ADVANCES IN FORESTRY SCIENCE

OPEN ACCESS

Spatio-temporal dynamic of forest cover distribution in Omo-Shasha-Oluwa Tropical Forest Complex, Nigeria, (2014 – 2022)

Stephen Aina[1] Joseph Onoja [1], Muhtari Aminu-Kano [1]

[1] Department of Technical Programmes, Nigerian Conservation Foundation, Lagos.
[2] Gashaka Biodiversity Support Initiative, Serti, Taraba State, Nigeria.

Original Article

***Corresponding author:**
globastat@gmail.com

Keywords:
Vegetation Index
Deforestation
Forestlands
Protected Areas
Forest Management
Landsat

Palavras-chave:
Indice de Vegetação
Desmatamento
Florestas
Áreas protegidas
Gestão florestal
dados Landsat

Received in
2024/09/01

Accepted on
2024/0919

Published in
2024/10/04

DOI:
http://dx.doi.org/10.34062/afs.v11i3.14876

ABSTRACT: Forest Reserves (FRs) constitute a significant portion of the forested lands within protected areas, and their conservation is essential for Nigeria to achieve the United Nations' Sustainable Development Goals (SDGs). Our study conducted an analysis of the dynamics of forested lands in the study area to evaluate and rank management performance over the period of 2014-2022. The forest bloc in OSO witnessed an expansion by 1.39% (3,929.67 ha) from 27.73% to 29.12% forest cover in 2014 and 2022, respectively. Forest fragments declined from 16 to 10 units for the forest bloc (>201.1 ha) with a proportionate increase in the Largest Patch Index (LPI) from 5,815.53 ha to 39,234.15 ha, in the period 2014 -2022, respectively. Omo, Ago-Owu, Ife and Shasha FRs all witnessed negative changes in the percent forest cover representing a decline of about -0.43% (529.52 ha), -37.62% (9028.8 ha), -8.54% (1217.43 ha) and -0.29% (89.55 ha), respectively. Oluwa FR had an increase in the forest cover by 17.64% or 14,596.38 ha in the period 2014 - 2022. The forest cover retention rates in the period 2014 – 2022, ranks Oluwa FR ahead of other FRs in terms of Protected Area (PA) management efficiency. The results highlight the existence of a relatively better and effective forest management system in the reserve. Landsat data are capable of providing near real-time forest cover information that can be integrated into existing tracking tools for periodically gauging management efficiency and performances across the PAs of Nigeria.

Avaliação baseada em Landsat da distribuição da cobertura florestal no Complexo Florestal Tropical de Omo-Shasha-Oluwa, Nigéria, (2014 – 2022)

RESUMO: As Reservas Florestais (FRs) representam uma grande proporção das áreas florestais em áreas protegidas e são importantes para alcançar os Objetivos de Desenvolvimento Sustentável (ODS) das Nações Unidas na Nigéria. Nossa pesquisa tentou desagregar a extensão da cobertura florestal e as taxas de retenção em cada um dos compartimentos como base para avaliar e classificar os desempenhos de manejo no período 2014-2022. O bloco florestal em OSO teve uma expansão de 1,39% (3.929,67 ha) de 27,73% para 29,12% de cobertura florestal em 2014 e 2022, respectivamente. Os fragmentos florestais diminuíram de 16 para 10 unidades para o bloco florestal (>201,1 ha) com aumento proporcional no Índice de Maior Mancha (LPI) de 5.815,53 ha para 39.234,15 ha, no período 2014 -2022, respectivamente. As RFs Omo , Ago - Owu , Ife e Shasha testemunharam mudanças negativas na porcentagem de cobertura florestal representando um declínio de cerca de -0,43% (529,52 ha), -37,62% (9028,8 ha), -8,54% (1217,43 ha) e - 0,29% (89,55 ha), respectivamente. Oluwa FR teve um aumento na cobertura florestal de 17,64% ou 14.596,38 ha no período 2014 - 2022. As taxas de retenção da cobertura florestal no período 2014 - 2022, classifica Oluwa FR à frente de outros FRs em termos de gestão de Área Protegida (AP) eficiência. Os resultados destacam a existência de um sistema de manejo florestal relativamente melhor e eficaz na reserva. Os dados do Landsat são capazes de fornecer informações sobre a cobertura florestal quase em tempo real que podem ser integradas às ferramentas de rastreamento existentes para avaliar periodicamente a eficiência e o desempenho do gerenciamento nas APs da Nigéria.

Introduction

Forests lie at the center of the discourse on two critical societal challenges: the crisis of biodiversity and climate change (IPBES 2019; Asbeck, et al., 2021). Protected Areas (PAs), therefore, play critical roles in addressing these environmental crises. This is because forests store a large quantity of carbon, thereby providing means of addressing global warming (IPCC, 2013; Adetoye, et al. 2018). Forest Reserves (FRs) belong to category VI under the IUCN PAs classification and hold a significant proportion of the country's forest cover and a wide range of flora and fauna biodiversity. These reserves are managed at the state level by different State Forestry (Igu, et al. 2017).

The creation of forest reserves in Nigeria by the colonial administration in the early 20th century was intended to serve a noble purpose (Akpan-Ebe, 2017). However, the flora within these vast forest estates has suffered severe devastation and degradation. According to Mbaya and Hashidu (2017), many forest reserves in Nigeria exist only on maps, and in reality, most of them have been de-reserved. This trend is concerning because it negatively impacts the biodiversity functions of these reserves. In addition, Ezealor, (2001), reported by Olmos and Turshak (2009) concluded that only a few reserves, in remote or sparsely populated areas, are still in good condition. This, according to (Pearce, et al 2013: Ali, et al. 2021), is due to improper management of forest resources, which is a key issue in developing countries and poses a significant threat of damage to land and other natural resources. These changes in forest cover affect important ecosystem services, including biodiversity, climate regulation, and carbon storage (Achard et al. 2002; Foley et al., 2005; Mbaya and Hashidu, 2017). Therefore. forest inventory systems are required to regularly assess these changes to support early and precise decisions for sustainable forest management in Nigeria.

However, a continuous forest inventory system is lacking and mostly ineffective, where available, due to limited technical support and capacities at the state-level. Nigeria falls short of the basic standard for acquiring regular and up-to-date data on the forest resources, and where information on the forests is available, it is either obsolete or based on extrapolation from very old data (Akindele (2012; Akpan-Ebe, 2017). Therefore, effectively managing the world's growing system of protected areas is a key challenge for global biodiversity conservation in the 21st century (Carlos, et al. 2013). In addition, our understanding of the impact of PA management interventions on conservation outcomes has been impeded by a lack of data (Geldmann, et al. 2013; Coad, et al., 2015).

In recent times, emerging improvements in geospatial techniques and the increasing accessibility to open-source software and spaceborne data are adding to developing countries' potentials to report forest cover changes across a wide range of habitats in real-time. According to Kaliraj, et al. (2012), the continuous observations of forest cover through the spaceborne technology provide relative accuracy for (the assessment of) temporal variation, changes and spatial distribution of forest biodiversity. Nigeria, therefore, urgently require a system for continuous observation of FRs to generate forest cover data as a tool for evaluating the management efficiency of PAs. Classifying and mapping vegetation is an important technical task for managing natural resources as vegetation provides a base for all living beings and plays an essential role in affecting global climate change (Xiao, et al. 2004; Xie, 2008; Farooq, 2012).

In this paper, we analysed the forest cover extent, using the Enhanced Vegetation Index (EVI) to discriminate between photosynthetically active vegetation and other terrain features in Omo-Shasha-Oluwa (OSO) forest complex. We disaggregated the forest cover extent into five (5) compartments corresponding to the forest reserves (FRs) in the study area to generate location-specific information for management actions. The performances of the different Forest Management Units (FMUs) were further evaluated and ranked, vis-à-vis their forest retention rate, between 2014 and 2022, as a baseline for conservation-based decision-making.

In addition, this research will demonstrate the potentials of Landsat Operational Land Imager (OLI) data to provide pragmatic information about forest canopy distribution and variation, especially where the scale of dynamics is significant, from 2014-2022. It is envisaged that the outputs of our research will help promote understanding of each FR's contribution to the overall percentage forest cover in the study area, rather than the generic assessments in several co-authored journals in circulation.

Material and Methods

Description of Study Area

Omo-Shasha-Oluwa (OSO) forest complex is a cluster of three (3) neighbouring and largest Forest Reserves (FRs) found in Ogun, Osun and Ondo States, respectively. OSO is an appellation derived from Omo, Shasha and Oluwa Forest FRs. However, Shasha FR is seamlessly flanked (like a flagellated insect antennae) by two other FRs, namely: Ago-Owu FR and Ife FR, on the westward and eastward fringes, respectively. The forest complex is an example of a tripartite state-wide collaboration designed to preserve a significant block of forest and corridors for the exchange of materials and conservation of iconic species, such as the Nigeria-Cameroon chimpanzee (*Pan troglodytes ellioti*), wild dogs (Lycaon pictus) and the African forest elephant (*Loxodonta cyclotis*). OSO has a landmass of approximately 284,643.60 hectares that is confined within the geographic coordinates of 6.5933 N – 7.2666 N (Latitudes) and 4.0760 E – 4.8592 E (Longitudes). The mean annual rainfall ranges from 1,200mm to 1450mm and temperatures are high throughout the year with a mean of about 27oC and an annual range of about 3oC (Orimoogunje and Ekanade, 2010).

The earliest recognition of the forest complex that is traceable to literatures was in 1925. According to (Isichei, 1995, Ogunseasn, et al., 2011), these five forest reserves were all originally part of the Shasha Forest Reserve, established in 1925 prior to the creation of state administration in Nigeria. These forests are of considerable biological interest because they occupy a geographically intermediate position between the Upper Guinea forests that extend from Sierra Leone to the Ghana-Togo border and the Central African (or Lower Guinea forests) that reach into eastern Nigeria (PNI, 2011; Adepoju and Salami, 2017). However, agriculture has destroyed many forested areas in Nigeria. As a result, there are existing recommendations to upgrade and designate the forest complex under the IUCN category II status (National Park).

Data Sources and Analysis

The EarthExplorer database maintained by the United State Geological Survey (USGS) holds vast collections of declassified satellite imageries, including the Landsat 8/9 (Operational Land Imager) data (190 Path/55 Row) used for creating the Enhanced Vegetation Index (EVI) and the thematic land use/land cover (LULC) raster for the imageries acquired on December 14, 2014 and January 26, 2022. The shapefiles for the FRs (Fig. 1) were accessed from the World Database on Protected Area (UNEP-WCMC and IUCN (2022). The interoperability of SAGA GIS 8.0, ArcGIS 10.5,

Landscape Fragmentation Tool 2.0v and Fragstat 4.0 (McGarigal and Marks, 1995) generated the various outputs presented in the study. The EVI formula (Huete, et al., 2002) with the traditional coefficient values is given as (Eq. 1):

$$EVI = 2.5 * \left(\frac{NIR-RED}{NIR+(6*RED)-(7.5*BLUE)+1}\right) \quad (1)$$

Top-of-Atmosphere (ToA) Reflectance

Radiometric corrections were applied to the BLUE (B2), RED (B4) and NIR (B5) spectral bands for 2014 and 2022 image data; to convert pixel values (brightness values) to the Top-of-the-Atmosphere (ToA) reflectance units. ToA helps to improve the spectral parity of terrain features of the same class for multitemporal images. The conversion was implemented with Eq. (2) and Eq. (3) in the Landsat 8 Handbook. About dimensions, one hundred fibers of each raw material were measured; the basic density and the chemical characterization for each raw material were performed in five replicates.

$$\rho\lambda' = M_\rho Q_{cal} + A_\rho \quad (2)$$

Where: $\rho\lambda' = TOA$ planetary reflectance, without correction for solar angle; M_ρ = Band-specific multiplicative rescaling factor; Q_{cal} = Quantized and calibrated standard product pixel values (DN); A_ρ = Band-specific additive rescaling factor.

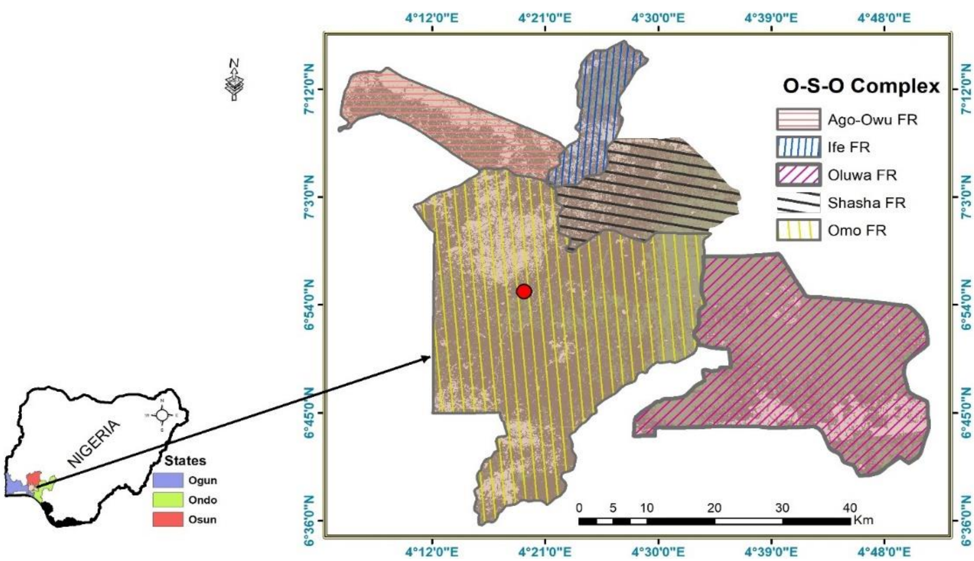

Figure 1: Map of the Omo-Shasha-Oluwa Forest Reserves, southwestern Nigeria.

$$\rho\lambda = \frac{\rho\lambda'}{\sin(\theta_{SE})} \quad (3)$$

Where: ρ_{λ}= TOA planetary reflectance; θ_{SE}= Local sun elevation angle; θ_{SZ}= Local solar zenith angle ($90^0 - \theta_{SE}$).

Topographic Correction

Correcting satellite imagery for variations in topography and/or satellite viewing perspectives (Tucker, et al., 2004), was accomplished with the Minnaert Correction with Slope algorithm (Law and Nichol, 2004). This operation is essential to correct for any topographic distortion to pixel values where the characteristic rocky outcrops of the study area impose various shades of spectral responses to similar terrain features. The tiles of 30-meter resolution SRTM elevation data applied for the topographic normalization of the respective spectral bands was sourced from the NASA Earthdata database through the Derek Watkins user's interface. The algorithm for the Minnaert Correction (with slope) is given as Eq. (4).

$$L_m = L\,.\left(\frac{cos^k\theta_s\,.\,cosS}{cos^k i}\right) \quad (4)$$

Where: L_m = radiance after correction; L = radiance before correction; θ_s = solar zenith angle; S = Slope; i = solar incident angle. k = Minnaert constant.

Core Forest Analysis

LFT 2.0v toolbox within ArcGIS workspace accomplished the identification and reclassification of the forest cover in Fig. 3 into six (6) forest classes (Fig. 4), namely: (i) Patch -small fragments of forest that are degraded by edge effects (ii) Edge – forests along the outside edge of a forest patch (iii) Perforated - forest along the inside edge of small (iv) Core [< 101.15 ha] (v) Core [101.15 ≥ 202.3 ha] – interior forest pixels that are not influenced from edge effects and (vi) Core > 202.3 ha. The descriptions of the forest classes were as provided by Parent and Hurd (2007).

Protected Area Performance Index

Core forest landscapes changes, between 2014 and 2022, for the individual FRs in the study area formed the basis for performance evaluation and the assignment of relative ranks to each of the FRs. Forest cover permanence is one of the key criteria for assessing forest health and management performance in the different FRs.

Results

The landmass of the study area (283054.15 hectares) is allotted by 46.60% (131,874 ha), 10.88% (30799.88 ha), 29.10% (82370.02 ha), 8.42% (23843.72 ha) and 5% (14166.63 ha) to Omo, Shasha, Oluwa, Ago-Owu and Ife Forest Reserves, respectively. Eq. (1) implemented within SAGA GIS 8.0 workspace generated the 3-band EVI values. EVI gives an indication of forest canopy distribution in the study area, with a range of 0.0576 – 0.3605 and 0.0063 – 0.3501, in the period 2014 -2022, respectively.

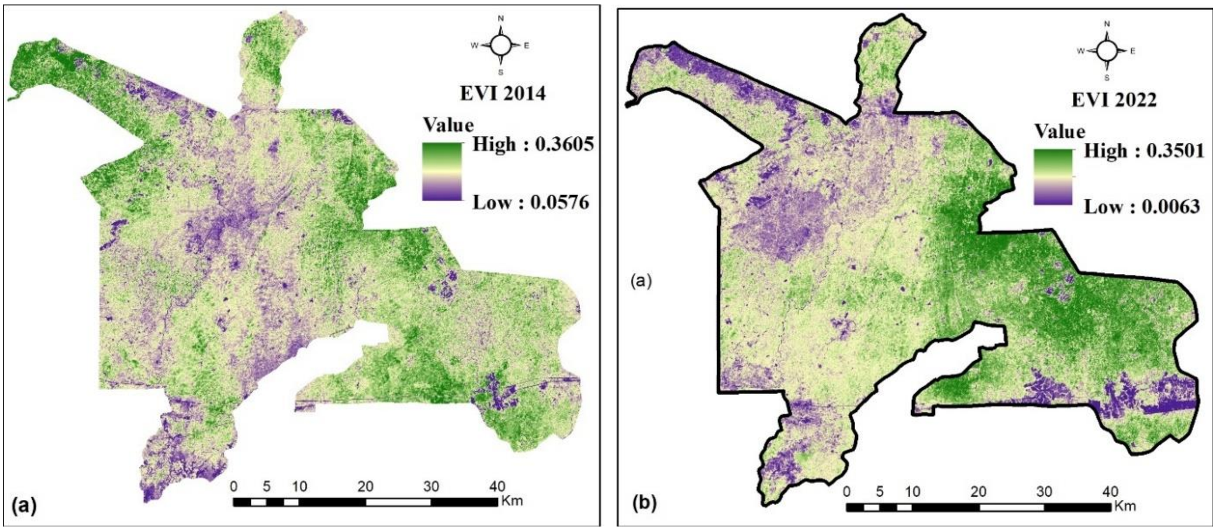

Figure 2: EVI showing the distribution of photosynthetically active vegetation in OSO forest complex for the year (a) 2014 and (b) 2022.

The radiometric corrections applied to the required Landsat bands stretched the reflectance values and yielded a better visual quality for the EVI maps.

The EVI maps had the values sliced (with minimal adjustments to the natural breaks) into three (3) classes, namely: (i) Bare soils/Farmland (ii) Orchards/Disturbed forests (iii) Dense Forest. The reclassified maps in Fig. 3 had the following breaks 0.00 – 0.202, 0.202 - 0.23, 0.23 – 0.361; and 0.00 – 0.16, 0.16 – 0.21, 0.21 - 0.351; representing the named thematic classes for the epoch periods (2014 – 2022).

The image (Fig. 3) depicts the spatial coverage of Bare soils/Farmland, Orchards/Disturbed vegetation and Dense Forest land-use/landcover (LULC) classes in OSO. In the former and later images, the bare soil/farmland and orchards/disturbed vegetation LULC categories accounted for 29.72% (46865.97 ha) and 55.71% (157688.64 ha), and 17.55% (49677.75 ha) and 53.33% (150947.2 ha), respectively.

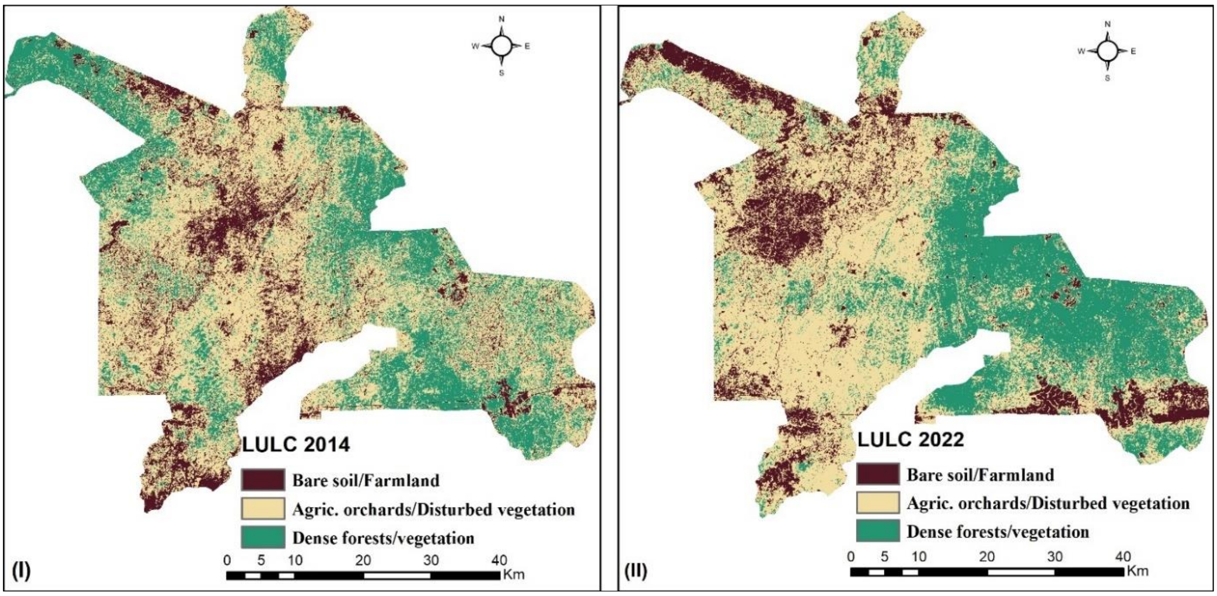

Figure 3: Land use/Land cover categories for OSO forest complex in the period 2014 – 2022.

Within the Region of Interest (RoI), areas characterized by dense forests account for 27.73% (78499.71 ha) and 29.12% (82429.38 ha) in the periods of 2014 – 2022, respectively. Thus, signaling an increase of 1.39% in the forest cover distribution over a period of eight (8) years. The forest cover category is the input data for further analyses in the study.

In Fig. 4 and Fig. 5, the named forest classes covered an area of 7430.31 ha (9.47%), 24615.54 ha (31.36%), 5599.71 ha (7.13%), 15056.82 ha (19.18%), 1329.12 ha (1.69%) and 24468.21 ha (31.17%), as well as 3569.04 ha (4.33%), 18050.67 ha (21.90%), 4351.95 ha (5.28%), 10074.06 ha (12.22%), 691.02 ha (0.84%) and 45692.64 ha (55.43%), in the former and later images, respectively. All the forest classes declined in their areal coverage and distribution, with the exception of the core forests. The core forests (> 202.3 ha) accumulated forest pixels by 24.26% over a period of eight (8) years (2014 – 2022).

The landscape fragmentation metrics showed that the forest cores (<101.2 ha), (101.2 – 202.3 ha) and (> 202.3 ha) were distributed over 12,495, 11 and 16 forest fragments in the former epoch, while the later image had 6,973, 5 and 10 fragments, respectively. In the period 2014 -2022, forest fragmentation was noticeably reduced by 44.19%. The core forests (in hectares) have a dimensional range of 0.09 – 98.46, 101.52 – 162.27 and 226.8 – 5815.53 for the former image data, and 0.09 – 97.29, 121.05 – 150.12 and 216 – 39234.15 for the later epoch data. In Fig. 4, the core forest class (> 202.3 ha) had the most remarkable improvement in Landscape Patch Index (LPI) of 7.4083 to 47.5770, in 2014 and 2022, respectively.

In Tab. 1, Oluwa FR ranks top with an observed gain of forest cover amounting to about 17.64% (14596.38 ha) in the period 2014 – 2022. Ago-Owu FR had the least rank (-37.62%) in-terms of forest cover retention in the same period.

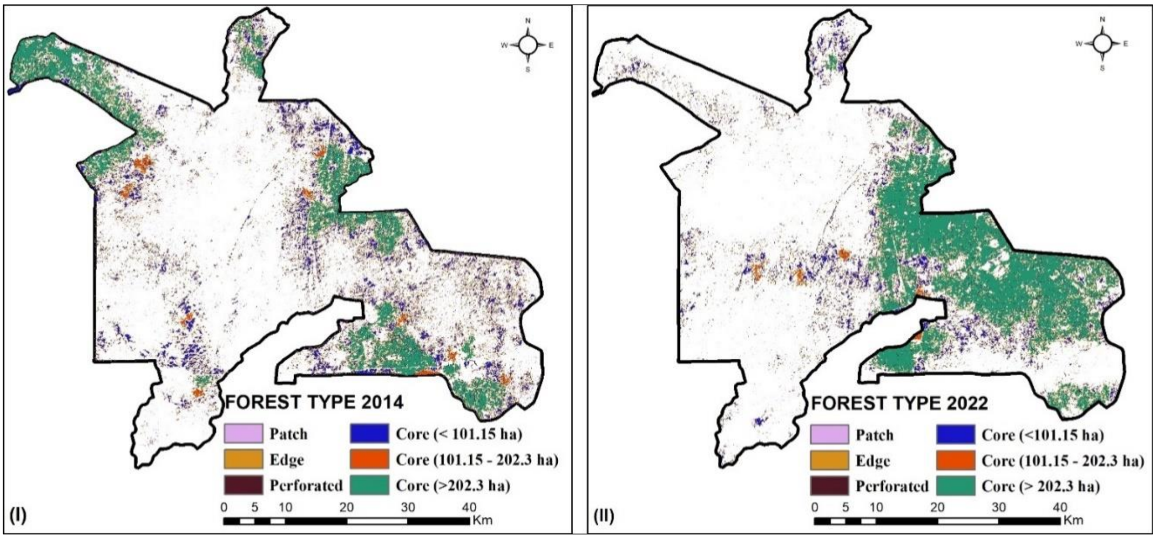

Figure 4 (I-II): Spatial distribution of forest landscape classes in the study area (2014 – 2022).

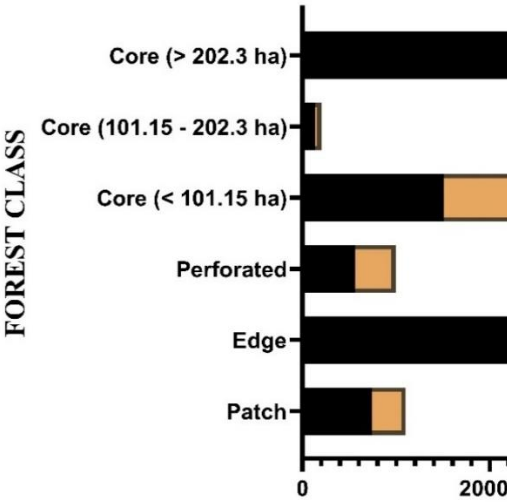

Figure 5: Areal distribution of forest cover classes in the study area between 2014 and 2022.

Discussion

The Minnaert-C (with slope) topographic correction applied on the images improved the visual quality of the image data and the final EVI outputs. EVI appears to be superior in discriminating subtle differences in areas of high vegetation density (Ahmad, et al., 2012). EVI is a good indicator of the phenology of the land cover types (Farooq, 2012). Pimple et al., (2017), in their analyses also disclosed that 30m SRTM DEM is able to improve the topographic correction of satellite imagery, and it can therefore be concluded that the SRTM DEM is suitable for removing the topographic effect from Landsat series imagery. EVI provided an indication of the forest cover extent in the analyses presented. It has not been established the threshold at which forest cover fractions in OSO and other PAs can be regarded as significant, however, in the former (2014) and later (2022) images, the 25% forest cover benchmark was exceeded by 2.73% and 4.12%, respectively. The expansion in the forest block by 1.39% highlights the possible role of forest protection and the potentials for natural and assisted forest regeneration within the study area. The forest edge (Fig. 4) set at a buffer distance equivalent to 100m, witnessed a significant reduction to about 9.46% or 65.64sq.km in the later image.

Table 1: Disaggregated Forest cover change analysis between 2014 and 2022 for the study area.

	2014		2022				
Forest Reserves	**Forest Cover (ha)**	**% Forest Cover**	**Forest Cover (ha)**	**% Forest Cover**	**Forest Gain/Loss (ha)**	**% Gain/Loss**	**Rank**
OMO	22323.15	16.83	21753.63	16.40	-569.52	-0.43	3
SHASHA	8477.55	27.37	8388	27.08	-89.55	-0.29	2
OLUWA	32890.86	39.74	47487.24	57.38	14596.38	+17.64	1
AGO-OWU	11340.18	47.26	2311.38	9.63	-9028.8	-37.62	5
IFE	3467.88	24.33	2250.45	15.79	-1217.43	-8.54	4

The reduction signifies potential improvements in the forest conditions of the research area.

Fragmentation of the forest landscapes had a reduction by 44.19%, in addition to the increase in forest cover possibly due to a more coordinated resource allocation and exploitation within the study area, particularly in Oluwa FR. However, the largest forest core in the later image (equivalent to 39,234.15 ha), although aggregated to include natural and plantation forests, may be at risk of commercial exploitation and non-forest land uses, if the study area operates the short-rotation forestry management system. This is due to the enormous emphases place on production forestry and revenue generation in most of Nigeria's forest reserves. In the words of Carnus, et al. (2006); Brockerhoff et al. (2008); Onyekwelu and Adeola, (2016), the issue of biodiversity conservation in forest plantations is highly debated.

FRs with large patch sizes are suitable for improved wildlife gyration (corridor) and flow of genetic materials. There is no doubt that large, intact patches are vitally important for the maintenance of some key ecological processes (Watson, 2018; Lindernmayer, 2018) and biodiversity conservation (Gibson, 2011; Lindernmayer, 2018). Among the five (5) FRs, the gains in forest cover for Oluwa FR in eight (8) years signals an improvement in management investments into the administration of the FR. Therefore, Oluwa FR ranked better than the other FRs in terms of recorded gains in the forest cover extent. The loss of about 37.62% of the forest cover in Ago-Owu FR ranked it least in terms of the management performance index. This could be as a result of other competing non-forest land uses in Ago-Owu FR between 2014-2022.

Several past studies have treated the forest complex as a single unit of management, despite obvious differences in the regimes of forest management and administration across the three (3) collaborating state governments (Ogun, Osun and Ondo). This paper explored the potentials of Landsat data for short-term forest cover assessment, while also decomposing forest losses in the OSO forest complex on the basis of its organic parts. Many authors [Adedeji and Adeofun, 2014; Fasona, et al., 2018], only attempted an overview analysis of the forest extent in the study area neglecting the perception of compartmentalization and different management regimes that could impact forest conservation in the study area. This level of analyses is too conservative and often fail to account for the skewness in forest losses and gains. In terms of forest-based management efficiency, evidence available ranks Ondo state (Oluwa FR) ahead of other FRs, while more conservation supports may be required by Osun state to address the challenges of massive deforestation noticeable in Ago-Owu and Ife FRs. Adedeji and Adeofun (2014) and Fasona, et al., (2018) reported significant losses of natural forest cover in the study area between 1986 – 2002; and 1984 – 2015, respectively. The marginal increase in forest cover reported herewith could be due to the short temporal scale (2014 -2022) of the image data deployed and/or improvements in regimes of forest management in Oluwa FR that absorbed the negative forest changes in other FRs in the study area.

Our research has established that within a period of eight years (2014-2022), forest cover dynamics can be significant enough to be detected by Landsat imageries a with medium spatial image resolution (30m). Monitoring information is used to characterize the status of the protected area at different points in time for the purpose of assessing the state and drawing inferences about changes in state over time (Yoccoz and Boulinier, 2001; Rao et al., 2009). The Food and Agricultural Organization (FAO) Global Forest Resources Assessment (FRA) is a demi-decadal document reporting on the state of forest cover extent across the globe. This helps to track progress in different countries towards sustainable forest management (SFM). Our research, therefore, has the advantage to support the assessment of management efficiency in FRs against available social, economic and environmental metrics of the SFM goals. In our paper, we supplied relevant information to facilitate knowledge management and the early adoption of measures to address the challenges of biodiversity conservation in the study area.

Conclusions

Landscape productivity in terms of biological diversity is at the core of operational objectives for PA management in Nigeria. Limited technical expertise on data mining is impeding the possibilities for evaluating the efficiency of management operations in territories dedicated to biodiversity conservation in Nigeria. To maximize the potentials of protected areas, managers and policymakers need information on the strengths and weaknesses in their management and on the threats and stresses that they face (Hockings, 2003). Unregulated commercial exploitation of forest resources is creating unexpected changes within protected areas.

This and other factors are widening the gap for effective performance analysis of forest managers in our FRs. The observations in Ago-Owu FR calls for the assessment of the current operational status of the FR. The techniques adopted in our research offer a practical step towards generating useful data on forest cover variation and distribution, while also creating a body of information to guide biodiversity managers. Ground-truthing is recommended in the study area to establish the nature of landscape interventions that led to some improvements in the core forests of Oluwa FR.

Capacity for continuous forest cover monitoring is ideal to be developed for staff in the PAs of Nigeria. Within protected area management, capacity-building initiatives (should) target individual managers and aim to promote professional development through building on existing knowledge and experience and providing new concepts and tools to address contemporary challenges (Carlos, et al., 2013).

Acknowledgements

The authors are thankful to Professor I.O. Ajewole and Professor S.O. Jimoh of the University of Ibadan for the supports and guidance provided over the course of the research and manuscript preparation.

References

A.W. Don Carlos, T.L. Teel, M.J. Manfredo, and V.B. Mathur (2013). Building Capacity to Enhance Protected Area Management Effectiveness: A Current Needs Assessment for the Asian Context. The George Wright Forum, 30(2), pp. 154–162. www.georgewright.org/302doncarlos.pdf.

Achard F, Eva H, Stibig HJ, Mayaux P, Gallego J, Richards T, Malingreau JP (2002). Determination of deforestation rates of the world’s humid tropical forests. Science 297(5583):999-1002. https://doi.org/10.1126/science.1070656.

Adedeji, OH and Adeofun, C.O. (2014). Spatial Pattern of Land Cover Change using Remotely Sensed Imagery and GIS: A Case Study of Omo-Shasha-Oluwa Forest Reserve, SW Nigeria (1986-2002), Journal of Geographic Information System, 6:375-385.

Adepoju, KA, Salami, AT (2017). Geospatial Assessment of Forest Fragmentation and its Implications for Ecological Processes in Tropical Forests. Journal of Landscape Ecology, 10 (2): do:10.1515/jlecol-2017-0002.

Ahmad, Farooq (2012). Detection of Change in Vegetation Cover using Multi-Spectral and Multi-Temporal Information for District Sargodha, Pakistan. Sociedade & Natureza, 24(3): 557-571. Available in: http://www.redalyc.org/articulo.oa?id=321327330013.

Akindele SO (2012). Status of Forest Cover in Nigeria. In: Onyekwelu, JC, Agbeja BO, AdeKunle VAJ, Lameed JA, Adesoye PO, Omole AO (eds) Research for Development in Forestry, Forest Products and Natural Resources Management. Proceedings of the third National Conference of the Forest and Forest Products Society. 3rd – 6th April, 2012.

Ali, S.; Wang, D.; Hussain, T.; Lu, X.; Nurunnabi, M. (2021). Forest Resource Management: An Empirical Study in Northern Pakistan. Sustainability, 13, 8752. https://doi.org/10.3390/su13168752.

Ayoade Matthew Adetoye, Samuel Ayodele Adewuyi, Dare Akerele (2018). Determinants of forest land use decisions among rural farm households in south western Nigeria. Agricultura Tropica Et Subtropica, 51(2), 83–91. DOI: 10.2478/ats 2018 0009.

Brockerhoff EG, Jactel H, Parrotta JA, Quine CP, Sayer J. 2008. Plantation forests and biodiversity: oxymoron or opportunity? Biodivers Conserv., 17:925–951.

Carnus JM, Parrotta J, Brockerhoff EG, Arbez M, Jactel H, Kremer A, Lamb D, O’Hara K, Walters B. 2006. Planted forests and biodiversity. J For., 104:65–77.

Coad, L. et al. (2015). Measuring impact of protected area management interventions: current and future use of the Global Database of Protected Area Management Effectiveness. Phil. Trans. R. Soc. B 370: 20140281. http://dx.doi.org/10.1098/rstb.2014.0281.

USGS EarthExplorer, (2022). Available on: https://earthexplorer.usgs.gov.

Fasona MI, Soneye AS., Gregory AJ., Egonmwan RI. (2018). Geo-spatial evaluation of the landuse and landscape metrics of omo-shasha-oluwa forest reserves: the wildlife conservation challenge. LJGIS, 5(1): 5 – 23.

Fifonsi Ayélé DANGBO, Oliver GARDI, Kossi ADJONOU, Atsu K. Dogbeda HLOVOR, Juergen BLASER and Kouami KOKOU (2020). An analytical assessment of forest cover changes over the last 30 Years in the semi-deciduous forest zone of Togo. Journal of Horticulture and Forestry, 12(2), pp. 70-83, DOI: 10.5897/JHF2020.0631.

Foley J, DeFries R, Asner G, Barford C, Bonan G, Carpenter S, Chapin F, Coe M, Daily G, Gibbs H (2005). Global consequences of land use. Science, 309(5734):570-574. https://doi.org/10.1126/science.1111772

Geldmann J, Barnes M, Coad L, Craigie ID, Hockings M, Burgess ND. (2013). Effectiveness of terrestrial protected areas in reducing habitat loss and population declines. Biol. Conserv., 161, 230–238. doi:10.1016/j.biocon.2013.02.018.

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002): Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote sensing of environment, 83(1-2), 195-213, 10.1016/S0034-4257(02)00096-2. http://www.sciencedirect.com/science/article/pii/S0034425702000962.

IPCC (2013): In Climate Change: The Physical Science Basis (Eds Stocker, T. F. et al.), Cambridge University Press, Cambridge, United Kingdom.

Isichei, A.O. 1995. Omo Biosphere Reserve, Current Status, Utilization of Biological Resources and Sustainable Management (Nigeria). Working Papers of the South-South Cooperation Programme on Environmentally Sound Socio-Economic Development in the Humid Tropics. UNESCO, Paris.

Isidore N. Akpan-Ebe (2017). Reforestation in Nigeria: History, current practice and future perspectives. REFORESTA, 3:105-115. DOI: https://dx.doi.org/10.21750/R EFOR.3.09.33.

JEM Watson, et al., (2018). The exceptional value of intact forest ecosystems. Nat Ecol Evol, 2, 599–610.

Jonathan C. Onyekwelu & Adeola A. Olabiwonnu (2016) Can forest plantations harbour biodiversity similar to natural forest ecosystems over time?, International Journal of Biodiversity Science, Ecosystem Services & Management, 12:1-2, 108-115, DOI: 10.1080/21513732.2016.1162199.

L Gibson, et al., (2011). Primary forests are irreplaceable for sustaining tropical biodiversity. Nature, 478, 378–381.

Landsat 8 (L8) Data Users Handbook (2016) Department of the Interior U.S. Geological Survey. https://landsat.usgs.gov/sites/default/files/documents/Landsat8DataUsersHandbook.pdf

Law, K. H., and J. Nichol. 2004. "Topographic Correction for Differential Illumination Effects on IKONOS Satellite Imagery." International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences, 35: 641–646.

Lindernmayer, David (2018). Small patches make critical contributions to biodiversity conservation. PNAS,116(3):717-719, DOI.org/10.1073/pnas.182016911.

Marc Hockings (2003). Systems for Assessing the Effectiveness of Management in Protected Areas. BioScience, 53(9):823-832, DOI.org/10.1641/0006-3568(2003)053[0823:SFATEO]2.0.CO;2.

Mbaya, L.A. and Hashidu, M.S. (2017). Status of forest reserves (savanna woodland) biodiversity and rural livelihoods in Gombe state. International Journal of Development and Sustainability, Vol. 6 No. 12, pp. 2173-2192.

McGarigal, K.; Marks, B. FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure; General Technical Report; PNW-GTR-351; USDA Forest Service, Pacific Northwest Research Station: Portland, OR, USA, 1995.

Nwabueze I. Igu, Chukwudi P. Nzoiwu, Evaristus U. Anyaeze (2017). Biodiversity and Carbon Potentials of a Nigerian Forest Reserve: Insights from the Niger Basin. Journal of Environmental Protection, 8(8), 914-922. DOI: 10.4236/jep.2017.88057.

Ogunsesan D., Oyedepo J., Oates J., Adeofun C. O., Ikemeh R. and Bergl R (2011). GIS-Supported Survey of Low-Land Rain Forests in South-Western Nigeria. In: O. Martins, E. A. Meshida, T. A. Arowolo, O. A. Idowu and G. O. Oluwasanya (Eds.), Proceedings of the Environmental Management Conference, September 12 -15, 2011, Federal University of Agriculture, Abeokuta, Nigeria. Vol. 1: 141 – 154.

Olmos, Fabio and Turshak, Longtong G. (2009). A Survey of Birds in Omo Forest Reserve. South-western Nigeria. Bulletin of the African Bird Club, 16(2):184-196. https://doi.org/10.5962/p.309880.

Orimoogunje, OOI and Ekanade, O (2010). Ecological implications of land use dynamics: the case of Oluwa forest reserve in Southwestern Nigeria. Trop. Agric., 87(2): 49 – 57.

Parent, J., Hurd, J (2007). An Improved Method for Classifying Forest Fragmentation - The presentation provides an overview of the Landscape Fragmentation Tool v2.0. The presentation discusses the input data required for the tool, the definitions of the fragmentation classes, and the output results generated by the tool. NEARC 2008. https://clear.uconn.edu/publications/research/presentations/parent_nearc2008_ff.ppt.

Pearce, D.; Barbier, E.; Markandya (2013). A. Sustainable Development: Economics and Environment in the Third World; Routledge: London, UK, 2013.

PNI (2011). Omo-Shasha-Oluwa Forest Elephant Initiative, Project Progress Report for the International Elephant Foundation.

S. Kaliraj, S. Muthu Meenakshi and V. K. Malar (2012). Application of Remote Sensing in Detection of Forest Cover Changes Using Geo-Statistical Change Detection Matrices – A Case Study of Devanampatti Reserve Forest, Tamilnadu, India. Nature Environment and Pollution Technology, 11(2). pp. 261-269.

Tucker, CJ., Grant, DM., and Dykstra, JD (2004). NASA's Global Orthorectified Landsat Data Set. Photogrammetric Engineering & Remote Sensing, Vol. 70, No. 3, March 2004, pp. 313–322. https://www.asprs.org/wp-content/uploads/pers/2004journal/march/2004_mar_313-322.pdf

Uday Pimple, Asamaporn Sitthi, Dario Simonetti, Sukan Pungkul, Kumron Leadprathom and Amnat Chidthaisong (2017). Topographic Correction of Landsat TM-5 and Landsat OLI-8 Imagery to Improve the Performance of Forest Classification in the Mountainous Terrain of Northeast Thailand. Sustainability, 9(258), 1-26,; doi:10.3390/su9020258.

USGS EarthExplorer (2022). Available on: https://earthexplorer.usgs.gov (08 March 2022).

Xiao, X. M., Zhang, Q.; Braswell, B. (2004). Modeling gross primary production of temperate deciduous broadleaf forest using satellite images and climate data. Remote Sensing of Environment, 91, pp256-270.

Xie, Y. (2008). Remote sensing imagery in vegetation mapping: A review. Journal of Plant Ecology, 1(1):9-23. doi: 10.1093/jpe/rtm005.

Yoccoz NG, Boulinier JDNaT (2001) Monitoring of biological diversity in space and time. TRENDS in Ecology & Evolution 16: 446-453.

UNEP-WCMC and IUCN (2022), Protected Planet: The World Database on Protected Areas (WDPA) and World Database on Other Effective Area-based Conservation Measures (WD-OECM) [Online], December 2022, Cambridge, UK: UNEP-WCMC and IUCN. Available at: www.protectedplanet.net.