MAPPING OIL PALM EXPANSION WITHIN THE PROTECTED LOWLAND RAINFOREST OF NIGERIA USING GOOGLE EARTH ENGINE

Ralph Adewoye*, Peace Ukoha and Stephen Okonkwo

*Corresponding author: adewoye.ralph@frin.gov.ng / ralphadewoye@gmail.com

Remote Sensing of Tropical Ecosystems and Climate Change Modelling Group, Forestry Research Institute of Nigeria, Ibadan, Nigeria.

ABSTRACT

Increasing demand for *Elaeis guineensis* (African Oil Palm) products both for domestic and industrial use has led to its continuous expansion. The influence of oil palm plantation establishment on the economic well-being of communities and ecosystems cannot be over-emphasised. The study focuses on the rapid expansion of oil palm plantations within all protected areas and forest reserves in the lowland rainforests of Ondo State, Nigeria using. Object-Based Image Analysis (OBIA) was used to map oil palm expansion using 10-metre resolution Sentinel-2A images for 2015 and 2020 in Google Earth Engine (GEE). We found expansion of both smallholder and commercial oil palm plantations within eight of the thirteen protected areas with three protected areas (Ipele, Onisere and Akure Ofosu) showing a significant increase in oil palm plantation establishment. The use of object-based classification techniques, which combines contextual information within the image domain to discriminate landscape features such as oil palm canopy features, was effective in delineating oil palm from the forest canopy and other crops. While Google Earth Engine, a server-based remote sensing domain with petabytes of data, is effective for monitoring large-scale tropical forests.

Key words: oil palm, satellite remote sensing, deforestation rates, Google Earth Engine.

INTRODUCTION

A protected area is a geographical location that has been defined, dedicated and managed for the long-term conservation of nature and its related ecological services and cultural values, via legal or other effective measures (Dudley & Stolton, 2007). The IUCN further defines a protected area as an area of land and/or sea dedicated to the protection and maintenance of biological diversity, and of natural and associated cultural resources, and managed through legal or other effective means (DeFries et al., 2007). Protected areas include forest reserves, strict nature reserves, wilderness areas, national parks and management areas, and are important for biodiversity conservation while also contributing to livelihood through the provision of ecosystem services such as food, safe drinking water, medicines and protection from adverse climate elements.

Protected areas are at the heart of attempts to conserve nature and the services it renders, and represent a key strategy to conserve biodiversity at a small or large scale (Belote & Wilson, 2020; Hummel et al., 2019; Wang et al., 2020). Also, Ward et al. (2020) suggested that protected areas are a core tool in abating the biodiversity crisis and their importance is reflected in the new Strategic Plan for Biodiversity under the Kunming-Montreal Global Biodiversity Framework. Efforts at increasing percentages of protected areas led to the international agreement calling for the expansion of the global protected area network to cover 17 per cent of terrestrial areas and 10 per cent of marine areas by 2020 (Ward et al., 2020). Despite concerted efforts to increase the percentages of protected areas, growing human population density and land-use intensification on surrounding lands are major causes of biodiversity degradation in protected areas especially in tropical rainforests. One of the major forces of anthropogenic disturbance is the expansion of oil palm plantations into protected areas of tropical rainforest ecosystems.

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Oil palm (*Elaeis* spp.) is one of the world's most rapidly expanding agricultural tree crops and is grown across more than 13.5 million ha of the tropical region (Fitzherbert et al., 2008; Yaap et al., 2010). The growing belt for oil palm is the high-rainfall zone, naturally occupied by moist tropical forests and the most biologically diverse terrestrial ecosystem on Earth (Gutiérrez-Vélez & DeFries, 2013; Miettinen et al., 2012). Oil palm is an important driver of tropical deforestation and contributes to deforestation in the following ways: a) as the primary motive for clearance of intact forests; b) by replacing forests previously degraded by logging or fire; c) as part of a combined economic enterprise, such as with timber, plywood or paper pulp, profits are used to offset the costs of plantation establishment; or (d) indirectly, through generating improved road access to previously inaccessible forest or displacing other crops into forests (Butler & Laurance, 2009).

The availability of Satellite Remote Sensing (SRS) with repeated time series has allowed for research on oil palm expansion and its implications on forest ecosystems. Oil palm mapping using satellite remote sensing data has been carried out in many studies across the tropics using various satellite remote sensing images ranging from coarse or low resolution to medium resolution and high-resolution satellite images. The Moderate Resolution Imaging Spectroradiometer (MODIS) data (a coarse low-resolution satellite image) with a pixel size of 250 m were utilised successfully to produce an oil palm map covering an area of 939,204 km^2 in the Amazon Forest of Brazil (Gutiérrez-Vélez & DeFries, 2013). A similar study using MODIS data was conducted in Southeast Asia; the study successfully classified a total of 13 classes together with mangrove forests, rainforests and large-scale palm plantations (Miettinen et al., 2012).

The use of medium and higher spatial resolution data for the delineation and mapping of oil palm has been successfully conducted in many studies. For instance, the impacts of oil palm on deforestation and biodiversity loss were published using 30-metre Landsat images of three epochs between 1984 and 2010 (Vijay et al., 2016). The results of the study revealed historical deforestation caused by oil palm plantations in 20 tropical countries. The above studies were carried out using the pixel-based classification method. The major disadvantages of the pixel-based method are the 'salt and pepper' effects, due to the intrinsic characteristics of the land cover elements (spectral heterogeneity) and the random variation of the sensor's response which often lead to misclassifications (Whiteside et al., 2011). Another classification procedure known as Object-based image analysis (OBIA) was preferred to solve the salt and pepper problem and improve classification accuracies.

OBIA is a robust method suitable for the classification of medium to high-resolution satellite imagery. An object is a group of pixels, and object characteristics such as mean value, standard deviation, ratio, etc., can be calculated; there are also shapes and texture features of the objects available which can be used to differentiate land cover classes with similar spectral information. In object-based techniques, contextual information such as texture, geometry and compactness are combined with spectral information of the satellite image for change detection analysis (Aguirre-Gutiérrez et al., 2012; Desclée et al., 2006). The main objective of OBIA is to improve image classification through the full exploitation of salient information within the satellite image for change detection analysis. The salient information includes texture, shape and spatial relations with neighbouring objects (Hussain et al., 2013).

OBIA uses objects produced by image segmentation and combines visual interpretations with the quantitative aspect of the pixel-based approach. It interprets images using characteristics such as spectra, texture, as well as spatial and topological characteristics (Desclée et al., 2006). These extra forms of information give OBIA the potential to produce land cover thematic maps with higher accuracies than those produced by the traditional pixel-based method. OBIA comprises two parts: 1) image segmentation and 2) classification based on objects' features in spectral and spatial domains. Image segmentation is a kind of rationalisation, which delineates objects according to certain homogeneity criteria and at the same time requires spatial contingency (Desclée et al., 2006). Although the application of OBIA was initially focused on high-resolution satellite images, it has been successfully applied using medium-resolution images. The application of OBIA in forest ecosystems includes forest cover mapping, canopy modelling, change detection studies, above-ground biomass estimations, species distribution modelling and habitat mapping (Abbas et al., 2010; Desclée et al., 2006; Duro et al., 2012; Duveiller et al., 2008; Lu & Batistella, 2005; Lu et al., 2014). For example, OBIA was used in the change detection optimisation of the mountainous forest of Mexico with a medium-resolution Landsat image (Aguirre-Gutiérrez et al., 2012). An accuracy assessment of 0.77 was obtained using the object-based classification algorithm.

Oil palm plantations have a distinct canopy cover from forest trees and other agricultural tree crops, thus the application of OBIA which uses contextual textural information to discriminate crops is well suited for mapping and discriminating oil palm in lowland rainforest. This study, therefore, aims to determine the status of protected areas in Ondo State and the extent of

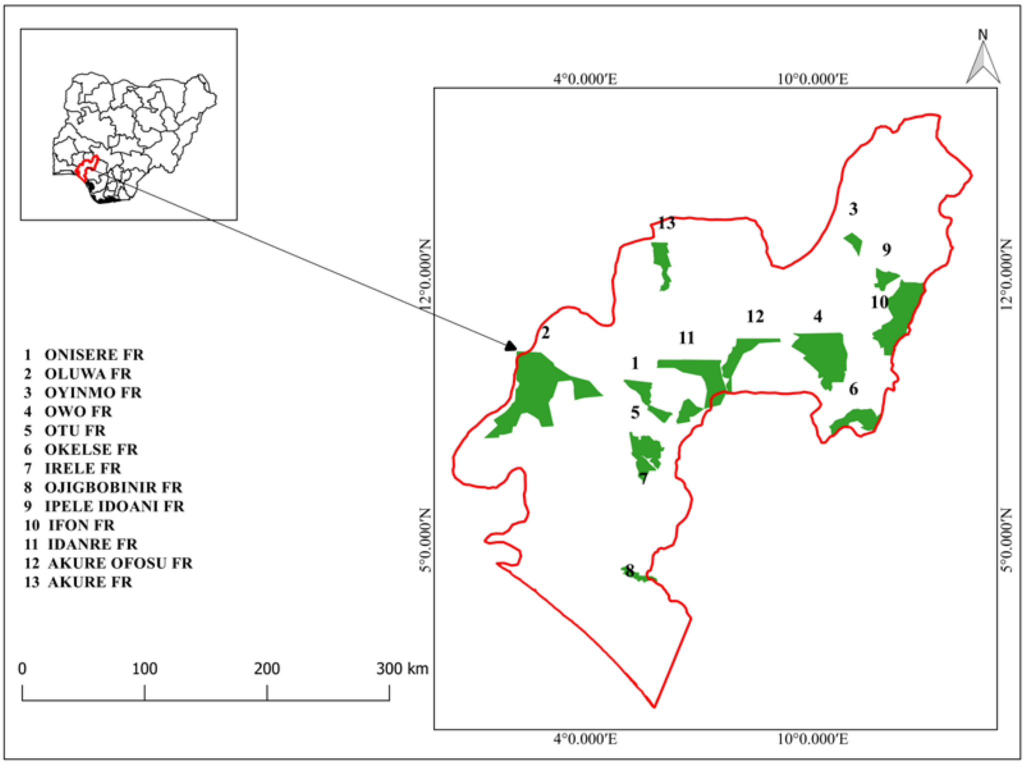

Figure 1. Protected areas of the lowland rainforest of Ondo State, Nigeria.

oil palm incursion within the protected areas using OBIA with high-resolution Sentinel-2A.

MATERIAL AND METHODS

Study areas

Ondo State is bordered to the east by Edo and Delta states, to the west by Ogun and Osun states, to the north by Ekiti and Kogi states, and to the south by the Atlantic Ocean and the Bight of Benin. The state is endowed with lowland forest cover which is highly diverse in both flora and fauna species. The study areas are the 13 forest reserves of Ondo State (Figure 1), which are highly diverse ecological niches ranging from lowland rainforest to savannah at the border with Kogi in the north. The lowland climate supports oil palm plantations because of its rainfall and rich soil.

METHODS

Digitisation of archived forest reserve maps of Ondo State

Archived maps of the protected areas were obtained from the State Forestry Department (Ondo State, Nigeria). The acquired maps dated back to the colonial eras showing the boundary and extent of each of the forest reserves. The forest maps were the original surveyed maps by the then-British colonial forestry administration. Included in the maps were the beacon numbers and the coordinate reference points for each of the forest reserves. The paper maps were scanned, georeferenced, then digitised and saved as shapefiles. The georeferencing and digitisation were to enable the maps to be imported into a remote sensing interface such as the Google Earth Engine platform. A total of 13 forest reserves were georeferenced and digitised using the QGIS (3.1.8) software.

Forest, oil palm and other land use delineation in Google Earth Engine

Google Earth Engine (GEE) is a web-based and cloud computing Remote Sensing (RS) portal that provides global time series of satellite data and other ancillary data (Lalit & Mutanga, 2019). The GEE portal provides enhanced opportunities for undertaking Earth observation studies and has the capabilities of performing raster and vector manipulations on free archival images such as Landsat, Moderate Imaging Spectroradiometer (MODIS) and the European Copernicus Earth Observation data (Sentinel-2, Sentinel-1, Sentinel-3, Sentinel-4, Sentinel-5, Sentinel-5P, Sentinel-6), etc. Embedded within GEE are petabytes of other time-series satellite images and ancillary data and several image classification and machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), Deep Learning and Artificial Neural Network (ANN) algorithms (Kumar & Mutanga, 2018; Lalit & Mutanga, 2019).

The shapefiles from the digitised maps were imported into the GEE interface and were used to clip the dry season Sentinel-2A satellite images for the years 2015

Table 1: Statistics of annual changes between the classified maps of 2015 and 2020 and the overall accuracies of the maps

Protected area (PA)	Year	Forest	Oil palm	Farmland	Settlement	Water	Overall accuracy (%)
		Km^2					
Akure Ofosu	2015	72.0813	9.6333	11.3321	6.1622	0.8379	62.07
	2020	65.4845	12.4916	13.0624	7.1268	1.9184	62.01
Changes		-6.5968	2.8583	1.7303	0.9646	1.0805	
Irele	2015	12.3014	19.9809	1.4062	0.3491	0.0523	77.78
	2020	11.1474	20.3873	2.0749	0.3886	0.0917	73.33
Changes		-1.154	0.4064	0.6687	0.0395	0.0394	
Onisere	2015	67.2543	0.3334	3.9463	0.528	0.3061	66.67
	2020	62.7333	2.7482	5.73	0.9642	0.1924	75.76
Changes		-4.521	2.4148	1.7837	0.4362	-0.1137	
Otu	2015	43.5607	33.7863	8.6923	1.7231	0.8612	66.04
	2020	37.7812	37.107	11.058	2.3358	0.3416	60.71
ChangeS		-5.7795	3.3207	2.3657	0.6127	-0.5196	
Oluwa	2015	307.38	135.526	12.5204	2.6867	1.037	64.84
	2020	264.258	164.251	22.3767	7.0135	1.2502	
Changes		-43.122	28.7257	9.8563	4.3268	0.2132	
Ipele Idoani	2015	22.4748	0.2267	15.7467	0.3183	0.043	78.38
	2020	19.7984	0.4108	18.9192	0.5781	0.103	72.97
Changes		-2.6764	0.1841	3.1725	0.2598	0.06	
Idanre	2015	200.932	10.3471	11.4362	3.3323	0.8918	75
	2020	193.459	12.1636	5.5545	5.5545	1.5697	86.77
Changes		-7.473	1.8165	-5.8817	2.2222	0.6779	
Ifon	2015	187.146	21.7715	87.8108	1.0022	NIL	58.53
	2020	153.455	23.2138	118.438	2.6241	NIL	75.61
Changes		-33.691	1.4423	30.627	1.6219	NIL	

The overall accuracy statistics range from 53.53 per cent to 78.38 per cent (OA* in Table 1).

and 2020 for each of the forest reserves using JavaScript. Atmospheric and geometric corrections were performed on the acquired Sentinel-2A images to remove noise and artefacts and the satellite digital number (DN) was subsequently converted to surface reflectance. Reference data for the classifications were obtained using high-resolution time-series Google Earth Engine Pro and in situ data (obtained during field visits). The training samples were divided into 70/30 for classification and validation. The satellite images were then classified into four major classes, namely; Forest, oil palm plantation, Agricultural land and Settlement or built-up.

Accuracy assessments

The conventional method for determining accuracy is to create an 'error matrix'. The land cover classes from the categorised image are represented by the rows and columns of this square matrix. To determine overall

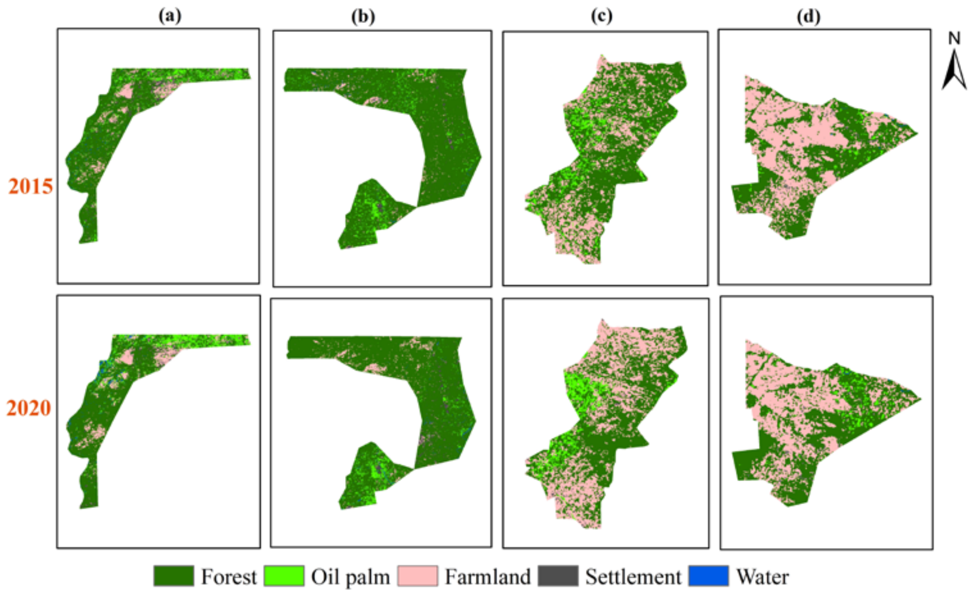

Figure 2. LULC classifications for (a) Akure Ofosu, (b) Idanre, (c) Ifon (d) Ipele Idoani

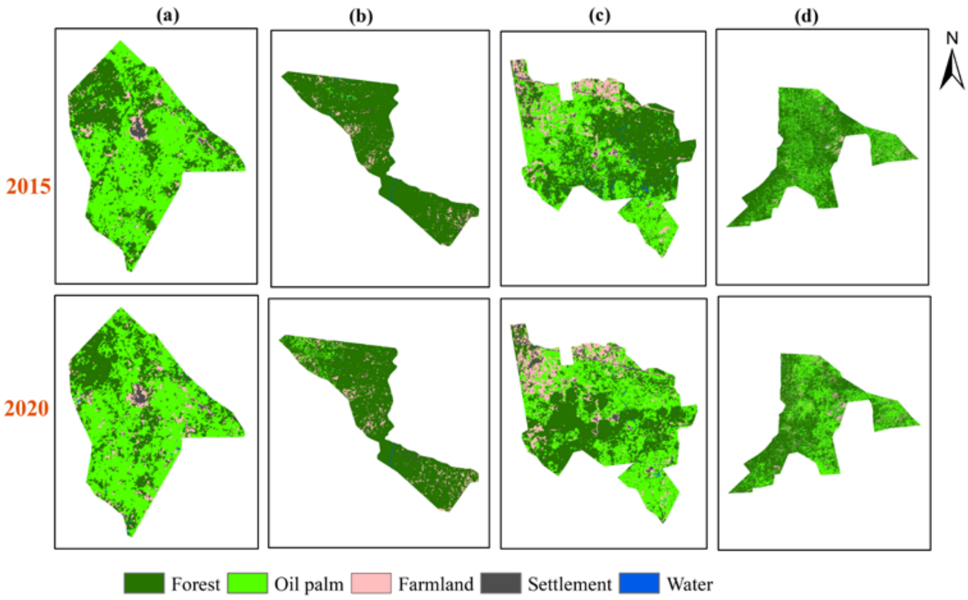

Figure 3. LULC classifications for (e) Irele, (f) Onisere, (g) Otu (h) Oluwa

accuracy, the total number of correctly classified sites is multiplied by the total number of reference sites. This can also be expressed as an error percentage, which is the complement of accuracy: error + accuracy = 100 per cent.

Also, deforestation rates were calculated for all the forest reserves / protected areas using the annual deforestation rate formula of the Food Agriculture Organization below:

$$r = \left(\left(\frac{1}{t_2 - t_1} \right) \ln \frac{A_2}{A_1} \right) \text{--------------------------------------} 1$$

A_1 and A_2 indicated in the formula are the areas of the forest cover mapped between time t_1 and t_2 which are 2015 and 2020 respectively.

RESULTS

The land uses land cover change analysis of the 13 digitised forest reserves with the 10-metre resolution Sentinel-2A satellite images revealed that eight of the forest reserves are currently under small-scale oil palm groves or large-scale plantations (Table 1, Figures 2 and 3). Oil palm groves are smaller hectarages of plantations, distinguishable from large commercial/industrial plantations, and are further classified as either dense, thinned or sparse providing livelihoods for small-scale farmers (Okolo et al., 2019). The oil palm groves are mainly composed of *Dura* species which have hard shells around the kernel, and are also protected plantations arising from shifting cultivations and are often scattered around the farmlands.

Table 2. Statistics on deforestation rates in the protected areas.

Forest reserve	Ipele Idoani	Irele	Onisere	Otu	Oluwa	Akure Ofosu	Idanre	Ifon
Deforestation rates	-0.55	-0.85	-0.60	-1.23	-1.32	-0.44	-0.23	-1.72

Oil palm establishment in protected areas of Ondo State ranges from 0.29 (Ipele Idoani) to 41.8 per cent (Otu Forest Reserve). Three forest reserves (Ipele, Onisere and Akure Ofosu) showed a considerable increase in oil palm plantation establishment while the annual deforestation rates within the eight forest reserves are between 0.23 and 1.32 per cent (Table 2). Changes observed from the results in Table 1 included negative changes for forest reserves which connotes forest degradation and the negative changes range from loss of forest cover -1.15 km^2 to -43.12 km^2 within the period 2015–2020. Similarly, oil palm and the other land use classes increased in the same proportion to the loss of forest cover.

DISCUSSION

The extent to which oil palm contributes to deforestation has been a subject of debate. Oil palm activities potentially contribute to deforestation, which can have serious detrimental effects on the environment, and therefore require adequate monitoring. While protected areas are at the heart of attempts to conserve biodiversity and ecosystem services, the protected areas within the lowland rainforest have been gradually eroded by the incursion of oil palm plantations. Two types of oil palm plantations were observed during the data collection phase, the 'grove' plantations and the large-scale commercial plantations, and both contributed to the loss of biodiversity within the protected areas. From observations, the grove plantations are smaller patches of oil palm plantation (not greater 1 ha). The grove plantations of oil palm are offshoots of incursions into protected areas by inhabitants farming within the boundaries of protected areas. These farmers practise shifting cultivation which in itself is destructive to biodiversity conservation. The large-scale plantations are commercial oil palm production encouraged by the government with the aim of providing employment to the growing population. However, the 10-metre resolution satellite data used in this study is limited in its ability to discriminate between grove and large-scale plantations. A higher resolution satellite image between 5 metres and 0.5 metres provided by commercial satellite providers will adequately distinguish the grove oil palms from the large-scale oil palm plantations.

While Nigeria is a signatory to several biodiversity and conservation treaties, a key question arises as to why such incursions into protected areas are occurring when it is the policy of the Government of Nigeria to make community lands available to would-be commercial farmers. The answer appears to be that the expansion of oil palm plantations into protected areas is encouraged by the state governments (Chukwu, 2022; Ekubge, 2023; Olu-Esho, 2023). Although it is an unwritten policy, the state government aims to promote employment through agricultural expansion and industrialisation (Ekubge, 2023). With the result that industrial or large oil palm plantations existing within forest reserves are mostly permitted by the state governments (Olu-Esho, 2023). This policy is, therefore, the driving force for deforestation through agricultural expansion. Oil palm demand has resulted in a massive increase in plantations in tropical rainforests hence the clearance and destruction of the ecosystem.

Implications of oil palm on lowland forest biodiversity and climate change

Structurally connected landscapes allow fundamental ecological mechanisms to operate unimpeded, such as meta-population retention and successful dispersal and migration (Ward et al., 2020). Beyond species-specific benefits, structurally connected landscapes allow for increased ecosystem function and resilience by ensuring nutrient cycling can continue unabated, as well as other important abiotic conditions, such as radiation, wind, light regimes, humidity and key hydrological regimes (Ward et al., 2020; Welborn & Langerhans, 2015). It is well known that land uses such as farming, urbanisation, mining and unsustainable forestry disrupt the connectivity of landscapes to various degrees (Ward et al., 2020). None of the protected areas are currently structurally connected; anthropogenic activities such as farming and settlement expansions were observed to have disrupted the structural connectivity of the protected areas.

Therefore, the future of the protected areas for biodiversity conservation is at risk. The protected areas of the lowland rainforests are principally designated for biodiversity conservation; however, this study has shown an increase in deforestation rates within the protected areas of the lowland rainforest of Nigeria. Deforestation is known to be the major cause of biodiversity erosion; the biodiversity of the lowland rainforests is currently in decline owing to an increase in the rate of deforestation arising from oil palm incursions into protected areas. Previous studies on the biodiversity of the tropical

An oil palm plantation devoid of biodiversity © R. Adewoye

lowland rainforest have revealed the decline due to socio-economic factors such as shifting cultivations, illegal wood harvesting and oil palm plantations, especially within protected areas (Ikemeh, 2013; Koh & Wilcove, 2008; Usman & Adefalu, 2010).

Landscape-level quantification over time

Fitzherbert et al. (2008) asserted that is difficult to quantify the extent to which oil palm contributes to deforestation because of a lack of reliable data. The availability of satellite remote sensing with high spatial resolutions and frequent temporal visits has made monitoring and quantifications of oil palm expansion and its contribution to deforestation possible. The Sentinel-2A images used in this study were sufficient to quantify the magnitude of change and the deforestation rates in the study area. The magnitude of the changes observed within the study period is an indication of the severity of the incursions of oil palm into protected areas of the lowland rainforest of Nigeria. Similarly, the conversion of forest land to oil palm and the changes in other land uses in the study areas are interrelated. The traditional farming system in West Africa is often practised whereby oil palm is cultivated with other crops such as yam, cassava and maize. By the third year, the oil palm seedlings are well established, thus a new area of land is cleared for farming and oil palm establishment. In addition, farming communities tend to settle within a short distance of existing oil palm plantations. Thus, the increase in farmlands and settlements are all secondary activities to the oil palm incursions in protected areas.

Satellite remote sensing provides a reliable means of detecting and mapping oil palm from space. The deployment of Sentinel-2A satellite images with 10-metre resolution and the use of object-based classification techniques which combine contextual information within the image domain to discriminate landscape features such as oil palm canopy features were effective in the delineation of oil palm from the forest canopy and other crops. Several studies have demonstrated the advantages of OBIA and the ability to maximise the aggregation of pixels to objects in the segmentation algorithm. This has enabled object characterisation through sub-objects thereby allowing discrimination of heterogeneous landscapes such as forest canopy and gaps, vegetation patchiness or landscape complexity (Blaschke, 2010). The advantages of the object-based approach were maximally exploited for oil palm plantation discrimination and delineation of the lowland rainforest.

The current advance in the technology of monitoring land uses through cloud computing and big data allows rapid mapping to be performed over large geographical scales. In this study, 10-metre Sentinel-2A data were processed using the GEE cloud computing platform. The GEE platform offers various options and can be tailored, especially when it comes to selecting processing techniques, algorithms and data input. It also allows users to customise the workflow for both preprocessing the satellite data and the speed of satellite data processing with maximum accuracy. The programmable platform also creates opportunities for GEE cloud computing to be combined with potent deep learning techniques.

CONCLUSION

The principal driving forces for the expansion of all agricultural activities are population increase and the need to sustain the livelihoods of the ever-increasing population which runs counter to the Kunming-Montreal Global Biodiversity Framework which aims to halt biodiversity decline and increase global biodiversity by ten-fold. The oil palm industry requires adequate management and monitoring due to its significant impact on the ecosystem, environment, and economy. Without proper oversight, unchecked oil palm activities will contribute to deforestation, which would have serious negative effects on the environment. To manage and plan the sustainable operations of oil palm plantations, a map showing the distribution of oil palm is essential. Effectively identifying and mapping oil palms is made possible by satellite remote sensing.

The object-based classification approach uses contextual information within the image domain to differentiate landscape elements such as oil palm canopy from other land features, hence was successfully used in the delineation of oil palm from the forest canopy and other crops. In this study, OBIA was successfully applied to precisely track and assess the environmental, ecological, and climate change implications of oil palm expansion on the forest ecosystem.

ABOUT THE AUTHORS

Dr. Ralph Adewoye is a Remote Sensing scientist and Senior Research Fellow at the Forestry Research Institute of Nigeria. His research interests include tropical forest monitoring, above-ground biomass, and climate change modeling. https://orcid.org/0000-0001-6986-6345

Ms. Peace Ukoha. Peace Ukoha is a Research Fellow at the Forestry Research Institute of Nigeria. Her research focuses on applying Remote Sensing to tropical Ecosystems and Climate Change monitoring. https://orcid.org/0000-0002-6230-8313

Mr. Stephen Okonkwo is a Principal Statistician with the Forestry Research Institute of Nigeria. His work focuses on Statistical Machine Learning, Stochastic Processes, and Artificial Intelligence. https://orcid.org/0000-0002-2074-5283

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RESUMEN

La creciente demanda de productos de Elaeis guineensis (palma aceitera africana) tanto para uso doméstico como industrial ha provocado su continua expansión. Nunca se insistirá lo suficiente en la influencia del establecimiento de plantaciones de palma aceitera en el bienestar económico de las comunidades y los ecosistemas. El estudio se centra en la rápida expansión de las plantaciones de palma aceitera dentro de todas las áreas protegidas y reservas forestales de los bosques húmedos de las tierras bajas del estado de Ondo, Nigeria, utilizando. Se utilizó el Análisis de Imágenes Basado en Objetos (OBIA) para cartografiar la expansión de la palma aceitera utilizando imágenes Sentinel-2A de 10 metros de resolución para 2015 y 2020 en Google Earth Engine (GEE). Encontramos expansión de plantaciones de palma aceitera tanto de pequeños agricultores como comerciales dentro de ocho de las trece áreas protegidas, con tres áreas protegidas (Ipele, Onisere y Akure Ofosu) mostrando un aumento significativo en el establecimiento de plantaciones de palma aceitera. El uso de técnicas de clasificación basadas en objetos, que combinan información contextual dentro del dominio de la imagen para discriminar características del paisaje como las del dosel de la palma aceitera, resultó eficaz para delimitar la palma aceitera del dosel del bosque y de otros cultivos. Por su parte, Google Earth Engine, un dominio de teledetección basado en servidores con petabytes de datos, resulta eficaz para supervisar bosques tropicales a gran escala.

RÉSUMÉ

La demande croissante de produits d'Elaeis guineensis (palmier à huile africain), tant pour l'usage domestique qu'industriel, a conduit à une expansion continue. On ne saurait trop insister sur l'influence de l'établissement de plantations de palmiers à huile sur le bien-être économique des communautés et des écosystèmes. L'étude se concentre sur l'expansion rapide des plantations de palmiers à huile dans toutes les zones protégées et les réserves forestières dans les forêts pluviales de basse altitude de l'État d'Ondo, au Nigeria, en utilisant. L'analyse d'images basée sur les objets (OBIA) a été utilisée pour cartographier l'expansion des palmiers à huile à l'aide d'images Sentinel-2A d'une résolution de 10 mètres pour 2015 et 2020 dans Google Earth Engine (GEE). Nous avons constaté une expansion des plantations de palmiers à huile à la fois artisanales et commerciales dans huit des treize zones protégées, trois zones protégées (Ipele, Onisere et Akure Ofosu) montrant une augmentation significative de l'établissement de plantations de palmiers à huile. L'utilisation de techniques de classification basées sur les objets, qui combinent des informations contextuelles dans le domaine de l'image pour distinguer les caractéristiques du paysage telles que les caractéristiques de la canopée du palmier à huile, s'est avérée efficace pour délimiter le palmier à huile de la canopée de la forêt et d'autres cultures. Google Earth Engine, un domaine de télédétection basé sur un serveur avec des pétaoctets de données, est efficace pour surveiller les forêts tropicales à grande échelle.