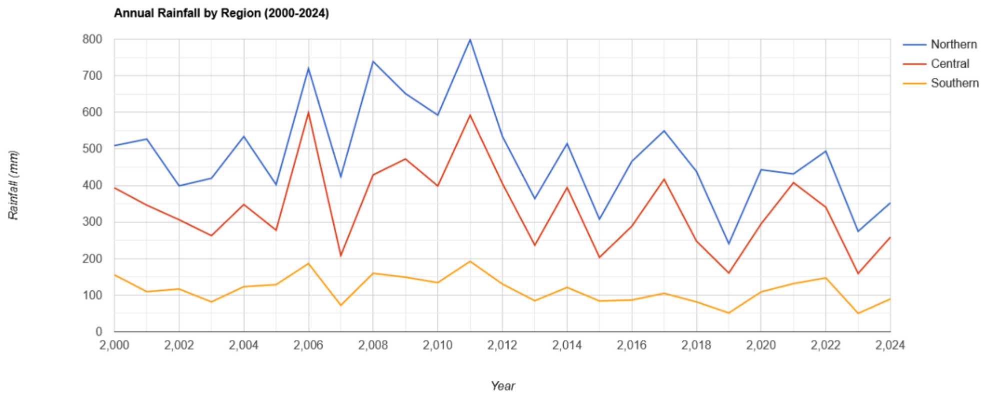

Figure 7. Annual rainfall totals by region (Northern, Central, Southern Namibia), 2000–2024

3.4 Land productivity dynamics and degradation attribution

The LPD framework revealed complex patterns of ecosystem change (Figures 8-11). Trajectory analysis demonstrated a clear east-west divide where eastern half expressed predominantly increasing productivity, while western regions displayed stable trajectories and scattered declining patches in central/north-central areas.

The performance component showed extensive areas in eastern Namibia and northeastern corridor displaying better-than-expected performance where the productivity is exceeding rainfall-predicted levels, spatially concordant with community-based conservancies. Conversely, north-western and north-central patches presented worse-than-expected performance, indicating anthropogenic stress factors. Degradation attribution differentiated the driver types. Showing that stable or recovering terrain dominated national extent (670,232 km², 81.3%). Climate-driven degradation covered 69,270 km² (8.4%), revealing pronounced concentration in a north-central degradation corridor, unexpected given moderate baseline rainfall, suggesting heightened vulnerability to recent drought intensification. Anthropogenic degradation enclosed about 84,419 km² (10.3%) of the area, displaying fragmented spatial patterns with concentrated clusters in northwestern communal lands and dispersed patches in southern regions. Spatial overlay with LPD performance confirmed strong concordance, validating the dual-method attribution approach.

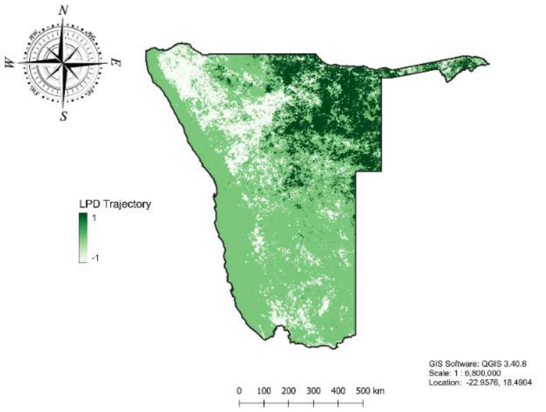

Figure 8. Land Productivity Dynamics (LPD) trajectory across Namibia

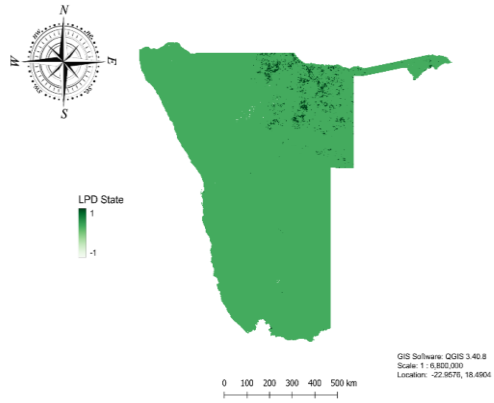

Figure 9. Land Productivity Dynamics (LPD) state across Namibia, comparing recent and baseline conditions

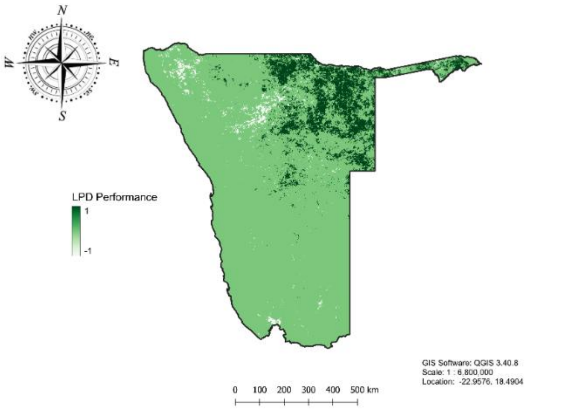

Figure 10. Land Productivity Dynamics (LPD) performance across Namibia, showing deviations from rainfall-predicted productivity

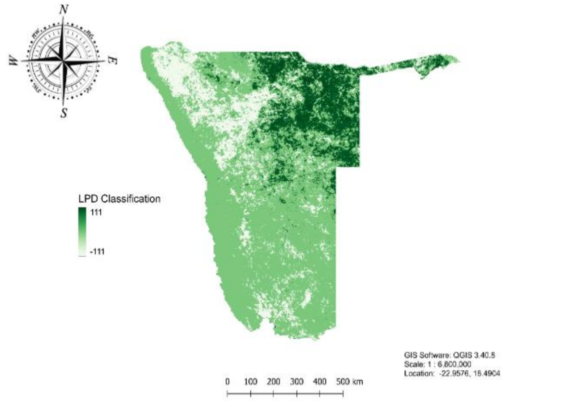

Figure 11. Combined Land Productivity Dynamics (LPD) classification across Namibia (2000–2024), integrating trajectory, state and performance indicators

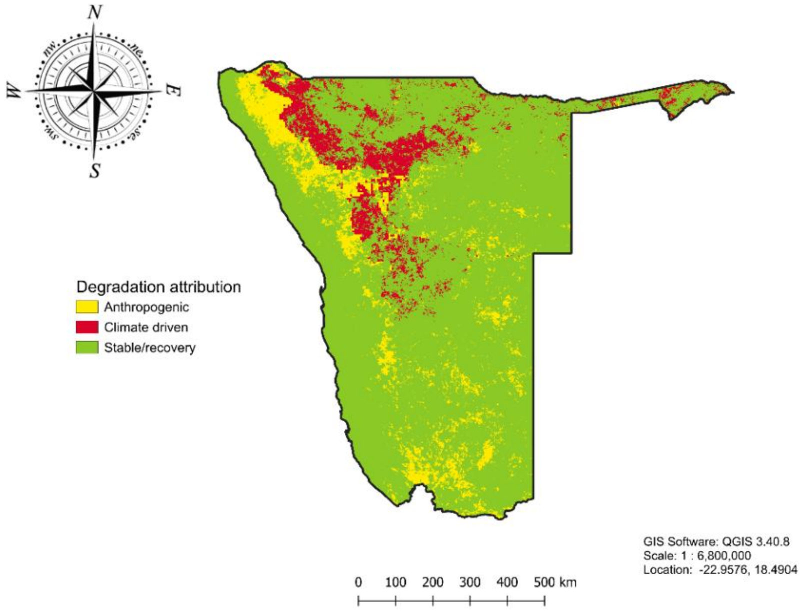

Figure 12. Degradation attribution map for Namibia (2000–2024), distinguishing anthropogenic, climate-driven, stable and recovery classes

3.5 Regional carbon trajectories and divergence

Northern Namibia demonstrated the strongest positive dynamics with a mean of 5.2 kg C/m² and NPP rebounding to its 2021 peak (0.564 kg C/m²/yr) despite a 37% rainfall decline during 2020-2024 versus 2000-2019 baseline. The northeastern corridor emerged as a restoration hotspot, with carbon trends of 5-7 kg C/m² and +0.2 to +0.34 kg C/m²/yr, indicating sustained recovery consistent with community-based conservation initiatives. Central Namibia indicated moderate but vulnerable dynamics with a mean of 3.6 kg C/m². Despite a strong 2021 recovery of about 0.436 kg C/m²/yr NPP and a 199% increase from 2019, the subsequent climate stress severely impacted productivity, with NDVI declining from 0.307 in 2021 to 0.239 in 2024 following the catastrophic 2023 drought. Southern Namibia maintained stable but persistently low dynamics with a mean of 1.2 kg C/m², NPP 0.066-0.159 kg C/m²/yr, reflecting adaptation to chronic aridity and climate-limited equilibrium. Regional productivity ratios of Northern:Central:Southern NPP shifted from 2.3:1.9:1 in 2000 to 3.6:2.8:1 2021, respectively, indicating increasing divergence in ecosystem performance with critical implications for spatial targeting of restoration investments.

4. DISCUSSION

4.1 Carbon terrain dynamics and management drivers

The four-fold carbon density gradient across Namibia reflects fundamental climatic controls on dryland productivity. However, localised moderate-carbon clusters in central-southern transition zones, appearing as discrete patches rather than continuous gradients, suggest anthropogenic modification. The spatial concordance between conservancy distributions and the northeastern restoration hotspot (5-7 kg C/m²) indicates that transferred resource governance has generated measurable carbon sequestration co-benefits alongside biodiversity conservation outcomes. On the other hand, studies like Tariq et al. (2024) have shown that minimal carbon stocks such as <1 kg C/m²) reflect the structural limitations of ancient hyperarid terrain, which supports primarily ephemeral vegetation with negligible sequestration potential. This suggests that land degradation neutrality targets should prioritise maintenance rather than ambitious enhancement goals, which are inappropriate for naturally hyperarid systems.

4.2 Resilience versus threshold vulnerability

The widespread positive carbon trends across 81% of Namibia represent a counter-intuitive finding given increasing drought frequency. This contradiction is a result of drought-recovery cycles (record-high NPP in 2021 after the devastating 2019 drought), the expansion of CBNRM from 4 conservancies in 1998 to 86 spanning 166,000 km² in 2020 and possible effects of CO_2 fertilisation (MEFT & NACSO, 2023). However, the 2023-2024 downturn signals concerning vulnerability. The 2023 drought showed a slower rebound than the rapid 2020-2021 recovery, with NDVI declining from 0.307 to 0.239 in Central Namibia (Iilonga and Ajayi, 2025). Post-2015 major droughts (2015, 2019, 2023), compared to more sporadic earlier events, align with CMIP6 projections, as shown by Almazroui et al. (2020). If drought return intervals continue shortening, recovery periods may prove insufficient for full biomass restoration, potentially driving systems toward alternative stable states with reduced woody cover and diminished carbon storage.

4.3 Attribution and policy implications

Human management signals were separated from climate variability by the LPD framework (European Commission, Joint Research Centre [JRC], 2019). North-eastern conservancy zones exhibited a cluster of overperformance compared to climate projections, indicating that decentralised governance facilitated vegetation regeneration above climate baselines and incorporated a mitigation component into the CBNRM assessment. Consistent with anthropogenic pressure associated with tenure instability, high livestock concentrations and restricted livelihood options, underperformance was concentrated in communal areas in the northwest (Heita et al., 2023). Despite moderate rainfall (300–450 mm/yr), climate-driven degradation was surprisingly concentrated in the north-central corridor (69,270 km²), highlighting vulnerability in transitional semi-arid systems near tree–grass thresholds; the 2023 drought (rainfall 47% of the long-term mean) may have forced some areas into persistently degraded states that need restoration.

Namibia's UNFCCC reporting and UNCCD LDN implementation are informed by these carbon dynamics. Estimates are limited because NPP represents gross primary productivity (not including heterotrophic respiration, herbivory and fire), the assumed 10-year residence time may bias herbaceous versus woody accumulation and 2023–2024 downturns indicate vulnerability under projected drying, despite positive trends suggesting terrestrial ecosystems currently act as a net carbon sink (Nzuma, 2025).

Degradation attribution maps that are spatially explicit offer useful information for tailored policy solutions. While anthropogenic degradation hotspots require interventions addressing governance and livelihood causes, climate-driven degradation zones necessitate investments in drought resilience (Geneva Environment Network, 2025). Differentiated targets are also necessary to achieve land degradation neutrality: The climate-limited baseline in southern Namibia (113 mm/yr, well below the 250 mm sustainability threshold) suggests concentrating on preventing additional degradation; the vulnerability of the central region supports giving priority to drought resilience and threshold prevention; and the northern regions offer the greatest potential for net positive outcomes through expanded restoration interventions (UNCCD, n.d.)

4.4 Regional equity and climate adaptation imperatives

The diverging regional carbon dynamics, with Northern Namibia strengthening its productivity advantage from 2.3:1 (2000) to 3.6:1 (2021) over southern regions, raise concerns about spatial inequality in ecosystem service provision. Northern regions demonstrate greater responsiveness to management and faster drought recovery, creating positive feedback that risks concentrating restoration resources in already productive terrain while neglecting southern regions where communities face greater livelihood vulnerability. The increasing frequency of droughts aligns with CMIP6 projections of intensified hydrological extremes (Almazroui et al., 2020). If projections materialise with 10-20% rainfall decline by mid-century, doubled drought frequency, Namibia's ecosystems face shorter recovery intervals, potentially overwhelming resilience mechanisms. Central Namibia's heightened vulnerability underscores the non-linear nature of climate impacts in semi-arid systems near critical transition thresholds. Recommended proactive adaptation measures surround the promotion of drought-tolerant species, ex situ seed banking and assisted migration to introduce ecotypes better suited to future climatic conditions (Franco-Navarro et al., 2025).

4.5 Methodological contributions and transferability

The GeoAI framework shows how cloud computing and open-source Earth Observation data may revolutionise operational monitoring in situations with limited data (Ghamisi et al., 2025; Vitale, 2025). While Google Earth Engine implementation enables processing 25 years of multi-sensor data spanning 824,292 km² without local computational equipment, the exclusive use of publicly accessible datasets such as MODIS NPP, CHIRPS rainfall removes acquisition cost limitations (Gorelick et al., 2017). However, the detection of fine-scale degradation processes is limited by the 500m-1km MODIS resolution, indicating that hybrid techniques that combine focused high-resolution assessment with coarse-resolution trend analysis may provide the best resource allocation (Ituen, 2024). Establishing permanent monitoring plots stratified among vegetation types, rainfall zones and land-tenure regimes constitutes a priority for operationalising the system with validation against ground-based measurements also being crucial. In a related study, Bonannella (2024) emphasises the importance of robust field validation. Given that the methodological approach does not require site-specific parameterisation or commercial datasets, the framework's transferability to other African drylands is a significant advantage. This enables comparative degradation pattern analysis and the identification of transboundary processes that align with the UNCCD's Global Land Outlook emphasis on consistent, repeatable methodologies (Dronin, 2023).

5. CONCLUSION

This study showed how GeoAI-driven analytics can effectively monitor land degradation and carbon sequestration dynamics throughout Namibia's diverse semi-arid regions (Shen et al., 2023). Climate-driven degradation corridors were distinguished from anthropogenic stress zones and human-managed recovery areas through the integration of multi-sensor Earth Observation data with machine learning-based attribution frameworks (Esri, n.d.). This provided actionable intelligence for spatially targeted restoration investments. The results showed that 81% of Namibia has steady or recovering productivity and that community-based natural resource management has real carbon sequestration co-benefits due to concentrated restoration success in northeastern conservancy zones. However, the discovery of anthropogenic impacts throughout 84,419 km² of northwestern community lands and climate-driven deterioration affecting 69,270 km² in north-central regions highlights ongoing vulnerability necessitating distinct policy responses.

Despite generally good 25-year carbon trends, the increasing frequency of droughts recorded through 2023–2024, especially the disastrous effects on Central Namibia where rainfall hit 25-year lows, indicates serious susceptibility. The need for context-appropriate land degradation neutrality targets that accept biophysical realities rather than imposing uniform enhancement goals across climatic gradients is highlighted by the divergent regional trajectories, with northern zones strengthening productivity advantages while southern semi-arid systems remain extremely limited (Sahara and Sahel Observatory, 2024). In the face of escalating climate change, the framework's sole reliance on open-source data and cloud computing platforms shows scalability potential across African drylands, advancing data-driven approaches to carbon assessment and climate-resilient land governance crucial for fulfilling SDG 13 (Climate action) and SDG 15 commitments (Life on land) (United Nations, n.d.)

6. REFERENCES

Almazroui, M., Islam, M.N., Saeed, S., Saeed, F. and Ismail, M., 2020, Future changes in climate over the Arabian Peninsula based on CMIP6 multimodel simulations, Earth Systems and Environment, 4(4), 611–630. https://doi.org/10.1007/s41748-020-00183-5

Atlas of Namibia Team, 2022, Atlas of Namibia: Its land, water and life, Windhoek, Namibia Nature Foundation.

Berhane, T., Lane, C., Wu, Q., Autrey, B., Anenkhonov, O., Chepinoga, V. and Liu, H., 2018, Decision-tree, rule-based and random forest classification of high-resolution multispectral imagery for wetland mapping and inventory, Remote Sensing, 10(4), 580. https://doi.org/10.3390/rs10040580

Bonannella, C., 2024, Spatiotemporal modeling of vegetation dynamics in a changing environment: Combining earth observation and machine learning, ProQuest Dissertations & Theses Global, Ann Arbor, MI, ProQuest. https://www.proquest.com/openview/fce6cbc21ec243df4a5eb757d5311bfe/1?pq-origsite=gscholar&cbl=2026366&diss=y

Didan, K., 2015, MOD13A1 MODIS/Terra vegetation indices 16-day L3 global 500 m SIN grid V006 [Data set], NASA Land Processes Distributed Active Archive Center (LP DAAC), Sioux Falls, SD, NASA. https://doi.org/10.5067/MODIS/MOD13A1.006 (retrieved 28 December 2025)

dos Santos, A.B.C., Lamberti, P.P., Oliveira, D.R., Nogueira, M.L., Álvarez, C.I. and Costa, R.B., 2025, Global trends in vegetation carbon stock monitoring using Google Earth Engine and NDVI: A systematic review (2017–2024), Remote Sensing Applications: Society and Environment, in press, 101863. https://doi.org/10.1016/j.rsase.2025.101863

Dronin, N., 2023, Reasons to rename the UNCCD: Review of transformation of the political concept through the influence of science, Environment, Development and Sustainability, 25(3), 2058–2078. https://doi.org/10.1007/s10668-022-02149-1

Esri, n.d., GeoAI: Accelerated data generation and spatial problem-solving, Redlands, CA, Esri. https://www.esri.com/en-us/capabilities/geoai/overview (retrieved 20 December 2025)

European Commission, Joint Research Centre, 2019, Land productivity dynamics, World Atlas of Desertification, Ispra, Italy, Joint Research Centre, European Commission. https://wad.jrc.ec.europa.eu/landproductivity

Food and Agriculture Organization of the United Nations, n.d., Namibia at a glance, Rome, Food and Agriculture Organization of the United Nations.

https://www.fao.org/namibia/our-office/namibia-at-a-glance/en (retrieved 29 December 2025)

Franco-Navarro, J.D., Padilla, Y.G., Álvarez, S., Calatayud, Á., Colmenero-Flores, J.M., Gómez-Bellot, M.J., Hernández, J.A., Martínez-Alcalá, I., Penella, C., Pérez-Pérez, J.G., Sánchez-Blanco, M.J., Tasa, M. and Acosta-Motos, J.R., 2025, Advancements in water-saving strategies and crop adaptation to drought: A comprehensive review, Physiologia Plantarum, 177(4), e70332. https://doi.org/10.1111/ppl.70332

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. and Michaelsen, J., 2015, The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes, Scientific Data, 2(1), 150066. https://doi.org/10.1038/sdata.2015.66

Geneva Environment Network, 2025, Desertification, land degradation and drought and the role of Geneva, Geneva, Switzerland, Geneva Environment Network. https://www.genevaenvironmentnetwork.org/resources/updates/desertification-land-degradation-and-drought-and-the-role-of-geneva/

Geodatos, 2025, Namibia geographic coordinates – Latitude and longitude, Madrid, Geodatos. https://www.geodatos.net/en/coordinates/namibia

Ghamisi, P., Yu, W., Marinoni, A., Gevaert, C.M., Persello, C., Selvakumaran, S., Girotto, M., Horton, B.P., Rufin, P., Hostert, P., Pacifici, F. and Atkinson, P.M., 2025, Responsible artificial intelligence for Earth observation: Achievable and realistic paths to serve the collective good, IEEE Geoscience and Remote Sensing Magazine, 13(3), 72–96, Piscataway, NJ, IEEE. https://doi.org/10.48550/arXiv.2405.20868

Global Center on Adaptation, 2021, Drylands, State and trends in adaptation report 2021: Africa (Section 2), pp. 312–329, Rotterdam, Global Center on Adaptation.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R., 2017, Google Earth Engine: Planetary-scale geospatial analysis for everyone, Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hallman, T.A. and Robinson, W.D., 2024, Supplemental structured surveys and pre-existing detection models improve fine-scale density and population estimation with opportunistic community science data, Scientific Reports, 14(1), 11070. https://doi.org/10.1038/s41598-024-61582-6

Hanan, N.P., Milne, E., Aynekulu, E., Yu, Q. and Anchang, J., 2021, A role for drylands in a carbon neutral world?, Frontiers in Environmental Science, 9, 786087. https://doi.org/10.3389/fenvs.2021.786087

Heita, H.T., Dressler, G., Schwieger, D.A.M. and Mbidzo, M., 2023, Pastoralists' perceptions on the future of cattle farming amidst rangeland degradation: A case study from Namibia's semiarid communal areas, Rangelands, 46(1), 1–12. https://doi.org/10.1016/j.rala.2023.10.001

Iilonga, S.N., and Ajayi, O.G., 2025, Implementation of deep learning algorithms to model agricultural drought towards sustainable land management in Namibia's Omusati region, Land Use Policy, 156, 107593. https://doi.org/10.1016/j.landusepol.2025.107593

Ituen, I.I.-O.S., 2024, On the impact of land use and land cover change on GHG emissions using advanced remote sensing technology (Doctoral dissertation), Toronto, York University.

Mechiche-Alami, A. and Abdi, A.M., 2020, Agricultural productivity in relation to climate and cropland management in West Africa, Scientific Reports, 10(1), 3393. https://doi.org/10.1038/s41598-020-59943-y

Ministry of Environment and Tourism, 2018, Final report: Land Degradation Neutrality pilot project, Windhoek, Republic of Namibia (with support from Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ)).

Ministry of Environment, Forestry and Tourism, 2021, Namibia's updated nationally determined contribution, Windhoek, Republic of Namibia.

MEFT/NACSO, 2023, The state of community conservation in Namibia (Annual Report 2022), Windhoek, MEFT/NACSO.

Nzuma, T.M., 2025, Aligning climate and biodiversity agendas in Namibia: A country case study on synergies between NDC and NBSAP processes, Windhoek, Ministry of Environment, Forestry and Tourism.

Olsson, L., Barbosa, H., Bhadwal, S., Cowie, A., Delusca, K., Flores-Renteria, D., Hermans, K., Jobbagy, E., Kurz, W., Li, D., Sonwa, D.J. and Stringer, L., 2019, Land degradation, Climate Change and Land: An IPCC Special Report on climate change, desertification, land degradation, sustainable land management, food security and greenhouse gas fluxes in terrestrial ecosystems, pp. 345–436, Cambridge, Cambridge University Press. https://doi.org/10.1017/9781009157988.006

Osman, A.I.A., AlDahoul, N., Chong, K.L., Huang, Y.F., Ng, J.L., Elshafie, A., Sherif, M. and Ahmed, A.N., 2025, A review on machine learning models for drought monitoring and forecasting, Climate Risk Management, 50, 100758. https://doi.org/10.1016/j.crm.2025.100758

Ruppel-Schlichting, K., 2022, Namibia and its environment, in Ruppel, O.C. and Ruppel-Schlichting, K. (eds), Environmental law and policy in Namibia: Towards making Africa the tree of life, pp. 65–73, Baden-Baden, Nomos. https://doi.org/10.5771/9783748933564-65

Sahara and Sahel Observatory, 2024, African land: The degradation and the absolute requirement of sustainable management, Tunis, Sahara and Sahel Observatory. https://www.oss-online.org/sites/default/files/2024-09/OSS-LivreTerres_dAfrique_En.pdf

Shen, T., Li, X., Chen, Y., Cui, Y., Lu, Q., Jia, X. and Chen, J., 2023, HiLPD-GEE: High spatial resolution land productivity dynamics calculation tool using Landsat and MODIS data, International Journal of Digital Earth, 16(1), 671–690. https://doi.org/10.1080/17538947.2023.2179675

Siyum, Z.G., 2020, Tropical dry forest dynamics in the context of climate change: Syntheses of drivers, gaps and management perspectives, Ecological Processes, 9(1), 25. https://doi.org/10.1186/s13717-020-00229-6

Sims, N.C., Newnham, G.J., England, J.R., Guerschman, J., Cox, S.J.D., Roxburgh, S.H., Viscarra Rossel, R.A., Fritz, S. and Wheeler, I., 2021, Good practice guidance: SDG indicator 15.3.1, proportion of land that is degraded over total land area (Version 2.0), Bonn, United Nations Convention to Combat Desertification.

Tariq, A., Sardans, J., Zeng, F., Graciano, C., Hughes, A.C., Farré-Armengol, G. and Peñuelas, J., 2024, Impact of aridity rise and arid lands expansion on carbon-storing capacity, biodiversity loss and ecosystem services, Global Change Biology, 30(4), e17292. https://doi.org/10.1111/gcb.17292

United Nations, n.d., The 17 goals | Sustainable Development, New York, United Nations. https://sdgs.un.org/goals (retrieved 29 December 2025)

United Nations Convention to Combat Desertification (UNCCD), n.d., Land degradation neutrality, Bonn, United Nations Convention to Combat Desertification. https://www.unccd.int/land-and-life/land-degradation-neutrality/overview (retrieved 20 December 2025)

Vitale, A., 2025, A GeoAI-based approach for long-term monitoring of urban fabric transformations, ACTA IMEKO, 14(2), 1–9. https://doi.org/10.21014/actaimeko.v14i2.2117

World Bank Group, 2021, Climate risk country profile: Namibia (Report No. 15931), Washington, DC, World Bank Group.

https://climateknowledgeportal.worldbank.org/sites/default/files/2021-08/15931-WB_Namibia%20Country%20Profile-WEB.pdf

Wu, B., Smith, W.K. and Zeng, H., 2024, Dryland dynamics and driving forces, in Fu, B. and Stafford-Smith, M. (eds), Dryland social-ecological systems in changing environments, pp. 23–68, Singapore, Springer Nature. https://doi.org/10.1007/978-981-99-9375-8

Yan, Z., Guo, Y., Sun, B., Gao, Z., Qin, P., Li, Y., Yue, W. and Cui, H., 2024, Combating land degradation through human efforts: Ongoing challenges for sustainable development of global drylands, Journal of Environmental Management, 354, 120254. https://doi.org/10.1016/j.jenvman.2024.120254

BIOGRAPHICAL NOTES

Ryan Theodore Benade is a Namibian geospatial and environmental management specialist with academic and professional experience in GIS, Remote Sensing and Environmental Studies. He currently serves as a parttime lecturer at the Namibia University of Science and Technology (NUST). He holds a Bachelor of Geo-Information Technology and an Honours degree in Geo-Information Technology from the Namibia University of Science and Technology (NUST), as well as a Postgraduate Diploma in Environmental Studies from the International University of Management (IUM), where he is currently pursuing a Master of Science in Integrated Environmental Management and Sustainable Development. His research interests focus on mineral exploration using multispectral and hyperspectral remote sensing, climate change impacts on vegetation and land use, precision agriculture through soil nutrient mapping and renewable energy planning with a focus on green hydrogen site suitability.

CONTACTS

Mr. Ryan Theodore Benade
Organisation: Department of Land and Spatial Sciences (DLSS), Namibia University of Science and Technology (NUST), Namibia
Address: Erf 597 Block A
City: Rehoboth
Country: Namibia
Tel: +264 81 716 5949
Email: ryanbenade20@gmail.com, rbenade@nust.na

Oluibukun Gbenga Ajayi is an Associate Professor of Geoinformation Technology in the Department of Land and Spatial Sciences at the Namibia University of Science and Technology. He leads the Geospatial Intelligence Research Lab (GIRL) and serves as Research Coordinator for the School of the Built Environment, as well as Coordinator of the Master of Spatial Science programme. He also holds an extraordinary appointment in the Department of Geography, Geoinformatics and Meteorology at the University of Pretoria, South Africa. His academic work focuses on geospatial artificial intelligence and remote sensing applications, with a strong interest in applied research that supports planning, infrastructure, and environmental decision making. He has extensive university teaching experience, supervises postgraduate research, and contributes actively to capacity development through interdisciplinary collaboration and academic leadership.

COUNTRY: Namibia/ South Africa
Tel. +264813124631
Email: oajayi@nust.na /oluibukun.ajayi@up.ac.za
Web site: https://febe.nust.na/oluibukun-gbenga-ajayi