Turkish Journal of Forestry | Türkiye Ormancılık Dergisi
2025, 26(2): 129-136 | Research article (Araştırma makalesi)

Spatio-temporal analysis of vegetation dynamics in derived savannah, Ogun State Nigeria from 2002 to 2023

Oluseun Bamidele Banjo[a,*], Daniel Abiodun Akintunde-Alo[b], Peter Oluwagbemiga Ige[b]

Abstract: Vegetation covers is a significant component of biogeochemical cycles. Derived savannah of Ogun State has been affected by vegetation loss and climate change in recent times. There is lack of information on the rate/extent of vegetation loss in the last two decades. This study assessed changes in vegetation cover in derived savanna ecosystem of Ogun State from 2002 to 2023. Landsat images were downloaded from the repository of the United States Geological Survey (USGS). Composites of red, green, blue and near-infra-red spectral bands of study period were obtained and classified using Maximum Likelihood (ML) algorithm into Land Use Land Cover (LULC) categories as follows: bare soil; built-up areas; forest; and grassland. Change in area extent and rate of change of area of classified images were determined for the study period. Confusion matrix of classified images were generated and compared with Google Earth satellite image with accuracy assessed using kappa coefficients. Overall accuracy of the classified images ranged between 79% and 88% with kappa coefficients of between 0.71 and 0.83. Results showed that built-up area increased from 10.3% cover in 2002 to 35.9% cover in 2023. However, there was a significant decline in forest cover from 31.5% to 13.7% for the same period. Significant increase at 4.2 km^2 per year in area extent was observed for built-up LULC class while a decline of 2.0 km^2 per year in forest cover was recorded for Forest LULC category from 2002 to 2023. The study revealed that urbanization increased as extent of initial forest cover were degraded and replaced with physical infrastructure. Therefore, there is urgent need for policies that promote conservation and sustainable management of forests and grasslands, as well as measures to promote green infrastructure and urban greening initiatives to address the decline in vegetation cover in the derived savanna ecosystem of Ogun State.
Keywords: Land use land cover (LULC)**,** Derived savannah ecosystem, Vegetation loss, Maximum likelihood classification

Bitki örtüsü dinamiklerinin 2002-2023 yılları arasında Ogun Eyaleti Nijerya'da seçilen savanada zamansal-mekansal analizi

Öz: Bitki örtüsü biyojeokimyasal döngülerin önemli bir bileşenidir. Ogun Eyaleti'nin savanları, son zamanlarda bitki örtüsü kaybından ve iklim değişikliğinden etkilenmiştir. Son yirmi yılda bitki örtüsü kaybının oranı/derecesi hakkında bilgi eksikliği bulunmaktadır. Bu çalışma, 2002'den 2023'e kadar Ogun Eyaleti'nin savan ekosistemindeki bitki örtüsündeki değişiklikleri değerlendirmiştir. Landsat görüntüleri Amerika Birleşik Devletleri Jeolojik Araştırma Kurumu'nun (USGS) web sitesinden indirilmiştir. Çalışma dönemine ait kırmızı, yeşil, mavi ve kızıl ötesi spektral bantların kompozitleri elde edilmiş ve Maksimum Olasılık (ML) algoritması kullanılarak Arazi Kullanımı/Arazi Örtüsü (LULC) kategorilerine göre şu şekilde sınıflandırılmıştır: çıplak toprak, yerleşim alanları, orman ve otlak. Çalışma dönemi için sınıflandırılmış görüntülerin alan büyüklüğündeki değişim ve alan değişim oranları belirlenmiştir. Sınıflandırılmış görüntülerin hata matrisi oluşturulmuş ve kappa katsayıları kullanılarak değerlendirilen doğrulukla Google Earth uydu görüntüsüyle karşılaştırılmıştır. Sınıflandırılan görüntülerin genel doğruluğu, 0,71 ile 0,83 arasında, kappa katsayıları ise %79 ile %88 arasında değişmektedir. Sonuçlar, yerleşim alanının 2002'deki %10,3 kapalılıktan 2023'te %35,9'a yükseldiğini göstermiştir. Ancak aynı dönemde orman örtüsünde %31,5'ten %13,7'ye önemli bir düşüş göze çarpmaktadır. 2002'den 2023'e kadar, yerleşim LULC sınıfı için alan büyüklüğünde yılda 4,2 km^2'lik önemli bir artış gözlemlenirken, orman LULC kategorisi için yılda 2,0 km^2'lik bir azalma kaydedilmiştir. Çalışma, başlangıçtaki orman örtüsü azaldıkça ve yerini fiziksel altyapıya bıraktıkça kentleşmenin arttığını ortaya çıkarmıştır. Bu nedenle, ormanların ve otlakların korunmasını ve sürdürülebilir yönetimini destekleyen politikaların yanı sıra, Ogun Eyaleti'nin savan ekosistemindeki bitki örtüsündeki azalmayı ele almak için yeşil altyapıyı ve kentsel yeşillendirme girişimlerini teşvik edecek önlemlerin alınmasına acil ihtiyaç bulunmaktadır.
Anahtar kelimeler: Arazi kullanımı/arazi örtüsü (LULC), Savana ekosistemi, Bitki örtüsü kaybı, Maksimum olasılık sınıflandırması

1. Introduction

Nigeria's total land area is covered by forests to the tune of about 12.18%, supporting a range of ecosystem services and livelihood opportunities (Ogundele et al., 2016). From 1976 to 1990, the country experienced an annual deforestation rate of 40,000 hectares across both protected and unprotected forest areas (Roby, 1991). Specifically, during the periods of 1981 to 1985 and 1986 to 1990, deforestation rates in Nigeria's savannah regions were

[a] Department of Forestry, Wildlife and Fisheries, Olabisi Onabanjo University, Ayetoro Campus, Ogun State, Nigeria
[b] Department of Social and Environmental Forestry, University of Ibadan, Oyo State, Nigeria
[*] **Corresponding author** (İletişim yazarı): oluseun.banjo@oouagoiwoye.edu.ng
✓ **Received** (Geliş tarihi): 25.04.2024, **Accepted** (Kabul tarihi): 08.06.2025

Citation (Atıf)**:** Banjo, O.B., Akintunde-Alo, D.A., Ige, P.O., 2025. Spatio-temporal analysis of vegetation dynamics in derived savannah, Ogun State Nigeria from 2002 to 2023. Turkish Journal of Forestry, 26(2): 129-136.
DOI: 10.18182/tjf.1473757

recorded at 3.48% and 3.57%, respectively (FAO, 2020) due to increased anthropogenic activities such as clearing of forests for arable farming (Okorondu et al., 2022) and infrastructural development that leads to irreversible loss of biodiversity (Ola et al., 2020). Furthermore, between 2000 and 2005, Nigeria saw a dramatic loss of 55.7% of its primary forests, with the annual rate of forest loss accelerating by 31.2%, reaching 3.12% (Odekunle et al., 2019). Over the two decades from 1990 to 2010, the forest cover in Nigeria significantly reduced, falling from 17,234 hectares to 9,041 hectares (FAO, 2020; FORMECU, 1996).

Nigeria's derived savannah ecosystem holds critical ecological significance and the area's vegetation provides essential ecosystem services (Yang et al., 2021), including carbon sequestration, soil stability, and water regulation, which are vital for both local communities and the larger environment (Adetola and Solanke, 2013). It serves as a habitat for various plant and animal species that have adapted to the specific conditions of this transitional zone (Afolayan et al., 2021). Moreover, the derived savanna ecosystem plays a pivotal role in the intricate balance between natural processes and human activities. Traditional land use practices, such as agriculture, grazing, and resource extraction, intersect with conservation efforts and development aspirations within this transitional derived savannah ecosystem (Ying, 2019). The exploration of vegetation dynamics in derived savannah ecosystem holds immense potential for shedding light on the impacts of land use practices, climate variability, and conservation initiatives (Gomez-Brandon et al., 2018).

In the derived savanna, urban expansion, land conversion and infrastructural development are precipitated by population increase that result in clearing of remnant forest patches in the rural and the peri-urban for road construction, residential, commercial and industrial purposes, thus reducing biodiversity and disrupting ecological balance (Seifollahi-Aghmiuni et al., 2022). There is substantial increase in energy demand to meet the need of the emerging cities from encroachment into forested land, forcing unsustainable harvest of trees for firewood and charcoal (affordable and accessible primary energy sources for cooking and heating) that contribute to forest degradation (Hido et al., 2023). Human-induced activity such as overgrazing by cattle and other livestock are further exacerbated by climate change from evidence of reduced rainfall and prolonged dry seasons leading to soil compaction and slow vegetation regeneration, and eventual forest degradation (Cao et al., 2023; Cao et al., 2013; Quaranta et al., 2020).

The application of time series remote sensing datasets alongside Geographic Information Systems (GIS) is becoming more prevalent in analyzing the spatial and temporal trends of vegetation dynamics from regional to global extents (Cao et al., 2018; Son et al., 2012). Remote sensing offers a reliable, consistent, and cost-efficient means of gathering data across vast areas for the purpose of monitoring changes in vegetation (Hou et al., 2013). Furthermore, remote sensing techniques are indispensable in examining the spatial and temporal fluctuations of vegetation and identifying the root causes of droughts, especially when on-the-ground drought data is scarce or inconsistent (Naumann et al., 2014; Rojas et al., 2011).

Temporal remote sensing data has been widely utilized to generate vegetation indices that identify periods of vegetative stress (Skakum et al., 2016). The Normalized Difference Vegetation Index (NDVI) is particularly prevalent across numerous applications, serving to examine and track the spatial and temporal distribution of vegetation at both regional and continental levels (Son et al., 2012). The scarcity and inadequacy of data on Land Use Land Cover (LULC) classes within ecosystems have raised significant concerns regarding how vegetation responds to anthropogenic activities and climate change (Afuye et al., 2021). However, these concerns have been mainly restricted to analysis of climate and time series NDVI data (Zhe and Zhang, 2021; Ying, 2019).

Following the lack of data on the rate/extent of vegetation loss in the last three decades in the derived savannah ecosystem of Ogun State, there is the need to provide information on deforestation and forest degradation in the derived savannah ecosystem of Ogun State to support government's program in providing updated information about the spatial and temporal patterns of LULC categories. Therefore, this study sets out to determine the LULC features, extent and change pattern of derived savanna ecosystem of Ogun State from 2002 to 2023 with the view to providing interventions to control land degradation and restore degraded ecosystem.

2. Materials and method

2.1. Study area

The study area (Figure 1) encompasses derived savanna ecosystem situated within Ogun State, Nigeria. This unique ecological zone is characterized by a distinctive blend of open grasslands and scattered trees, representing an eco-zone between grassland and forest ecosystems. Geographically, the study area covers approximately 938251.28 ha, located on the following coordinates 6.3°N to 7.8°N latitude and 2.5°E to 4.1°E longitude, encapsulating a diverse range of microclimates and landforms. The region experiences a tropical climate with pronounced wet and dry seasons, profoundly influencing vegetation dynamics and land use practices.

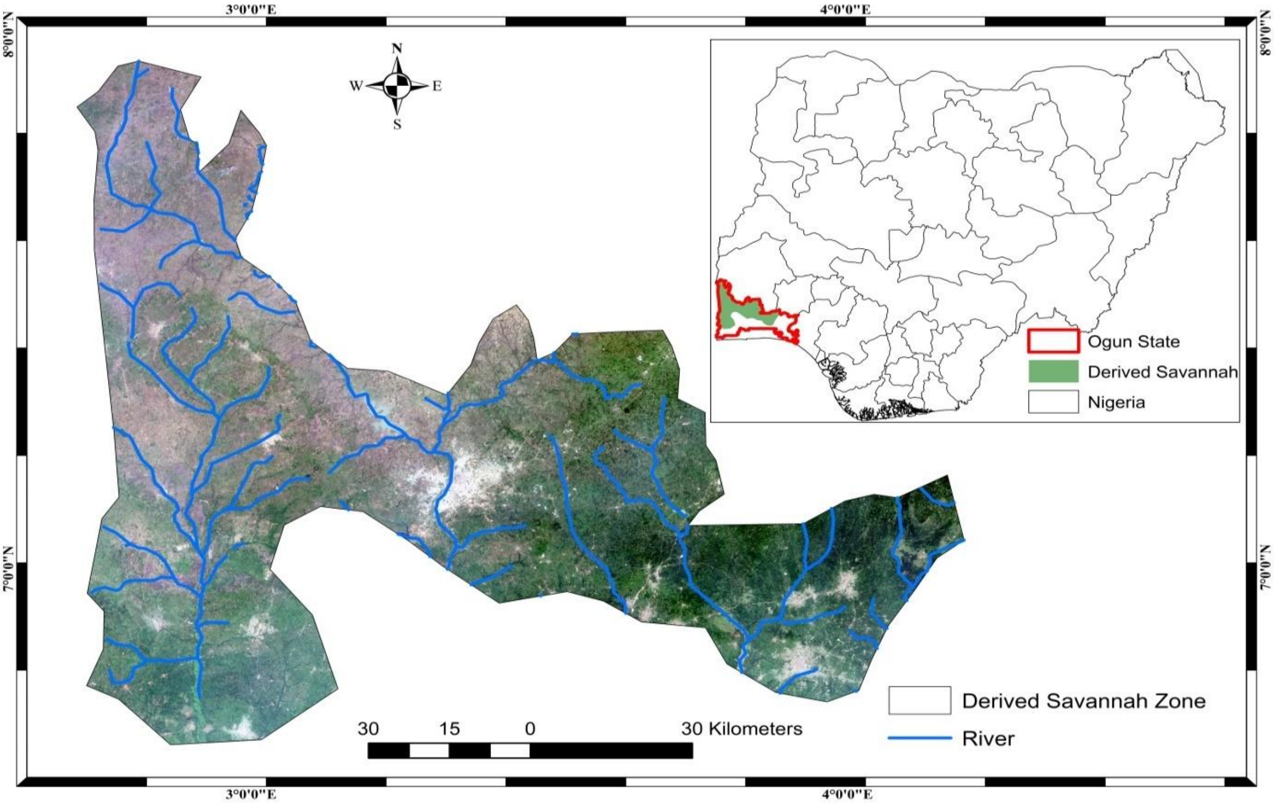

Figure 1. Map of derived savannah zone, Ogun State (Inset: Nigeria, Ogun State shown in red boundary)

2.2. Data collection and image processing

Satellite image data of the study area were obtained from United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov). Cloud coverage of the study area was usually minimal during the dry season periods between December and February. An image of the study area was available in December 2002 on Landsat 7 Enhanced Thematic Mapper Plus (ETM+). Scan line corrector failure rendered the image of the study area un-usable for year 2012. Therefore, an imagery of January 2013 was used instead of the 2012 image. Imagery for the year 2023 was only available in image archive on Landsat 8 Operational Land Imager (OLI) sensor which became operational in February 2013. Image data with more than 5% cloud cover were not used for the assessment. Therefore, cloud-free Landsat 7 ETM+ imageries (December 2002 and January 2013) and Landsat 8 OLI (January 2023) were downloaded and used for the LULC assessment. Four spectral bands that included Red, Green, Blue and Near Infra-Red as presented in Table 1 were combined to provide RGB composite of the respective epoch in order to enhance the visual classification of the land use and land cover features. Sample combination of bands is presented in Figure 2. Healthy vegetation is represented by deep red hue, while lighter red depicts sparsely vegetated areas, and densely populated urban areas represented by light blue.

Table 1. Spectral description of satellite imagery

Band name	Landsat 7 TEM+	Landsat 8 OLI	Resolution (m)
Blue	B1(0.45-0.52)	B2(0.45-0.51)	30
Green	B2(0.52-0.60)	B3(0.53-0.59)	30
Red	B3(0.63-0.69)	B4(0.64-0.67)	30
Near Infra-Red	B4(0.77-0.90)	B5(0.85-0.88)	30

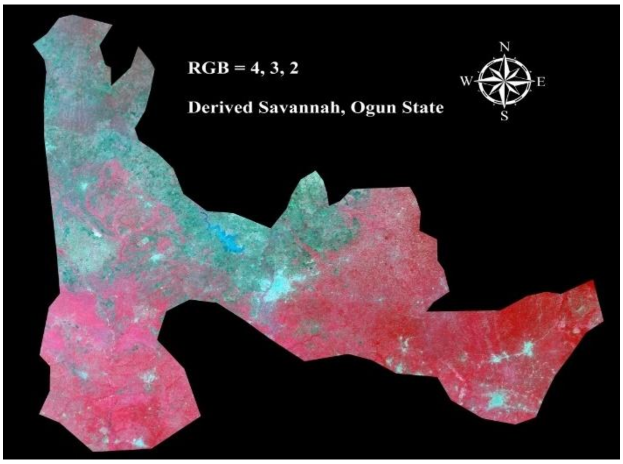

Figure 2. Sample combination of spectral bands

Following the reliability of Maximum Likelihood (ML) statistical procedures in allocating classes for image classification over other techniques, it has become very useful in LULC categorization (Mather and Tso, 2010). Maximum Likelihood (ML) supervised classification algorithm (Rawat and Kumar, 2015) was used to categorize images into the following LULC classes: bare soil, built-up areas, forest and grassland (Anderson, 1976; Srivastava et al., 2012). Training sample data were acquired from Google Earth (http://earth.google.com) to conduct ground-truthing exercise and validate the accuracy of the classified images. The workflow procedure used for the study is shown in Figure 3.

2.3. Data analysis

Change in area extent over the years and average rate of change in area of each LULC class were determined as expressed in Equations 1 and 2 respectively (Li et al., 2016; Xu et al., 2011). Data were processed and analyzed using ArcGIS 10.3 and Microsoft Excel software. Confusion matrix was generated to ascertain the accuracy of the classified images. Accuracy assessment of the classified images were measured by kappa coefficient which relates the level of agreement between pixel value of classified image from ML classification algorithm and the ground truth value from Google Earth image. Kappa coefficient is expressed by Equation 3 (Twumasi et al., 2019) whereby Kappa value 1 indicates accurate map result, while value 0 represents inaccurate map output.

$$\text{Change in Area extent (\%)} = \frac{\text{Area of LULC class}}{\text{Total Area of all LULC classes}} \text{ X } 100 \quad (1)$$

$$\text{Average Rate of Change } (\Delta/\text{year}) = \frac{\text{Change in Area of LULC class}}{\text{Number of Years}} \quad (2)$$

$$\text{Kappa coefficient, K} = \frac{\gamma a - \beta}{\gamma \hat{} 2 - \beta} \quad (3)$$

where: γ – Total number of points
a – sum of correctly classified points
β – sum of the products of classes between the ground truth points and the classified points

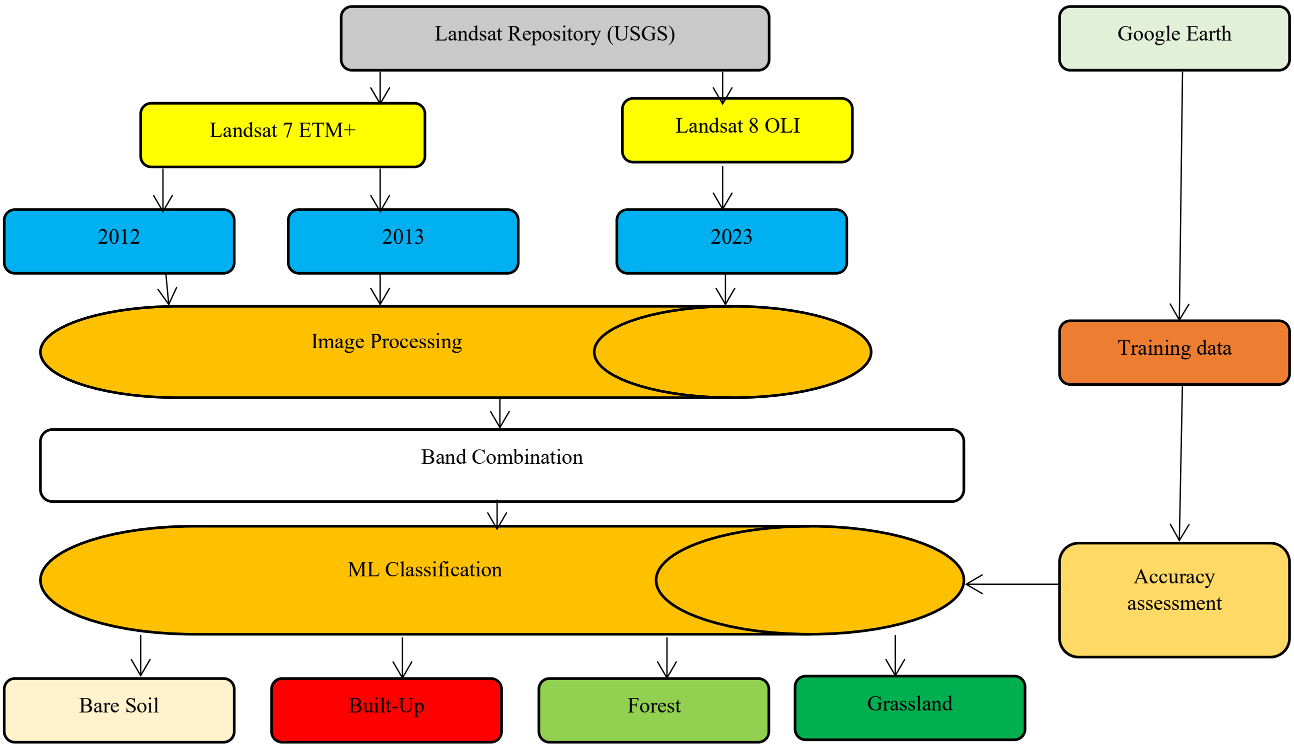

Figure 3. Diagram of workflow for the study

3. Results and discussion

Accuracy assessment results, showing the producer, user, overall accuracy levels and kappa coefficients of the classified images are presented in Table 2. The overall accuracy of the classified images ranged between 79% and 88% while kappa coefficients was between 0.7129 and 0.8326. These values show substantial level of agreement between the classified image (ML classification) and the ground truth reference data from Google Earth. The classified images appeared to have relatively high level of accuracy, comparable to findings of Dash et al. 2023.

The LULC classes included bare soil, built-up (urban areas), forest, and grassland. Figure 4 shows the fluctuations in areal extent of LULC classes in the derived savannah region of Ogun State from 2002 to 2023. Significant fluctuation was observed in extent of “built-up” LULC class when compared to other classes. However, there were no significant fluctuations among the LULC classes that included the bare soil, forest and grassland. The spike observed in “built-up” LULC class between 2002 and 2013 could be attributed to substantial urban sprawl during that period as reported in research carried out by Olayiwola et al. 2018. Sharp decline in built-up area between 2013 and 2023 was probably due to strict enforcement of urban planning rules to regulate uncontrolled land clearing for infrastructural development (Odekunle et al., 2019).

Built-up area covers almost 60% of the study area by 2023. This is an indication of increase in urbanization which significantly contributes to adverse environmental impacts such as increased air pollution, water runoff, and heat island effects (Ohwo and Abotutu, 2015). Table 3 shows the land use/cover classes and their respective areas (in square kilometers and percentages) for three different years: 2002, 2013, and 2023. As at 2002, bare soil was (31.9%), followed by forest (31.5%), grassland (26.3%), and built-up (10.3%) of the study area. By 2013, the area covered by bare soil decreased significantly to 15.5%, while built-up areas increased significantly to 57.0%. The area covered by forest also decreased to 16.2%, while the area covered by grassland decreased to 11.3%. The sizes of LULC features were as follows by 2023: bare soil (29.8%); built-up areas 35.9%; forest (13.7%); grassland (20.6%). Significant increase in built-up area was observed between 2002 and 2023. However, significant decline in green space of forest cover and grassland was observed between 2002 and 2023. These observations appeared to support the assertion by Areola and Ikporukpo, 2020 about green spaces being cleared for the construction of urban infrastructure.

Table 2. Accuracy levels and kappa coefficients of the LULC images

Year	LULC Class	PA (%)	UA (%)	OA (%)	Kappa
2002	Bare Soil	68.00	94.44	79.00	0.7144
	Built-Up	66.67	92.31		
	Forest	82.76	75.00		
	Grassland	92.86	70.27		
2013	Bare Soil	84.62	84.62	88.00	0.8326
	Built-Up	94.60	87.50		
	Forest	82.14	92.00		
	Grassland	86.36	86.36		
2023	Bare Soil	82.76	82.76	79.00	0.7129
	Built-Up	78.13	78.13		
	Forest	67.86	86.36		
	Grassland	99.00	68.75		

PA – Producer’s Accuracy; UA – User’s Accuracy; OA – Overall Accuracy

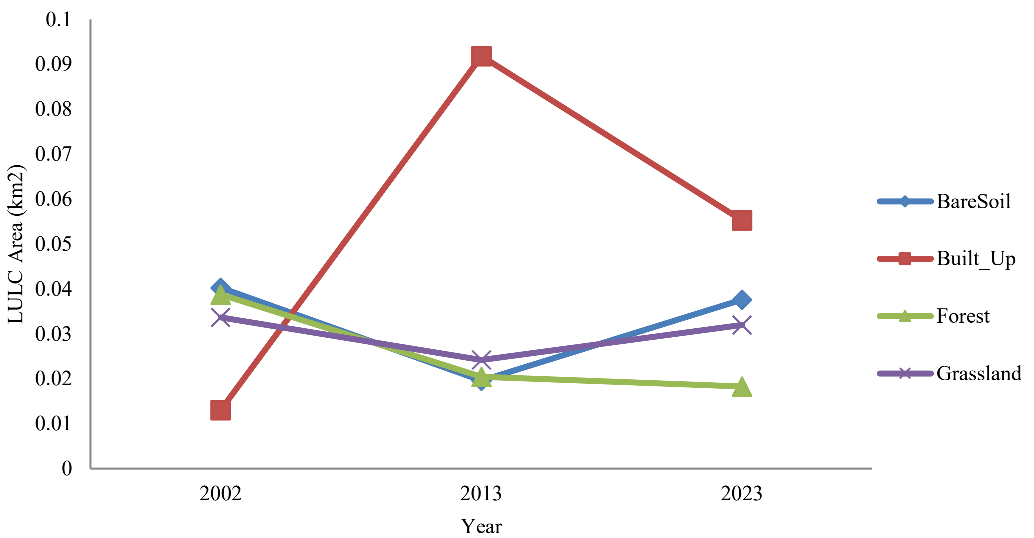

Figure 4. Pattern of changes in LULC features from 2002 to 2023

Table 4 represents the rate of change in sizes of LULC classes. Forest cover class from 2002 to 2023 decreased at the rate of 2.0 km^2/year resulting into an annual 0,02 km^2 loss of forest cover. However, substantial increase in built-up area at an annual rate of 4.2 km^2, indicating 0.04 km^2 of land space yearly converted for infrastructural development, was observed between 2002 and 2023. In between the study periods from 2002 and 2013, a decrease in annual rate of change in area of bare soil (-0.021 km^2/year) may attest to the various factors such as afforestation efforts, reforestation projects, or natural regeneration processes (Lambin and Meyfroidt, 2011). However, during the period of 2012-2023, there was an increase in area for built-up (+0.042 km^2/year) and a decrease in area for forest (-0.020 km^2/year). This assertion appears to support the notion of rapid urban expansion that often leads to habitat fragmentation, loss of biodiversity, and increased pressure on natural resources that underscore continued threat of deforestation, driven by factors such as infrastructure development, agricultural expansion and human settlement (Seto et al., 2012). The rate of change for built-up between 2013 and 2023 declined at 3.65 km^2 per year, indicating a slow-down in urbanization during this period. As reported by Foley et al. 2005, stability in land cover dynamics and slow-down in urbanisation could be due to prohibitive land use policy, harsh economic and environmental conditions.

As shown in Figure 5, LULC composition of derived savanna ecosystem of Ogun State has undergone significant changes between 2002 and 2023. The results indicate a decline in vegetation cover, with forest and grassland areas experiencing significant decrease in area, while urbanization has largely increased. The decline in forest cover is particularly concerning, as forests play a crucial role in regulating the environment, providing habitat for wildlife, and mitigating the impacts of climate change. However, the rate of forest loss has slowed down during the more recent period, but it is still a cause for concern given the projected further decline in forest cover. The slowing down of the rate of forest loss in the more recent period may offer some glimmer of hope, suggesting that conservation efforts or policy interventions might be having some impact. However, the persistence of forest loss, albeit at a reduced rate, remains alarming, especially considering the projected further decline. This underscores the need for continued and intensified efforts to address the drivers of deforestation, such as agricultural expansion, logging, infrastructure development, and urbanization (Hansen et al., 2013).

The significant decrease in grassland areas also raises concerns, as grasslands support diverse plant and animal species and provide essential ecosystem services, including soil stabilization, carbon sequestration, and support for livestock grazing. The conversion of grasslands to other land uses, such as agriculture or urban development, can lead to habitat fragmentation, loss of biodiversity, and disruption of ecological processes (Foley et al., 2005). The observed increase in urbanization reflects ongoing global trends of rapid urban growth, driven by factors such as population growth, rural-to-urban migration, and economic development. While urbanization can offer socioeconomic opportunities, it also brings about environmental challenges, including habitat loss, air and water pollution, increased energy consumption, and greenhouse gas emissions. Managing urban expansion sustainably is crucial to mitigate its adverse environmental impacts while maximizing its potential benefits (Seto et al., 2012).

Table 3. Sizes of LULC categories

	2002		2013		2023	
	Area(km^2)	Area (%)	Area(km^2)	Area (%)	Area(km^2)	Area (%)
Bare soil	0.0402	31.9	0.0196	15.5	0.0376	29.8
Built-Up	0.0130	10.3	0.0718	57.0	0.0453	35.9
Forest	0.0398	31.5	0.0205	16.2	0.0170	13.7
Grassland	0.0330	26.3	0.0141	11.3	0.0261	20.6
Total	0.1260	100.0	0.1260	100.0	0.1260	100.0

Source: Fieldwork, 2023

Table 4. Rate of change in sizes or extent of LULC classes

LULC	2002-2013		2013-2023		2002-2023	
	Δ in Area (km^2)	Rate Δ Area (km^2/year)	Δ in Area (km^2)	Rate Δ in Area (km^2/year)	Δ in Area (km^2)	Rate Δ in Area (km^2/year)
Bare soil	-0.021	-2.069	0.018	1.805	-0.003	-0.264
Built-Up	0.079	7.876	-0.037	-3.652	0.042	4.224
Forest	-0.018	-1.829	-0.002	-0.218	-0.020	-2.048
Grassland	-0.009	-0.947	0.008	0.779	-0.002	-0.168

Source: Fieldwork, 2023

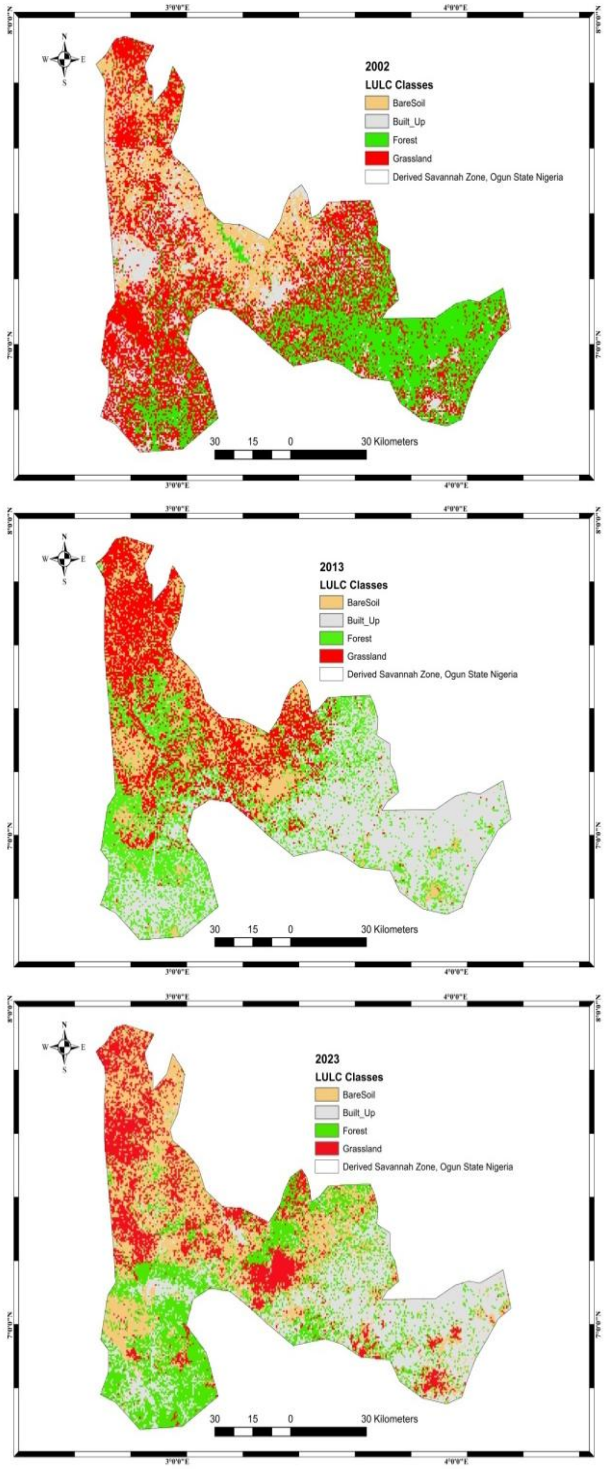

Figure 5. Changes in LULC classes from 2002 through 2013 to 2023

The reported decline in grassland cover over the specified periods is indeed significant and warrants attention due to the vital ecological functions that grasslands provide. Grasslands are diverse ecosystems that support a wide array of plant and animal species and play crucial roles in nutrient cycling, soil formation, carbon sequestration, and water regulation. Grassland cover decline could have several implications for biodiversity conservation, ecosystem services, and human well-being. Furthermore, grasslands contribute to carbon storage and sequestration, helping to mitigate climate change. Their loss may result in increased carbon emissions and reduced resilience to climate variability (Milchunas and Lauenroth, 1993).

4. Conclusion

Derived savannah ecosystem serves as habitat for various plant and animal species. The ecosystem also provides essential ecosystem services that help to maintain the balance between natural processes and human activities. Over the years, increased anthropogenic activities have resulted in changes of biodiversity structure and composition of derived savannah ecosystem. Thus, LULC features have been significantly altered.

The study examined the extent and rate of change in LULC within the derived savanna ecosystem of Ogun State over three decades. Specifically, decline was most pronounced in forested and grassland areas, indicating substantial ecosystem degradation. The escalation of urbanization emerges as the predominant driver behind this concerning trend. The discernible increase in built-up areas underscores the rapid urban expansion witnessed in Ogun State. As urban centers expand, they encroach upon and fragment natural habitats, leading to the displacement and degradation of native vegetation.

Loss of vegetation cover diminishes the capacity of ecosystems to provide essential services, such as carbon sequestration, biodiversity conservation, and regulation of hydrological cycles. Furthermore, it exacerbates vulnerabilities to environmental hazards such as soil erosion, flooding, and heat island effects. In light of these findings, urgent and concerted efforts are imperative to address the drivers of vegetation loss and promote sustainable land management practices. By way of policy intervention through strict regulation of logging activities, prompt resolution of land tenure and ownership conflicts and provision of incentives for sustainable land management would significantly reduce the degradation of forested land in the derived savanna zone. Comprehensive strategies that encompass land-use planning, conservation initiatives and community engagement are essential to mitigate further degradation and foster resilience within the derived savanna ecosystem of Ogun State.

References

Adetola, O., Solanke, A., 2013. Ecological significance and environmental problems of savanna ecosystems. Journal of Scientific Research and Reports, 2(2): 345-356.

Afolayan, W. A., Akanbi, W. B., Afolayan, A. F., Adekunle, V. A., 2021. Ethnobotany and agro-ecological significance of savanna pockets in southern Nigeria. Journal of Applied Life Sciences International, 26(2): 27-40.doi: 10.9734/jalsi/2021/v26i230236.

Afuye, G.A., Kalumba, A.M.,Orimoloye, I. R., 2021. Characterisation of vegetation response to climate change: A review. Sustainability, 13(13): 7265

Anderson, J.R., 1976. A land use and land cover classification system for use with remote sensor data. US Government Printing Office.

Areola, A. A.,Ikporukpo, C. O., 2020. Spatial analysis of urban spaces in an indigenous African city. International Journal of Development Research. 10(01): 33190-33203.

Cao, J., Yeh, E. T., Holden, N. M., Qin, Y., Ren, Z., 2013. The roles of overgrazing, climate change and policy as drivers of degradation of China's grasslands. Nomadic Peoples, 17(2):82 – 101.

Cao, L., Yang, P., Li, Y.Y., Li, Z.L., Fang, H., 2018. Combining multiple remote sensing datasets to assess the spatiotemporal dynamics of vegetation in the northwest of China. Remote Sensing, 10(2):196.

Cao, L., Xu, M., Liu, Y., Yu, Z., Sun, L., Tian, X., Zhang, W. 2023. Response of soil nitrogen components and its vertical distribution to rainfall redistribution during Robinia pseudoacasia forest restoration on the Loess Plateau. Ecological Indicators, 155, 111036.

Dash, P., Sanders, S.L., Parajuli, P., Quyang, Y., 2023. Improving the accuracy of land use land cover classification of landsat data in an agricultural watershed. Remote Sensing, 15 (16): 4020.

FAO, 2020. The State of the World's Forests: Forests, biodiversity and people. Food and Agriculture Organization of the United Nations, Rome, http://www.fao.org/state-of-forests/en/ Accessed: 13.03.2024.

FORMECU, 1996. The World Resources Institute's Global Forest Watch: Programme and Projects: An Overview of Forestry Development. FORMECU, Yaoundé, Cameroon.

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Helkowski, J. H., 2005. Global consequences of land use. Science, 309(5734): 570-574.

Gómez-Brandón, M., Lores, M., Domínguez, J., 2018. Long-term impact of human land-Use on soil microbial communities in a Mediterranean area. Science of the Total Environment, 619-620: 103-112. doi: 10.1016/j.scitotenv.2017.11.174.

Hansen, M. C., Potapov, P. V. Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Townshend, J. R., 2013. High-resolution global maps of 21st-century forest cover change. Science, 342(6160): 850-853.

Hido, A., Teka, A., Alemayehu, A., 2023. Analysis of charcoal producers perception of its production, forest degradation, and governance in Wolaita, Southern Ethiopia's Dry Afromontane Forests. International Journal of Forestry Research, 2023(1): 3352702.

Hou, X., Niu, Z., Gao, S., Huang, N., 2013. Monitoring vegetation phenology in farming pastoral zone using SPOT-VGT NDVI data. Transactions of the Chinese Society of Agricultural Engineering, 29(1): 142-140.

Lambin, E. F., Meyfroidt, P., 2011. Global land use change, economic globalization, and the looming land scarcity. Proceedings of the National Academy of Sciences, 108(9): 3465-3472.

Li, W., Ciais, P., MacBean, N., Peng, S., Defourny, P., Bontemps, S. 2016. Major forest changes and landcover transitions based on plant functional types derived from the ESA CCI Land Cover product. International Journal of Applied Earth Observation and Geoinformation, 47, 30-39.

Mather, P., Tso, B. 2010. Classification Methods for Remotely Sensed Data. (Ed: Second). CRC Press. Boca Raton.

Milchunas, D. G., Lauenroth, W. K., 1993. Quantitative effects of grazing on vegetation and soils over a global range of environments. Ecological Monographs, 63(4): 327-366.

Naumann, G., Barbosa, P., Garrote, L., Iglesias, A., Vogt, J. V., Prompt, E., 2014. Global changes in drought conditions under different levels of warming. Wiley Interdisciplinary Reviews: Climate Change, 5(2): 219-232.

Odekunle, J. F., Akindele, D. B., Adebayo, G. O., 2019. The problems and challenges of development control in Abeokuta-West zonal planning area, Ogun State, Nigeria. African Journal of Economics and Sustainable Development, 2(1): 9-27.

Ogundele, F. T., Okeola, O. G., Ogunwale, A. B., Oladapo, A. A., 2016. Assessment of the dynamics of forest cover changes in Nigeria. Journal of Environmental Science and Water Resources, 5(6): 164-174.

Ohwo, O., Abotutu, A., 2015. Environmental impact of urbanization in Nigeria. British Journal of Applied Science and Technology, 9(3): 212 – 221.

Okorondu, J., Umar, N. A., Ulor, C. O., Onwuagba, C. G., Diagi, B. E., Ajiere, S. I.,Nwaogu, C., 2022. Anthropogenic activities as primary drivers of environmental pollution and loss of biodiversity: A review.. International Journal of Trend in Science, Resources and Development, 6: 621-643.

Ola, A.B., Adewale, Y.Y., Raheem, W. A., Afonja, A.A., 2020. Anthropogenic activities and their impacts on biodiversity survival in Ifelodun Area, Kwara State, Nigeria.

Olayiwola, A. M., Lawal, M. O., 2018. Mapping urban growth and its impact on agricultural land in Abeokuta, Nigeria: 1966 – 2016. Interdisciplinary Environmental Review, 19(3-4): 289-305.

Quaranta, G., Salvia, R., Salvati, L., Paola, V.D., Coluzzi, R., Imbrenda, V., Simoniello, T., 2020. Long-term impacts of grazing management on land degradation in a rural community of Southern Italy: Depopulation matters. Land Degradation and Development, 31(16): 2379 – 2394.

Rawat, J. S., Kumar, M., 2015. Monitoring landuse/landcover change using remote sensing and GIS technique: a case study of Hawalbagh block, district Almora, Uttarakhand, India. Egyptian Journal of Remote Sensing and Space Science, 18(1): 77-84.

Roby, C., 1991. An overview of deforestation in Nigeria. Landscape and Urban Planning, 20(4): 265-275.

Rojas, O., Senay, G., Singh, R. K., Verdin, J. P., 2011. Developing an operational drought monitoring system for Somalia. Journal of Arid Environments, 75(12): 1266-1272.

Seifollahi-Aghmiuni, S., Kalantari, Z., Egidi, G., Gaburova, L., Salvati, L., 2022. Urbanisation-driven land degradation and socioeconomic challenges in peri-urban areas: Insights from Southern Europe. Ambio, 51 (6): 1446 – 1458.

Seto, K. C., Güneralp, B., Hutyra, L. R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proceedings of the National Academy of Sciences, 109(40): 16083-16088.

Skakun, S., Lucanus, O., Fraser, R., 2016. Towards operational vegetation stress monitoring using Landsat surface reflectance data. Remote Sensing of Environment, 184: 557-575.

Son, N. T., Chen, C. F., Chen, C. R., Chang, L. Y., 2012. Evaluating the MODIS LAI product using MODIS and Landsat data fusion. International Journal of Remote Sensing, 33(1): 67-89.

Srivastava, P.K., Han, D., Rico-Ramirez, M.A., Bray, M., Islam, T. 2012. Selection of classification tecniques for land use/land cover change investigation. Advances in Space Research, 50(9): 1250 – 1265.

Twumasi, N. Y. D., Shao, Z., Altan, 2019. Mapping built-up areas using two band ratio on Landsat imagery of ACCRA in Ghana from 1980 to 2017. Applied Ecology & Environmental Research, 17(6).

Xu, Y., Tang, O., Fan, J., Bennett, S. J., Li, Y. (2011). Assessing construction land potential and its spatial pattern in China. Landscape and Urban Planning, 103(2), 207-216.

Yang, Y., Li, M., Feng, X., Yan., H., Su, M., Wu, M., 2021.Spatiotemporal variation of essential ecosystem services and trade-off/synergy along with rapid urbanization in the Lower Pearl River Basin, China. Ecological Indicators, 133: 108439.

Ying, L., 2019. Traditional land use systems, agrobiodiversity conservation, and sustainable development in China's ecological fragile areas. Journal of Cleaner Production, 237: 117835. doi: 10.1016/j.jclepro.2019.117835.

Zhe, M., Zhang, X., 2021. Time-lag effects of NDVI responses to climate change in the Yamzhog Yumco Basin, South Tibet.Ecological Indicators, 124: 107431.