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Detection and Spatio-Temporal Analysis of Oil Palm (*Elaeis Guineensis*) Plantations Using Multi-Temporal Sentinel-2 Satellite Imagery in Ekiadolor Forest Reserve, Edo State, Nigeria

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ABSTRACT

Oil palm (*Elaeis guineensis*) cultivation is an important agricultural activity in tropical regions, but its expansion can alter natural forest landscapes and influence land-use patterns. This study assessed the spatial and temporal changes in oil-palm plantations within Ekiadolor Forest Reserve, Edo State, Nigeria, between 2020 and 2025 using multi-temporal Sentinel-2 satellite imagery and geographic information system (GIS) techniques. Sentinel-2 imagery for 2020 and 2025 was obtained from the Copernicus Data Space Ecosystem. Bands 2 (Blue), 3 (Green), 4 (Red), and 8 (Near-Infrared) were combined to produce multispectral composites, which were subsequently clipped to the study-area extent. The Normalized Difference Vegetation Index (NDVI) was used to support vegetation interpretation and land-cover discrimination. The imagery was classified into four land-cover classes: forest, bare soil, mature oil palm, and young oil palm. Classification accuracy was evaluated using confusion matrices, producer's accuracy, user's accuracy, overall accuracy, and the kappa coefficient in ArcGIS Pro. The 2020 classification achieved an overall accuracy of 87.88% and a kappa coefficient of 0.834, while the 2025 classification achieved 90.48% overall accuracy and a kappa coefficient of 0.856. Post-classification comparison revealed that total mapped oil-palm area increased from 5,909.51 ha in 2020 to 9,388.04 ha in 2025, representing a net increase of 3,478.53 ha or 58.86%. Mature oil palm increased substantially from 586.71 ha to 7,058.60 ha, while young oil palm declined from 5,322.80 ha to 2,329.44 ha, indicating substantial plantation maturation during the study period. The transition matrix further indicated that 3,765.35 ha of land classified as forest in 2020 was classified as oil palm in 2025. The findings demonstrate the usefulness of Sentinel-2 imagery and GIS-based post-classification comparison for monitoring plantation expansion and landscape transformation within forest-reserve environments.

Keywords: oil palm, Sentinel-2, remote sensing, land-use change, change detection, NDVI, GIS, Ekiadolor Forest Reserve, Nigeria

1. Introduction

Oil palm (*Elaeis guineensis*) is one of the most economically important tropical crops, its yield of vegetable oil per hectare far exceeding that of soybean, sunflower, or rapeseed, which has driven a steady global expansion of cultivated area over the past two decades. Climate suitability projections have shown that favorable growing conditions for oil palm in the humid tropics are expected to persist and, in some areas, expand under future climate scenarios, reinforcing the crop's continued economic attractiveness to smallholder and commercial growers alike. However, this expansion is not without environmental cost: uncontrolled growth of oil-palm plantations is widely associated with the conversion of natural forest and other native land cover, with attendant consequences for biodiversity, carbon storage, and local hydrology. Remote sensing has become an indispensable tool for monitoring these land-cover transformations, offering repeatable, large-area observation that is difficult to achieve through ground-based survey alone. A review of the field noted that multi-sensor data fusion, drawing on freely available imagery from Sentinel-1, Sentinel-2, ALOS PALSAR, and Landsat, has proven especially effective for oil-palm classification, while UAV platforms increasingly complement satellite data by providing regular, timely monitoring where cloud cover limits optical satellite acquisition (3). Since that review, the launch and maturation of the Sentinel-2 mission has made 10 m resolution, multi-band optical imagery freely available at a temporal frequency well suited to plantation monitoring across the tropics.

Within Africa specifically, a growing body of work has applied these tools to oil-palm monitoring. In Nigeria, object-based classification of Sentinel-2A imagery was used to map oil-palm expansion within protected lowland rainforest reserves of Ondo State between 2015 and 2020, revealing expansion of both smallholder and commercial plantations within the majority of the protected areas assessed (1). Elsewhere on the continent, a 2025 study quantified oil-palm extent change in Cameroon between 2015 and 2025 using Sentinel-1 SAR imagery and a Random Forest classifier, reporting increases in cultivated area of 13–55% across the focus regions studied, with the greatest change in forest cover recorded in the South Region. More broadly within Nigeria's forested southern belt, NDVI derived from Landsat imagery has similarly been applied to track land-cover disturbance in the Niger Delta region between 2010 and 2020 (2), underscoring the utility of vegetation indices for detecting vegetation-cover change in comparable ecological settings, while more recent Nigerian-focused remote sensing work continues to expand multi-index approaches to land-surface monitoring in the wider Niger Delta (8).

Despite this expanding literature, spatially explicit, multi-temporal assessments of oil-palm plantation dynamics within specific forest-reserve landscapes of southern Nigeria, particularly at the scale of individual reserves such as Ekiadolor Forest Reserve in Edo State, remain limited. Most existing Nigerian studies have focused on broader regional or state-level extents, leaving finer-scale reserve-level transitions, such as the maturation of young into mature plantations and the direct conversion of forest into oil palm, comparatively under-documented. This study addresses that gap by applying multi-temporal Sentinel-2 imagery and a post-classification comparison approach to quantify spatial and temporal changes in oil-palm plantations within Ekiadolor Forest Reserve, thereby contributing reserve-level evidence to the broader understanding of oil-palm-driven land-cover change in West Africa.

This study applies a supervised Random Forest classification algorithm to multi-temporal Sentinel-2 multispectral imagery to estimate oil-palm extent and assess land-cover change between 2020 and 2025. The analysis uses Sentinel-2 Bands 2, 3, 4 and 8, together with NDVI, to distinguish forest, bare soil, young oil palm and mature oil palm. The classified images are subsequently compared using post-classification change detection to quantify changes in oil-palm extent and identify major land-cover transitions within Ekiadolor Forest Reserve.

2. MATERIALS AND METHODS

2.1 STUDY AREA

The study was conducted in Ekiadolor Forest Reserve, Edo State, Nigeria. The reserve lies within the humid tropical environment of southern Nigeria, where forest vegetation and agricultural land uses occur within a landscape increasingly influenced by human activities. Ekiadolor is one of the forest-reserve areas associated with Edo State.

The study area was defined using the project extent used during the GIS analysis. The same spatial extent was applied to the satellite imagery from the two observation years to ensure that the resulting land-cover maps were spatially comparable.

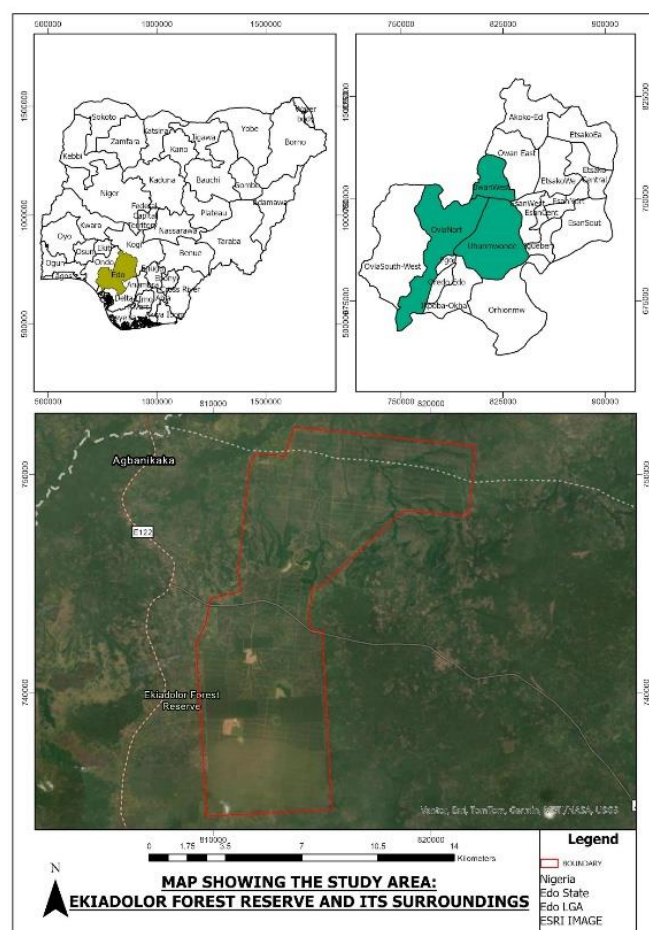


Fig 1: Study area map of the Ekiadolor Forest.

2.2 MEDOTHOLOGY FLOW CHART

This was the method used in carrying out this study.

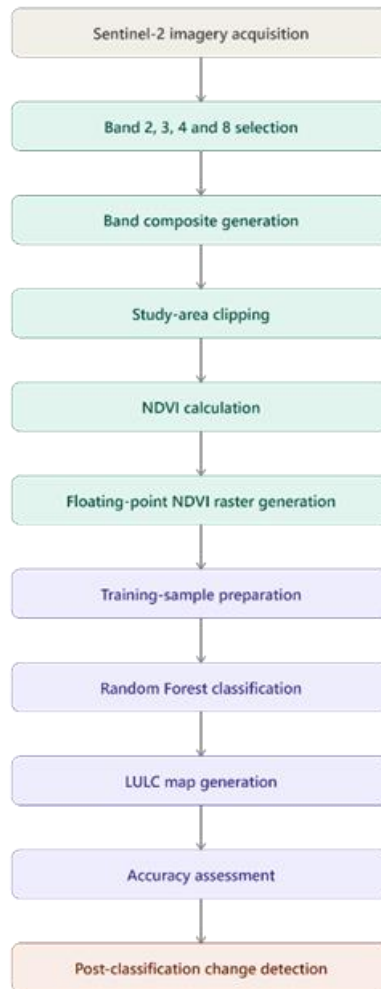


Fig 2: Showing the flow chart

2.3 SATELLITE DATA

Multi-temporal Sentinel-2 satellite imagery was acquired from the Copernicus Data Space Ecosystem for two observation dates: 28 January 2020 and 11 January 2025. The January acquisition dates were relatively close in the annual seasonal cycle, which helped improve temporal comparability by reducing differences associated with seasonal vegetation conditions. Sentinel-2 was selected because its MultiSpectral Instrument provides multispectral observations suitable for vegetation and land-cover analysis. Bands 2, 3, 4, and 8 have a spatial resolution of 10 m and represent the blue, green, red, and near-infrared portions of the electromagnetic spectrum, respectively.

2.4 IMAGE PRE-PROCESSING AND COMPOSITE GENERATION

The Sentinel-2 imagery for 2020 and 2025 was imported into ArcGIS Pro. Bands 2, 3, 4, and 8 were combined to create a multispectral composite for each observation year. The composite images were then clipped to the defined study-area extent. Using the same band configuration and spatial extent for both years allowed the two dates to be compared using a consistent classification framework.

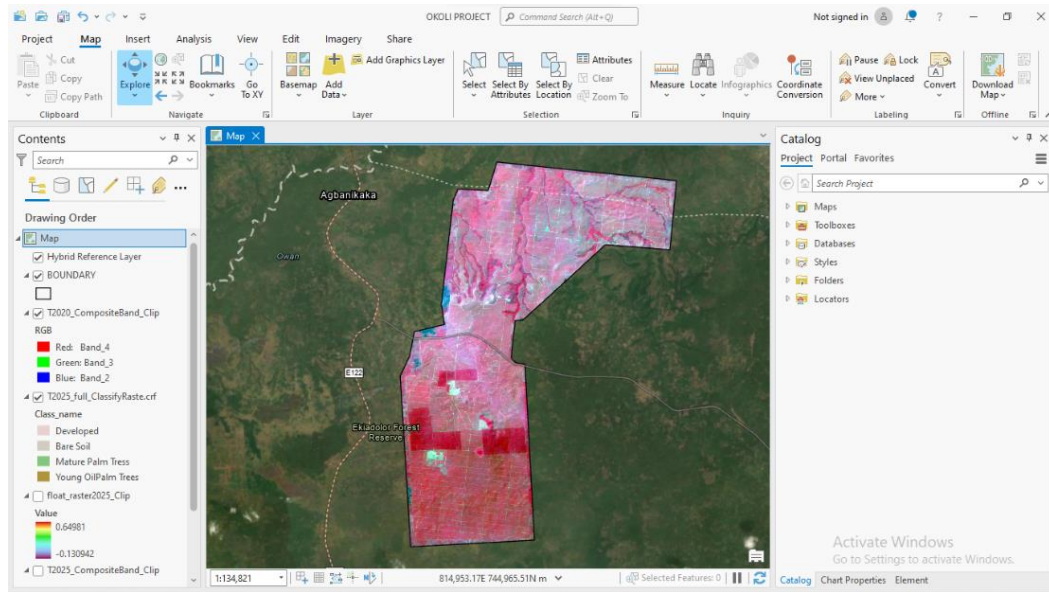


Fig 3: showing NDVI for 2020 imagery

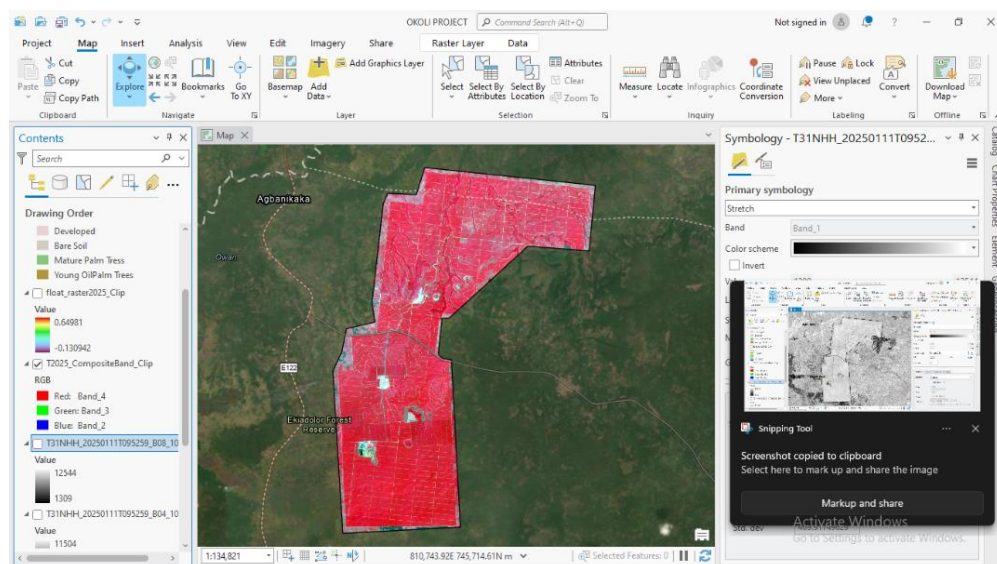


Fig 4: showing NDVI for 2025 imagery

The NDVI was subsequently generated to assist in examining vegetation characteristics. NDVI is based on the contrast between red and near-infrared reflectance and provides an indication of vegetation presence and density.

2.5 LAND-COVER CLASSIFICATION

The study classified the landscape into four principal classes:

1. Forest
2. Bare soil
3. Mature oil palm
4. Young oil palm

The classification was performed in ArcGIS Pro using the spectral information contained in the Sentinel-2 composites and the vegetation information provided by the NDVI layer. The distinction between mature and young oil palm was particularly important because the objective was not only to determine the total extent of oil-palm plantations but also to evaluate the transition of younger plantations toward mature plantations.

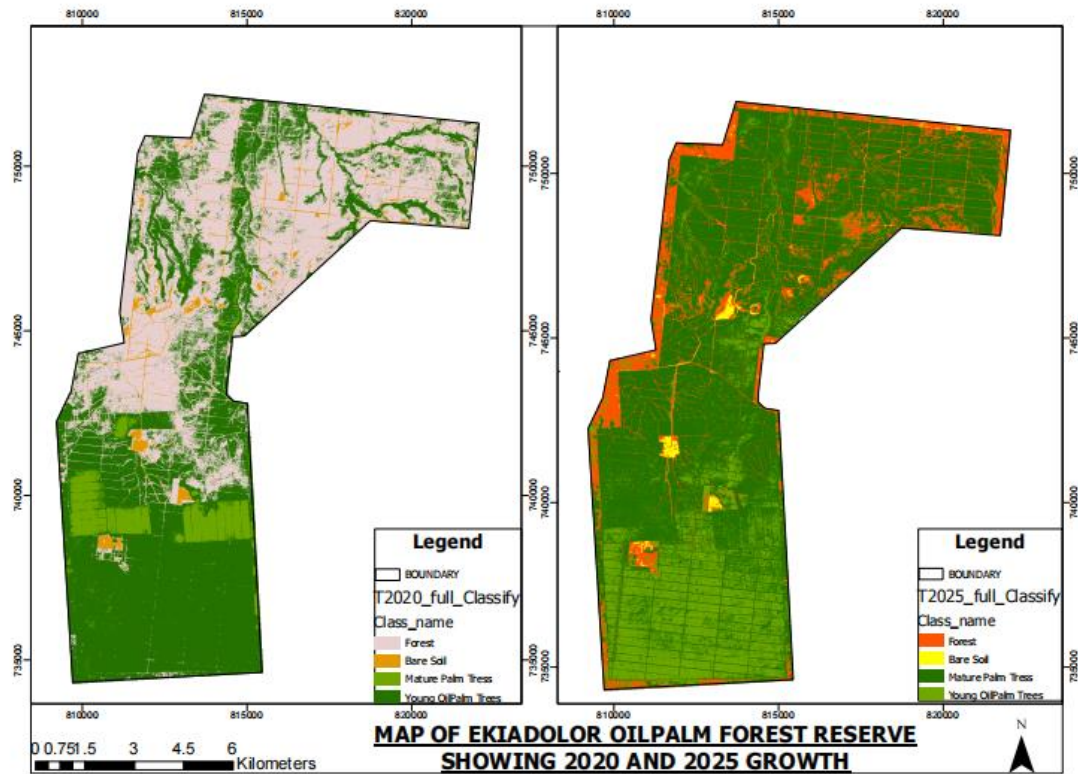


Fig 5: Showing LULC for 2020 and 2025

2.6 ACCURACY ASSESSMENT

Accuracy assessment was conducted separately for the 2020 and 2025 classification results. Confusion matrices were used to compare the classified classes against reference information. ArcGIS Pro's accuracy-assessment workflow provides user's accuracy, producer's accuracy, overall accuracy, and the kappa coefficient as measures of classification performance. User's accuracy indicates the reliability of a mapped class from the user's perspective, whereas producer's accuracy indicates how effectively reference observations of a class were correctly identified.

Table 1: 2020 Accuracy Table

OBJECT ID	ClassValue	C_20	C_30	C_40	C_50	Total	U_Accuracy	Kappa
1	C_20	16	4	1	1	22	0.727273	0
2	C_30	0	10	0	0	10	1	0
3	C_40	0	0	10	0	10	1	0
4	C_50	0	2	0	22	24	0.916667	0
5	Total	16	16	11	23	66	0	0
6	P_Accuracy	1	0.625	0.909091	0.956522	0	0.878788	0
7	Kappa	0	0	0	0	0	0	0.834067

Table 2: 2025 Accuracy Table

OBJECT ID	ClassValue	C_20	C_30	C_40	C_50	Total	U_Accuracy	Kappa
1	C_20	8	2	0	0	10	0.8	0
2	C_30	0	8	2	0	10	0.8	0
3	C_40	0	0	30	2	32	0.9375	0
4	C_50	0	0	0	11	11	1	0

OBJECT ID	ClassValue	C_20	C_30	C_40	C_50	Total	U_Accuracy	Kappa
5	Total	8	10	32	13	63	0	0
6	P_Accuracy	1	0.8	0.9375	0.846154	0	0.904762	0
7	Kappa	0	0	0	0	0	0	0.855835

For 2020, 66 assessment observations were included in the confusion matrix. The classification correctly assigned 58 observations, producing an overall accuracy of 87.88% and a kappa coefficient of 0.834. For 2025, 63 assessment observations were used, with 57 correctly classified observations, giving an overall accuracy of 90.48% and a kappa coefficient of 0.856.

2.7 POST-CLASSIFICATION CHANGE DETECTION

A post-classification comparison was used to identify changes between 2020 and 2025. The classified maps from both years were compared spatially to generate a transition matrix. Each cell of the transition matrix represents the area that changed from one 2020 land-cover class to another 2025 class.

The transition analysis allowed the study to determine not only the net change in the area of each class but also the direction of change. For example, forest-to-mature-oil-palm conversion could be distinguished from young-oil-palm-to-mature-oil-palm transition. This approach is consistent with established remote-sensing change-detection methods in which separately classified multi-temporal images are cross-tabulated to identify land-cover trajectories.

3. RESULTS

3.1 CLASSIFICATION ACCURACY

The accuracy assessment demonstrated acceptable classification performance for both observation years. The 2020 classification achieved an overall accuracy of 87.88% with a kappa coefficient of 0.834, while the 2025 classification achieved an overall accuracy of 90.48% with a kappa coefficient of 0.856.

For the 2020 classification, user's accuracy was 72.73% for forest, 100% for bare soil, 100% for mature oil palm, and 91.67% for young oil palm. Producer's accuracy was 100% for forest, 100% for bare soil, 90.91% for mature oil palm, and 95.65% for young oil palm.

For the 2025 classification, user's accuracy was 80% for forest, 80% for bare soil, 93.75% for mature oil palm, and 100% for young oil palm. Producer's accuracy was 100% for forest, 80% for bare soil, 93.75% for mature oil palm, and 84.62% for young oil palm.

The increase in overall accuracy from 87.88% in 2020 to 90.48% in 2025 indicates that the 2025 classification performed slightly better according to the available reference observations. The kappa values also indicate substantial agreement between the classified maps and reference observations. ArcGIS Pro defines the kappa statistic as an overall measure of agreement between the classified and reference datasets.

3.2 LAND-COVER DISTRIBUTION

The total study area represented approximately 11,065.81 ha in both years. The distribution of the four mapped classes changed substantially between 2020 and 2025.

Land-cover class	2020 area (ha)	2025 area (ha)	Net change (ha)	Percentage change
Forest	4,828.24	1,569.16	-3,259.08	-67.50%
Bare soil	328.06	108.61	-219.45	-66.89%
Mature oil palm	586.71	7,058.60	+6,471.89	+1,103.08%
Young oil palm	5,322.80	2,329.44	-2,993.36	-56.24%
Total	11,065.81	11,065.81	—	—

The most pronounced change occurred in the mature oil-palm class. Its mapped area increased from 586.71 ha in 2020 to 7,058.60 ha in 2025, representing an increase of 6,471.89 ha, or approximately 1,103.08%.

In contrast, young oil palm decreased from 5,322.80 ha to 2,329.44 ha, a reduction of 2,993.36 ha (56.24%). This pattern is consistent with substantial maturation of areas previously classified as young oil palm.

Forest showed a major reduction, decreasing from 4,828.24 ha in 2020 to 1,569.16 ha in 2025, corresponding to a net loss of 3,259.08 ha (67.50%).

3.3 CHANGE IN TOTAL OIL-PALM AREA

When young and mature oil palm were combined, total mapped oil-palm area increased substantially during the study period. In 2020, the total mapped oil-palm area was 5,909.51 ha, consisting of 586.71 ha of mature oil palm and 5,322.80 ha of young oil palm. By 2025, the total mapped oil-palm area had increased to 9,388.04 ha, consisting of 7,058.60 ha of mature oil palm and 2,329.44 ha of young oil palm.

Consequently, the total mapped oil-palm area increased by 3,478.53 ha, equivalent to 58.86% over the five-year period. The estimated compound annual rate of increase was approximately 9.70% per year. This result directly addresses the primary objective of the study: the mapped extent of oil-palm plantations increased between 2020 and 2025.

3.4 SPATIO-TEMPORAL TRANSITION OF LAND COVER

The transition matrix revealed that the largest individual land-cover transition was from young oil palm in 2020 to mature oil palm in 2025, covering approximately 3,135.60 ha. This represents an important component of the observed increase in mature oil palm and indicates substantial plantation maturation over the study period. A second major transition was from forest to oil palm. Approximately 3,765.35 ha classified as forest in 2020 was classified as oil palm in 2025. This comprised 3,452.97 ha transitioning from forest to mature oil palm and 312.38 ha transitioning from forest to young oil palm.

Other transitions were also observed. Approximately 326.08 ha of young oil palm in 2020 was classified as forest in 2025, while 215.31 ha of bare soil transitioned to forest. These transitions indicate that the landscape experienced multiple forms of land-cover change rather than a single-direction conversion process.

3.5 Interpretation of Oil-Palm Expansion

The combined classification results indicate that the increase in total mapped oil-palm area was associated with two major processes: plantation maturation and expansion into areas previously classified as forest or other land-cover classes.

The transition of 3,135.60 ha from young to mature oil palm demonstrates that plantation maturation contributed substantially to the increase in mature oil palm. At the same time, the 3,765.35-ha forest-to-oil-palm mapped transition indicates substantial spatial expansion of oil-palm classes into areas classified as forest in 2020.

It is therefore more appropriate to interpret the results as land-cover conversion from forest to oil palm as mapped by the classification, rather than referring to the result as direct or confirmed deforestation. This distinction is important because classification uncertainty, spectral similarity between vegetation classes, and differences in vegetation condition can influence post-classification change estimates.

4. DISCUSSION

The results show that oil-palm plantations underwent considerable spatial and structural change within Ekiadolor Forest Reserve between January 2020 and January 2025. The total mapped oil-palm area increased by 3,478.53 ha, corresponding to a 58.86% increase. This provides strong evidence of an expansion in the mapped extent of oil-palm land cover during the study period.

However, the transition analysis demonstrates that the increase in mature oil palm cannot be interpreted solely as new plantation establishment. The transition of 3,135.60 ha from young oil palm to mature oil palm indicates that plantation maturation was a major contributor to the observed increase. The reduction in young oil palm from 5,322.80 ha to 2,329.44 ha is consistent with this interpretation.

The forest-to-oil-palm mapped transition is also substantial. A total of 3,765.35 ha changed from the forest class in 2020 to either mature or young oil palm in 2025. This finding suggests that oil-palm expansion was spatially associated with areas that had previously been classified as forest. Nevertheless, the result should be interpreted as a mapped land-cover transition, because satellite-image classification does not independently establish the exact cause, timing, ownership, or management history of each transition.

The use of Sentinel-2 imagery was appropriate for the study because the sensor provides multispectral information at spatial resolutions suitable for regional land-cover mapping. Bands 2, 3, 4, and 8 provide visible and near-infrared information useful for vegetation discrimination, while NDVI provides an additional measure of vegetation response.

The Random Forest approach also provided a suitable supervised classification framework for the study. ArcGIS Pro describes Random Trees as a classification approach based on multiple decision trees whose predictions are combined through majority voting. The ensemble structure helps reduce the sensitivity associated with using a single decision tree.

The classification accuracy results provide confidence in the subsequent change analysis. Overall accuracy increased from 87.88% in 2020 to 90.48% in 2025, while kappa increased from 0.834 to 0.856. However, accuracy was not uniform across all classes. For example, the user's accuracy for forest was 72.73% in 2020 and 80% in 2025, indicating some commission error associated with this class. Such classification uncertainty should be considered when

interpreting the magnitude of the forest-to-oil-palm transition. ArcGIS Pro's accuracy-assessment framework explicitly recognizes that confusion-matrix results provide information about omission and commission errors associated with individual classes.

Another important consideration is the use of imagery acquired on 28 January 2020 and 11 January 2025. The similarity of the acquisition period is advantageous because it reduces the likelihood that seasonal differences alone account for major differences in vegetation appearance. Nevertheless, differences in atmospheric conditions, illumination, soil moisture, cloud contamination, plantation management, and vegetation condition may still affect the spectral response between dates.

Overall, the combination of Sentinel-2 multispectral imagery, NDVI, Random Forest classification, accuracy assessment, and post-classification comparison provided an effective framework for quantifying oil-palm change in the study area.

5. CONCLUSION

This study used multi-temporal Sentinel-2 satellite imagery and ArcGIS Pro to assess changes in oil-palm plantations within Ekiadolor Forest Reserve, Edo State, Nigeria, between 2020 and 2025. Four land-cover classes—forest, bare soil, mature oil palm, and young oil palm—were mapped using multispectral imagery supported by NDVI analysis.

The accuracy assessment produced overall accuracies of 87.88% for 2020 and 90.48% for 2025, with corresponding kappa coefficients of 0.834 and 0.856, respectively. These results indicate that the classifications provided a reasonable basis for subsequent change analysis.

The principal finding was a substantial increase in mapped oil-palm plantation area. Total oil palm increased from 5,909.51 ha in 2020 to 9,388.04 ha in 2025, representing a net increase of 3,478.53 ha or 58.86%. The most significant component of this increase was mature oil palm, which increased by 6,471.89 ha, while young oil palm declined by 2,993.36 ha. The transition matrix indicates that this pattern was strongly associated with plantation maturation, with 3,135.60 ha transitioning from young to mature oil palm.

The analysis also identified 3,765.35 ha of forest-to-oil-palm transition, indicating substantial conversion of areas classified as forest in 2020 to oil-palm plantation classes by 2025. This finding has implications for forest conservation and land-use management within the reserve. However, the results should be interpreted as classified land-cover transitions rather than definitive evidence of the socioeconomic causes of each change.

Overall, the study demonstrates that Sentinel-2 imagery combined with GIS-based classification and post-classification comparison can provide a useful framework for monitoring oil-palm expansion and forest-land transformation. Continued monitoring using additional dates, higher-resolution reference imagery, field verification, and more detailed plantation information would improve the reliability of future assessments.

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