Are deforestation and degradation in the Congo Basin on the rise? An analysis of recent trends and associated direct drivers.

Aurélie Shapiro (aurelie.shapiro@fao.org)
Food and Agriculture Organization of the United Nations https://orcid.org/0000-0001-9693-9394
Rémi d'Annunzio
Food and Agriculture Organization of the United Nations
Quentin Jungers
Université Catholique de Louvain
Baudouin Desclée
European Commission, Joint Research Center
Héritier Kondjo
Food and Agriculture Organization of the United Nations
Josefina Mbulito Iyanga
Food and Agriculture Organization of the United Nations
Fancis Gangyo
Food and Agriculture Organization of the United Nations
Pierrick Rambaud
Food and Agriculture Organization of the United Nations
Denis Sonwa
Center for International Forestry Research (CIFOR)
Benoît Mertens
Institut de Recherche pour le Développement (IRD)
Elisée Tchana
Food and Agricultural Organization of the United Nations (FAO)
Conan Obame
Gabonese Agency for Space Studies and Observation (AGEOS)
Damase Khasa
Université Laval
Clement Bougouin
European Commission, Joint Research Center
Tatiana Nana
United States Forest Service
Chérubins Ouissika

Ministère de l’Economie Forestière
Daddy Kipute
Université Officielle de Mbujimayi

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Authors

1. Aurélie Shapiro (ORCID: https://orcid.org/0000-0001-9693-9394), Food and Agriculture Organization of the United Nations (FAO), Viale delle Terme di Caracalla, 00153 Rome, Italy. Italy. +39 06 57051. aurelie.shapiro@fao.org*
2. Rémi d'Annunzio, Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.
3. Quentin Jungers, Université Catholique de Louvain, Observatoire des Forêts d'Afrique Centrale, Kinshasa, République Démocratique du Congo
4. Baudouin Desclée, European Commission, Joint Research Centre, Ispra, Italy.
5. Heritier Koy Kondjo, Food and Agriculture Organization of the United Nations (FAO), Kinshasa, Democratic Republic of the Congo
6. Josefina Mbulito Iyanga, Organización de las Naciones Unidas para la Alimentación y la Agricultura (FAO), Malabo, Equatorial Guinea.
7. Francis Inicko Gangyo, Food and Agriculture Organization of the United Nations (FAO), Bangui, Central African Republic.
8. Pierrick Rambaud, Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.
9. Denis Jean Sonwa, CIFOR (Center for International Forestry Research), Yaoundé, Cameroun.
10. Benoît Mertens, Institut de Recherche pour le Développement (IRD), Montpellier, France
11. Elisée Tchana, Food and Agriculture Organization of the United Nations (FAO). Rome, Italy.
12. Conan Vassily OBAME, Gabonese Agency for Space Studies and Observation (AGEOS), Libreville, Gabon.
13. Damase Khasa, Centre for Forest Research, Department of Wood and Forest Sciences, Université Laval, Québec City, Québec.
14. Clement Bourgoin European Commission, Joint Research Centre, Ispra, Italy.
15. Tatiana Nana, United States Forest Service (USFS), Brazzaville, Congo
16. Ouissika Chérubins Brice, Ministère de l'Economie Forestière, République du Congo, Brazzaville, Congo
17. Daddy D. KIPUTE, Université Officielle de Mbujimayi, Mbujimayi, Democratic Republic of the Congo.

Abstract

The Congo Basin hosts the largest continuous tract of forest in Africa, regulating global climate while providing essential resources and livelihoods for humans, while harbouring extensive biodiversity. The threats to these forests are expected to increase. A regional collaborative effort has produced the first systematically validated remote sensing assessment of deforestation and degradation in six central African countries for 2015-2020 period, along with a quantification of associated direct drivers of change. Deforestation and degradation (DD) are not observed to be increasing since 2017 are occurring primarily in already fragmented corridor forests. We assess multiple, overlapping drivers and show that the rural complex, a combination of small-scale agriculture, villages, and roads contributes to the majority of DD. Industrial drivers such as mining and forestry are far less common, although their impacts on carbon and biodiversity could be more permanent and significant than

informal activities. Artisanal forestry is the only driver that is observed to be consistently increasing over time. Our assessment produces information relevant for climate change mitigation which require detailed information on multiple direct drivers to target activities and investments.

Introduction

Forests and climate

Central African forests play a major role in mitigating anthropogenic climate change, acting as an important carbon sink[1–4]. Deforestation, through forest conversion to other land uses is the second largest source of carbon emissions after fossil fuel combustion[5–8], while the emissions associated with forest degradation remain uncertain and mostly unaccounted for or underestimated[9]. These forests are also providing important natural resources to populations around the world, supporting food security and livelihoods for local communities, and are home to a large proportion of the world's terrestrial biodiversity[10]. The ecosystem services provided by intact tropical forests which are relatively free from human influence and disturbance, are even larger[11]. Despite the intrinsic link to human activities and economies, forests remain under constant threat of conversion and disturbance. Climate change threatens forest goods and services, as well as the relationships between humans and forests including traditional ones, affecting all stakeholders who expect ecosystem services of forests into the future[12,13].

There have been many targeted efforts in the last decade to accurately estimate deforestation and forest degradation over time using earth observation data and help countries meet their climate targets and engagements. These datasets provide unprecedented, up-to-date information on various aspects of forest change for global or tropical forests. While there is a great scientific interest in providing wall-to-wall global forest data products and analysis, these data alone are often not sufficient for robust, accurate deforestation estimates and trends[14] and are often not relevant to decision making at national or subnational scales. Countries are more likely to use, understand and value data they produce and update themselves, and can apply to national forest monitoring systems for decision making and implementation of policies. Given the release of freely available satellite data and the need for comprehensive forest monitoring, there has been an associated increase in interoperable, open source and cloud-based platforms to provide toolkits for remote sensing, land cover mapping and forest monitoring[15], including Google Earth Engine (GEE) and SEPAL (https://sepal.io).

The Congo Basin

The six countries of the Congo Basin are home to the largest continuous tract of tropical forest in Africa, a crucial biome supporting global climate, rainfall and water cycles[16,17]. The region is known for its largely intact forests[18,19] globally significant carbon stocks[4,20,21] and unique biodiversity[22]. Low access to infrastructure, notably electricity[23], high reliance on natural resources, and rapid population growth, coupled with vulnerability to climate change are expected to place additional pressures on these forests. The region scores relatively low on the human development index[24], signalling the potential for rapid economic growth that can significantly increase existing pressures on natural ecosystems[25,26] – creating a complex situation to meet the needs for sustainable development investments, global climate targets all while ensuring food security [27].

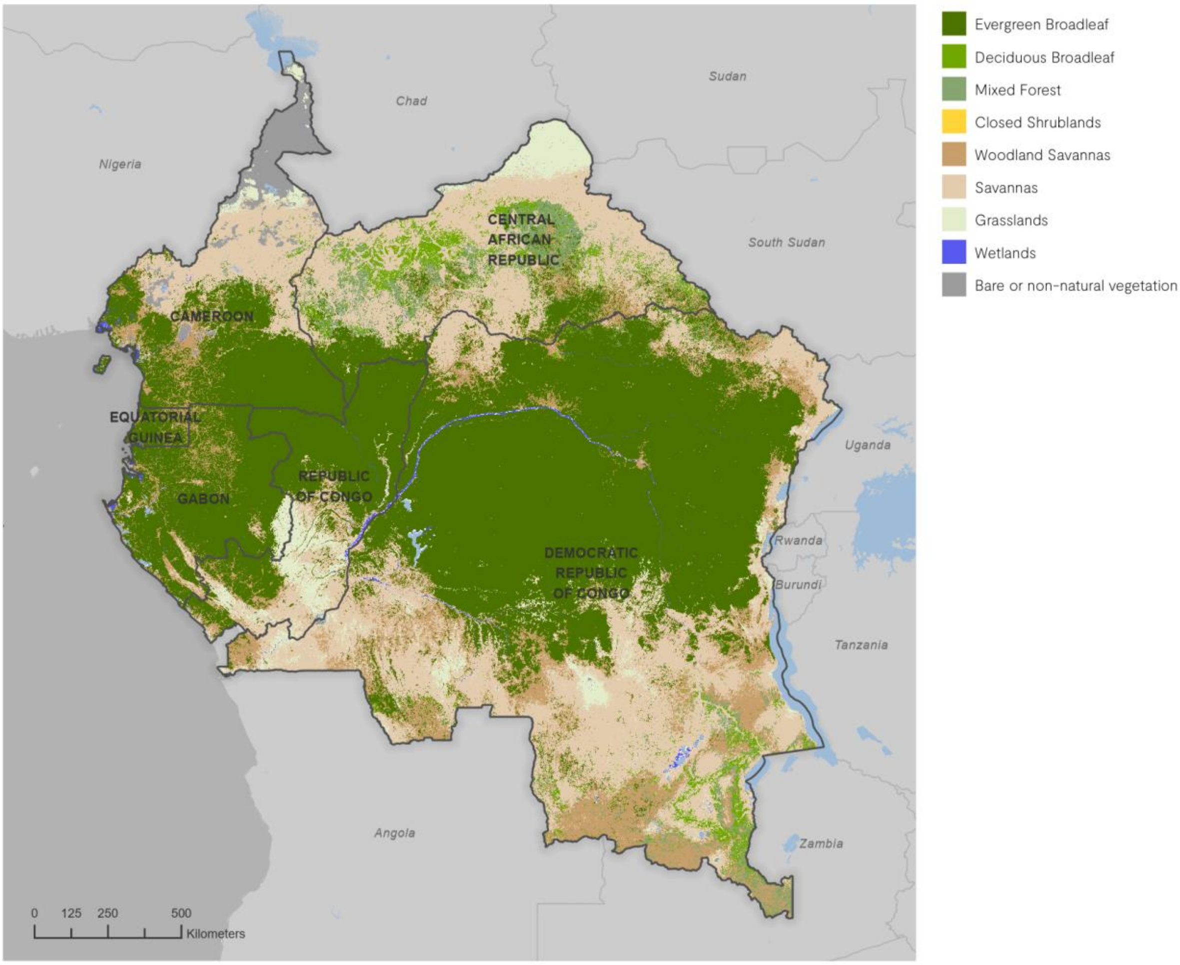

Figure 1. The study area covers six countries of the Congo Basin (Cameroun, Central African Republic, Equatorial Guinea, Gabon, Republic of Congo and The Democratic Republic of Congo) cover more than 4.04 million km^2 in Central Africa comprising various forest types and savannas (data source: MODIS MCD12Q1 Land Cover [28]).

This study assesses forest cover change in the six central African countries (Figure 1) supported by the Central African Forest Initiative (CAFI), a coalition of donor and partner countries aiming to reduce deforestation and degradation in a globally important carbon sink[21,29]. Despite being such an important resource for the planet, the Congo Basin is relatively understudied and receives significantly less funding than countries on other continents[30,31]. New carbon finance opportunities supporting High Forest Low Deforestation (HFLD) countries could help fill some of these gaps, when sufficient information is available to target interventions and investments.

Direct Drivers of Forest Disturbance

Monitoring forest change, and disturbance is one aspect of monitoring, whereas the understanding of the direct drivers of forest change is critically important for implementing required mitigation activities and policies, for example to tackle forest disturbances associated with activities by large companies or individual smallholders for local subsistence activities[32–34]. There are many claims of large potential threats to Central African forests from infrastructure development[27,35–38], industrial mining and extractive industries[39–41], industrial agriculture[42,43] and large-scale forestry[44]. More recently, oil exploration is expected to begin in the heart of the Congo basin’s vast swamp forests[29,45,46]. Most studies identify expanding small-scale agriculture as the primary cause of forest loss[41,47,48] while others cite forestry activities as having the greatest impact on forest areas[2]. It is important to comprehensively assess drivers because not all will have the same impact on carbon stocks, biodiversity[49,50] or communities[51,52].

This study addresses the proximate or direct drivers of Deforestation and Degradation (DD), defined as the immediate human actions that directly affect forest cover and biomass[49,53,54] which is different from post-deforestation land use. As explained above, we assess multiple overlapping direct drivers on both deforestation and degradation as this reflects the realities of local processes, stakeholders and decisions that result in DD[33]. The effect of scale is also very important. Many studies have only identified one possible direct driver[47,48,55], whereas direct drivers are multiple, and more significantly correlated to changes in forest cover at smaller scales[56], providing contextual information to properly define and focus interventions and mitigations.

Operational Definitions of Deforestation and Degradation

The Food and Agriculture Organization of the United Nations (FAO) provides a generally accepted definition of deforestation as "a conversion of forest to other land use, or a permanent reduction in tree cover below an established forest definition threshold"[57]. Meanwhile, forest degradation definitions vary widely, and there is an urgent need for standard operational definitions to support monitoring, decision making and restoration efforts[58]. Many definitions for degradation, such as the reduction of ecosystem services delivery are very broad and difficult to quantify. We define forest degradation for the purposes of this research, and in contrast to deforestation, as "a permanent or temporary change in forest cover that does not fall below the established forest definition threshold". Operational definitions enable the assessment of deforestation separately from degradation through remote sensing and visual interpretation approaches.

Objectives

This study provides an open-source, statistically validated DD assessment at the regional scale covering six countries of the Congo Basin over the 2015-2020 time period. A dedicated approach was developed to make best use of all available global datasets and dense satellite time series to quantify forest cover disturbance and discriminate deforestation from degradation. The derived products were validated by a team of regional experts to enhance the validity to central African conditions. The relative contribution of multiple anthropogenic direct drivers in relation to deforestation and degradation were determined, and the impacts of changes within fragmentation classes, forest types, and their associated biomass were quantified. The methodology is globally applicable, replicable, and open access to support decision making activities such as land use planning.

Results

Regional Forest Cover

We mapped land cover types and forest to provide baseline information on the study area and limit change detection analysis to forested areas. In order to apply national forest definitions, a percent tree cover product was derived. The resulting forest mask (Figure 2) includes all forest types (including woodland savannas, dry open types) derived from supervised classification, validated with 12,260 visually interpreted points and an estimated overall area-weighted accuracy of 71.14%. The classification tends to overestimate forest area (commission errors 28.6%), particularly in the woodland and shrubland savannas in northern Cameroon.

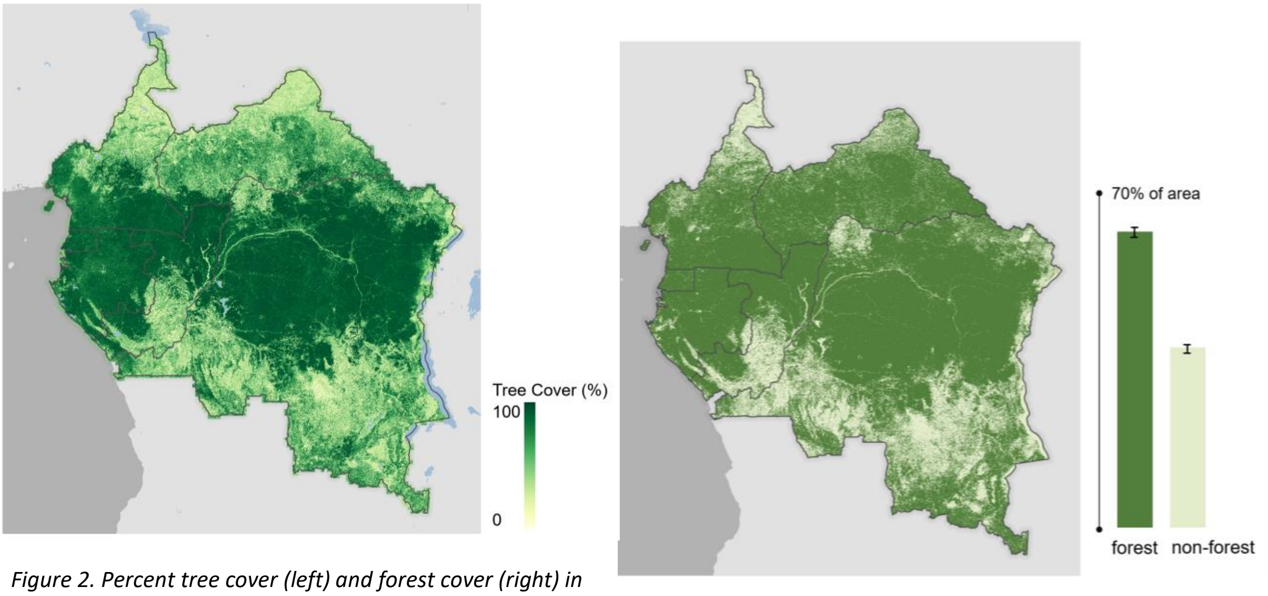

Figure 2. Percent tree cover (left) and forest cover (right) in the Congo Basin countries integrate four different national definitions, which may result in border effects, notably between the Democratic Republic of Congo and Central African Republic

The sampling-based area estimates a total of 247.8 ±3.65 million ha of forest cover over the Congo Basin, or about 61.2% of total land area. Of these, 52% are core, intact forests, while 4.2% and 13% are inner and outer edge respectively, 27.4% corridor forests and 3.4% in small patches or islands (Figure 3). A large intact forest block extends throughout the tropical forest zone in southeast Cameroun, Gabon, Republic of Congo and Democratic Republic of Congo, with several large contact patches in central Cameroun and the Central African Republic.

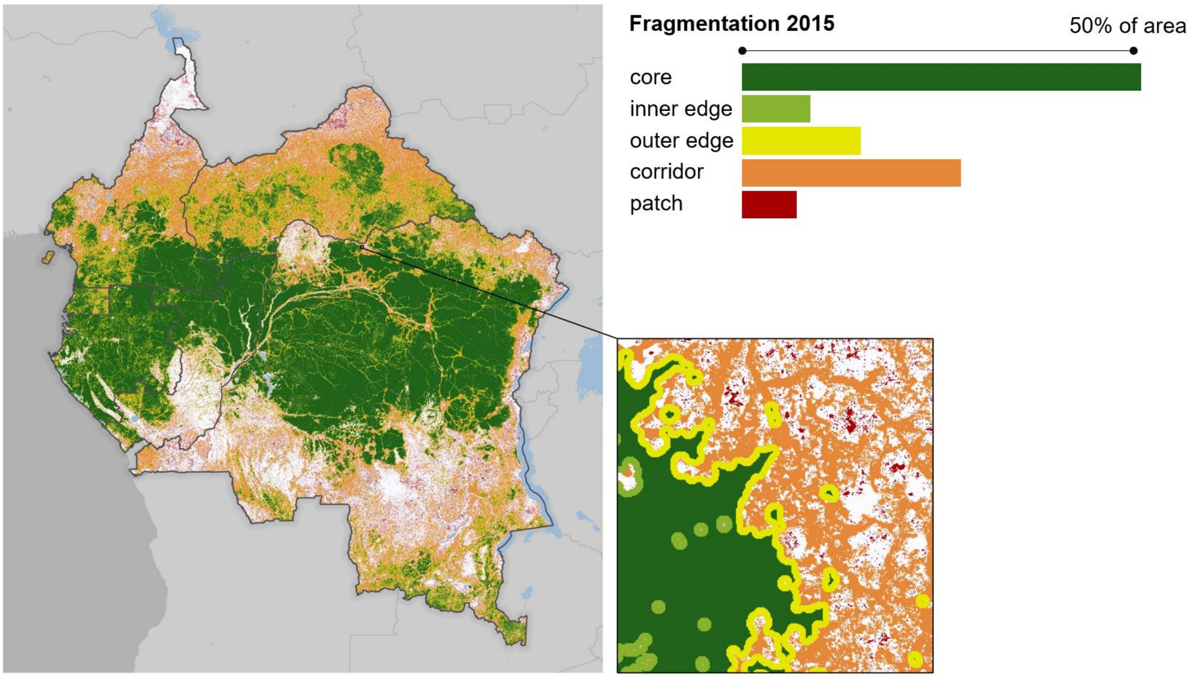

Figure 3. Forest fragmentation (2015) derived from Morphological Spatial Pattern Analysis (MSPA).

Forest Cover Trends

The forest change detection analysis from Landsat imagery over the 2015-2020 monitoring period included the processing of up to 1,222 Landsat observations per location. The sample-based area estimates for each type of change are shown in Table 1. Deforestation is estimated to affect about 50% more area than degradation.

Table 1. Sample-based area estimates of deforestation, degradation, stable forest and non-forest in the study region

Class	Prod. Accuracy	Weighted Prod. Accuracy	User's Accuracy	Estimated Map Area (ha)	Corrected Area Estimate (ha)	Std. Err. (ha)	Conf. Int. (ha)	# samples	Area Estimate (% of total area)	Conf. Int. (% of class area)
Deforestation	0.6542	0.5721	0.2344	5,719,784	2,343,336	42,657	83,609	2,779	0.58	3.57
Degradation	0.1581	0.1167	0.2350	786,255	1,583,539	38,152	74,779	1,739	0.39	4.72
Non-Forest	0.9682	0.9760	0.9918	97,688,921	99,269,135	52,649	103,193	88,566	24.53	0.10
Stable Forest	0.9835	0.9888	0.9921	300,466,900	301,465,850	66,093	129,543	266,886	74.50	0.04

The sample-based area assessment provides an estimate of forest disturbance area per year, with derived confidence intervals[59–61]. Our results indicate no increase in the rate of forest disturbance area since 2017, with a small increase in degradation during the 2019-2020 period (Figure 4). This is similar to assessments using global products, such as the Global Forest Change and the Tropical Moist Forest (TMF) dataset[62], which both show a similar trend from 2017, until an increase in disturbances observed in 2020. The FAO Forest Resources Assessment (FRA) Remote Sensing Survey also observed a general reduction in rates of forest conversion in central and western Africa in the 2010-2018 time period, compared to 2000-2010[63].

Our analysis estimates a smaller area is affected by deforestation than degradation, with the exception of 2020. According to accuracy statistics in Table 1, our map tends to overestimate deforestation and while underestimating degradation.

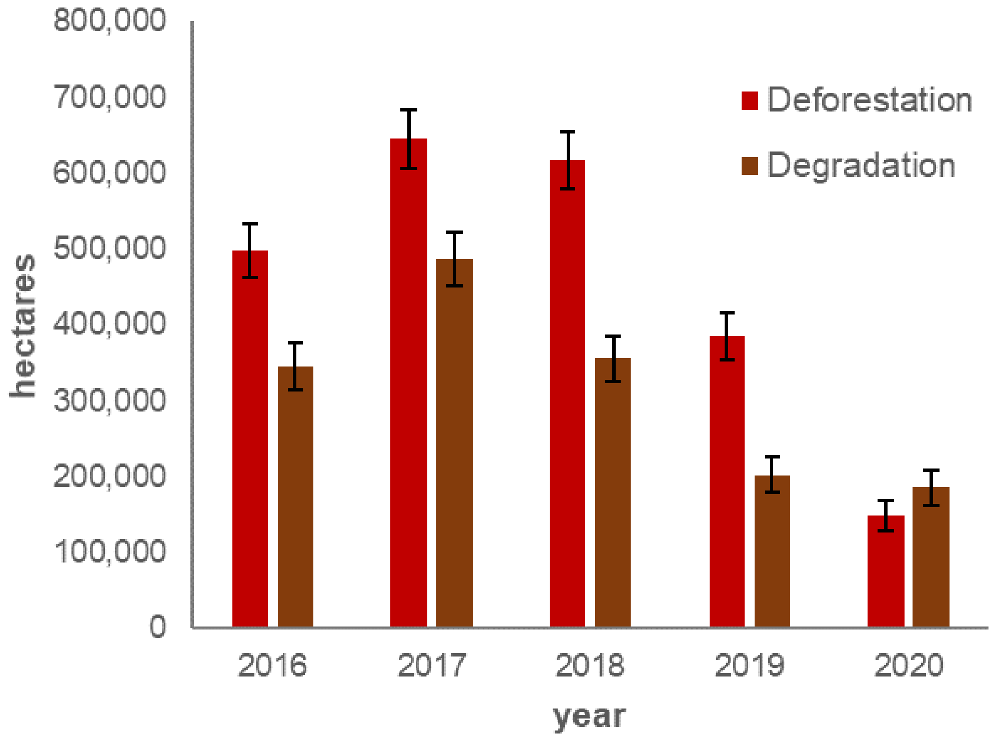

Figure 4. Forest disturbance estimated through sample-based area assessments. More than 2.2 million hectares of forest were lost during 2015-2020, and more than 1.5 million hectares of forest affected by degradation.

The spatially explicit map of deforestation and degradation shows DD in all forest types, and reveal some associated drivers (Figure 5).

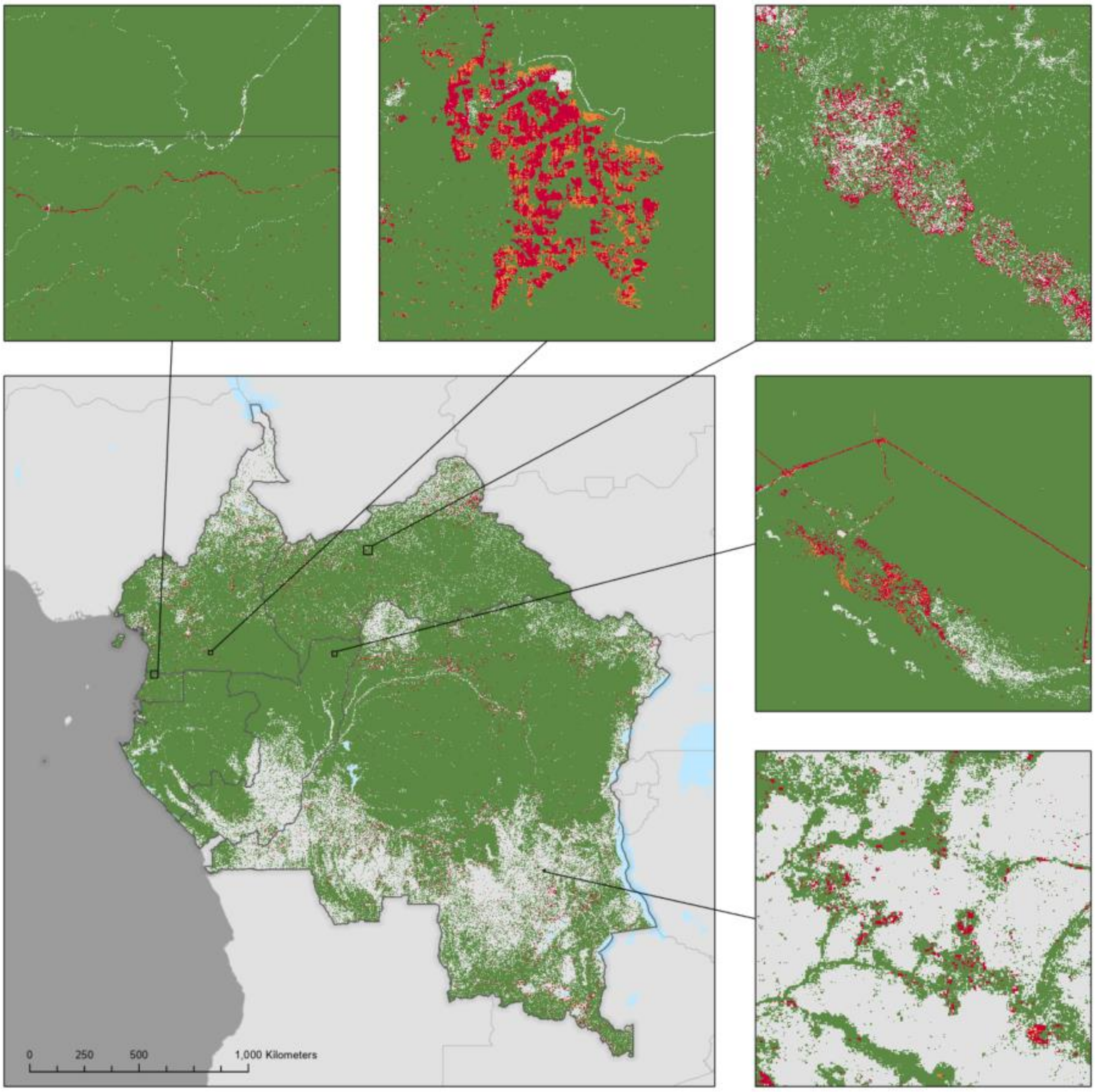

Figure 5. Patterns of detected deforestation and degradation, from top left: infrastructure development in Equatorial Guinea; industrial plantations in Cameroon; forest disturbance around a village in Central African Republic; industrial mining in Republic of Congo; Impacts on gallery forests in the Democratic Republic of Congo.

Disturbances by forest type

We evaluate the trends of annual DD associated with each type of forest and its estimated above-ground biomass (Figure 6). DD are largely occurring in dense forests, which are also the most common, followed by dry open and secondary forests. A majority of forests are identified as dense humid evergreen (59%), but we observe a relatively smaller proportion of disturbances in this class, meaning DD is occurring primarily outside of these forest types. The dry open and secondary forests store relatively low above ground biomass, while higher carbon density ecosystems make up a lower proportion of changes. The proportion of annual deforestation is increasing in dry open forests over time, while degradation is decreasing. We observe an opposite trend in dense dry forests.

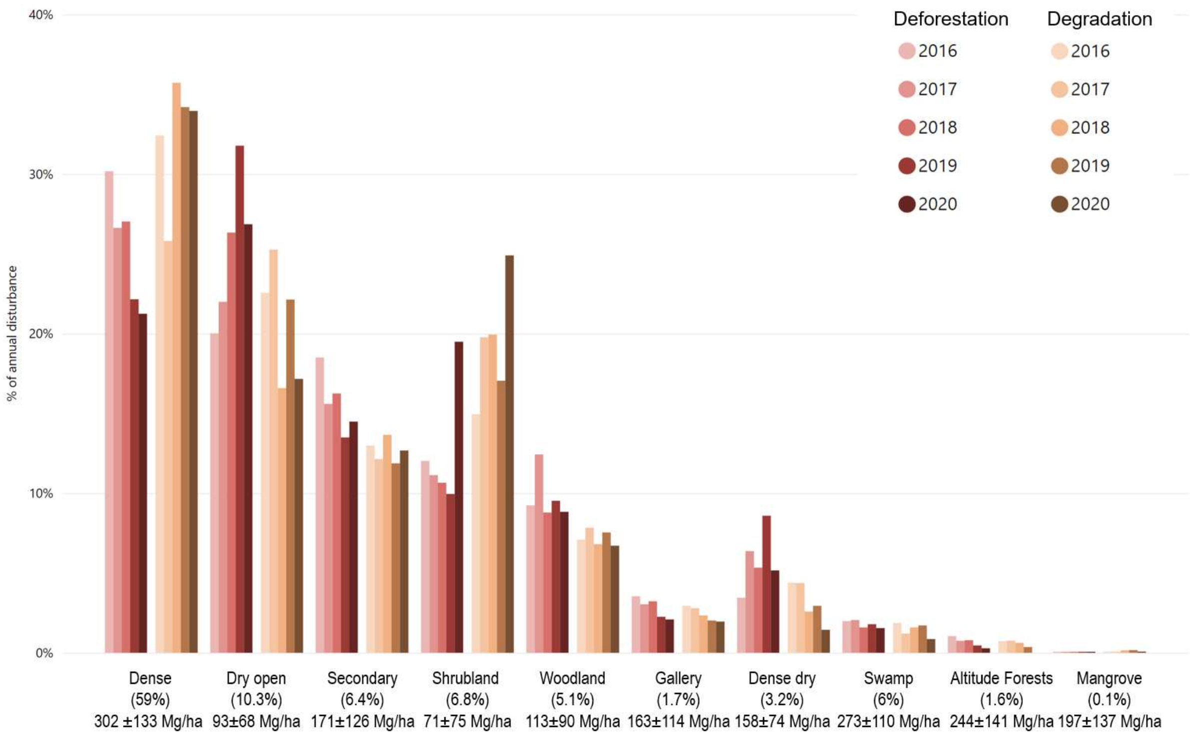

Figure 6. Proportion of annual deforestation (left bars in red) and degradation (right bars in orange) by forest type. The proportion of each forest type as a percentage of forest area is shown in parentheses, and the mean and standard deviation of above-ground biomass derived from the ESA Biomass product[64] for 2010 is shown in Mg/ha.

Forest Disturbance and Fragmentation

The assessment of fragmentation classes for annual forest cover maps allows the identification of fragmentation transitions[65,66]. During the study period, 6% of forests underwent a change to a more fragmented class. More than 11% of regional deforestation, or about 650,000 ha were first fragmented before being deforested, and of these areas, 18% (119,000 ha) were core, intact forests in 2015.

Forest disturbances are disproportionately occurring in corridor forests (Figure 7), which are about 27% of all forest area but comprise over 60% of annual deforestation and degradation. These forests have relatively low above-ground biomass compared to intact core forests. While over half of the region’s forests are intact, only a small percentage of disturbances are occurring in these areas. Both deforestation and degradation are increasing in small patch forests, the most fragmented class with the least biomass.

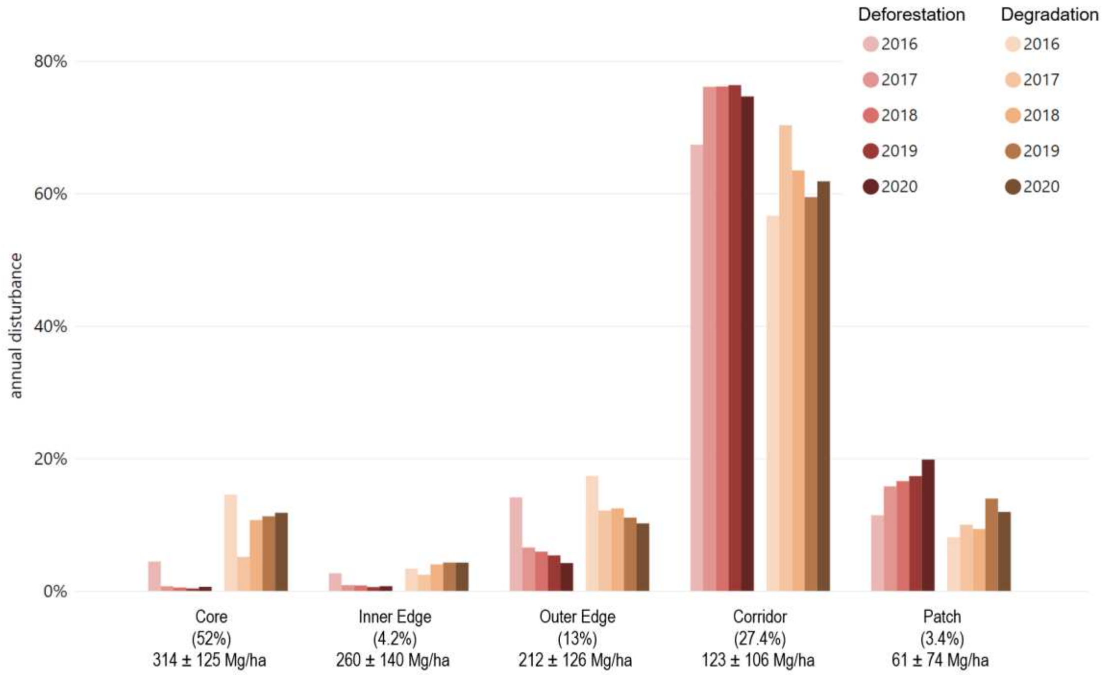

Figure 7.Proportion of annual disturbance by fragmentation class, shown with the proportion of forest in each class and average biomass estimated from ESA Biomass 2010 [64].

Direct Drivers of Disturbance

We confirm that most of our detections of DD are anthropogenic by assessing forest disturbances with respect to human presence and infrastructure. We observe that about 80% of all deforestation is located within 3 km of the nearest road or settlement (Figure 8). In contrast, degradation generally extends slightly further, with 80% of degradation occurring within 4 km of the nearest road or settlement.

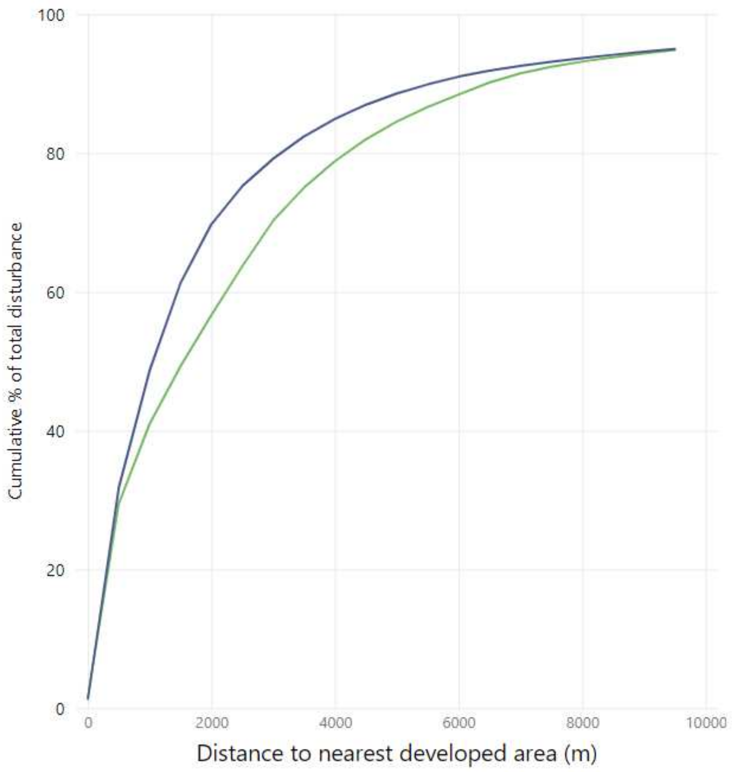

Figure 8. Cumulative proportion of deforestation and degradation relative to distance to nearest road or settlement

Next, we quantify the presence of one or more direct drivers in plots located around areas of DD. Eight unique drivers associated with deforestation or degradation were identified through their characteristics in high resolution satellite imagery and are described in Table 2.

Table 2. A total of eight direct drivers were defined by their specific characteristics identifiable in high resolution satellite imagery

Driver	Characteristics
Artisanal agriculture	Small irregular fields, generally less than 5 ha
Industrial agriculture	Large regular fields of homogenous crops
Infrastructure	Roads or paths suitable for vehicular traffic
Settlements	Presence of houses, buildings, huts or other built-up features
Artisanal forestry	Forest with small canopy gaps or perforations and felled trees
Industrial forestry	Large consistent cuts (>5ha) and felled trees
Artisanal mine	Small muddy clearings, often along waterways with turbid water
Industrial mine	Extensive infrastructure, open pits and exposed soils

Of all plots with identified forest disturbance (N=3,811), the most commonly observed driver was artisanal agriculture, followed by infrastructure, artisanal forestry and settlements (Figure 9). A majority of plots have more than one driver observed, with only 20% of all change plots with a single driver identified. The most common number of drivers is 2 (N=1,018), followed closely by 3 (N=1,006).

The four most common drivers are also commonly observed together, while certain drivers never overlap, for example industrial mining is only found with few of the other drivers and is never found with industrial agriculture.

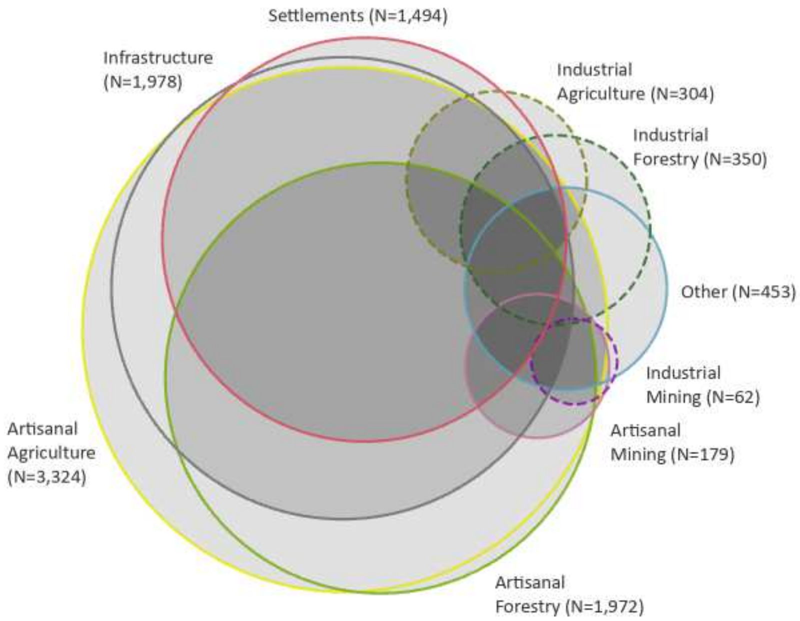

Figure 9. Representation of overlapping drivers in the Congo Basin. The size of the circle indicates the observation frequency of each driver in the validation data set. Grey shading shows how many drivers are observed in one plot, and overlapping circles indicate which drivers are commonly found together and which never overlap.

Representative Driver Archetypes

To address the overlap of drivers and derive local context, we identify archetypes, or common driver combinations which represent realities and processes on the ground. Common driver combinations were grouped according to drivers with the most permanent potential impact (for example, industrial activities such as mining), and frequent occurrence with other drivers (e.g. mining activities are associated with infrastructure and agriculture for local workers). The overlapping drivers were grouped according to their combinations shown in Table 3. Due to the wide definition of the "other" driver category, it was not included in the grouping (and it was never observed alone).

The most common archetype consists of at least three drivers, which include artisanal agriculture, roads and settlements, and is representative of the agricultural mosaic, or so-called "rural complex" which is a particular feature of the study region[66–69].

Table 3. The observed combinations of drivers were grouped into thematic classes or archetypes based on specific criteria

Archetype	Drivers	# of plots
Rural complex	Artisanal agriculture with roads and settlements, with or without artisanal forestry, and no presence of industrial drivers	2,607
Artisanal forestry	Artisanal forestry with or without "other" driver, or with settlements or roads without any artisanal agriculture	187
Industrial Agriculture	Industrial agriculture and other drivers	253
Industrial forestry	Industrial forestry and other drivers	223

Industrial Forestry and Agriculture	Industrial Forestry and Agriculture identified together	84
Industrial mining	Presence of industrial mining with or without other drivers	59
Artisanal mining	No more than 2 drivers, including artisanal mining, no industrial drivers present	37
Human infrastructure	Roads and settlements observed alone or together	56
Infrastructure related agriculture	Infrastructure and artisanal agriculture observed together	237

We assess these archetypes in space and time (Figure 10). The rural complex has the largest contribution to DD in all years and is decreasing before increasing in relation to deforestation, and relatively stable with regards to degradation. The presence of artisanal forestry (observed alone), and agriculture associated with infrastructure are increasing over time. There are similar trends for degradation, of which artisanal forestry has a greater contribution than for deforestation. Industrial drivers related to forestry, agriculture and mining are generally observed to be stable or decrease.

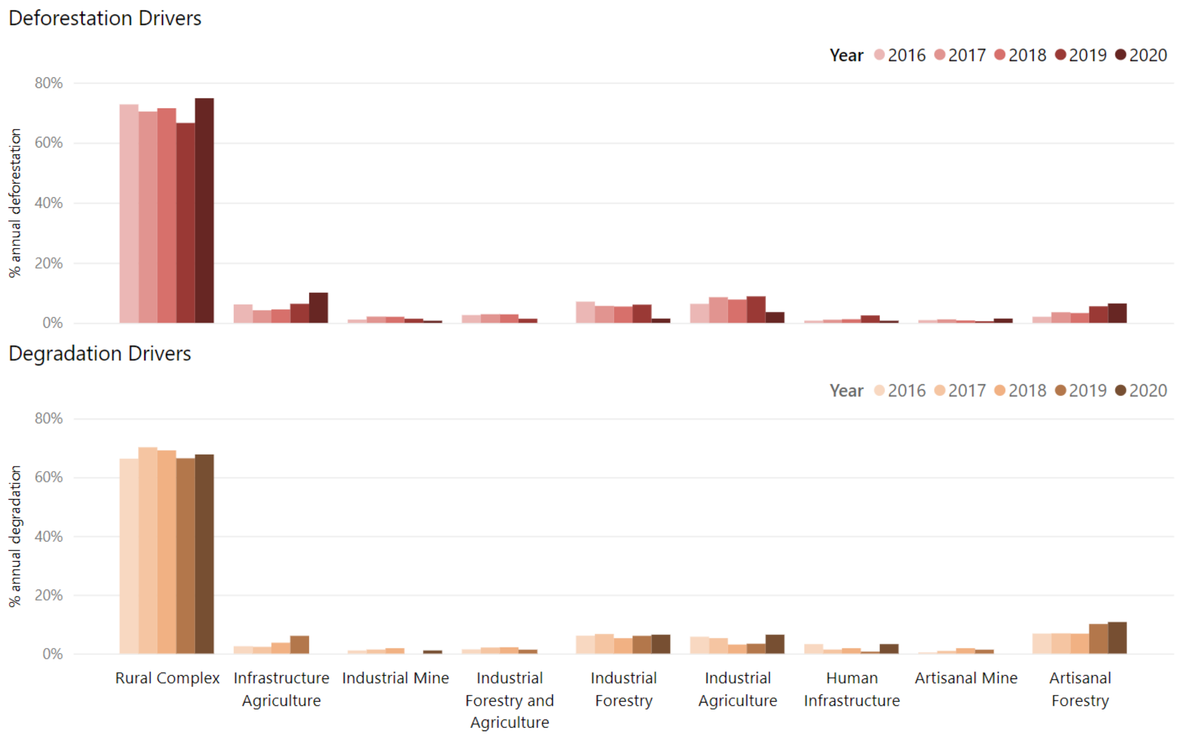

Figure 10. Grouped drivers over time shown by proportion of annual deforestation and degradation (2015-2020).

Each archetype was observed in relation to fragmentation class. Figure 11 shows the overall distribution of fragmentation classes over the entire study region, and the proportion of each class associated with each archetype. Although most forests are in the intact core class, and over a quarter are corridors, drivers are disproportionately affecting fragmented forests albeit differently. Industrial activities such as forestry, forestry and agriculture affect core forests more than other drivers, along with artisanal mining and forestry.

Figure 11. Distribution of fragmentation classes in all forests of the study region (left); the proportion of fragmentation classes affected by disturbances associated with each driver archetype. The proportions are estimated by the number of visually interpreted points.

Discussion

Mapping all of Central Africa's Forests

We assess forest cover of the entire area of the study region, integrating four unique forest definitions enabling a comprehensive forest monitoring of both tropical and seasonal, dry forests, particularly those in northern Central African Republic. The wide diversity of vegetation types in Central Africa presents significant challenges for mapping forest with EO due to interannual dynamics and heterogeneity, and as a result many efforts are often focused on tropical dense forest despite being technically considered forest according to some national definitions[70,71]. The ecosystems outside the tropical zone are nevertheless widely present in Africa, important to global carbon cycles, local livelihoods and biodiversity hotspots[72,73] and expected to rapidly expand as a result of climate change making them important to currently assess[74]. We overcome the obstacles to mapping dry and open forest via specific national forest definitions that are applied to high-resolution imagery with visual interpretation, and sensor fusion classification approaches.

Trends in Forest Disturbance (2015-2020)

In comparison with existing global datasets on forest disturbances, we observe similar trends in the 2015-2020 time period for Congo Basin countries. Data from Global Forest Change (GFC)[75] and Tropical Moist Forests (TMF)[62,76] report higher rates of forest disturbance after 2015, which decrease from 2017 until an increase in disturbances in 2020 in contrast to our study, which observes a smaller area of deforestation in 2020, with an increase in degradation. Estimated burned area has also been observed to be generally decreasing since 2001[77] which could be associated with the trends we are observing, particularly related to the drivers of change (see below). The FAO Forest Resources Assessment Remote Sensing survey also observed an overall slowing of deforestation in 2010-2018 in comparison to 2000-2010, which diverges from the Global Forest Resources Assessment (2020) which identifies an increase in rates of loss between 1990 and 2020[71] which demonstrates how different methodologies may not reach consensus, and that assessments should be tailored to regional or national scales.

While disturbances may appear to be declining, it is important to also evaluate the trends in the context of a longer time period, as we could be potentially observing a return to 2015 levels of disturbance after a significant spike in 2017. Several studies report relatively stable rates of deforestation before and after 2015, but an overall higher rate of deforestation in the region after 2015[62,76]. The estimation of deforestation trends before and after this date may be unreliable due to updated algorithms applied by global analyses, and biases due to an increased data availability since 2015[78]. One hypothesis for the increase in forest disturbance in 2017 is the unusually warm year after an El Niño in 2016, incurring additional deforestation and degradation from forest fires, storms, climate-related mortality or associated further deforestation[79]. Extreme heat and drought can increase deforestation associated with slash and burn practices[80] or cause an expansion of agriculture as a result of reduced yields[81].

As for decreases in disturbances post-2017 there are several reasons contributing to this trend. Small-scale agricultural activities are generally spatially limited around inhabited areas due to practical reasons –minimal travel time to fields is more efficient, and secondary forests and fallow areas are preferred to primary forests, meaning that the agricultural expansion is not endless. Political instability, conflicts and insecurity have long driven migration patterns in the region, which could force people away from forests[50,82,83]. In the Central African Republic, civil war, combined with a lack of infrastructure, low population density has driven many people from rural areas to cities, and limited the expansion of industrial agriculture which could potentially deforest large areas once stability returns[84,85]. This pattern of urbanisation, with decreasing population in impoverished and economically deteriorating areas has been documented in the region for many decades, and the growth of cities in African countries largely outpaces the rest of the developing world, and can be further fuelled by insecurity and climate change[86]. In the Democratic Republic of Congo a long-standing moratorium on new logging concessions could have slowed extraction since 2002, while a presidential decree in 2016 provided new opportunities for indigenous and local communities to govern concessions, which has shown to be successful in reducing deforestation[87].

Our area estimates of disturbance are generally more conservative than global products, with an overall loss of 2.2 million ha of forest over five years, and degradation in nearly half that area. This total area of disturbance is not insignificant, and justifies climate concerns from the international community[88]. There are differences in rates of disturbance within the large study area - while countries might be classified as HFLD, some sub-jurisdictions are hotspots of change with higher rates of forest disturbance than the region[18,33,89,90]. We refrain from direct comparison between sample-based area assessments from our study with pixel counts from global products as it is fundamentally flawed. Global data have not been statistically validated, and the omission and commission errors are simply unknown, making direct comparisons impossible. Additionally, areas of forest loss reported by Global Forest Watch (GFW) from the Hansen dataset may overestimate forest disturbances relative to other datasets, as this product identifies tree cover loss, which is not necessarily deforestation[14,78].

The estimates of deforestation and degradation provided by our study were robustly evaluated by experts, where a statistically representative sample of disturbance events were validated by visual interpretation. The inaccuracies of the maps could be due to incompatible spatial and temporal resolutions between validation and processing data. This difference in degradation estimates, notably that we observe a smaller area of degradation than deforestation in all years of the study with the exception of 2020, agrees with some studies[91] but is in contrast to other research[62,65,92]. Our method relies heavily on visual interpretation of high-resolution imagery to validate results, which can provide very detailed and accurate information and contributes to capacity development. But this validation can be affected by user bias, and image quality and clouds. We overcome user bias through training and calibration of users and methodological guides, along with independent cross validation[93]. Degradation is a subtle process which can occur over short or long time periods, and as a result could be difficult to accurately identify visually in imagery, as images vary in quality or brightness over time which could appear as degradation; while the use of higher resolution may in fact reveal more degradation than is detected by coarser resolution analysis. In summary, degradation remains extremely difficult to validate.

Fragmented forests

The fragmentation analysis identified more than half of the region's forest as intact, including swamp forests which are also known store the largest carbon stocks[94]. We identify several large patches of core forests observed in the Central African Republic and central Cameroun which are not identified as Intact Forest Landscapes (IFLs)[95,96] but nevertheless are large, continuous and not significantly affected by anthropogenic activities[19]. DD were found to occur in already fragmented forests, which are more likely to contain smaller trees, open canopies and lower biomass which are easier to access and clear and as a result may have lower species diversity[97,98]. More specifically, the most affected forests are corridors which are significant functional components of the forest ecosystem spatial structure[99] indicating the need to promote conservation activities outside of intact forests through what are known as "integrated landscape approaches" incorporating multiple land uses that balance human activities with conservation[100]. DD were also found to be increasing over time in small forest patches, which follows published observations of greater forest loss in small fragments with non-primary forest, as larger fragments are more difficult to clear[101]. From these assessments we can see how human encroachments on forests are typical of the agricultural frontier at forest edges, and we can identify several such fronts in the region[102].

Evaluation of carbon stock per fragmentation class and forest type indicate that disturbances are occurring disproportionately in open, secondary and shrubland forests, which represent a small area of overall forests, and low carbon stocks - but are twice as likely to be deforested or degraded. Dense tropical forest types, meanwhile, which contain the greatest above-ground carbon per hectare, and comprise 60% of all forests, but encompass less than 30% of all deforestation and degradation. This shows how the large intact and carbon rich ecosystems are potentially less affected by human disturbances, which can be a result of inaccessibility, lack of machinery required to clear dense forests with large trees, preference for secondary forests[67], or management - most forest concessions in the region are located within these intact forest blocks. Effective and inclusive forest management could be a pathway to securing carbon in these commercially exploited forests[103].

Direct Drivers of Change

We provide the first assessment of direct drivers in the Congo Basin which addresses deforestation and degradation separately, and also over time – essential for targeting management and interventions[104]. A majority of DD are found within walking distance of settlements or roads, which is expected as accessible forests are easier and more available to clear[101,105]. Other studies have explored the role of roads and settlements on deforestation inside forest concessions, an effect which can be counteracted with effective management plans[103].

The dominant direct driver associated with deforestation and degradation is observed to be artisanal agriculture, more specifically subsistence activities which have a long history and tradition[41,47,54]. The rural complex archetype, which is a combination of artisanal agriculture, forestry, roads and settlements without the presence of industrial activities is also the most commonly reported in other studies[106] is targeting fragmented forests, while industrial activities such as mining, forestry and agriculture are observed far fewer overall, and do not currently appear to be increasing, despite numerous reports and predictions[41]. The dominance of the rural complex is not surprising given the significant dependency of rural populations on agriculture and its long history, and links to culture and economy[107,108]. While this archetype is the most common throughout the region, its potential impacts on carbon, biodiversity are likely much lower and less permanent due to fallow periods which can allow for natural regeneration of vegetation[109] and its presence in corridor and fragmented forests. Subsistence agricultural activities tend to be localized around settlements and existing clearings[67], limiting the spatial extent of impact, which is what we observe in the context of fragmentation. In contrast, the impacts of industrial drivers are present in core forests, and more permanent or can extend beyond concession boundaries with additional impacts that may not be entirely visible with EO[106,110]. The contribution of this archetype to forest disturbance is potentially increasing with unsustainable agricultural practices, and expected to expand with increasing population which leads to reduced fallow times[106]. There is a need for the improvement of rural agricultural practices, which are particularly vulnerable to climate change which can subsequently affect food security, health and livelihoods[108,111,112].

The central premise of our approach is the identification of multiple overlapping drivers, which is representative of DD occurring at national and sub-national scales[50,56,82,113] and the result of the actions of multiple actors, multiple processes and motivations[33,104,114]. Global assessments, or post-disturbance land use cannot adequately discern multiple drivers[56,104] and are not relevant for decision making which requires national context[41]. Furthermore, drivers need to be considered beyond their spatial footprint: any direct driver of forest disturbance does not solely affect the direct area it covers, but inevitably influences what is around it which is particularly true for linear infrastructure such as roads[37,115], or industrial activities which inevitably incur changes outside permit boundaries, through connecting infrastructure or land clearing to support the livelihoods of local communities drawn to these areas[110]. Agriculture that is not associated with infrastructure will tend to be subsistence activities whereas agriculture along roads is better connected to markets, which increases the potential to produce for sale[106].

One specific driver absent from our conclusions is the extraction of fuelwood and harvesting for charcoal, which is being reported as a significant cause of deforestation and degradation in Congo Basin countries and has the potential to increase[116–118]. Access to electrical infrastructure is very limited in the study region, making populations entirely dependent on charcoal for preparing food[116,119]. Large-scale harvesting of fuelwood is mostly driven by demand from urban centres, and is mostly informal and uncontrolled, although demand, the importance of meeting energy needs and increasing prices are driving larger, more industrial forms of fuelwood collection in some countries[118]. Within our methodology we lack specific information to be able identify the scope and impact of such practices[110]. The artisanal forestry driver definition includes the harvesting of such forest products, and we observe a consistent increase over the time period, particularly associated with degradation, but we cannot discern from satellite for what purpose forests are being degraded. The 5m resolution of Planet imagery, which is the only high-resolution source consistently available throughout the study period limits the collection of specific and robust evidence to identify charcoal production such as the presence of kilns. Given the increasing scale of these activities as explained above, they could in fact be large enough to be identified as industrial forestry according to our definitions[120]. Additional research, including socio-economic surveys, which are currently underway are necessary to understand the scale of this driver in more detail.

Responses for Climate Change Mitigation

In Sub-Saharan Africa and more specifically in the Congo Basin, an overwhelming majority of the predominantly rural communities depend on agricultural and forest-related activities for their basic needs[12,121] and meeting the requirements for food and livelihoods are inevitably associated with forest disturbance. A large majority of crops in Central Africa are rainfed, with citizens largely employed in agriculture, making the population particularly vulnerable to climate change, which is already reducing yields and slowing growth of the agricultural sector[122]. Therefore, climate change adaptation should be mainstreamed into national planning mechanisms, with development uncoupled from deforestation. By identifying small-scale agriculture and related activities as the main drivers of deforestation in the Congo Basin, the study highlights the importance of decarbonizing the food system in Central Africa. The information provided here on direct drivers is directly relevant to improving policies that meet the needs of local communities through sustainable development, land use and agricultural planning which can be supported by international climate mitigation efforts.

Conclusions

For public and private finance to be successful, they need to be focused towards targeting relevant direct and indirect drivers of deforestation. This research can provide for a better understanding of recent areas of forest loss, degradation, the different rates of disturbance and the dynamics, interactions of direct drivers on carbon stocks to help countries fulfil their commitments to meeting climate change mitigation targets[123]. The current study also supports crucial institutional capacity development of partner nations to derive information that will be useful in the monitoring, reporting and verification efforts, through transparent methods and approaches, while providing specific information to focus mitigation activities, and respond to specific drivers of change and define development pathways to avoid further climate degradation.

Nevertheless, a five-year time period is likely too short to realistically observe dynamics and trends, therefore an update is urgently needed to validate these assessments. Over a longer study period, we could validate these trends and potentially observe forest regrowth or regeneration, which is not yet considered here. Also, the evaluation of potential impacts on biodiversity, in addition to standing carbon stocks to determine relative emissions will complement this effort.

Methods

An overview of the methods is provided in Figure 12 .

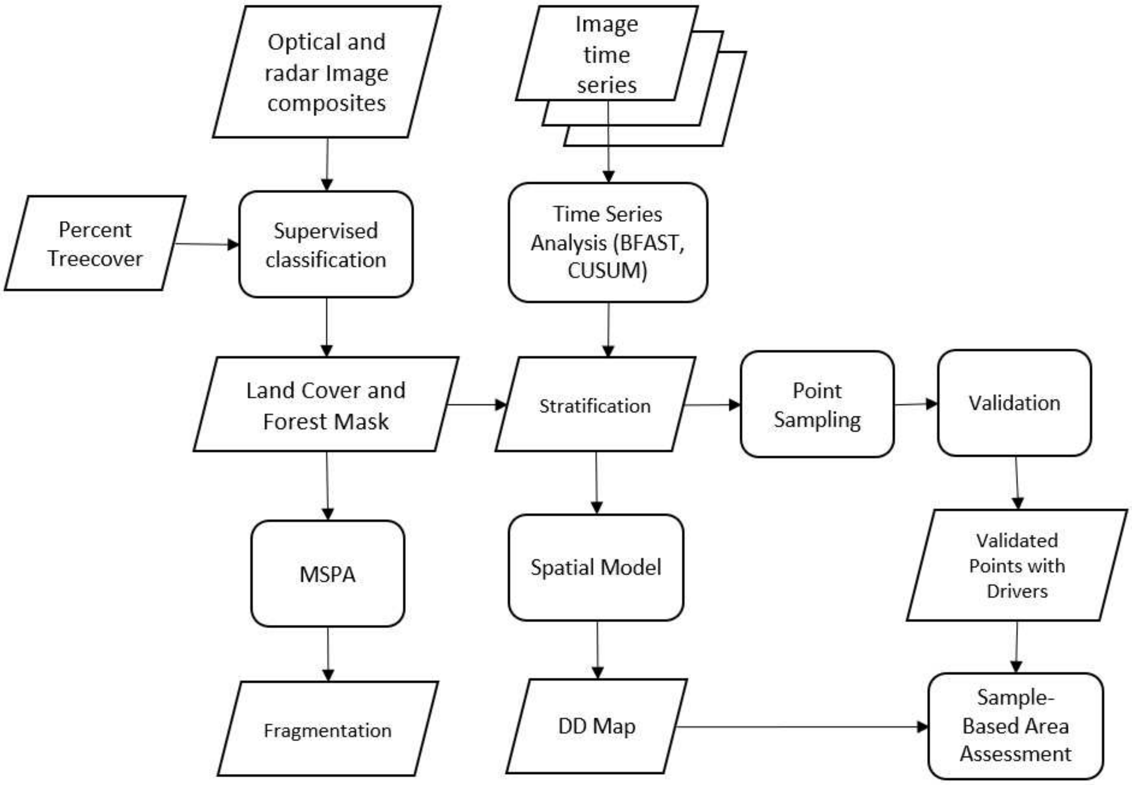

Figure 12. Methodological approach for image processing and validation for sample-base area assessment.

Image Composites

Best pixel image composites were developed to provide cloud-free imagery for the 2015 baseline year. In some locations, up to three years of data (as early as 2012) were needed to fill gaps from clouds. The SEPAL optical mosaic module was used to develop medoid composites from all Landsat satellites, applying BRDF correction and excluding pixels in the 50% percentile of NDVI values. A radar composite was created from ALOS Palsar 2015 backscatter data, with a layover/shadow mask applied, with a quegan filter[124] and an additional band for the radar forest deforestation index (RFDI)[125].

Percent Tree Cover

For the integration of national forest definitions, a percent tree cover product(0-100% at 30m resolution) for the year 2015 was created by classifying samples of cloud-free PlanetScope images (5m resolution) from 2015 in each country using 824 manually digitised points and a Random Forest classifier in Google Earth Engine[126]. These sample forest/non-forest masks were upscaled to percent tree cover at 30m resolution, from which 5139 random tree cover samples were collected as training data. These were input into a Random Forest regression model applied to an image stack of Landsat, Sentinel-1 and ALOS Palsar composites and an additional 19 derived spectral indices.

Regional Land Cover Classification

We developed a regional land cover achieved by synthesising vegetation classifications from each of the six countries and harmonising them using the universal Land Cover Classification System (LCCS) framework[127]. The integration of four different national forest definitions was performed by assigning the specific percent tree cover thresholds from each country's definition (Table 4).

*Table 4. Regional Land cover classification system. * In Central African Republic and Cameroon, shrub savannas with >10% tree cover were identified as forest, in adherence to the national forest definitions*

Code DDD	Forest/non-Forest	English	Description
1	Forest	Dense Forest	Dense humid primary evergreen forest on terra firme, >60% tree cover
2	Forest	Dense Dry Forest	Dense dry forest, >60% tree cover, with dry seasons
3	Forest	Secondary Forest	Open forest, 30-60% tree cover, degraded or secondary
4	Forest	Dry Open Forest	Dry open forest, 30-60% tree cover, with dry seasons
5	Forest	Sub-Montane Forest	Forest >30% tree cover, 1100-1750m altitude
6	Forest	Montane Forest	Forest >30% tree cover >1750m altitude
7	Forest	Mangrove	Forest >30% tree cover on saline waterlogged soils
8	Forest	Swamp Forest	Swamp mixed forest, >30% tree cover, flooded > 9 months
9	Forest	Gallery Forest	Riparian forest in valleys or along river edges
10	Forest	Mature Forest Plantation	Tree cover >15%, cultivated or managed
11	Forest	Woodland Savanna	Woodland savanna 15-30%, tree cover > national forest definition
12	Forest*	Shrubland Savanna	Shrubland savanna >15% shrub cover > national forest definition
13	Non-Forest	Herbaceous Savanna	Grassland savanna <15% tree cover
14	Non-Forest	Aquatic grassland	Grassland regularly flooded
15	Non-Forest	Bare Land	<15% vegetation cover
16	Non-Forest	Cultivated Areas	Cultivated vegetation >15% vegetation cover
17	Non-Forest	Developed Areas	Human dominated and artificial surfaces
18	Non-Forest	Water	Water > 50%
19	Non-Forest	Shrubland Savanna	Shrubland savanna >15% tree cover < national forest definition

Next the satellite image composites along with auxiliary information on elevation[128], the percent tree cover dataset, and water sources[129], were classified into the defined 19 land cover classes. A supervised training algorithm was executed in SEPAL using the random forest machine learning approach, calibrated with 2,190 training points provided by partners and derived from visual interpretation of 5m resolution image mosaics for 2015-2020 provided by Planet, through a program financed by the Norwegian Government (NICFI), along with other high-resolution images using Collect Earth Online, a tool provided by the Open Foris Initiative of the FAO[130]. Additional cleaning steps were applied, including defining montane and sub-montane forests according to elevation criteria; removing mangroves that were mapped inland or above 35m elevation; data on seasonal and permanent water areas[129] were used to identify aquatic grasslands and water bodies, while the

Global Human Settlement Layer (GHSL)[131] was used to correct the developed areas class. We integrated the official 2015 national land cover data for Gabon[132]. These classes were recoded into forest/non-forest based on the appropriate national forest definition (% tree cover) to effectively mask and target the analysis area.

Fragmentation

We apply the Multi-Spatial Pattern Analysis (MSPA) tool in Guidos Toolbox[133] to the forest mask to define core, inner and outer edge, corridor and patch forests (table 5), using an edge size of 9 pixels[65]. The process was executed in Guidos Work Bench version 1.8.8 on Ubuntu 22.04 LTS.

Table 5. Forest fragmentation classes ordered from intact to most fragmented

class	description	fragmentation
core	interior forest area; pixels surrounded by other forest	low
inner edge	forest bordering non-forest perforation inside core forest	
outer edge	forest bordering exterior non-forest	
corridor	forest pixels connecting core areas	high
patch	forest islands too small to contain core forest	

Using outputs from the annual deforestation analysis (following section), we can also determine fragmentation classes for each annual forest cover layers and identify the transitions between classes to identify stable fragmented areas (the same fragmentation class over all years), areas that are progressively fragmented (change from a lower to higher fragmentation class), as well as those which are fragmented and then deforested[65,134].

Biomass assessment

We calculate the average and standard deviation of 2010 above-ground biomass from the ESA BIOMASS mission[64] for each vegetation type and fragmentation class using the zonal statistics tool in arcGIS Pro (version 2.9.3)[135].

Time series analysis

The Breaks for Additive Seasonal and Trend (BFAST) is a change detection algorithm designed to detect and characterise changes in spectral values over time while decomposing seasonal dynamics[136]. BFAST is an iterative process which estimates the timing, magnitude and direction of change of an index or a decimal value over a monitoring period compared to a historical time period. The normalised difference forest index (NDFI) was selected for assessment in BFAST, as it is a composite of fraction images which are sensitive to canopy disturbance in tropical forests[137]. Landsat time series were compiled from January 1, 2012 to December 31, 2020 to encompass a 3 year historical time period to calibrate seasonal dynamics, and a monitoring period from January 1, 2015 to December 31, 2020.

BFAST demands large processing resources. In order to effectively analyse the entire study area, the study region was divided into 508 100km square blocks, which were then grouped into 103 batches comprising 4-6 connected blocks and distributed among the project partners to process in their SEPAL accounts. The results were then re-assembled for the region after processing.

The raw outputs from the BFAST module in SEPAL consist of a 2-band image for each tile, which include the magnitude of change (positive or negative) at the estimated date of the detected break. The simplest approach to determine changes from magnitudes and breaks was applied using the mean and standard deviation of magnitudes by forest class. BFAST date and magnitude outputs were post-processed by forest type to separate stable areas from change, with more extreme negative magnitudes (mean + 2 standard deviations of magnitude for specific forest type) classified as deforestation, and smaller magnitudes (mean + 1 standard deviation of the magnitude for specific forest type) as degradation[136,138]. This output contains 139 unique classes identifying stable land cover types (19), and the year of detected deforestation or degradation for each forest type. This layer was used as the stratification for random sampling point selection for validation and sample-based area assessments.

The stratified BFAST magnitudes were observed to include many artefacts from cloud cover and Landsat data gaps. A spatial model was developed to classify magnitudes and auxiliary data layers into an improved map of deforestation and degradation[139]. The boosted regression trees model was developed in Google Earth Engine[126] using 10% of the manually validated training data (see below) input into a boosted regression trees model, masked by negative BFAST magnitudes. Twelve auxiliary data layers, including altitude, slope, aspect, distance to nearest roads, distance to nearest non-forest, forest type, which are known variables influencing deforestation and degradation, along with the band ratio and RFDI index from a 2021 Sentinel-1 composite were stacked with the BFAST outputs for the classification. The output produced a thematic map of forest types and stable land cover classes with annual deforestation, which was assessed using sampling-based area assessment to estimate areas and associated uncertainty.

In addition, the cumulative spatial sum (CUSUM)[140] approach was used to provide a second source of change detection information, albeit only for deforestation. This algorithm was designed for synthetic aperture radar (SAR) data. We applied it to the NDFI index to produce a magnitude, date of break similar to the BFAST output, with an additional derived confidence estimate.

Sample-Based Area Assessment

Land cover change maps have inherent errors that, when used alone to make area estimates, can prevent the characterisation of land cover or land use changes to the standards required by the international community[60]. Sample based area estimation, in particular the practice of using a classified map to support the design a reference sample, is widely recognized as a good practice for producing area statistics of land cover change[78,153]. We followed the recommendations provided by the Group on Earth Observations (GFOI) for international reporting of emissions and removals of greenhouse gases in forests to estimate areas and confidence intervals of estimates from the derived maps[142].

Validation

Validation data points were visually interpreted to identify forest type, change (deforestation, degradation or stable), the date of change and presence of direct drivers was performed using OpenForis Collect Earth Online, and in particular, the high-resolution optical image mosaics provided by Planet since 2015. A stratified random sampling scheme was developed to select spatially balanced samples that are proportional to map classes[61]. Random samples were selected from the

BFAST stratification layer with enough samples to achieve the desired confidence interval of 0.05 and at least 150 points per class. This resulted in 359,978 random points distributed according to map class area (Table 5). However, as actual forest changes are rare, this results in a very large number of points that are potentially stable, which would be inefficient for visual interpretation assessments. Therefore, only points that were identified as potential change (N=11,078), along with a random sample of stable points (N=1,182) were selected for visual interpretation using Collect Earth Online. The remaining points (N= 347,718) were automatically assigned as change or stable based on consensus between available information from Global Forest Change (GFC)[4], Tropical Moist Forests (TMF)[62] and the outputs from CUSUM.

Table 5. Distribution of random samples for sampling-based area assessment and validation

Land Cover	stable	2016	2017	2018	2019	2020	TOTAL
Dense Forest	147820	715	239	150	150	150	**149224**
Dense Dry Forest	32985	604	290	165	150	150	**34344**
Secondary Forest	14949	319	165	150	150	150	**15883**
Dry Open Forest	1239	162	150	150	150	150	**2001**
Sub-Montane Forest	3329	150	150	150	150	150	**4079**
Montane Forest	703	150	150	150	150	150	**1453**
Mangrove	298	150	150	150	150	150	**1048**
Swamp Forest	21190	150	150	150	150	150	**21940**
Gallery Forest	6780	154	150	150	150	150	**7534**
Mature Forest Plantation	15488	227	150	150	150	150	**16315**
Woodland Savanna	37885	1046	472	220	150	150	**39923**
Shrubland Savanna	40819						**40819**
Grassland Savanna	4959						**4959**
Aquatic Grassland	11258						**11258**
Bare Land and Sparse Vegetation	4497						**4497**
Cultivated Areas	433						**433**
Built-up Areas	4268						**4268**
TOTAL	**348900**	**3827**	**2216**	**1735**	**1650**	**1650**	**359978**

In Collect Earth Online, each point was validated by three independent users to avoid user bias, and the final labelling was determined by the agreement of 2 or more users.

Direct drivers

We first evaluate the location of disturbances with respect to roads and settlements, using available vector road data[37] converted to raster with the same resolution as the forest cover and change products (30m). Best available settlement data[143] were scaled to the same resolution combined with the roads to create a combined layer. Euclidean distance was calculated in QGIS (version 3.22.7)[144] and classified into 500m buffer rings, and the area of deforestation and degradation for each year was summed in each distance class.

The identification of multiple drivers allow the understanding of the local context. Eight observable drivers were defined according to their visibility in high resolution satellite imagery available In Collect Earth Online. One or more drivers were observed within a 2km plot around all sample points. Drivers that could not be categorised into the defined categories (flooding, natural fires, or no visible cause) were labelled “other.”

All validation points with observed drivers were also assessed according to forest type, fragmentation class and assessed according to their relative contribution to annual deforestation or degradation.

Data Availability

all spatial and tabular data developed by the project is accessible via the online database as Google Earth Engine Assets and via arcGIS Online: https://congo.dddafrica.info/resultats/base_donnees, and also available in the Central Africa Forest Observatory (OFAC) library : https://www.observatoire-comifac.net/library

Code Availability

all modules used and developed in SEPAL are available via https://sepal.io and in the GitHub repository: https://github.com/aurelgrooves/sepal_DDD

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Author Contributions

The collaborative work was led by Aurélie Shapiro (senior and corresponding author), with methodological support and project management from Rémi d'Annunzio. All co-authors were members of the project technical committee and actively derived, tested and evaluated methods, performed the change analysis, executed the validation and driver interpretation, and contributed and edited the final manuscript, fulfilling authorship criteria described by Nature Communications.

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