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Characterizing Crop Distribution and the Impact on Forest Conservation in Central Africa

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Abstract: While the role of expanding agriculture in deforestation and the loss of other natural ecosystems is well known, the specific drivers in the context of small- and large-scale agriculture remain poorly understood. In this study, we employed satellite data and a deep learning algorithm to map the agricultural landscape of Central Africa (Cameroon, Central Africa Republic, Congo, Democratic Republic of Congo, Equatorial Guinea, and Gabon) into large- (including for plantations and intensively cultivated areas) and small-scale tree crops and non-tree crop cover. This permits the assessment of forest loss between the years 2000 and 2022 as a result of small- and large-scale agriculture. Thematic [user's] accuracy ranged between 91.2 ± 2.5 percent (large-scale oil palm) and 17.8 ± 3.9 percent (large-scale non-tree crops). Small-scale tree crops achieved relatively low accuracy (63.5 ± 5.9 percent), highlighting the difficulties of reliably mapping crop types at a regional scale. In general, we observed that small-scale agriculture is fifteen times the size of large-scale agriculture, as area estimates of small-scale non-tree crops and small-scale tree crops ranged between 164,823 ± 4224 km^2 and 293,249 ± 12,695 km^2, respectively. Large-scale non-tree crops and large-scale tree crops ranged between 20,153 ± 1195 km^2 and 7436 ± 280 km^2, respectively. Small-scale cropping activities represent 12 percent of the total land cover and have led to dramatic encroachment into tropical moist forests in the past two decades in all six countries. We summarized key recommendations to help the forest conservation effort of existing policy frameworks.

Keywords: multi-source remote sensing data; deep learning; agriculture; deforestation; forest conservation

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1. Introduction

The combination of a globally changing climate and rapid population growth has led to numerous challenges, amongst them food insecurity, the loss of natural ecosystems and biodiversity, increased pollution, and the exacerbation of existing health issues into epidemic outbreaks [1]. The World Summit on Food Security stated that in 2050, "The world's population is expected to grow to almost 10 billion, boosting agricultural demand—in a scenario of modest economic growth—by some 50 percent compared to 2013" [2]. This growing demand needs to be met either by increasing production on existing agricultural land or by expanding the agricultural production area. Both agricultural intensification and land expansion frequently harm natural ecosystems and biodiversity and can also negatively affect people—for instance, through pollution caused by agrochemicals [3–5]. As the demand for food continues to grow, it is crucial to ensure that increases in food production are accompanied by improved management of land, crops, and soils. This is necessary to mitigate soil erosion, land degradation, greenhouse gas emissions, and biodiversity loss [6–8].

Croplands and pastures are now one of the largest terrestrial biomes on the planet, occupying about 32.2 percent of the land surface [9]. These lands are increasingly degraded, with about 40 percent of global croplands experiencing some degree of soil erosion, reduced fertility, or overgrazing. The intensive use of agrochemicals (e.g., pesticides, fungicides, and fertilizers) further undermines the ecological functioning of these lands [6,8,10,11]. The expansion of cropland and pasture is occurring primarily at the expense of forests, savannahs, and grasslands. In tropical regions in particular, forests face continuous pressure from disturbance and conversion to agriculture and other land uses [12].

Agriculture in Central Africa plays a vital role in sustaining rural livelihoods, contributing to food security, and driving local economies [13,14]. However, the expansion of agriculture has significant implications for biodiversity conservation, especially in ecologically sensitive Congo forests [15–17]. Existing policy frameworks have sought to balance agricultural development and environmental sustainability; however, challenges persist [18,19]. Addressing these challenges requires robust, data-driven approaches to monitoring land use changes and assessing the impact of agricultural expansion on forest conservation. In this context, satellite-based earth observation and remote sensing techniques provide valuable tools for tracking land cover changes at scale, offering insights that can inform policy decisions. By improving the accuracy of crop classification and mapping, we contribute to efforts aimed at balancing agricultural development with forest conservation, thereby supporting policymakers in designing more effective strategies for sustainable land management.

While the role of expanding agriculture in deforestation and the loss of other natural ecosystems is well known, the specific drivers, contexts and scales remain poorly understood. This is especially a concern in Central Africa where forest loss rates are high, but on-the-ground land cover change dynamics are poorly understood [20]. As a result, some studies have attributed tropical forest losses in Central Africa primarily to small-scale agriculture [15,16,21,22], whereas others have attributed these losses to more industrial-scale processes. These include plantation agriculture [23,24], large-scale infrastructure development [25–29], industrial mining and extractive industries [22,30,31], and large-scale pulp and paper plantations [32,33]. The findings from these studies are mostly based on case studies of areas or industries, rather than regional studies using high-resolution maps of land cover change. This lack of such high-resolution land cover and land cover change maps makes it difficult to quantify the role of specific drivers (e.g., particular crop types) in the loss of forests and other natural ecosystems.

Better land cover data, especially distinguishing smaller- and larger-scale processes and different crop types, can foster a better understanding of the key drivers of land cover change and thus inform stakeholder discussions and policy formulation. This can further shape discussion around decarbonizing food systems, uncoupling development from deforestation and the urgency of improving agricultural practices (such as regenerative farming and climate-smart agriculture) and other key mitigation measures for sustainability [34].

Here, we present a novel analysis of scale and context of land cover change in Central Africa using satellite-based earth observation and remote sensing techniques. These technologies have revolutionized agricultural mapping, providing near real time and low-cost tools for regional-scale land monitoring. Over recent decades, advancements in the spectral, spatial, and temporal resolution of satellite data, including big data storage, have improved crop and land cover mapping. Notably, the integration of optical and radar data has improved crop classification accuracy, especially in heterogeneous settings [35]. Synthetic Aperture Radar (SAR) products, unaffected by clouds and haze, are often combined with optical images to improve crop classification accuracy and class discrimination [36,37].

Recent studies, such as those by Blickensdörfer et al. [3] and Rao et al. [38], utilized dense time series data from Sentinel-1, Sentinel-2, and other satellites for crop classification in Germany and India, respectively. Deep learning (DL) techniques have further advanced crop mapping, using trainable semantic segmentation models that analyze large datasets. For example, Masolele et al. [39] applied deep learning to identify land use following deforestation in Africa. Similarly, Descals et al. [40] and Ozigis et al. [41] have also explored DL and satellite image integration to characterize small-scale and large-scale oil palm. Despite these advances, challenges remain, particularly in the generalization of models across regions due to geographical biases and insufficient training data.

In addition, previous studies such as Tyukavina et al. [16] assessing forest cover change to agriculture in CA have utilized sample-based estimates and other related methods to ascertain forest cover change. This study provides new perspectives on crop classification by scale, using 10 m spatial resolution data and integrating both optical and radar imagery. By doing so, the study supports efforts to balance agricultural development and forest conservation in Central Africa, utilizing Google Earth Engine and Sentinel data to classify crop types into small- and large-scale production.

2. Materials and Methods

2.1. Study Area

This study focused on six countries in the Central African Region: The Democratic Republic of Congo, Central African Republic, Republic of Congo, Gabon, Cameroon, and Equatorial Guinea (Figure 1). The population of the countries in the CAR has increased from 71,532,000 to 138,511,000 over the last two decades, while in the same period the production of commodity products and industrial agriculture has also risen two-fold [16].

2.2. Input Variables

2.2.1. Sentinel-1

We used Synthetic Aperture Radar (SAR) and Multispectral Optical images of the European Space Agency. The SAR data are a Sentinel-1 C Band Level 1 Ground Range Detected (GRD) product through Google Earth Engine (GEE). The image covering the study area consisted of reflected beams in the vertical–vertical (VV) and vertical–horizontal (VH) polarizations. The Sentinel-1 images were preprocessed to eliminate the effect of noise. The scenes were processed using the local incident angle (LIA) correction, after which the median value was computed for images between 1 January 2021 and 31 December 2023 for the ascending and descending scenes separately. The final composite is the average of the two orbit composites. We used the nearest neighbor resampling method to reproject the final image to a standard 10 m grid GRD output in the World Geographic System 1984 (WGS84) reference system.

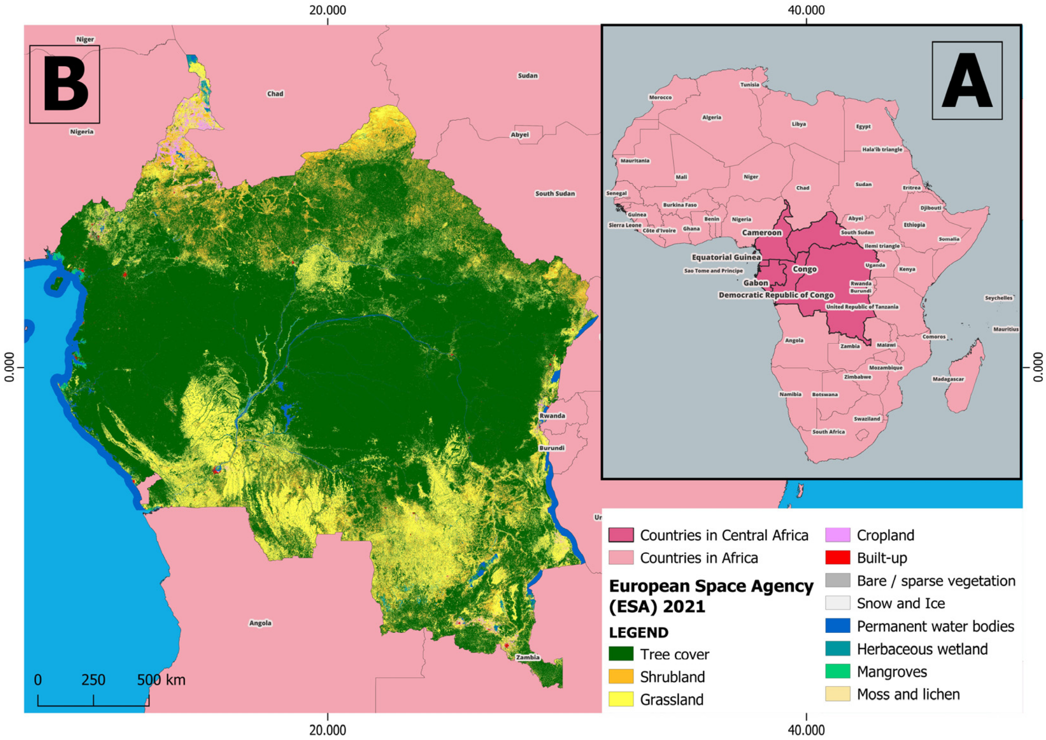

Figure 1. Study area coverage of Central Africa (CA) region with an approximate area of 373.3 million hectares (Mha). (**A**) The six CA countries (including Central Africa Republic, Republic of Congo, Democratic Republic of Congo, Cameroon, Equatorial Guinea, and Gabon around the Congo forest basin) within the Continent of Africa. (**B**) Recent land cover map for CA from the European Space Agency (ESA) Climate Change Initiative (CCI) land cover product, 2021.

2.2.2. Sentinel-2

The optical data from Sentinel-2 are also a product of the European Space Agency Copernicus Satellite program. We used Sentinel-2A (launched in June 2015) and 2B (launched in March 2017) carrying a single multispectral instrument with 13 spectral bands. This was to ensure more comprehensive and extensive coverage of the study area, which had significant all-year-round cloud presence. We used the Level-2A atmospheric-corrected product. All images were accessed and preprocessed through the Google Earth Engine API to generate a single image from the temporal observations from 1 January 2021 to 31 December 2024 for this study. Only Band 4 (red band) with a spatial resolution of 10 m was used. The rationale for the use of Band 4 was largely premised on the outcome of an experiment to identify the best Sentinel-1 and Sentinel-2 bands that provide the best visualization to discern all the classes of interest. This resulted in the selection of Sentinel-1 VV and VH and Sentinel-2 Band 4. Similarly, a previous study [40] in this regard also demonstrated the appropriateness of Sentinel-1 VV and VH and Sentinel-2 Band 4 integration in a random forest model. Following data preprocessing, we integrated this product with the preprocessed Sentinel-1 VV and VH backscatter products using a simple layer stacking approach to generate a Central Africa Region composite for the crop characterization segmentation process.

2.3. Reference Data

We obtained crop type ground truth reference point data (totaling 1540) from 140 parcels in Cameroon and DRC. Field parcels here represent the field boundary for a particular crop captured as polygon in GIS software (QGIS 3.28.2). The parcels were established during a field exercise conducted in Cameroon to establish crop types between 7 December 2023 and 19 January 2024. In addition, we obtained data to establish crop type parcels for Central DRC collected between 12 February 2020 and 17 February 2020 in the context of another study [42]. We generated 316 reference points used for the reference and validation of land cover maps developed by Copernicus Hotspot Land Cover Change (CHLCC) Explorer as part of our reference data (see Data Availability). The Reference Land Cover data represent the on-the-ground conditions of land cover features from 2015 to 2020, while the Land Cover Change data span 2000–2019. Both are archived and no longer updated, providing a valuable snapshot for understanding land cover and its transformation over time within critical ecological zones and biodiversity hotspot locations for Central Africa.

We extracted reference data from the tree cover class, which were validated using high-resolution planet images for the tree cover and other classes to ensure that they were still the corresponding classes during the model development phase. The planet image used in this study was a global monthly mosaic for February 2023 acquired at 5 m spatial resolution. We also obtained 3913 reference data points from the earth hub portal [43], mostly for non-tree (annual) crops based on their temporal profile. Appendix A shows the reference data obtained from field and secondary sources used in this study. We generated an additional 3860 sample points using a stratified random sampling method across the six countries of the study area to give an indication of other land cover types (based on the European Space Agency 2021 land cover data [44]) and reassigned the appropriate crop classes, making a total of 9313 reference data. The entire reference data can be accessed through the GEE platform.

2.4. Definition of Classes into Large- and Small-Scale Cultivation

In the context of this study, “scale” refers to the spatial extent and intensity of land use practices, where large-scale indicates mechanized, industrial-level production over extensive, uniform fields, while small-scale reflects smaller, often irregularly shaped plots operated by individual or community farmers with minimal mechanization. This definition of scale is key to distinguishing between land use classes in the classification scheme.

Large-scale tree crops (LSTCs) are generally cultivated landscapes with homogeneous green fields and a mean temporal NDVI value range of 0.5 to 0.7 [45], typically representing perennial crops. These areas are characterized by linear, rectilinear, and curvilinear paths across the fields, indicating high levels of mechanization and orderly cropping operations. Examples include rubber and sugarcane plantations.

Large-scale non-tree crops (LSNTCs) share similar landscape structure with LSTCs but differ in their mean annual NDVI values (0.2 to 0.4) [46], indicating sparse vegetation and non-evergreen crop types. Examples include rice, soy, and cereal plantations.

Large-scale oil palm (LSOP), also known as industrial oil palm, refers to oil palm fields produced on an industrial scale. These areas typically consist of large, homogeneous stands of oil palm trees separated by roads that form regular rectangular or geometric patterns [40,47–49].

Small-scale tree crops (SSTCs), by contrast, are cultivated by smallholders practicing subsistence or semi-subsistence agriculture. These fields tend to be patchy or clustered, without the regular patterns or road networks seen in large-scale operations. SSTCs are predominantly perennial, or a mix of perennial and annual crops, and are often found near forests due to various social, biophysical, and climatic influences [20].

Small-scale non-tree crops (SSNTCs) have spatial characteristics similar to SSTCs but differ in the types of crops cultivated, being primarily annuals with seasonal cycles. Small-scale oil palm plantations, typically managed by local farmers, are often located near settlements or alongside industrial plantations but lack the infrastructure, such as interlinking roads, found in LSOP. These plantations are usually under 5 hectares, with irregular shapes and sizes.

Finally, other land (OL) includes land cover types such as waterbodies, built-up areas, wetlands, bare land, rock outcrops, grasslands, and shrublands. These were grouped into a single class to minimize their interference with the main land use categories during classification. Tables A1 and A2 in Appendices C.1 and C.2, respectively, show the broad range of crops within the tree and non-tree crops category. Tree crops are typically permanent or semi-permanent, planted once and occupying the same land area for several years without the need for replanting after each annual harvest. In contrast, non-tree crops are temporary; they are sown and harvested within the same agricultural year, resulting in more dynamic changes in agricultural fields.

2.5. Training and Validation Samples

A total of 9313 reference sample points were obtained from both field and secondary datasets. The reference data were split using a 50:30:20 ratio for training, testing, and validating the U-Net model [50]. To this end, the number of sample sites for the LSTC, LSNTC, LSOP, SSTC, SSNTC, SSOP, and OL are 653, 846, 1680, 714, 1240, 320, and 3860, respectively, and 50 percent of these samples were used for model training, testing, and prediction. To assess the accuracy of the map product, we generated an additional 43,443 points using a stratified random sampling approach for the computation of the error matrix [51]. In this case, we generated 5 km-by-5 km grid cells across the entire CA region and later obtained the centroid of the polygon, which was then used to query existing field parcels and secondary datasets to generate the reference class. After this, the predicted class values were extracted to the same points and used for the validation process. We assessed the validity of the map based on the overall accuracy (OA), producer accuracy (PA), and user accuracy (UA). In addition, we also produced error-adjusted area estimates and 95 percent confidence intervals for both area estimates and accuracy assessment measures based on the method recommended by [52].

2.6. Forest Masking and Exclusion from Composite Image

The final integrated Sentinel-1 and Sentinel-2 images were tiles of 100 km × 100 km for the ease of implementation in the deep learning model. We masked out forest cover based on forest map provided by the Joint Research Council (JRC) for forest cover for 2023, while water and settlement were also masked out using the ESA Worldcover dataset from the integrated Sentinel 1 and Sentinel 2 product (see Data Availability section of this paper). The masking was conducted to limit the interference of obvious classes with similar spectral signatures and representations. All other classes, such as grassland, cropland, and shrubland, were left in the reference image since cultivated crop fields (especially small crop fields) exist within grass-, shrub-, and tree-covered areas [53]. The final image composite used for the classification is shown in Appendix B.

2.7. Image Classification Using the U-Net with ResNet-50 Encoder

We used a U-Net semantic segmentation deep learning model [53]. The U-Net model used a ResNet-50 encoder pre-trained on ImageNet and tailored for a 7-class semantic segmentation task. This methodological approach has been used in previous studies [40,41] and has proved very efficient in discriminating class labels in large-scale applications. The U-Net uses a ResNet-50 model as its encoder, which is responsible for down-sampling the input image to capture the context (high-level features). The encoder weights were pre-trained on the ImageNet dataset. In essence, the encoder was initialized with weights that were trained on the ImageNet dataset, which helped with faster convergence and better performance. The model produced an output with 7 channels, corresponding to the

7 classes. The training dataset from the reference data was further developed into a training mask by first creating a 10 km-by-10 km area around the point(s) of interest. After this, we used manual digitization to create the extent of the respective classes of tree- and non-tree crops based on a high-resolution image (as shown in Figure 2). The digitized shapefile extents were then converted into training masks of 10 km-by-10 km grids covering both the defined classes and other land cover types. In total, we developed a total of 350 labeled masks from the training data, as several reference points were within the proximity of the 10 km grids generated.

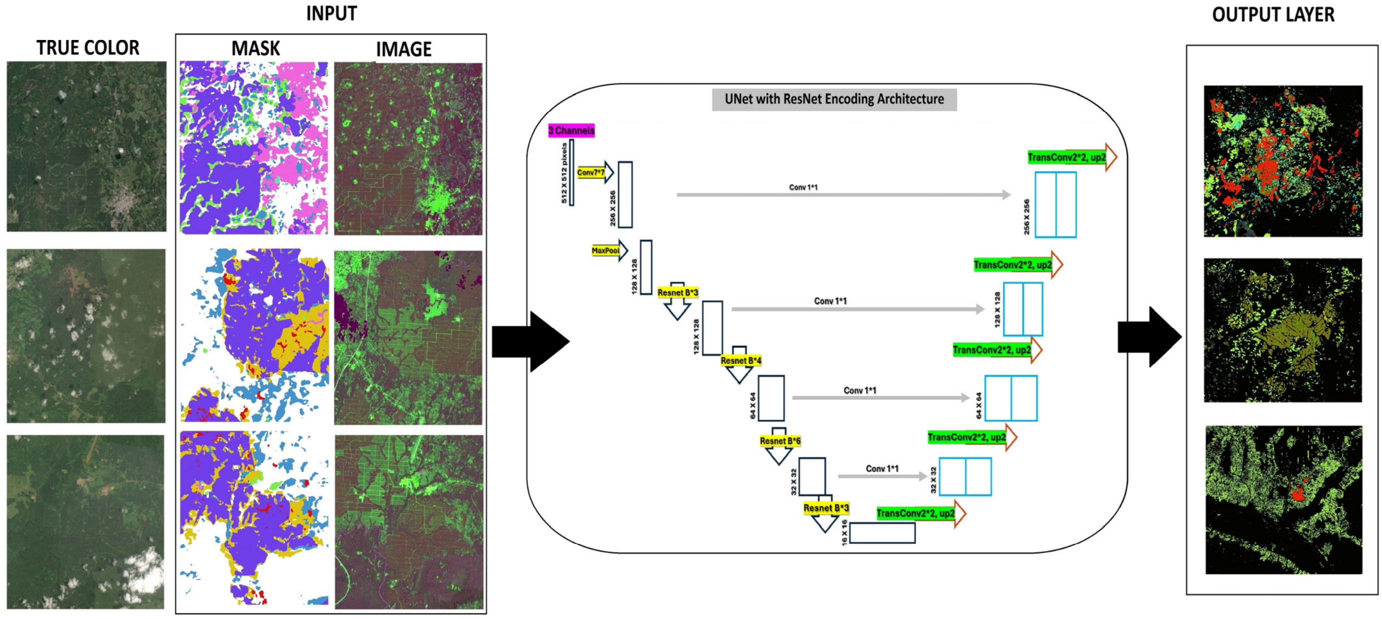

Figure 2. The semantic image segmentation process flowchart using the U-Net Resnet-50 encoder used for the image classification in this study.

2.8. Forest to Cropland Conversion

In addition, we also assessed the forest-to-cropland conversion in order to understand the change dynamics between the mapped classes and tropical moist forests in the region. This was carried out through an iterative and interactive process in GEE by using the developed crop cover distribution classes to mask over JRC tropical moist forest cover for the years 2000, 2005, 2010, 2015, 2020, and 2022.

3. Results

3.1. Classification Output and Class Accuracy

The results from the U-Net classification (as shown in Figure 3 and Table 1) show that OL was the dominant vegetation class (76.1 percent of the sampled area), followed by SSTC, SSNTC, LSNTC, LSTC, LSOP, and SSOP (see Data Availability). SSNTCs were concentrated in the northern and southern savannah belts of the region, while SSTCs were predominantly within the tropical moist forest zone. The accuracy assessment of the final map layer as shown in Table 1 indicates an 86.9 percent ± 0.32 OA. Classes with the highest PA and UA (above 50 percent) were OL, LSOP LSTC, and SSOP, while SSNTC and SSTC recorded a PA and UA below 50 percent. Specifically, OL had a PA and UA of 90 percent ± 0.3 and 99 percent ± 0.1, while LSOP and SSOP had a PA and UA of 88.3 percent ± 8.6 and 91.2 percent ± 2.5, and 82.7 percent ± 8.2 and 52.3 percent ± 8.6, respectively. Similarly, LSNTC and SSNTC had a PA and UA of 40.0 percent ± 7.4 and 17.8 percent ± 3.9, and 38.7 percent ± 2.9 and 20.9 percent ± 1.8, respectively. In addition, LSTC and SSTC had a PA and UA of 88.2 percent ± 5.1 and 60.5 percent ± 6.4, 63.5 percent ± 5.9 and 5.2 percent ± 0.8, respectively. Figure 3 shows the crop map layer for Central Africa by scale of production. Tables 1 and 2 show the error matrix and the spatial extent for each of the classes.

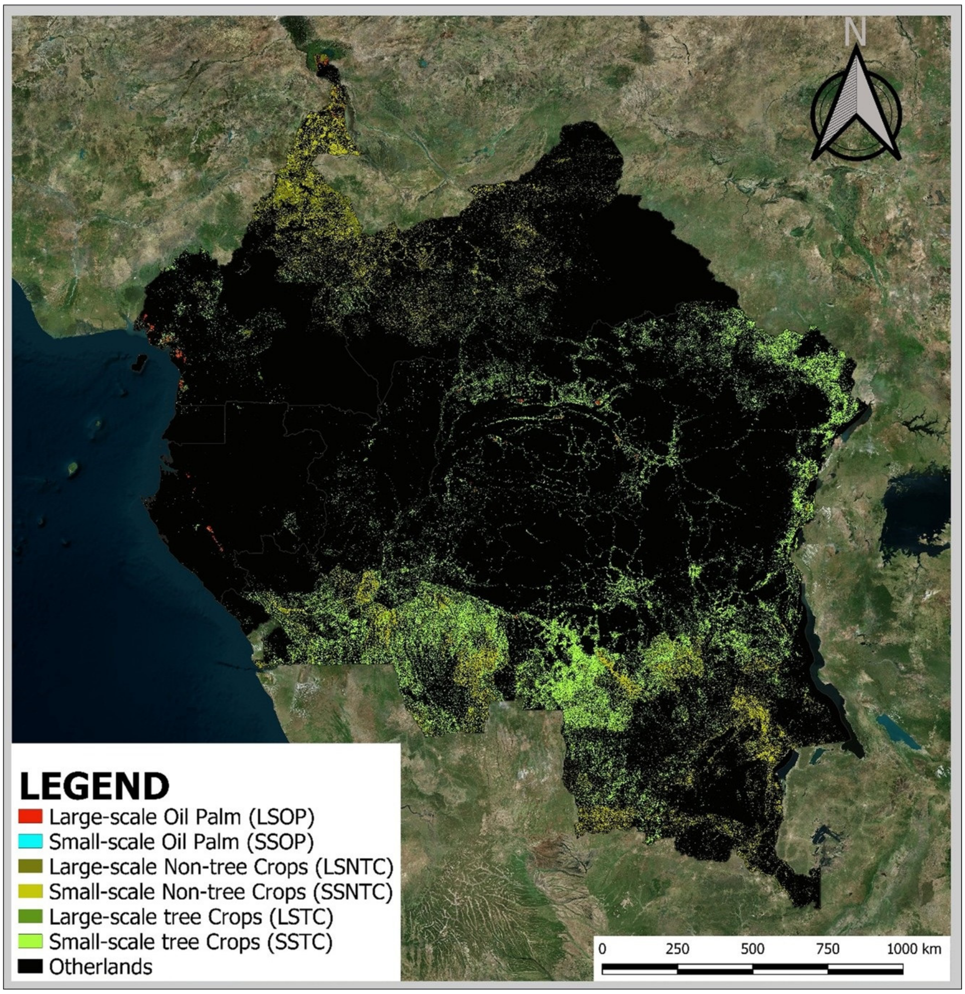

Figure 3. Land cover map generated in this study.

Table 1. Accuracy Assessment Result, Including User (UA) and Producer Accuracy (PA) and Total Number of Sampled Points.

Classes	OL	LSOP	SSOP	LSNTC	SSNTC	LSTC	SSTC	Total	UA	PA
OL	36,488	27	25	163	1557	65	2867	41,192	0.99	0.89
LSOP	20	455	34	0	0	6	0	515	0.91	0.88
SSOP	2	12	67	0	0	0	0	81	0.52	0.83
LSNTC	83	2	0	68	9	4	4	170	0.18	0.40
SSNTC	353	1	0	150	415	9	144	1072	0.21	0.39
LSTC	10	2	2	2	0	135	2	153	0.61	0.88
SSTC	86	0	0	0	5	4	165	260	0.05	0.63
Total	37,042	499	128	383	1986	223	3182	43,443		

3.2. Area Coverage and Estimate for Central Africa

Table 2 presents the results of the error-adjusted area estimates and the confidence intervals. This generally showed that, as expected, OL had the highest area coverage, with an estimated area of 3,555,998 ± 8011 km^2. The small-scale agricultural land had the second highest spatial extent; we recorded an area estimate of 293,248 ± 12,695 km^2 and 164,823 ± 4224 km^2 for small-scale tree crops and small-scale non-tree crops, respectively. Large-scale crops including trees and non-trees had area coverages of 7436 ± 280 km^2 and 20,153 ± 1195 km^2, respectively. Large industrial oil palm plantations and small-scale oil palm had an area coverage of 2812 ± 57 km^2 and 1386 ± 83 km^2, respectively.

Table 2. Adjusted Area and Confidence Interval for Crop Cover Classes.

Crop Cover Classes	Adjusted Area (m^2)	95% C.I.
Other Land	3,555,997.91	8011.09
Large-scale Oil Palm	2811.80	57.24
Small-scale Oil Palm	1385.72	83.38
Large-scale Non-tree Crops	20,152.83	1194.84
Small-scale Non-tree Crops	164,823.92	4223.87
Large-scale Tree Crops	7436.12	279.72
Small-scale Tree Crops	293,248.81	12,694.77

3.3. Crop Cover Characteristics

The extent of the tree crop class (for large- and small-scale cultivation) aligns with the corresponding spatial extent in the high spatial resolution satellite images (as shown in Figure 4). However, the results also suggest the presence of mixed cultivation within large plantations, as several large-scale tree crop areas had patches of SSNTCs within them. The observed heterogeneity in the classified extent of LSTCs is based on the diverse spectral difference in the region. Similarly, we also observed that LSTC plantations are within densely vegetated areas.

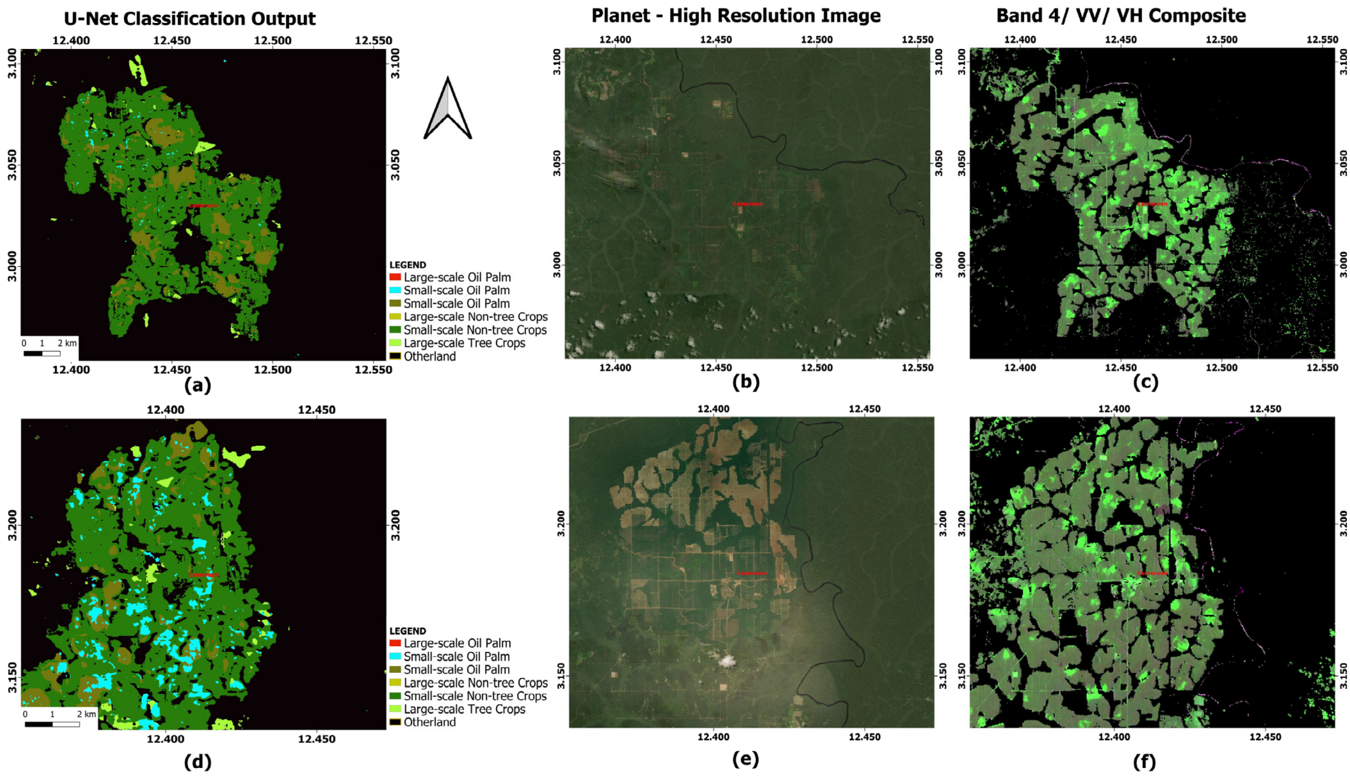

Figure 4. Example of an LSTC in Cameroon. (**a**,**d**) are the classified extents of observed LSTCs. (**b**,**e**) are high-resolution satellite images of areas shown in (**a**,**e**). (**c**,**f**) are the false color composites of the images used for the classification.

Conversely, the results of the LSNTCs (as shown in Figures 5 and 6) indicate substantial small-scale agriculture carried out around detected LSTC plantations. While good spatial alignment between detected LSNTC plantations and the corresponding high-resolution images were observed, the results indicate considerable mixed cropping activities within them. This is largely premised on the diverse spectral characteristics within the LSNTC areas (as shown in Figures 4a,d and 5a,d), suggesting the presence of different crop types, mixed farming, or an uneven planting date within LSNTC areas.

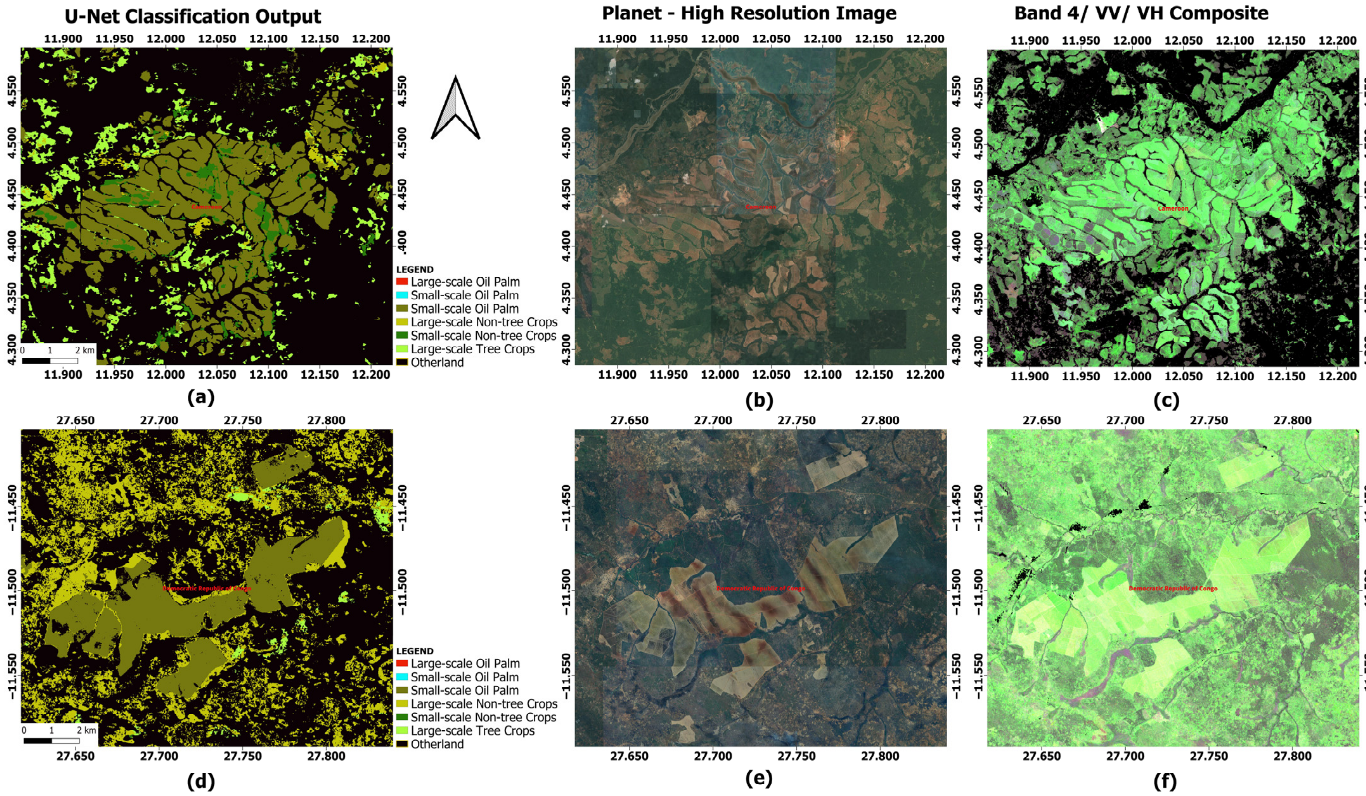

Figure 5. Example of an LSNTC. (**a**,**d**) are classified extents of LSNTCs, with observed SSTC and SSNTC patches around them. (**b**,**e**) are high-resolution satellite images of areas shown in (**a**,**e**). (**c**,**f**) are the false color composites of the images used for the classification.

SSTCs were primarily observed in the central part of the region close to the forest areas, suggesting favorable climatic and humid conditions as a driving factor to grow perennial crops like rubber, coffee, and tea. Figure 7 is an example of the clear disparity between detected SSTCs and SSNTCs, while Figure 7a shows extreme greenness and crop patches, and Figure 7d shows extreme dryness and crop patches. In addition, areas classified as SSTC were also observed to have patches of plain fields (suggesting potential annual crops) within predominantly SSTC areas, thereby implying potential mixed cropping practices.

3.4. Country Level Assessment of Crop Cover

The results for individual countries of the CA (as shown in Table 3) indicate that DRC had the largest area coverage of OL with 1,967,400 ± 5594 km^2, followed by CAR with 576,274 ± 4471 km^2. Similarly, the area coverage of OL in Congo was 318,680 ± 1383 km^2, while Gabon and Eq. Guinea had 26,886 ± 548 km^2 and 262,360 ± 1046 km^2, respectively. In terms of LSTC, the results show that DRC had the highest spatial extent of LSTC cover with an area estimate of 4000 ± 296 km^2, followed by Cameroon with 1819 ± 79 km^2, while Gabon and CAR had 180 ± 17 km^2 and 530 ± 162 km^2, respectively.

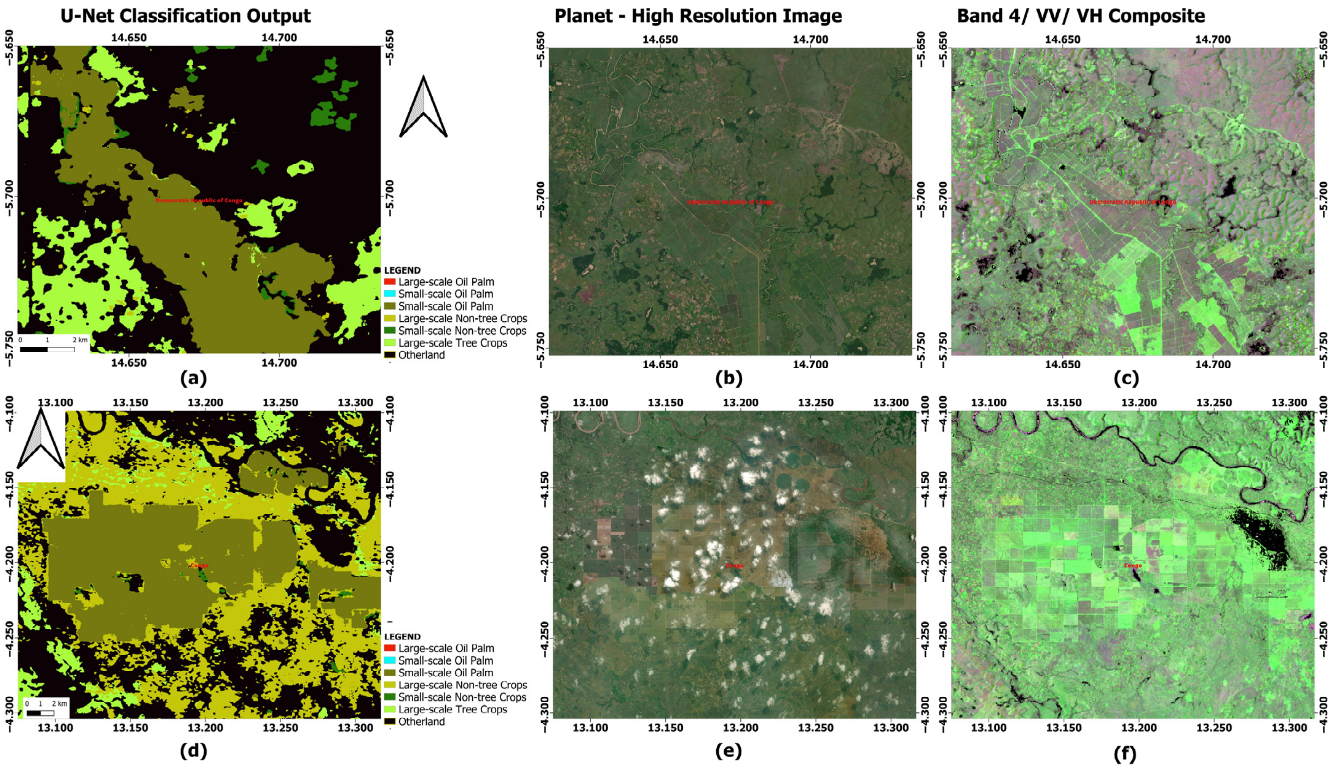

Figure 6. Example of an LSNTC in DRC. (**a**,**d**) are the classified extents of LSNTCs, with observed SSTC and SSNTC patches around them. (**b**,**e**) are high-resolution satellite images of areas shown in (**a**,**e**). (**c**,**f**) are the false color composites of the images used for the classification.

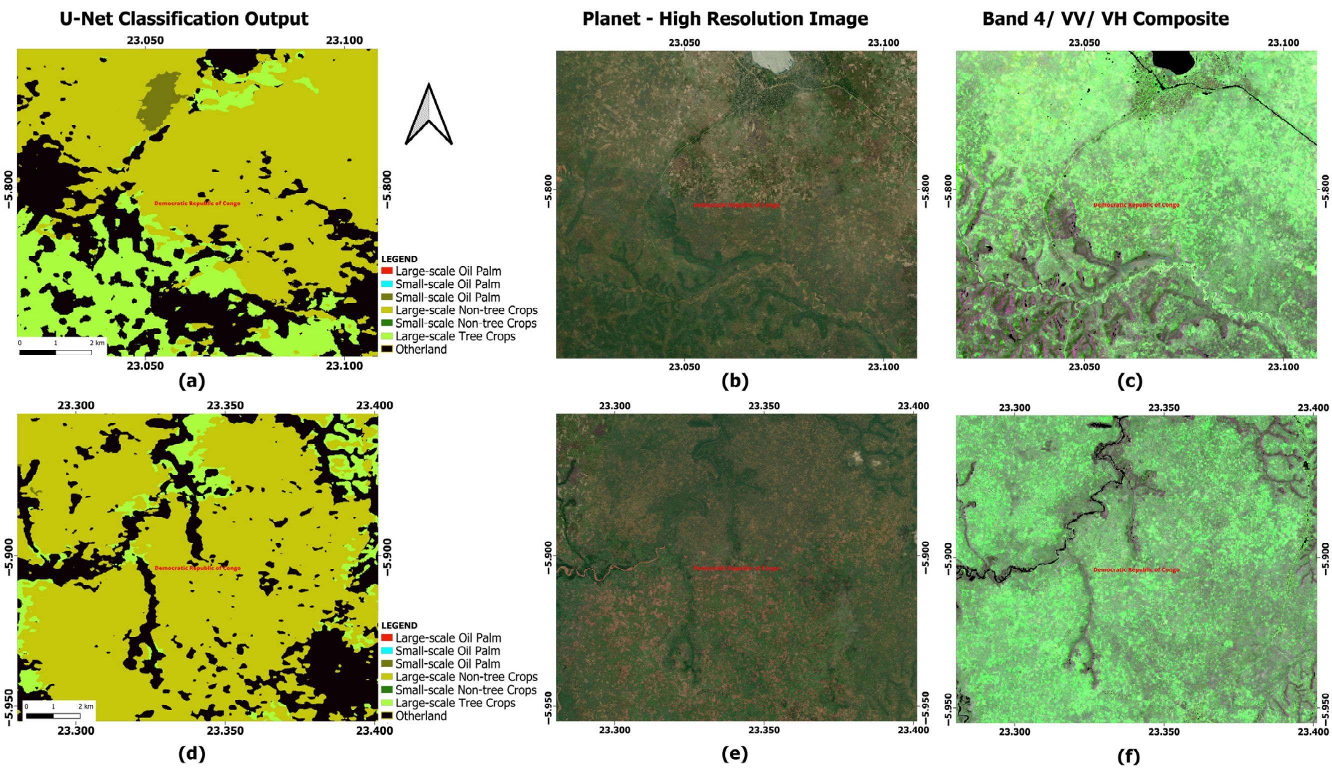

Figure 7. An example of SSTC and SSNTC. (**a**,**d**) are the output from the image classification. (**b**,**e**) are the high-resolution satellite images of (**a**,**d**). (**c**,**f**) are the false color composites of the image used for the classification. This showed extreme greenness in the SSTC patches and extreme dryness in the SSNTC crop patches.

Table 3. Adjusted Area and Confidence Interval of Crop Cover Classes within the Countries of Central Africa.

Classes	Adjusted Area (km^2)						Confidence Interval (C.I.)					
	Congo	CAR	Gabon	DRC	Cam	Eq.G	Congo	CAR	Gabon	DRC	Cam	Eq. G
OL	318,680	576,274	262,360	1,967,400	404,354.85	26,885.65	1383.2	4470.73	1045.72	5593.59	2852.61	547.77
LSOP	10	-	400	700	1646.38	-	1.52	-	34.69	26.43	36.55	-
SSOP	50	-	130	600	639.85	-	-	-	25.48	158.71	44.41	-
LSNTC	350	1393	120	2200	16,051.43	71.66	61.39	275.49	35	185.96	1762.21	-
SSNTC	7510	32,992	40	90,500	33,830.49	-	936.82	2020	7.3	3191.73	1691.57	-
LSTC	0	530	180	4000	1818.80	-	-	162.28	17.82	296.3	78.77	-
SSTC	13,100	8396	790	263,800	7163.49	-	2818.67	1299.93	244.77	14,646.35	625.89	-

For LSNTC, the results showed that DRC had the largest area coverage with an area estimate of 2200 ± 186 km^2, while Cameroon had 1646 ± 37 km^2. In contrast, Equatorial Guinea had the least coverage of LSNTCs with 72 km^2. Large-area coverages of SSNTCs were observed in DRC, Cameroon, and CAR with area estimates of 90,500 ± 3192 km^2, 33,830 ± 1692 km^2, and 32,992 ± 2020 km^2, respectively, while Congo and Gabon had lower SSNTC coverages with area estimates of 7510 ± 937 km^2 and 40 ± 7 km^2, respectively. DRC had the highest area cover of SSTC with an estimate of 263,800 ± 14,646 km^2, while Congo, CAR, and Cameroon recorded area estimates of 13,100 ± 2819 km^2, 8396 ± 1300 km^2, and 7163 ± 625 km^2. However, in contrast, no area estimates for SSNTC, LSTC, or SSTC were recorded for Equatorial Guinea owing to the small size of the country and reported small-scale agricultural activities.

3.5. Assessment of Crop Encroachment into Forest

The results (as shown in Figure 8) show that in most countries, the conversion of forest into agricultural land has declined over time (Figure 7). The conversion of forest to SSTC was observed to be the most prominent across the region. Of the six countries assessed, DRC had the highest conversion rate of forest to SSTC with the highest conversion occurring between 2000 and 2005, and 2010 and 2015, with an area coverage of 60,000 km^2 by 2015, before experiencing a decline and reaching a total of 2474 km^2 by 2022. This was closely followed by Congo, where SSTC conversion to forest steadily increased from 400 km^2 between 2000 and 2005 and reached its peak by 2015, with an area coverage of 1237 km^2.

We also observed a similar steady increase in SSTC-induced forest loss in Cameroon, where forest loss between 2000 and 2005 reached 270 km^2 and steadily rose to 405 km^2 by the end of 2020. We observed a unique convergence of forest loss to SSTC between 2010 and 2020 in Equatorial Guinea, with a total of 4.5 km^2, while in Gabon, LSOP and SSTC were the key drivers with a combined total of 265 km^2 between 2010 and 2020. In contrast, we observed a sharp temporal decline in SSNTC- and SSTC-induced forest loss in CAR. This started with a total of 48 km^2 between 2000 and 2005 and later reduced to 0.1 km^2 by the end of 2022.

With respect to SSNTC, the results showed that DRC had the highest forest-to-SSNTC conversion, with an estimated area of 374 km^2 between 2000 and 2005, and steadily declined to 230 km^2 between 2010 and 2015 before reaching its minimum of 19.6 km^2 by 2022. We observed a dynamic trend in forest conversion to SSNTC in Congo. The SSNTC-induced forest loss area rose from 27 km^2 between 2000 and 2005 to 75 km^2 by 2020, after which a significant decline of 3 km^2 was observed by 2022. The countries with the lowest forest-to-SSNTC conversion rates were Cameroon, CAR, and Gabon with a mean of 20 km^2, which declined to 0.3 km^2 between 2000 and 2022, respectively, while none was observed in Equatorial Guinea.

Figure 8. Bar plot showing the total area of forest converted to crop cover type by country between 2000 and 2005, 2005 and 2010, 2010 and 2015, 2015 and 2020, and 2020 and 2022. Results show extensive cultivation of SSTCs across the countries of CA, with the profoundly highest in DRC, Congo, and Cameroon. Statistics can be accessed through GEE.

A similar trend was observed for LSNTC, where DRC also had the highest forest-to-LSNTC conversion rate, with an area of 22 km^2 between 2000 and 2005, but gradually reduced to 1 km^2 by the end of 2022. LSNTC-induced forest loss in Cameroon had a dynamic trend as the area coverage ranged between 5.1 km^2, 11.6 km^2, and 17 km^2, and a sharp decline to 1.2 km^2 in 2005, 2010, 2020, and 2022, respectively. Congo also exhibited a similar trend but with a peak convergence period between 2010 and 2015 with an area of 8.3 km^2, before declining to 0.4 km^2 by 2022. The countries with the lowest conversion rates were Gabon, CAR, and Equatorial Guinea, with an average of 0.6 km^2 and 0.03 km^2, between the years 2000 and 2005, and 2020 and 2022, respectively. DRC, Cameroon, and Congo had the highest forest-to-LSTC conversion rate of 80 km^2, 19 km^2, and 14 km^2, respectively, between 2000 and 2005. These figures increased tremendously in all three countries to 90 km^2, 111 km^2, and 25 km^2 between 2015 and 2020, and by the year 2022, the total area decline to 20 km^2, 10 km^2, and 8.5 km^2, respectively. In contrast, CAR had the lowest forest-to-LSTC conversion area of 0.1 km^2 and no variation occurred in the years 2000 and 2022, respectively, while none was recorded for Equatorial Guinea.

4. Discussion

4.1. The Results from the Study

While the overall accuracy assessment of our study was 86.9 percent, we observed the significant misclassification of SSNTC reference sites as OL (i.e., grassland and shrubland), LSTC, and SSTC. In addition, significant errors of omission often led to LSNTC being misclassified as OL, LSOP, and SSNTC. This may be related to the diverse farming practices in the region, where farmers frequently engage in mixed farming [54–57], rotational farming [58,59], and intercropping [60], cultivating food crops (such as cassava, maize, and yam) alongside tree crops to meet both short-term livelihood needs and long-term income goals [61–64]. Furthermore, we also observed the misclassification of shrubland as SSNTC and LSNTC, mostly in the savanna-dominated (northern and southern) part of the region, especially in central parts of Cameroon, CAR, and the southern parts of DRC. We believe this could be because of the dryland ecosystem in the northern and southern part of the

CA region [65], which is characterized by low spectral diversity between grassland and cropland [66], causing a problem for the classifier.

Similarly, the results also show a small expanse of savanna (presumed to be rangeland and pastoral land) classified as SSNTC, mostly within the southern DRC. However, further investigation suggests that these areas are potentially grazing fields exhibiting similar spectral characteristics as annual crop fields across the region [67–69]. Ref. [69] particularly noted the accelerated conversion of grasslands, woodlands, and forests to croplands and pastures in the recent decade, particularly in the tropics, highlighting the close association between pastoral land, rangeland, and cultivated cropland landscapes. Moreover, while Cameroon, DRC, Congo, and CAR boast large expanses of LSNTCs and LSTCs of at least 1200 km^2 and 530 km^2, respectively, Gabon and Equatorial Guinea, on the other hand, have considerably small extents of both LSNTCs and LSTCs, highlighting the lower food crop production and the heavy reliance on food importation in both countries [9]. The major factors driving this trend are the limited agricultural land (as can be seen in Figure 6) in these countries and the large predominance of forest cover, rapid urbanization, and reliance on crude oil export [70].

4.2. Limitation of the Study

A major limitation encountered is the inaccessibility to sufficient ground reference data for specific tree and non-tree crop types. This affected our ability to expressly identify crop fields following the classification and was likely responsible for the observed disparity among several comparisons of SSNTC, OL, and LSTC. However, this product, developed to the best of our knowledge, is the first regional classification and crop scale characterization map for Central Africa. This product, therefore, presents a tool that can guide decision-making activities, and future studies can leverage its classes to gain insights into identifying areas currently cultivated in the region.

The observed spatial assessment and comparison with cropland extents from other studies such as [39,43,71] suggest a lower cropland area spatial coverage compared to this study, suggesting a sharp increase in cropping activities (especially SSNTC and SSTC) in the region. This aligns with observations of previous studies [16,21,22,72] where small-scale rural cropping has been identified as a key driver of deforestation and rapid expansion. A possible reason for this increasing trend is thought to be associated with increased population growth, the rapid expansion of the local production of crops to meet the demands of international export markets, and others (such as infrastructural development for roads and amenities).

4.3. Implications for Forest Change and Biodiversity Conservation

The results from this study show that small-scale agriculture is much larger than large-scale and plantation agriculture, and that encroachment into forest steadily increased in the last two decades. This corroborates results from previous studies that show significant agricultural encroachment into biodiversity-rich areas [15,16]. Small-scale agriculture is generally driven by subsistence farming in the traditional African farming ecosystem, where lands are cultivated over a period, then left to lie fallow for seven to ten years [73], consequently increasing the demand for new land for farming [74]. In contrast, large-scale plantations and agricultural operations, typically used to cultivate tree crops such as oil palm, cocoa, and rubber, tend to remain stable over long periods. Once established, they involve relatively minimal periodic interference with the forest ecosystem. The need for small-scale agriculture cannot be overlooked as it is being carried out by rural communities to meet the attendant needs of food production and energy to sustain livelihood.

Nevertheless, the expansion of small-scale agriculture in the Congo forest region poses both challenges and opportunities for biodiversity conservation. On one hand, unsustainable practices, such as slash-and-burn agriculture, contribute to habitat destruction, fragmentation, and biodiversity loss. On the other hand, sustainable farming practices can support biodiversity by maintaining ecosystem services, such as pollination, soil fertility, and water regulation [30]. It is therefore suggested that both new and existing policy frameworks must address and balance the demand for land to support subsistence agriculture. At the same time, they should ensure the conservation of forest ecosystems and promote biodiversity within agricultural landscapes. This requires integrating biodiversity conservation into agricultural policies and initiatives and a multi-faceted approach.

4.4. Policy Recommendations That Integrate All Facets

The nexus between small-scale and large-scale drivers of deforestation and its related biodiversity loss in Central African is of particular concern as small-scale farmers contribute between 50 and 70 percent of the total food supply, while industrialized farming also provides the necessary supply chain to support state economic activities. The WWF has noted that conversion to agricultural land and mining are two key threats to the Congo Basin Forests, including fuel wood and poaching. To address these threats, the Congo Basin countries under the African Forest Landscape Restoration Initiative (AF100) have committed to restoring degraded land, including 12.5 million hectares in Cameroon, 8 million hectares in DRC, 3.5 million hectares in Central African Republic, and 2 million hectares in Congo ROC [18].

While the existing policy frameworks struggle to achieve the full realization of biodiversity conservation with specific recourse to small-scale agriculture [75], evidence from this study suggests a decline over the past two decades. However, certain measures must be in place to conserve this rich forest. Collaborative governance, enhanced funding mechanisms, and capacity-building programs are few among the essential to ensure that smallholder farmers adopt sustainable practices. Moreover, aligning agricultural development goals with biodiversity conservation objectives will create synergies that benefit both people and nature. While existing frameworks and initiatives provide a foundation for progress, their effectiveness depends on robust implementation and monitoring. Strengthening institutional capacity, enhancing stakeholder engagement, and fostering cross-sectoral collaboration are critical steps toward achieving sustainable outcomes in the Congo forest region.

In addition, more investment in the rural market infrastructure will enable smallholder farmers to commercialize with ease, improve the availability of perishable products [76] while also fortifying local supply chain processes. Since different food systems offer different transformation pathways, there is generally the assurance that the local food supply chain either follows an agroecological direction based on the redesign and diversification of agroecosystems or follows new technology pathways characterized by greater economic prospects [77].

Similarly, there is a pressing need for a comprehensive transformation of food systems in the region. This transformation should involve governments, farmers, industries, financial institutions, scientists, and civil society working together to identify situations where the negative impacts of agricultural expansion outweigh its benefits, considering environmental, social, and economic factors. Such evaluations can guide the adoption of greener and more sustainable farming practices [78]. In addition, strong governance and increased conservation incentives can support land-sparing strategies [79] and enable targeted development planning that avoids placing key infrastructure, such as roads and buildings, in core forest areas.

Enhanced agricultural practices are also essential to mitigate soil degradation and other adverse environmental impacts while also contributing to climate solutions [80]. Key strategies include expanding the use of agroforestry systems, which are considered more resilient than monoculture-based annual cropping [81], and incorporating nitrogen-fixing legumes that improve soil fertility, reduce dependency on synthetic fertilizers, and minimize nutrient runoff [82].

5. Conclusions

In conclusion, we provide a unique and retrospective perspective on crop production scale for CA. We used both Sentinel-1 and Sentinel-2 satellite image composite for 2023 to distinguish LSOP, SSOP, LSNTC, SSNTC, LSTC, and SSTC based on a U-Net with a Resnet encoding deep learning model. The results obtained showed greater expansion of cropland (especially SSNTC and SSTC) than previously reported in CA, suggesting more local- and rural-based activities in the agricultural sector. The results also suggests less large-scale agricultural production in Gabon and Equatorial Guinea owing to the limited observed LSTC and LSNTC compared to Cameroon and DRC, which had extensive large-scale and small-scale crop cultivation. In addition, the study observed a steady rise in the encroachment of forest by small-scale agriculture in the last two decades, while the existing policy framework showed gaps in addressing small-scale agricultural expansion, necessitating robust recommendations to further strengthen forest conservation in the region.

With limited field training data across the extensive coverage of the six countries, this study was able to produce the very first crop production scale map for Central Africa, which can further guide policymaking actions, foster intervention activities, and strengthen various discussions around building resilience against climate change. Future studies can leverage the results provided to identify areas where crop cultivation activities are intensely being carried out within the region and further improve the results presented by utilizing an expanded classification scheme.

Author Contributions: S.W., E.M. and Z.S. conceived the ideas; S.W., M.S.O., A.D., E.M. and Z.S. designed the methodology; M.S.O., S.W. and A.D. collected the data; M.S.O. and M.A. analyzed the data; M.S.O., S.W., A.D., E.M. and Z.S. led the writing of the manuscript; M.S.O., S.W., E.M. and D.S. edited the manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Results from this study can be accessed through the Google Earth engine repository (GEE, https://ee-cropscalecharacterization.projects.earthengine.app/view/cropscalecharacterizationmap). The Copernicus Hotspot Land Cover Change Explorer can be accessed using this link (https://worldcover2021.esa.int/viewer, accessed on 2 April 2023). The ESA worldcover dataset for the year 2023 can be accessed using this link. The Tropical Moist Forest (TMF) Data used for the forest change analysis was accessed through the European Commission's Joint Research Centre tropical moist forests (TMF) annual forest cover change (https://forobs.jrc.ec.europa.eu/TMF/explorer, accessed on 2 April 2023).

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Conflicts of Interest: Author Erik Meijaard was employed by the company Borneo Futures. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Reference data (including field and secondary sources) used in this study.

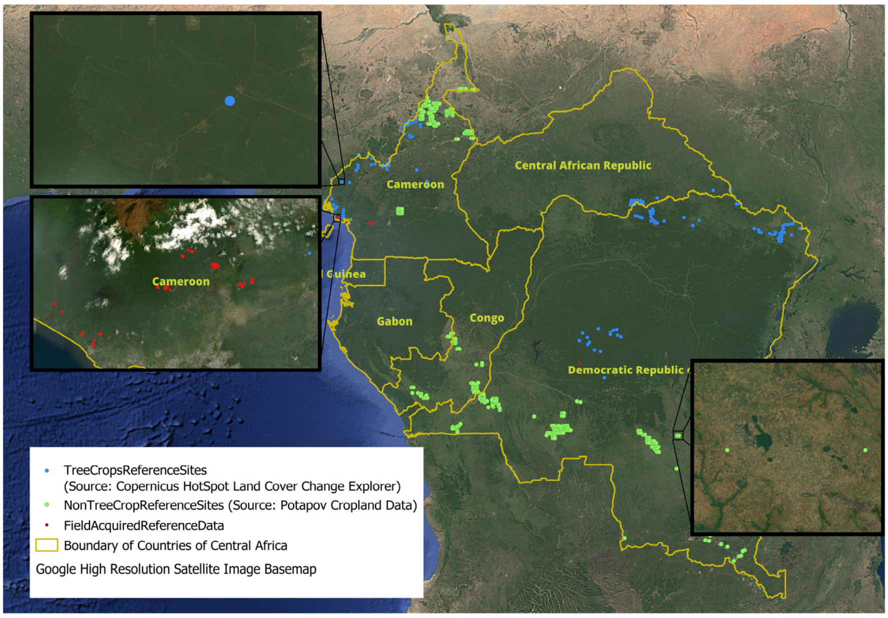

Figure A1. Showing the reference site location for the Tree Crops, Non-tree Crops and Field conducted surveys used in this study.

Appendix B

The final Sentinel-1 and -2 composites used for classification.

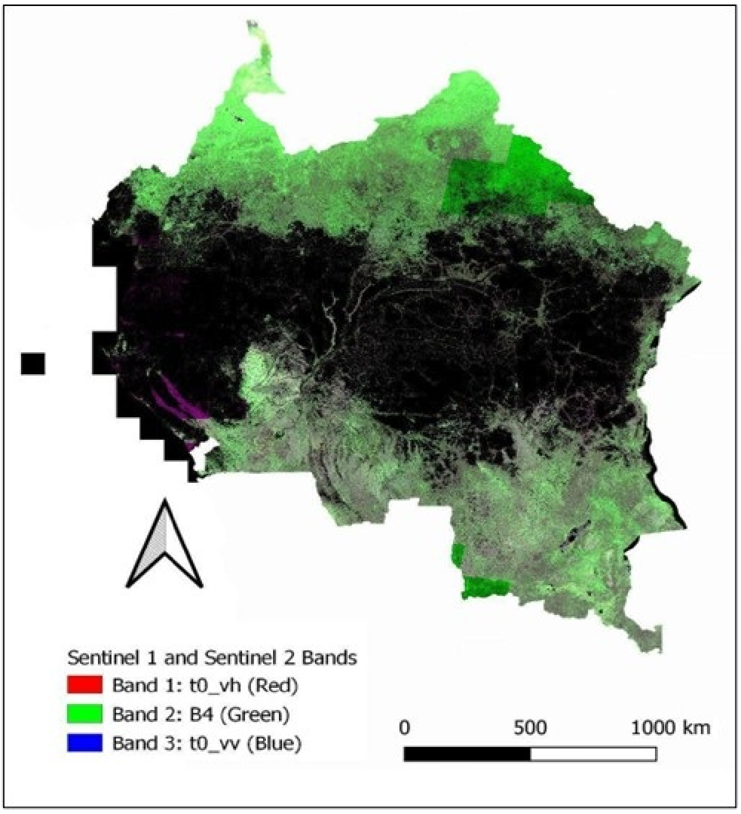

Figure A2. Showing the final image composite generated from Sentinel-1 VH, Sentinel-1 VV and Sentinel-2 (Red Band) mosaics used for the Image Classification in this study.

Appendix C

Crop types within the broad crop classes of tree and non-tree crops.

Appendix C.1

Table A1. Crop types within the tree crop class, importance, and uses of the crops.

Tree Crop	Countries	Importance	Uses
Cocoa	Cameroon, Gabon, DRC	Significant export crop, especially in Cameroon.	Processed into cocoa butter, powder, and chocolate.
Coffee	Cameroon, DRC, CAR	Major cash crop, particularly Robusta coffee.	Beans processed into coffee.
Palm Oil	Cameroon, Gabon, DRC, CAR	Critical for domestic consumption and export.	Used in cooking, food products, cosmetics, and biofuel.
Rubber	Cameroon, Gabon, DRC	Key industrial crop.	Used in tires, footwear, and industrial products.
Banana and Plantain	Cameroon, DRC, Gabon, CAR	Staple food and important cash crops.	Consumed as staple food and in various forms.
Timber Trees	Cameroon, Gabon, DRC, CAR	Major export product from tropical forests.	Used in furniture, construction, and wood products.
Kola Nut	DRC, CAR, DRC	Culturally significant and widely used.	Chewed as a stimulant and in traditional medicine.
Citrus Fruits	Cameroon, DRC, Gabon	Important for local consumption and export.	Consumed fresh, in juices, and food products.
Mango	Cameroon, Gabon, DRC	Popular fruit crop with regional demand.	Consumed fresh, in juices, jams, and dried fruits.
Cashew	DRC, Cameroon	Growing cash crop with increasing demand.	Processed nuts and cashew apple for beverages.
Avocado	Cameroon, Gabon, DRC	Gaining popularity due to high demand.	Consumed fresh, in salads, and for oil production.
Shea	DRC, CAR	Source of shea butter; valuable in cosmetics and food.	Used in cosmetics, cooking, and traditional medicine.
Papaya	Cameroon, Gabon, DRC	Widely consumed fruit with export potential.	Consumed fresh, in juices, and as an ingredient.

Appendix C.2

Table A2. Crop types within the Non-tree Crop group of class, importance and uses of the crops.

Crop	Countries	Importance	Uses
Maize	All Central African countries	Staple food; major carbohydrate source.	Porridge, boiled, roasted, and animal feed.
Cassava	All Central African countries	Key staple; drought resistant.	Flour, garri, and thickening soups.
Yams	Cameroon, Gabon, DRC	Culturally significant; used in traditional ceremonies.	Boiled, fried, and fufu.

Table A2. *Cont.*

Crop	Countries	Importance	Uses
Rice	Wetter regions of Central Africa	Increasing staple and high imports.	Cooked grain accompanying sauces and stews.
Sorghum	Semi-arid regions of Central Africa	Drought-tolerant and critical in less fertile regions.	Local beers, porridges, and flour.
Millet	Drier parts of Central Africa	Essential for food security and drought resistance.	Porridge, traditional beers, and bread.
Peanuts	Throughout Central Africa	Significant protein and economic value.	Raw, roasted, soups, sauces, oil, and peanut butter.
Beans	All Central African countries	Important protein source.	Side or main dish, with rice or maize, and soups.
Soybeans	Cameroon, DRC	Rising importance for protein and oil.	Cooking oil, animal feed, and food ingredients.

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