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To cite this article: Karimon Nesha *et al* 2024 *Environ. Res. Lett.* **19** 104031

ENVIRONMENTAL RESEARCH
LETTERS

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RECEIVED
8 March 2024

REVISED
10 July 2024

ACCEPTED FOR PUBLICATION
23 July 2024

PUBLISHED
30 August 2024

LETTER

An assessment of recent peat forest disturbances and their drivers in the Cuvette Centrale, Africa

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Keywords: peat forests, peat forest disturbances, RADD alert, direct drivers, visual interpretation, smallholder agriculture, Cuvette Centrale

Abstract

The largest tropical peatland complex in the Cuvette Centrale is marked by persistent knowledge gaps. We assessed recent peat forest disturbances and their direct drivers from 2019 to 2021 in Cuvette Centrale, spanning the Republic of Congo (ROC) and the Democratic Republic of Congo (DRC). Utilizing peatland maps and Radar for Detecting Deforestation alert data, we analyzed spatial and temporal patterns of disturbances. Further, we examined 2267 randomly sampled peat forest disturbance events through visual interpretation of monthly Planet and Sentinel 2A data to identify direct drivers. Our findings revealed that between 2019 and 2021, about 91% of disturbances occurred in DRC, with hotspots concentrated in the northwest Sud-Ubangi district. Disturbances predominantly followed a sharp seasonal pattern, recurring during the first half of each year with temporal hotspots emerging between February and May, closely associated with smallholder agriculture activities. Smallholder agriculture accounted for over 88% of disturbances in Cuvette Centrale, representing a leading role both in ROC (∼77%) and DRC (∼89%). While small-scale logging contributed 7% to the disturbances in the region, it constituted an important driver (18%) in the ROC. Other drivers included floods, roads, and settlements. Approximately 77% of disturbances occurred outside managed forest concessions in Cuvette Centrale, with 40% extending into protected areas. About 90% of disturbances were concentrated within 1 km of peat forest edges and ∼76% of the disturbances occurred within 5 km of road or river networks. The insights underscore the crucial need for effective peat forest conservation strategies in Cuvette Centrale and can inform national policies targeting peatland protection, aligning with commitments in the Brazzaville Declaration and the Paris Agreement. Further, our findings on direct driver assessment could serve as a reference dataset for machine learning models to automate the visual interpretation and upscale the assessment across the entire region.

1. Introduction

Peatlands are distinctive wetlands characterized by the presence of a carbon-rich peat soil layer formed from dead and decaying plant material under waterlogged and low oxygen conditions (Joosten and Clarke 2002, Charman 2009). Peatlands occupy only ~3% of the global land surface (Rydin *et al* 2013, Xu *et al* 2018), but store approximately one-third of the world's soil carbon (Page *et al* 2011, Yu 2012, Jackson *et al* 2017, Hugelius *et al* 2020), making them a vital component of the global carbon balance (Page *et al* 2011, Yu *et al* 2011, Scharlemann *et al* 2014). They are also crucial for maintaining global biodiversity providing habitats for various plants and animals including rare species (Posa *et al* 2011, Carroll *et al* 2015, Husson *et al* 2018). Further, these ecosystems offer important regulating, provisioning, and cultural services (Reed *et al* 2014, Bonn *et al* 2016, Gao *et al* 2016).

Peatlands, featuring mainly bogs and fens, (Charman 2009, Finlayson and Milton 2018), are extensively covered by rainforest in the tropics and denoted as peat swamp forests (Lähteenoja and Page 2011, Dargie *et al* 2017, Gumbricht *et al* 2017a). The tropics contribute to approximately one-quarter of the global peatlands extent, with South America accounting for 11.5%, Southeast Asia (SEA) 7.2%, and Africa 4.4% (Page *et al* 2011, Draper *et al* 2014, Gumbricht *et al* 2017b, Xu *et al* 2018, Melton *et al* 2022). Until recently, information on the peatlands extent in Africa was highly uncertain. Two recent studies have specifically mapped peatlands extent from 145 500 km^2 to 167 600 km^2, in the central Congo Basin in Africa, known as Cuvette Centrale (Dargie *et al* 2017, Crezee *et al* 2022). This marks the Cuvette Centrale as the largest tropical peatland complex, spanning the Republic of Congo (ROC) and the Democratic Republic of Congo (DRC) (Dargie *et al* 2017, Crezee *et al* 2022).

DRC and ROC are the second and third most significant countries for tropical peatlands following Indonesia (Xu *et al* 2018), storing 19.1–19.3 and 9.6–11.5 Pg C, respectively, and hosting together 29% of the total tropical peat carbon stock (Dargie *et al* 2017, Crezee *et al* 2022). Notably, belowground carbon stock of Cuvette Centrale is comparable to aboveground forest carbon stocks for the entire Congo Basin (Verhegghen *et al* 2012). The Cuvette Centrale peatlands are entirely overlaid by swamp forests, featuring mainly palm and hardwood dominated vegetation (Dargie *et al* 2017). The massive peat and vegetation carbon stocks underscore the importance of protecting and monitoring the peatlands in Cuvette Centrale. Recognizing this, DRC, ROC, and Indonesia jointly signed the Brazzaville Declaration in 2018 to protect and sustainably manage these ecosystems aligning with the Paris Agreement and UN-Reducing Emissions from Deforestation and Degradation (UN-REDD). Similarly, international partnerships e.g. United Nations Environment Programme's Global Peatlands Initiative, Tropical Peatland Initiative, International Tropical Peatlands Center, and International Peatland Society share a common vision.

Peatland disturbance drivers, carbon emissions, and management options have been studied in SEA, particularly in Indonesia (Hooijer *et al* 2010, Koh *et al* 2011, Tarigan *et al* 2015, Uda *et al* 2017, Danylo *et al* 2021, Yuwati *et al* 2021), and in Peruvian Amazon (Roucoux *et al* 2017, Baker and Coronado 2019, van Lent *et al* 2019, Bourgeau-Chavez *et al* 2021, Hastie *et al* 2022, Hergoualc'h *et al* 2023, Marcus *et al* 2024). The Cuvette Centrale peatlands have a clear history of disturbances (Dargie *et al* 2019), yet these ecosystems have until now remained relatively understudied. Previous studies have offered only general indications of prevailing threats to the peatlands in Cuvette Centrale, including land-use and climate change (Dargie *et al* 2019). If left unchecked, these threats could potentially accelerate, leading to irreversible damage to these ecosystems, necessitating an immediate investigation into the drivers of peat disturbances to undertake necessary actions at (inter)national levels.

A combination of earth observation data sources can play a critical role in monitoring disturbances and related drivers in Cuvette Centrale peat forests. Recent remote sensing (RS) based peatland maps offer detailed spatial information on their distribution (Dargie *et al* 2017, Gumbricht *et al* 2017b, Xu *et al* 2018, Crezee *et al* 2022). Further, satellite-based alert systems offer spatial and temporal information on new disturbances (Diniz *et al* 2015, Hansen *et al* 2016, Watanabe *et al* 2018, Reiche *et al* 2021). Being affected by persistent cloud cover (Lindquist *et al* 2008) and small-scale disturbances (Tyukavina *et al* 2018, Reiche *et al* 2021, Laso Bayas *et al* 2022, Slagter *et al* 2023), disturbance dynamics in Cuvette Centrale forests can only be evaluated using cloud-free and high-resolution data in space and time. Radar for Detecting Deforestation (RADD) alert offers cloud-free disturbance data weekly at 10 m resolution (Reiche *et al* 2021). Further, Planet Labs offers high-frequency and high-resolution earth observation imagery, with analysis-ready mosaics for tropical forests accessible through Norway's International Climate & Forests Initiative (NICFI) (Planet Labs 2019). Other data sources (e.g. Sentinel-2) are also available for forest applications. Visual interpretation of the Planet and other imagery can be used for driver analysis of peat forest disturbances in Cuvette Centrale, as employed for other tropical forest disturbances (Koh *et al* 2011, Leblois *et al* 2017, Murillo-Sandoval *et al* 2018, Turubanova *et al* 2018, Austin *et al* 2019, De Sy *et al* 2019, Laso Bayas *et al* 2022, Slagter *et al* 2023).

In this paper, we systematically assessed recent peat forest disturbances and related direct drivers in Cuvette Centrale, spanning DRC and ROC from 2019 to 2021 using multiple earth observation data. We mainly employed RADD alert forest disturbances data (Reiche *et al* 2021), two recent peatland maps (Gumbricht *et al* 2017b, Crezee *et al* 2022), and NICFI Planet and Sentinel-2A imagery for the analysis. Our study pioneers the analysis of peat forest disturbances and associated direct drivers in Cuvette Centrale. Given the current limited knowledge on this subject, this research offers a crucial contribution to filling existing knowledge gaps which could support more effective strategies to meet national and international commitments on peatland conservation and restoration, including those outlined in the Paris Agreement and Brazzaville Declaration.

Specifically, we answered the following research questions:

1. What are the spatial and temporal patterns of peat forest disturbances?
2. How do accessibility and protection status affect the distribution of disturbances?
3. What are the direct drivers of peat forest disturbances and how do they vary in space and time?

2. Data and methods

2.1. Study area, data and processing

2.1.1. Peatland extent and forest baseline map

For peatland extent in Cuvette Centrale (figure 2(a)), we relied on two peat maps (figure 2(b)): the Gumbricht map with 231 m spatial resolution (Gumbricht *et al* 2017b) and Crezee map with 50 m resolution (Crezee *et al* 2022). The Gumbricht map was the most recent and robust peatland dataset available for the entire tropical region, while the Crezee map was the most recent data specific to peatlands in Cuvette Centrale. The source RS data of the Gumbricht map were obtained from MODIS product for 2011 (Gumbricht *et al* 2017b), while the source RS data of the Crezee map were obtained from Landsat and ALOS PALSAR as composites of multiple years between 2000 and 2010 (Crezee *et al* 2022). Both peatland maps have been reported with different degrees of uncertainties (Gumbricht *et al* 2017b, Crezee *et al* 2022). We integrated these maps to include the maximum available extent of peatlands, which we termed as combined peat map. Additionally, we created agreement and non-agreement peat maps, with the former featuring matching peatland pixels from both Gumbricht and Crezee maps, and the latter including pixels present in either Gumbricht or Crezee map but not in both. We used a 10 m spatial resolution forest baseline mask in Africa for the year 2018 (Turubanova *et al* 2018) with the peat maps to generate a combined (figure 2(b)), agreement and non-agreement peat forest maps (figure 2(b)). We harmonized the resolutions of Gumbricht and Crezee peat maps to 10 m for these computations and subsequent processing, by employing the nearest neighbor resampling method in Google Earth Engine (GEE) (details in appendix A). An overview of the datasets and methodological framework employed in this study is shown in figure 1.

2.1.2. Peat forest disturbance data

For delineating forest disturbances, we utilized the RADD alert system, which is a Sentinel-1 based forest disturbances dataset in primary humid tropical forests in near real-time from 2019 onwards (Reiche *et al* 2021). In this system, forest disturbance refers to the complete (associated with stand-replacement disturbance) or partial (mainly associated with boundary pixels and selective logging) removal of tree cover within a 10 m Sentinel-1 pixel. The alert data contained two bands: Alert confidence and Date when the disturbance was first detected. The alert band had low (forest disturbance probabilities above 85%), and high confidence (forest disturbance probability surpassing 97.5%) alert values. We only employed the high confidence alert values in our analysis. We masked out peat forest disturbances from the RADD alert forest disturbances data using the combined peat forest map in Cuvette Centrale (figure 2(b)). Disturbances smaller than 0.2 ha until July 2020 and smaller than 0.1 ha thereafter were not mapped in RADD alert products due to the minimum mapping units (MMUs) applied (Reiche *et al* 2021). Further, RADD alerts include a number of false alerts in swamp forests (Reiche *et al* 2021). Consequently, our analysis may underrepresent the frequency and extent of disturbances, leading to conservative estimations reported in our study. Notably, the intersection of RADD alert data with the peatlands and forest base layer to determine the extent of peat forest disturbances resulted in some artifact disturbance areas being smaller than the MMU of 0.1 ha (appendix L).

2.1.3. Protection status and accessibility data

We compiled data on protection status, encompassing officially designated protected areas and managed areas such as forest concessions. Data on national protected areas was obtained from the forest atlas (MECNDD & MEDD-DIAF 2023) and world protected areas (e.g. strict natural reserve, Ramsar site) from the world database on protected areas (UNEP-WCMC & IUCN 2023). Forest concession boundaries were sourced from WRI (2021). For accessibility, we utilized road network data from Kleinschroth *et al* (2019), and river networks from the global land cover facility's inland water dataset (Feng *et al* 2016).

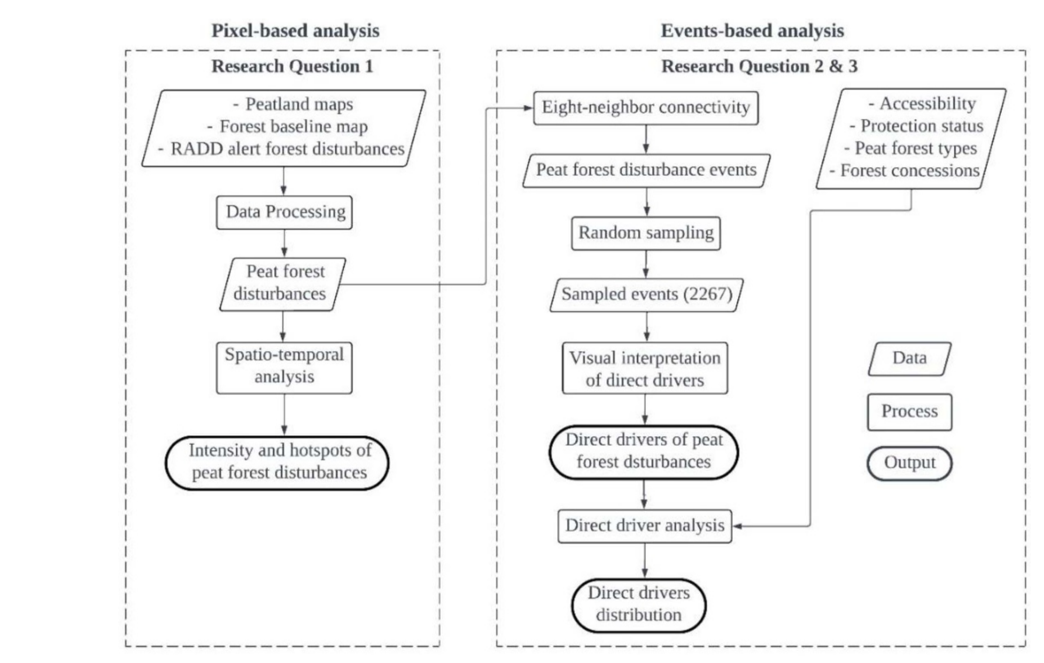


Figure 1. Methodological framework outlining key datasets and processes contributing to the analysis of peat forest disturbances and their direct drivers in Cuvette Centrale from 2019 to 2021.

2.2. Spatio-temporal analysis of peat forest disturbances

We assessed the spatial distribution of peat forest disturbances by calculating the relative intensity of disturbances per unit area using a 1 km × 1 km grid cell system. The relative intensity was quantified as the ratio of peat forest disturbance pixels (10 m) to peat forest pixels (10 m) in each grid cell. We categorized disturbances into low, medium, and high intensities. Grid cells exhibiting intensities below 2% were classified as low-intensity disturbances, cells ranging from 2% to 20% were categorized as medium-intensity disturbances, and those exceeding 20% were identified as high-intensity disturbances or spatial hotspots (appendix B).

Further, we analyzed the temporal pattern of peat forest disturbances on a monthly basis, aggregated per year. We examined intra-annual and interannual patterns of disturbances over the study period. We investigated whether certain months exhibited a notable increase in disturbances compared to the average monthly occurrence to identify the temporal hotspots, defined as instances where disturbances exceed 10% per month, aggregated annually. The temporal analysis was performed at the pixel level (10 m), utilizing the date values from the high confidence alert dataset.

2.3. Distribution of disturbances by protection status and accessibility

We analyzed disturbances distribution within and outside forest concessions, and national and world protected areas (figures 2(c) and (d), appendix A). Further, we evaluated the proximity of the disturbances to peat forest edges, by transforming the combined Gumbricht-Crezee peat map into a distance map using the Haversine equation (equation (1)) (van Brummelen 2017). In the distance map, edge pixels denoted a zero value, with values increasing for pixels towards the forest interior. We analyzed disturbances along road and river networks, measuring their distance in km (appendix C)

$$d = 2r\operatorname{asin}\left(\sqrt{\sin^2(\varphi_2 + \varphi_1/2) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2(\lambda_2 - \lambda_1/2)}\right) \quad (1)$$

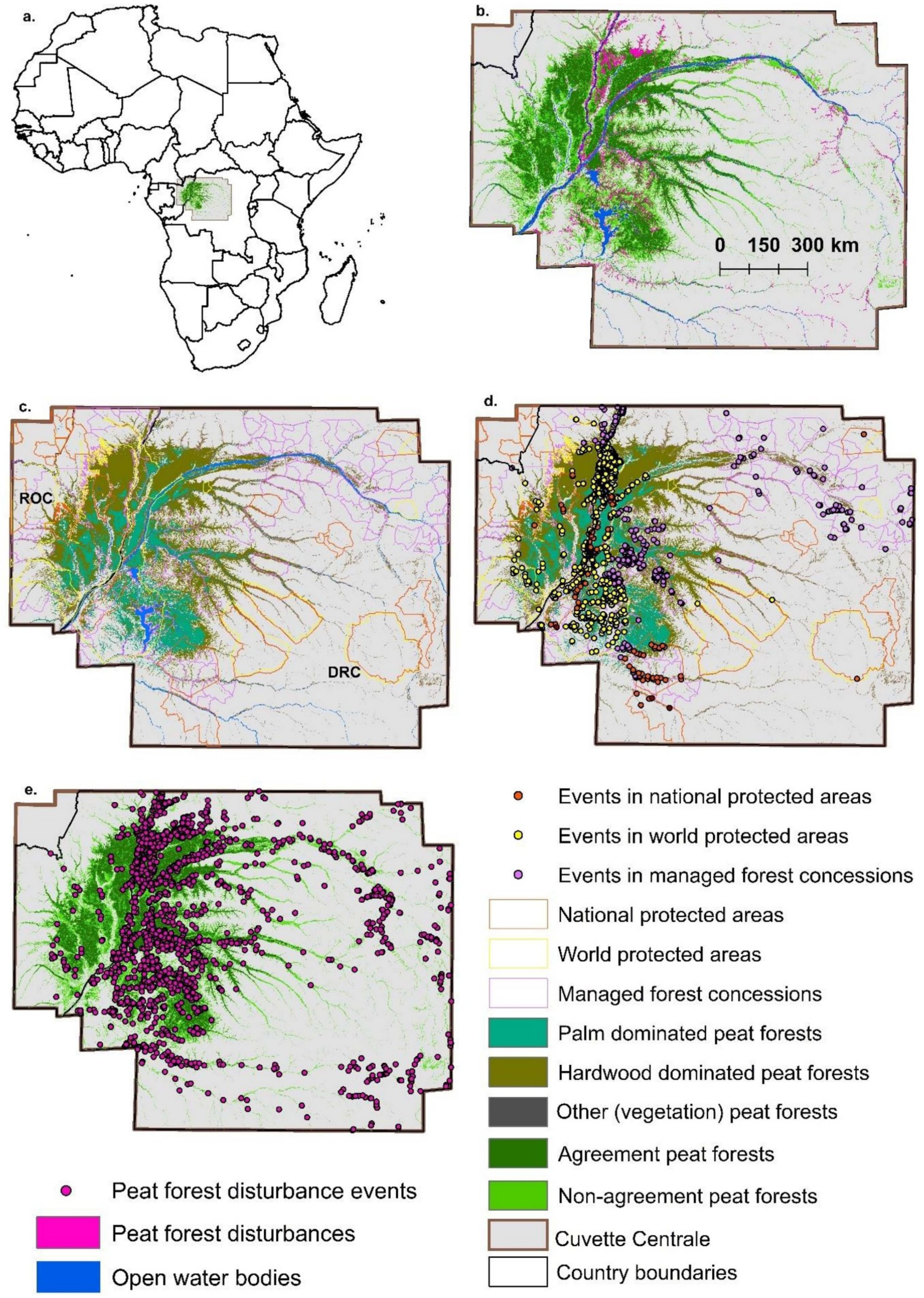


Figure 2. (a) Location of the study area in Cuvette Centrale, Africa. (b) Disturbances in peat forests (combined peat forests, segregating agreement and non-agreement peat forest areas). (c) Distribution of hardwood, palm dominated, and other peat forests (collectively representing the combined peat forests) overlayed with national and world protected areas and managed peat forest concessions. (d) Distribution of the sampled peat forest disturbance events intersecting national and world protected areas, and managed peat forest concessions. For visualization purposes, sampled peat forest disturbance events are shown on the map. Analysis is performed for all disturbances. Peat forests are shown according to vegetation types. (e) Distribution of randomly sampled 2267 disturbance events for direct driver analysis of peat forest disturbances.

where d stands for distance between pixel centers, r is the radius of the Earth, φ_1, φ_2 are latitudes of pixel 1 and pixel 2, λ_1, λ_2 are the longitude of pixel 1 and pixel 2.

2.4. Direct driver analysis of peat forest disturbances

2.4.1. Defining direct drivers

We considered exclusively the direct drivers of forest disturbances as defined in the framework of proximate causes (Geist and Lambin 2002). We identified five direct drivers namely smallholder agriculture, small-scale logging, floods, roads, and settlements (table 1). We excluded large-scale agriculture as we did not observe any such activities. This aligns with previous studies citing smallholder agriculture and logging as predominant drivers in the region (Tyukavina *et al* 2018, Dargie *et al* 2019). We adopted the globally most used criterion for defining smallholder agriculture with land size, including croplands operating on $\leqslant$2 ha (GRAIN 2014, Khalil *et al* 2017). We included flood as heavy rains frequently cause flooding along the Congo and Ubangi Rivers impacting large forest areas in the Congo Basin (OCHA 2019, 2020, Reliefweb 2020, 2021, 2022, Gou *et al* 2022). The study area also manifests infrastructure development e.g. roads and settlements (Kleinschroth *et al* 2016, Kleinschroth and Healey 2017). We assigned an 'unidentified' class for drivers that defied classification.

2.4.2. Sampling peat forest disturbance events for driver analysis

We employed random sampling on the peat forest disturbance pixels aggregated as events. The distinct spatially connected disturbance pixels were grouped into

Table 1. Direct drivers of peat forest disturbances in the Cuvette Centrale—class description and criteria that are visible on the Planet and/or Sentinel-2A imagery.

Driver class	Description
Smallholder agriculture	– Vegetation regrowth in the sample events within one year – At least one complete/partial harvesting at the sample events within two years of vegetation regrowth – In events with no visible harvesting vegetation texture smooth and comparable with adjoining crop fields i.e. similar vegetation patterns followed in the adjoining crop fields – Large events containing multiple croplands (appendix G) – Usually located adjacent to crop fields over large areas – No adjoining crop fields (i.e. an individual/isolated event), new disturbances expanding in its vicinity within a year – Small events usually expanding from an existing crop field (appendix H) – Usually located close to settlements/roads/river networks – Usually non-mechanized clearing of croplands (appendix H)
Small-scale logging	– No clearing of vegetation within a year after post-disturbance regrowth and tree canopy clearly visible in 1–2 years – No vegetation regrowth and the patch stays bare for more than a year – Usually small to medium events
Flood (appendix J)	– The event occurred in the second half of the year 2019 – Located along the rivers – No adjoining crop fields – No cropping pattern in the sample events
Roads	– Linear canopy opening visible for more than three months after opening – Usually part of existing road networks – Usually connected with disturbances/settlements
Settlements	– Houses and house roofs clearly visible – Appears very bright on the image – Usually, several houses collocated
Unidentified	– Events not presenting the criteria of the abovementioned classes – Significant spatial mismatch of the RADD alert events due to shifting in Planet images – Events not recognizable due to unclear/cloudy Planet and/or Sentinel-2 images

one single object that we defined as a peat forest disturbance event. The connectivity of pixels was specified based on the eight-neighbor connectivity (Liu and Mason 2016, ITC 2018). We randomly selected around 4% of events from the total (61779), leading to 2267 events (figure 2(e) and appendix D). Events delineation and event-based random sampling were implemented in the GEE. Following sampling, we classified the sampled events into small (<0.5 ha), medium (0.5–2 ha), and large (>2 ha) events based on their area sizes. We further grouped the events based on their distribution across countries, agreement vs. non-agreement peat forests, and hardwood vs. palm dominated peat forests (figure 2(d)). Data on hardwood and palm dominated peat forests were sourced from the Crezee *et al* (2022) study.

2.4.3. Visual interpretation of the direct drivers

We labeled the direct drivers through visual interpretation of post-disturbance land use on an event-by-event basis using the high-resolution 4.77 m Planet and 10 m Sentinel-2A satellite imagery (figure 3). For assigning a specific driver, we applied a set of distinct criteria for each driver class, discernible on the images following disturbances (table 1, appendices E and F). Previous studies have successfully implemented visual interpretation techniques for driver identification (De Sy *et al* 2019, Slagter *et al* 2023). We centered our analysis at the event level, however, we zoomed out to the neighboring areas to understand contextual land use patterns to support our driver assessment. We accessed the Planet dataset for tropical Africa through NICFI using the GEE platform and Planet QGIS Plugin in QGIS. We accessed Level 2A Surface Reflectance Sentinel Imagery from GEE archives. The Sentinel 2A images are atmospherically corrected using sen2cor (ESA 2013). We masked cloud and shadow following s2cloudless approach in GEE (2023).

3. Results

3.1. Spatial and temporal analysis of peat forest disturbances

From 2019 to 2021, disturbances encompassed an area of 30 294 ha in the peat forests of Cuvette Centrale. Most areas encountered medium-intensity disturbances, ranging from 2% to 20% disturbances spanning over 28% of the grid cells and covering an area of 21 049 ha (figure 6(a) and appendices B and D). Although low-intensity disturbances (<2% disturbances) spanned across 70% of the grid cells, they only covered an area of 6414 ha. Spatial hotspots were relatively less common, covering an area of 2831 ha across just 2% of the grid cells. Among these, certain grid cells exhibited a 100% loss of forest cover.

The great majority of the disturbances, accounting for around 91% of the total 30 294 ha were concentrated in DRC, with a substantial portion of spatial hotspots occurring in the northwest region, particularly in the Sud-Ubangi district. Many high-intensity disturbances were also observed along the Congo River. While there exists a disparity in the extent of forest disturbances between DRC and ROC, our analysis did not reveal substantial differences in the intensity of these disturbances between the two countries.

The temporal distribution of peat forest disturbances displayed a consistent interannual pattern, predominantly occurring during the first half of each year (figure 4(a) and appendix I(a)). Disturbances in the first half of the year accounted for 62% in 2019, 69% in 2020, and 78% in 2021. This seasonal trend began from January onwards, with temporal hotspots emerging between February and May, and it gradually declined thereafter. Although a minor peak occurred in the latter part of each year, this pattern was not consistent over the period. There was

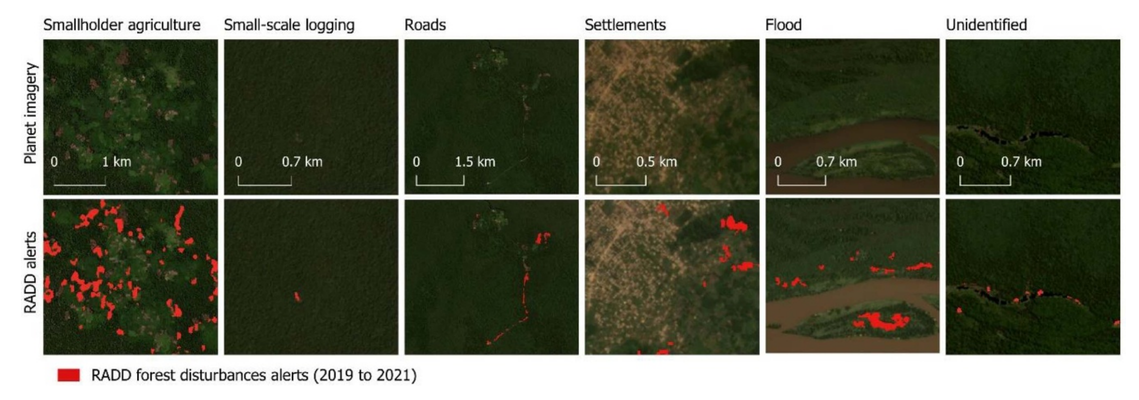


Figure 3. Example Planet images relating to direct drivers of peat forest disturbances in the Cuvette Centrale. Disturbances as detected in the RADD alerts from 2019–2021 and identified direct drivers following disturbances visualized on the 4.8 m spatial resolution Planet and 10 m resolution Sentinel-2 imagery. For each disturbance event, we examined 24 monthly images in the subsequent two years from both Planet and Sentinel-2. For example, if an event occurred later in 2021, we analyzed the subsequent monthly images from both Planet and Sentinel-2 over 2022 and 2023. While not all images were cloud-free, available time series of clear monthly images over two years were sufficient to reliably identify a driver to a disturbance event.

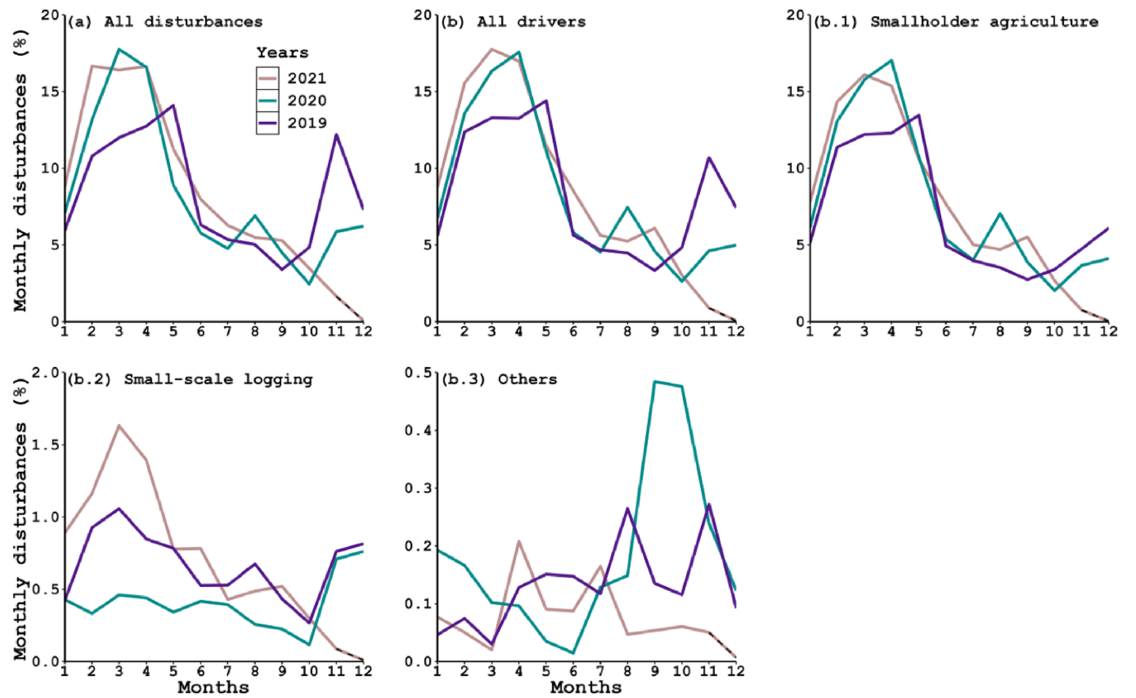


Figure 4. Temporal distribution of disturbances in Cuvette Centrale. The distribution of disturbances (in % on the y-axis) is depicted month-wise aggregated by year from 2019 to 2021 (x-axis). Lines for November and December 2021 are dashed in black to indicate that high-confidence data for these months was not fully available. (a) Temporal distribution of all disturbances. (b) Temporal distribution of all drivers. (b.1) Agriculture, (b.2) logging, (b.3) other events, respectively. Other events include roads, settlements, and unidentified. The monthly percentage of disturbances (y-axis) was calculated considering the total sum of all drivers per year, segregated by months on the x-axis. The scales are much lower in figures (b.2) to (b.3), with logging and other factors contributing only a small fraction of disturbances compared to agriculture in figure (b.1).

no intra-annual trend. The year 2019 was exceptional, featuring notably extensive disturbances (20%) during November and December.

3.2. Distribution of disturbances by protection status and accessibility

Our findings revealed that more than three-quarters of the disturbances (∼77%) occurred outside the managed forest concession areas (figure 2(d)), extending greatly to the designated national and world protected areas within the peat forests in Cuvette Centrale. Around 40% of the disturbances occurred within these protected areas, with ∼35% occurring specifically inside the world protected areas.

Disturbances were primarily concentrated along the peat forest edges, with the core region remaining relatively undisturbed (figure 5). Approximately 90% of disturbances took place within a 1 km distance from the edges and 99% of them within a 3 km distance. Further, around 76% of disturbances occurred within 5 km distance from the river or road networks, and around 94% within 10 km. More disturbances were observed along the road networks compared with river networks at equivalent distances. For instance, disturbances within a 5–10 km radius of road networks were approximately 1.3 times higher than those along the rivers.

3.3. Direct drivers of peat forest disturbances

Between 2019 and 2021, we identified five direct drivers of peat forest disturbances in Cuvette Centrale: smallholder agriculture, small-scale logging, floods, roads, and settlements (figures 6(b)–(d)). Smallholder agriculture was the most prevalent, accounting for over 88% of the 2267 sampled events, followed by logging at ∼7% (table 2). A small percentage of events (<1%) remained undefined. We reclassified roads, settlements, and undefined events into others.

3.3.1. Spatial distribution of direct drivers

Over 90% of the drivers were concentrated in DRC. In both countries, smallholder agriculture remained the leading driver of peat disturbances, accounting for roughly 89% of disturbance areas in DRC and 77% in ROC (table 2). Logging events constituted 18% of disturbance areas in ROC, which is nearly three times higher than those in DRC. The majority of flood events (98%) were located along the Congo River, where all small settlements were situated near rivers and water channels in DRC. Most of the road events (∼75%) were found in the ROC.

Most disturbances (74%) took place in the hardwood dominated peat forests (appendix K). The main driver in both palm (85%) and hardwood (89%) dominated forests was smallholder agriculture. Flood events (96%) occurred primarily in palm dominated

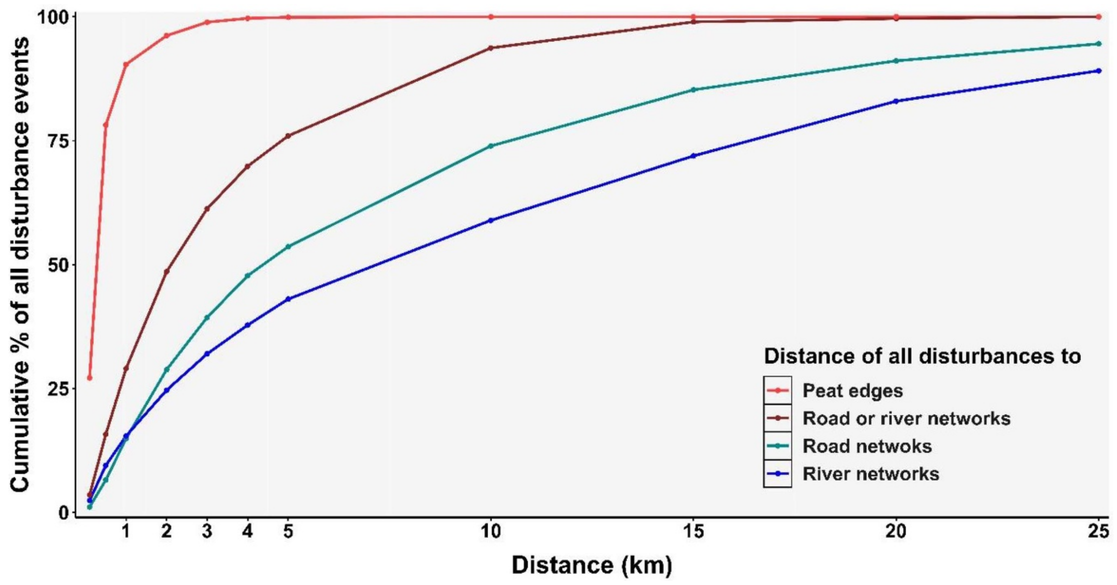


Figure 5. Distribution of all disturbances along peat forest edges, road and river networks in Cuvette Centrale from 2019 to 2021.

Table 2. Distribution of drivers of peat forest disturbances in the Cuvette Centrale by countries, DRC, and ROC from 2019 to 2021.

	ROC				DRC			
Drivers	Number of events	Events area (ha)	Area (%) relative to events in ROC	Area (%) relative to events in Cuvette Centrale	Number of events	Events area (ha)	Area (%) relative to events in DRC	Area (%) relative to events in Cuvette Centrale
Agriculture	142	80.7	77.0	6.7	1791	979.6	89.1	81.4
Logging	49	18.5	17.6	1.5	177	68.8	6.3	5.7
Flood	5	0.7	0.7	0.1	69	36.5	3.3	3.0
Roads	3	1.4	1.4	0.1	1	0.6	0.1	0.1
Settlements	0	0.0	0.0	0.0	12	4.3	0.4	0.4
Unidentified	3	3.5	3.3	0.3	16	9.4	0.9	0.8
Total		104.7	100.0	8.7		1099.2	100.0	91.3

forests. We observed more than three-quarters (76%) of the disturbances in the non-agreement peat forests (appendix L), with smallholder agriculture being the primary driver, accounting for around 88% of disturbances in both agreement and non-agreement peat forests.

Smallholder agriculture consistently emerged as the predominant driver across events of all sizes (appendix M). While small events occurred more frequently, constituting approximately two-thirds of all events, medium events (0.5–2 hectares) had a more substantial impact, covering 53% of the total disturbance area. With 80% of the total disturbance area was covered by small to medium events (appendix M) and large events typically encompassed multiple croplands (appendix G), this implies that disturbances were driven by smallholder activities.

3.3.2. Temporal distribution of direct drivers

We observed a distinct temporal pattern, with the majority of the drivers occurring prominently in the first half of each year (figure 4(b) and appendix I(b)). This trend was primarily linked to smallholder agriculture (figure 4(b.1) and appendix I(b.1)). Although less prominent, logging events were also concentrated during the first half of the year (figure 4(b.2) and appendix I(b.2)). Flood events were concentrated specifically from October to December in 2019 (appendix J). No clear pattern of seasonality was evident for other events, suggesting that they occurred randomly throughout the year (figure 4(b.3) and appendix I(b.3)).

4. Discussion

4.1. What are the patterns of peat forest disturbances?

Our findings reveal a total of 30 294 ha of peat forest disturbances in Cuvette Centrale from 2019 to 2021, representing less than 1% loss of peat forest area over this period. This reaffirms assertions by previous studies stating relatively undisturbed peat forests

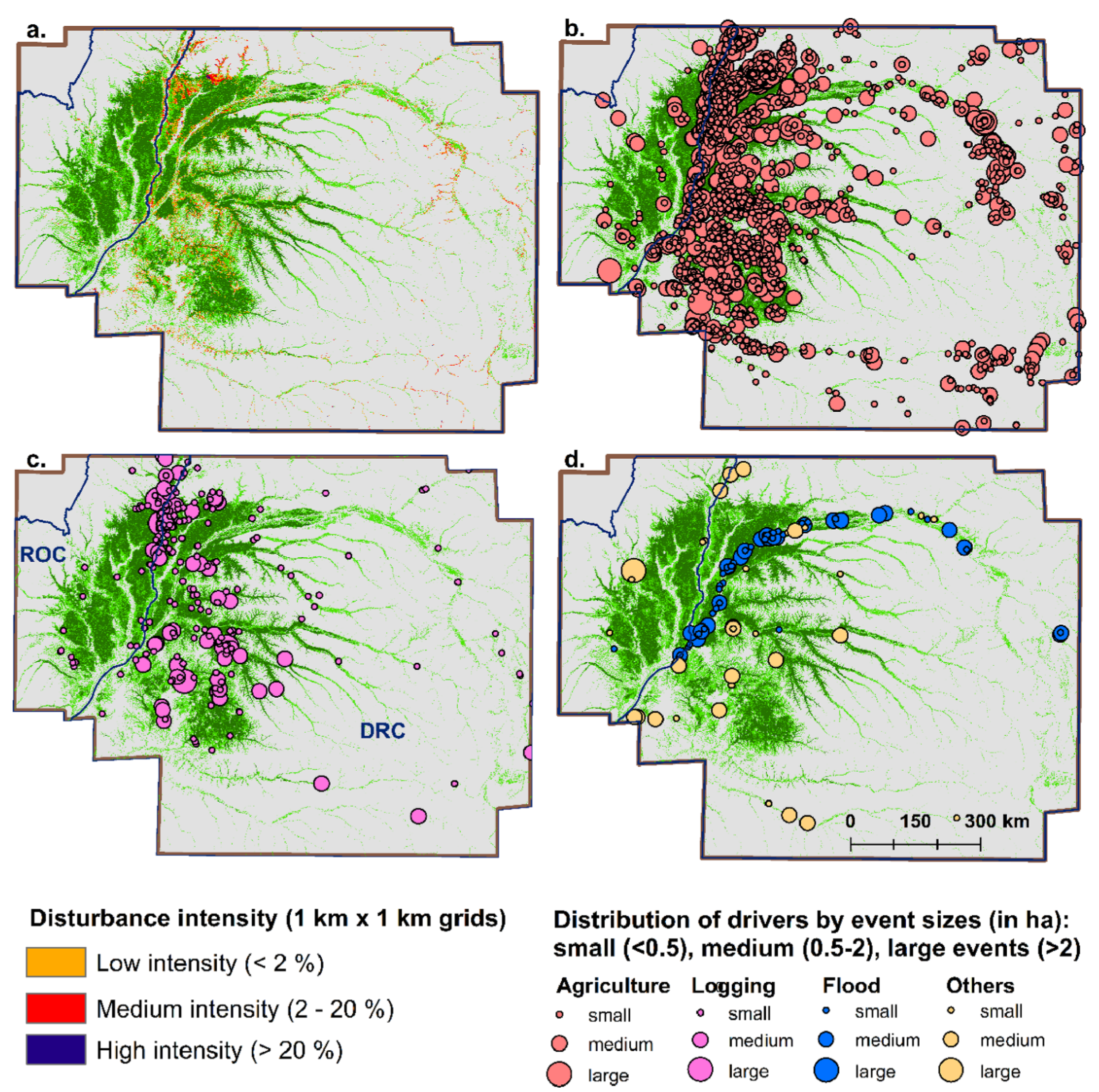


Figure 6. (a) Distribution of intensity of the disturbances in Cuvette Centrale in a 1 km × 1 km grid cell. Distribution of direct drivers of the peat forest disturbances: (b) smallholder agriculture, (c) logging, (d) flood, and others. Others include roads, settlements, and unidentified. The drivers are shown by the size of the events: small (<0.5 ha), medium (0.5–2 ha), and large (>2 ha) events.

in Cuvette Centrale (Dargie *et al* 2017, 2019, Miles *et al* 2017, Vancutsem *et al* 2021). Nevertheless, the cumulative area impact of disturbances may substantially expand over a longer period if left unaddressed. Examples from SEA and the Amazon underscore this concern: SEA lost nearly 60% of its peat forests from 11.9 Mha in 1990 to 4.6 Mha in 2015 (Miettinen *et al* 2016). In the Peruvian Amazon, 11% of the 4.2 Mha palm swamp peat forests underwent degradation, and 2% experienced deforestation from 1990 to 2018 (Marcus *et al* 2024).

Our analysis shows that 91% of the peat forest disturbances in Cuvette Centrale are concentrated within DRC. This is consistent with previous findings that DRC alone accounts for two-thirds of all forest loss in the entire Congo Basin (Tyukavina *et al* 2018). This underscores the predominance of forest loss in DRC, encompassing both peat and mineral soil. The occurrence of 91% disturbances in DRC is concerning given the share of peatlands between DRC (55%) and ROC (45%) does not differ greatly. Previous studies link the predominant forest loss in DRC with population growth, poverty, inadequate governance, and the dependence of the large population on forests for livelihoods (Tyukavina *et al* 2018, Cerutti *et al* 2023). These factors may also contribute to peat forest loss in DRC, necessitating further research for confirmation. The relatively low share of peat disturbances in ROC could be linked to the sparse population and infrequent human activities in its part of Cuvette Centrale (Dargie *et al* 2019).

A great majority of the total disturbances consistently occurred in the first half of each year from 2019 to 2021. This trend is primarily attributed to smallholder agriculture, responsible for 88% of the total disturbances, peaking in the first half of each year. This period in the Congo Basin consists of a dry season (January–February) and a short wet season

(March to May) (Creese *et al* 2019). Previous studies reported decreased precipitation from March to May and increased precipitation in the dry seasons—(December–February) and (June–August) in recent decades (Dyer *et al* 2017, Creese *et al* 2019, Jiang *et al* 2019, Wang *et al* 2021). The increasing drier conditions in the first half of the year could be linked to our observation of predominant disturbances during that period, suggesting a consistent interannual pattern. This aligns with earlier studies in the broader Congo Basin region (Sonwa *et al* 2020, Gou *et al* 2022, Slagter *et al* 2023). Nevertheless, a three-year study period is insufficient for discerning long term interannual patterns. Future research should use extended datasets to assess the persistence of these trends.

4.2. How do protection status and accessibility affect distribution of disturbances?

Our findings reveal that 99% of disturbances occurred within 3 km from the peat forest edges, possibly due to more accessibility for agricultural drainage. Further ground research is needed to investigate these aspects. The combination of 76% of disturbances in non-agreement forest areas and 90% within 1 km of the peat forest edges suggests a considerable overlap between them. Although core peat forests remain relatively intact, they could face considerable disturbances in coming years from agricultural drainage (Dargie *et al* 2017, 2019), lack of enforcement of protection regulations—supported by our findings, Lilleskov *et al* (2019) and Dargie *et al* (2017), high population pressure particularly in DRC (Tyukavina *et al* 2018, Cerutti *et al* 2023) and increased accessibility through roads and rivers as observed in our study. Although DRC has maintained a >20-year logging moratorium covering 18% of peatlands in its Congo Basin portion, the possibility of lifting it remains (Dargie *et al* 2019, Rainforest Foundation 2022). Approximately 80% of peatlands in Cuvette Centrale overlap with concessions for industrial agriculture, logging, or oil blocks (Greenpeace 2019). Recently, oil blocks have been granted for exploration in ROC and DRC, some spanning across peatlands (Feukeng 2021). Unless concessions are entirely halted and robust national protection measures are implemented, the Cuvette Centrale region may confront a fate similar to that of peatlands in Indonesia.

Approximately 76% of disturbances occurred within a 5 km distance from river or road networks and over 94% within 10 km. This aligns with prior research highlighting the role of accessibility in facilitating forest disturbances in the African rainforest (Ernst *et al* 2013, Barber *et al* 2014, Ordway *et al* 2017, Kleinschroth *et al* 2019). The greater share of disturbances within hardwood dominated peat forests compared to palm dominated, relative to their respective areas, indicates that hardwood dominated forests could host more valuable timber species, leading to increased local or external resource demands. Other factors such as ease of access or protection status could also contribute to the more frequent disturbances in the hardwood dominated forests. Future research should explore these underlying factors contributing to peat forest disturbances. Further, over three-quarters of the peat forest loss outside designated forest concessions suggests widespread illicit forest clearing in Cuvette Centrale. Moreover, a higher proportion of disturbances in world protected areas compared to national ones underscores the need for effective protection enforcement strategies targeting world protected areas. Contrary to the assumption that protection status guarantees peatland preservation, our findings, revealing 40% of disturbances within protected areas, underscore the necessity for stringent enforcement of (inter)national policies aligning with commitments in the Brazzaville Declaration and the Paris Agreement. The United Nations Environment Programme through the Global Peatlands Initiative, UN-REDD, International Tropical Peatlands Center, Tropical Peatland Initiative and International Peatland Society could also play a pivotal role in addressing peat forest disturbances.

4.3. What are the main drivers of peat forest disturbances and how do they vary?

We offer the first assessment of the direct drivers of peat forest disturbances in the Cuvette Centrale from 2019 to 2021. Smallholder agriculture emerges as the predominant driver, responsible for 88% of peat forest loss. This aligns with broader trends in the Congo Basin, where smallholder agriculture contributed 84% of total forest loss from 2000 to 2014 (Tyukavina *et al* 2018), consistent findings reported in several other studies (Geist and Lambin 2002, Tegegne *et al* 2016, Curtis *et al* 2018, Shapiro *et al* 2023). Drivers of peat loss in Cuvette Centrale differ from those observed in SEA. Industrial plantations have exhibited the most rapid expansion in SEA, covering 27% of peatlands while smallholder areas cover 22% (Miettinen *et al* 2011, 2016). Small-scale logging is the second most important driver in Cuvette Centrale, contributing 7% to peat forest disturbances. This mirrors prior research indicating logging shares 10% of the total forest loss across the entire Congo Basin (Tyukavina *et al* 2018).

At the country level, smallholder agriculture is the primary driver both in ROC and DRC, more prominent in DRC, accounting for around 90% of disturbances. This aligns with previous research attributing over 90% of total forest loss to smallholder agriculture in DRC (Tyukavina *et al* 2018). In ROC, logging also plays a considerable role, sharing 18% of peat disturbances, consistent with small-scale logging representing 20% of all forest loss in the country (Lawson 2014). National policies should address both agriculture and logging to mitigate peat forest loss in ROC, with specific interventions targeting smallholder agriculture in DRC. We observed that agricultural events cluster over areas, while logging disperses widely, mainly co-occurring with agriculture. This finding aligns with previous studies in tropical regions including the Congo Basin (Ferrer Velasco *et al* 2020, Shapiro *et al* 2023). Logging could serve as the initial stage of tropical forest degradation, eventually culminating in widespread forest clearing (Ahrends *et al* 2010). Further research with a longer time series is essential to validate this pattern in Cuvette Centrale peat forests. Although not directly comparable to broader Congo Basin forests, our findings reveal similar trends of small-scale clearing for agriculture and logging in Cuvette Centrale peat forests.

We observed potential higher disturbances in late 2020 and 2021, suggesting a connection to flood events. However, we did not include them as a flood driver due to limitations in identifying them using the RADD product and instead categorized them as unidentified. The impact of flood events on forest cover—whether complete or partial removal—remains unclear. While the area affected by flooding is relatively small compared to other disturbances, their regular occurrence and long-term consequences may be considerable. Future studies should assess the extent and long-term impact of flooding on forest cover.

Our findings could serve as a reference dataset for automating visual interpretation with machine learning, enabling the generation of a time series record of peat forest disturbance drivers in Cuvette Centrale. Recent studies have successfully implemented such automation (Curtis *et al* 2018, Masolele *et al* 2024). Our findings can further facilitate the upscaling of analysis using machine learning across the entire Cuvette Centrale region. We recommend conducting separate driver assessments in diverse peat forests, including South America and SEA, to create reference datasets. Combining findings from these distinct regions could facilitate upscaling the analysis to a pan-tropical level, as machine learning models perform better with region-specific input (Masolele *et al* 2021).

Our study lacks ground data for validating identified drivers and specific insights into the crop types. Reports suggest rice crops are grown in Cuvette Centrale (Cordon 2020). Future research should combine ground data with RS observations to identify specific crops, assess variations among field sizes, and validate the RS based findings. Smallholder agriculture may coexist with fuelwood extraction and charcoal harvesting, as most households, especially in DRC, rely on these for cooking (Bilonda 2020). However, identifying such small-scale activities through satellite imagery poses limitations. Future research should address these challenges in the region.

5. Conclusions

Our study provides a pioneering analysis of peat forest disturbances and their direct drivers in the Cuvette Centrale. The findings indicate that 91% of disturbances, totaling 30 294 ha, were concentrated in the DRC, necessitating increased emphasis on (inter)national policy interventions to address peat forest loss in the country. Most peat forest areas in Cuvette Centrale experienced medium-intensity disturbances (2%–20%), covering 21 049 ha, while spatial hotspots covered just 2831 ha, indicating the need to prioritize interventions on medium-intensity disturbances. Disturbances predominantly showed a seasonal recurring pattern during the first half of each year from 2019 to 2021 with temporal hotspots emerging between February and May, closely linked to smallholder agriculture activities. Smallholder agriculture accounted for over 88% of disturbances in Cuvette Centrale, representing a leading role in both the ROC (∼77%) and the DRC (∼89%). In the ROC, logging events constituted an important share (18%). National policy actions should address both agriculture and logging to mitigate peat forest loss in ROC, with specific interventions targeting smallholder agriculture in the DRC.

Approximately 76% of disturbances were concentrated within 5 km of river or road networks, with more disturbances observed along roads, underscoring their importance in providing greater accessibility to peat forests. Nearly 90% of disturbances occurred within 1 km of peat edges, with 99% within a 3 km distance, indicating that disturbances predominantly occurred at the peripheries, leaving core peat regions relatively undisturbed. Around 77% of disturbances occurred outside managed forest concessions in Cuvette Centrale, with a large proportion (40%) extending into protected areas. If these issues are not addressed, the disturbances could intensify in the coming years, leading to a substantial expansion of their cumulative area impact over time. Governments must proactively implement measures to meet their peatland protection commitments outlined in the Brazzaville Declaration and the Paris Agreement. International collaboration is also essential, necessitating proactive measures from related platforms and partners.

Our findings on direct driver assessment could serve as a reference dataset for machine learning models, facilitating the automation of visual interpretation to generate a time series record of drivers and enabling the upscaling of assessments across the entire Cuvette Centrale region. We recommend conducting separate direct driver assessments in diverse peat forests in South America and SEA to create reference datasets. Combining findings from these distinct regions could enable the upscaling of the analysis to a pan-tropical level. Future research should incorporate ground data with RS observations to identify specific crops and validate RS based findings for greater accuracy. Additionally, it is imperative to understand the dynamics of direct drivers of peat disturbances in relation to their underlying causes for a more profound understanding, laying the groundwork for informed policy formulation.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

This research is part of CIFOR's Global Comparative Study on REDD+ (www.cifor.org/gcs). The funding partners that have supported this research include the Norwegian International Climate and Forest Initiative (NICFI) (Agreement INS 2078-19/0010), the European Commission Horizon Europe project 'Open-Earth- Monitor' (Grant Number 101059548), the US Government's SilvaCarbon program,the Open Domain Science project (Project Number: OCENW.M.21.203) of the Nederlandse Organisatie voor Wetenschappelijk Onderzoek (NWO), and the USAID supported SWAMP project (Grant MTO- 069018). Planet imagery was made available by the NICFI program and the Planet Education & Research program.

Disclaimer

The usage of designations and the presentation of material in the maps do not indicate any opinion from the authors regarding the legal or constitutional status of any country, territory, or sea area, nor do they provide any stance on the delimitation of frontiers.

Appendix A

Harmonization of peatland maps with RADD alert dataset, and harmonizing protection status and forest concessions datasets with the peat forest disturbance data.

Nearest neighbor resampling method was chosen to harmonize the peatland datasets to 10 m resolution to match with RADD alert data as both peatland images contain categorical data. Nearest neighbor resampling preserves these original class values without introducing interpolated values that could misrepresent the data.

The protected area and concession boundary datasets were obtained as vector data, represented by polygons. To harmonize these datasets with the peat forest disturbances data, we employed a method of overlaying the polygon boundaries onto the disturbance events. The disturbance events were also converted into vector data, represented as point vectors. By intersecting the disturbance events with the polygons of the protected areas and concession boundaries, we were able to effectively integrate these datasets.

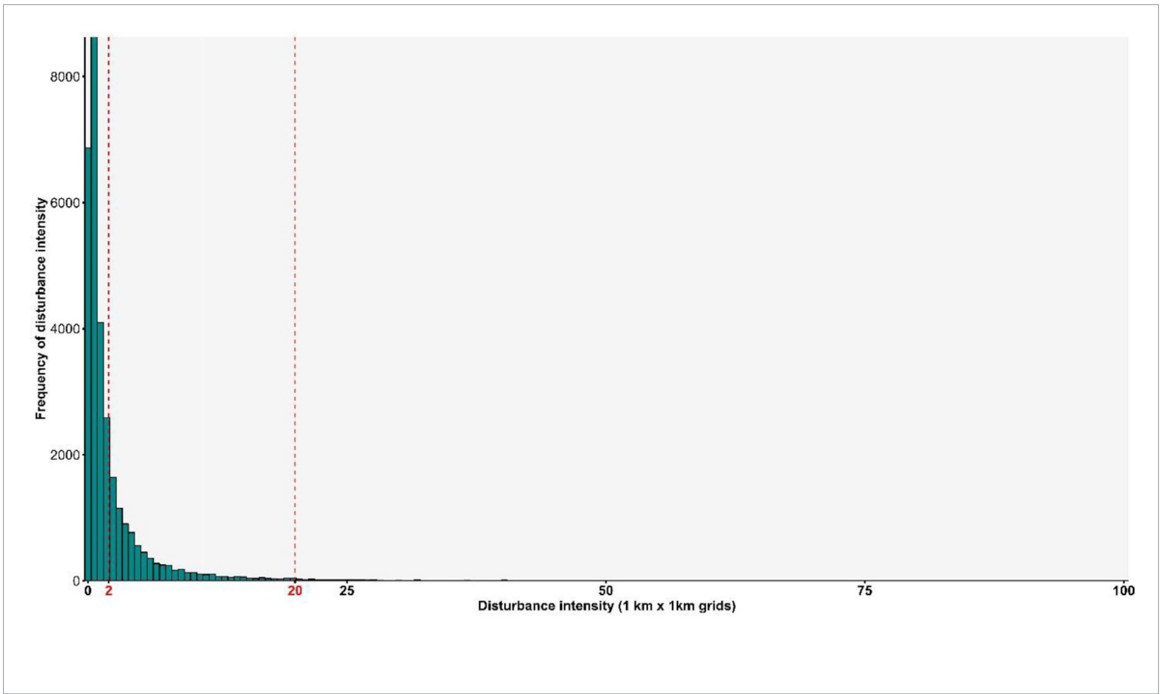
Appendix B

This appendix explains the rationale for the breakpoints used to group disturbance intensity into low (<2%), medium (2%–20%), and high (>20%) intensity categories. These categories are based on the natural breaks in the distribution of disturbance intensities as observed in the histogram, with a high frequency of low-intensity disturbances and a gradual decline towards high-intensity disturbances. More specifically,

Low-intensity disturbances (<2%): The histogram shows a high frequency of disturbances at very low intensities, clustered around the leftmost part of the distribution. Setting the breakpoint at 2% captures the bulk of these low-intensity disturbances, which represent the most common disturbances in the dataset.

Medium-intensity disturbances (2%–20%): The medium-intensity range captures the middle part of the distribution where the frequency of disturbances starts to decline more gradually. This range includes a substantial number of events that are considerably higher than the low-intensity disturbances but still not extreme, ensuring a meaningful distinction between low and high-intensity groups.

High-intensity disturbances (>20%): The histogram shows that disturbances above 20% are relatively rare, indicated by the sparse right tail of the distribution. Setting the high-intensity threshold at 20% effectively isolates the most severe disturbances, which, while less frequent, represent substantial changes.

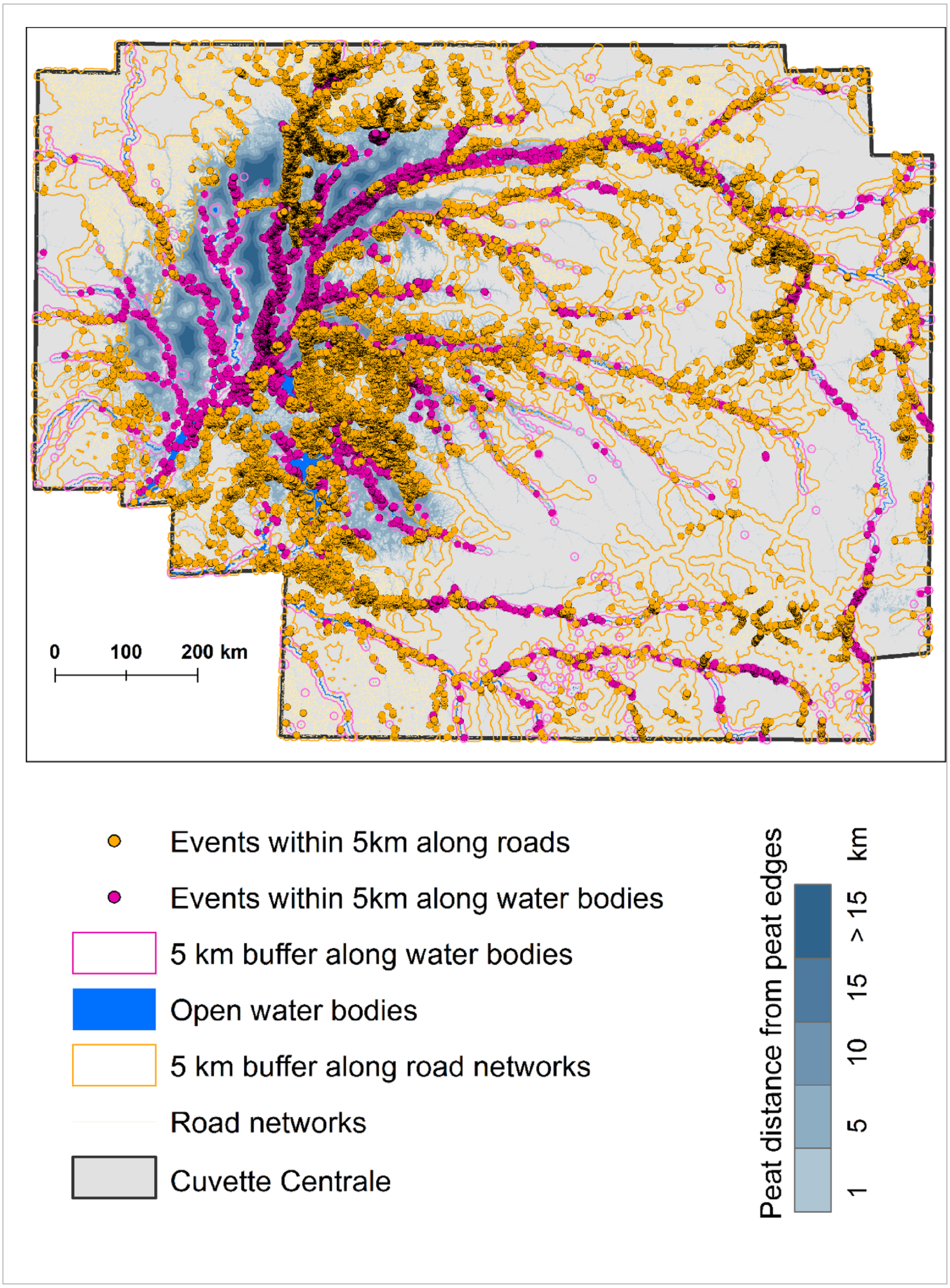


Appendix C

This appendix shows the distance map where peat edge pixels represent zero value and values continually increase towards the forest interior. It also shows disturbance events within a 5 km distance of road and river networks. It further details the methods employed for the harmonization of data used to produce the distance map.

Data harmonization:

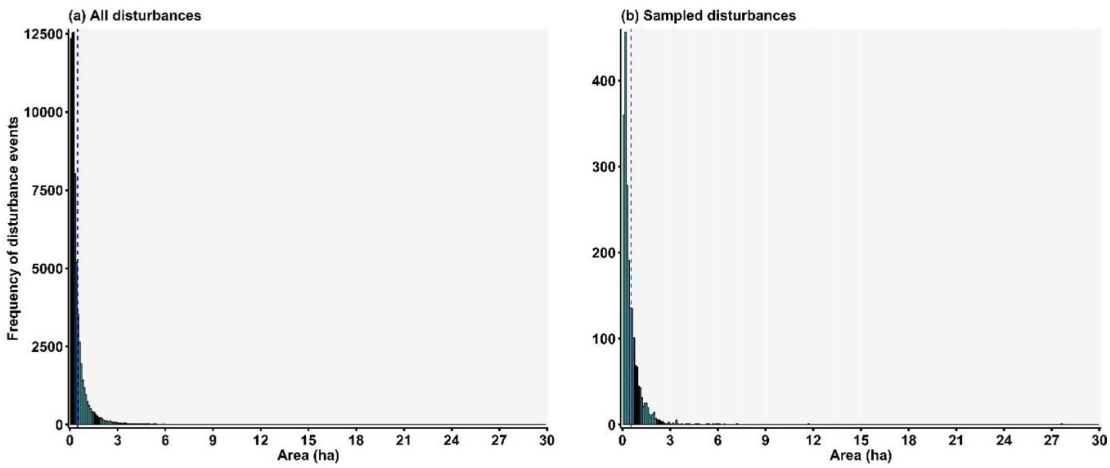
- We converted the disturbance events into vector data, represented as point vectors.
- To extract the pixel values from the distance map for the disturbance events, we used the 'Extract Values to Points' tool in ArcGIS Pro.
- We measured distances in km along river and road networks by creating buffer zones as polygon vectors.
- We intersected the disturbance events with the polygon boundaries of these buffer zones to determine the distances of disturbance events from the rivers and roads.



Appendix D

Histograms showing the distribution of all disturbances (figure (a)) and sampled disturbances (figure (b)).

Histograms are based on disturbance areas (in ha) in the peat forests in Cuvette Centrale from 2019 to 2021. The area of the sampled events was 1204 ha and all disturbances 30 293.81 ha. The histograms bin the disturbances with a bin width of 0.1 ha. The x-axis represents the area of disturbance events in ha, while the y-axis represents the frequency of disturbance events within each bin. The blue dashed line indicates the mean area of the disturbances in both figures. The mean for all disturbances and sampled disturbances were 0.48 ha and 0.52 ha respectively.



Appendix E

Guidelines for direct driver assessments using the driver class description in table 1.

We considered the description items in table 1 holistically, meaning not all criteria need to be met for classification. The presence of multiple indicators strengthens the confidence in the assignment, but the following key indicators are required for classification into each driver class:

Smallholder Agriculture:

- Evidence of vegetation regrowth
- At least one complete or partial harvesting within two years, or patterns similar to adjoining crop fields for events showing no harvesting.

Small-scale logging:

- Either visibility of tree canopy or bare patches in events with no vegetation regrowth in 1–2 years.

Floods:

- The event timing in the second half of 2019, location along rivers and absence of adjoining crop fields.

Roads:

- Linear canopy openings visible for more than three months.

Settlements:

- The visibility of houses and their bright appearance on images.

Unidentified events:

- Events not matching the criteria for the above classes, spatial mismatches or unclear imagery.

The key indicators must be present to initiate classification. Additional context and evidence such as proximity to settlements or existing crop fields (see table 1 for all additional criteria) were used to confirm the classification.

Appendix F

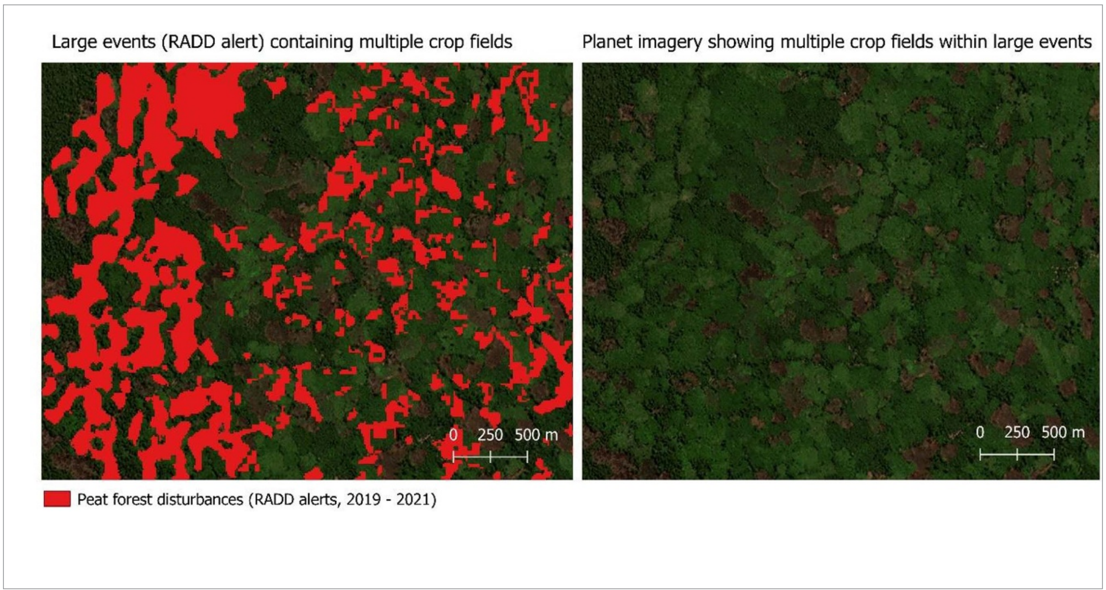
Measures to mitigate unintended interpreter bias.

We implemented several measures to mitigate any unintended interpreter bias. Specifically, when uncertainty arose concerning drivers to certain disturbance events, Karimon consulted with the supervision team and coauthors. Decisions were made together regarding these ambiguous cases. Additionally, to assess the reliability of the interpretations, a subset of sample events was independently reviewed by coauthors following the class description in table 1 and without prior knowledge of Karimon's labeling. The consistency between two assessments confirmed the validity of our interpretations. Furthermore, we sought input from local experts and engaged in collaborative efforts to validate our findings. We have presented the initial findings in two online country-level workshops, where we solicited feedback and validation from local experts. Additionally, we collaborated with a local expert who served as a co-author on the paper. His extensive field experience in the peat forests of the DRC further validates the key findings of our driver assessment.

Appendix G

Large events encompassing multiple adjacent croplands.

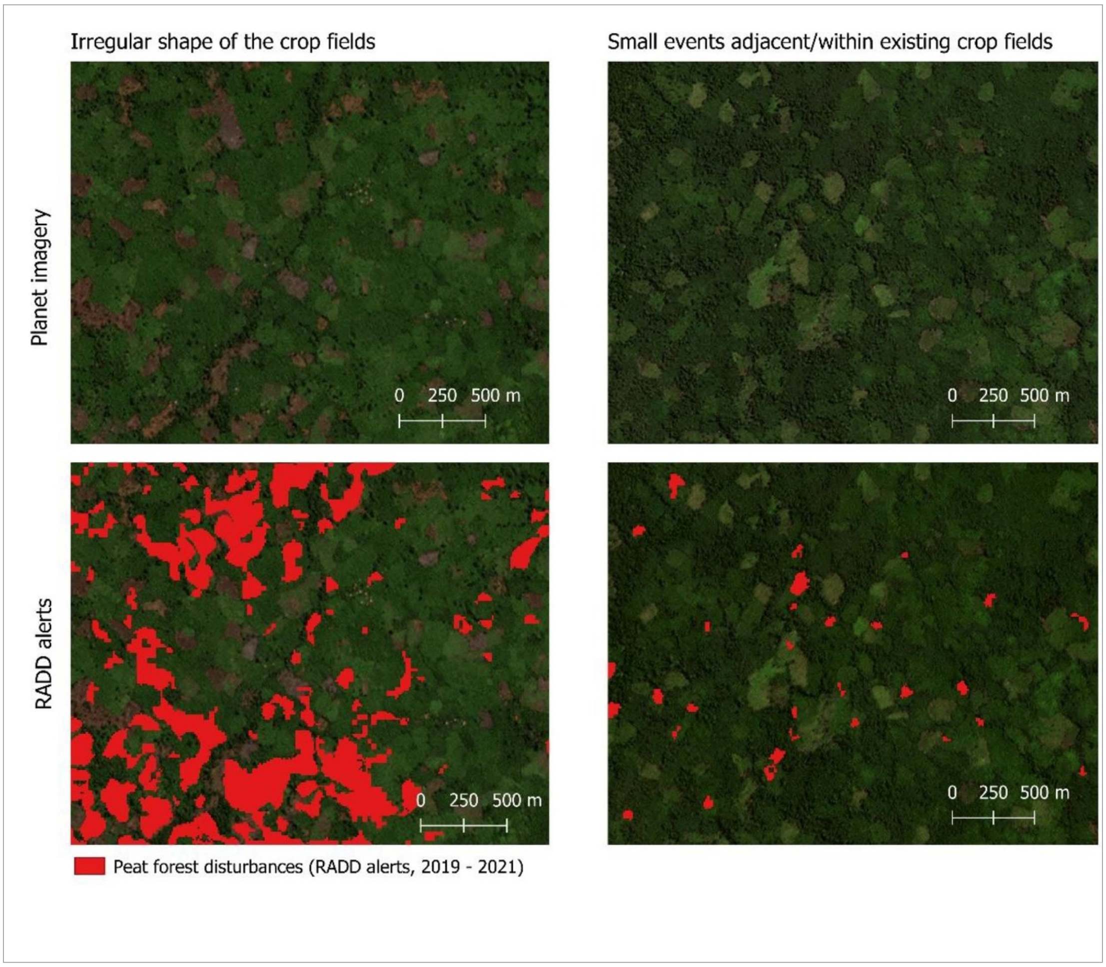
Large events containing multiple croplands were distinguishable by separate crop fields, cropping periods and patterns within the events. An example from Planet images showing large events with multiple croplands is shown in the following Figure.



Appendix H

Small events usually expanding from an existing crop field (right column Figures), and non-mechanized clearing of croplands (left column Figures).

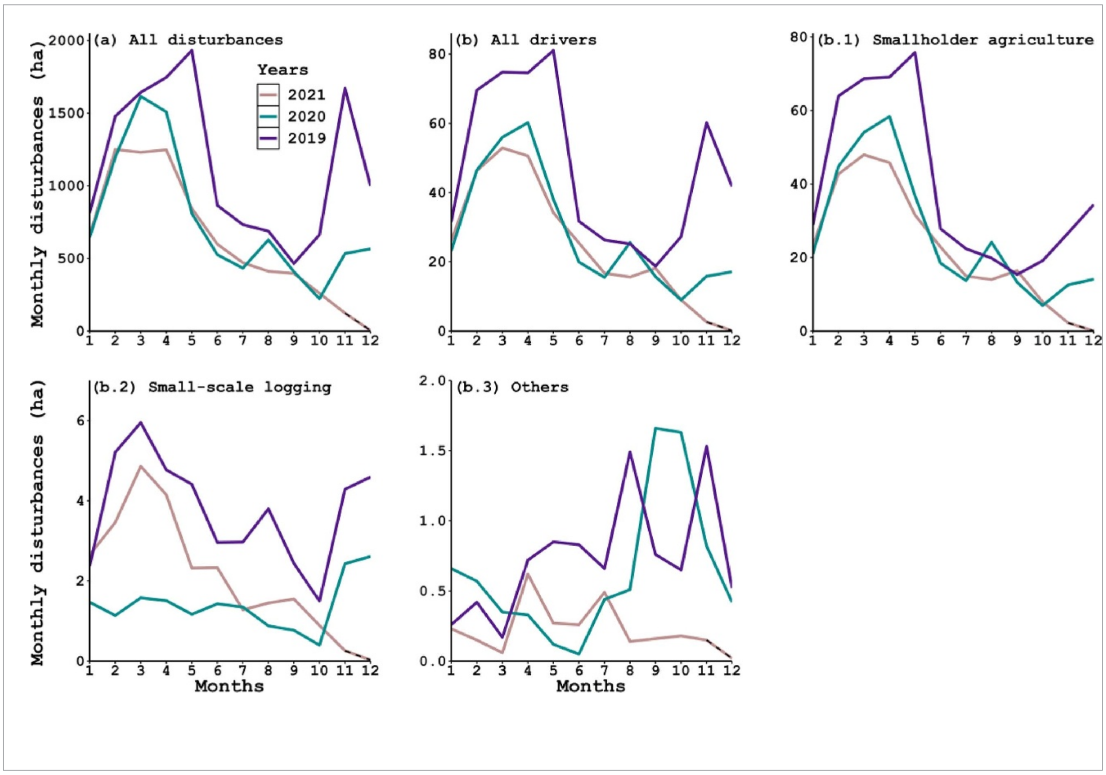
Small events are typically adjacent to existing crop fields, illustrating the expansion of agricultural land into nearby peat forest areas. We identified non-mechanized clearing of croplands by noting the irregular shapes of crop fields and the absence of machinery in their vicinity during the observed period.



Appendix I

Temporal distribution of disturbances (area ha) in Cuvette Centrale from 2019 to 2021.

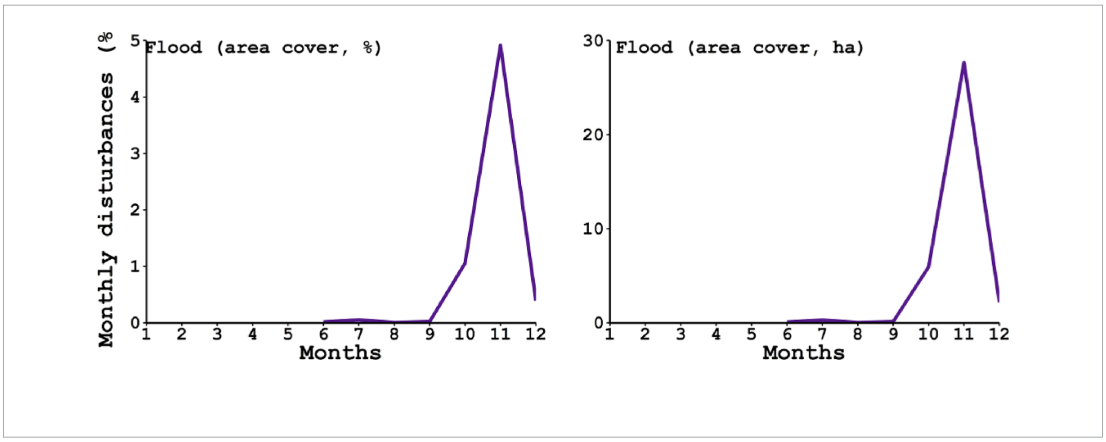
The distribution of disturbances (in ha on the y-axis) is depicted month-wise aggregated by each year from 2019 to 2021 (x-axis). Lines for November and December 2021 are dashed in black to indicate that high-confidence data for these months was not fully available. (a) Temporal distribution of all disturbances (all pixels). (b) Temporal distribution of all drivers (sample-based). All drivers represent 4% samples of the total disturbances. (b.1) Temporal distribution of agriculture, (b.2) Logging, (b.3) Other events, respectively. Other events include roads, settlements, and unidentified. The monthly disturbances (ha) on the y-axis in these figures were calculated in relation to the total sum of all drivers per year, segregated by months on the x-axis. The scales are much lower in figures (b.2)–(b.3), with logging, and other factors contributing only a small fraction of disturbances compared to agriculture in figure (b.1).



Appendix J

Distribution of flood events, mainly along the Congo River in the Cuvette Centrale in the year 2019.

We observed that the proportion of forest disturbances increased along the Congo River since October 2019. This is connected to heavy rains from October 2019 onwards that caused a major flood event in the region (OCHA 2019, Gou *et al* 2022). This explains the comparatively higher proportion of disturbances in 2019 compared to other years. We incorporated flood events exclusively for the year 2019 due to the well-documented major flooding event that year (OCHA 2019, Gou *et al* 2022), which we confidently identified using the RADD alert product. While flash floods were reported in 2020 and 2021, we excluded them due to limitations in identifying them using the RADD product.



Appendix K

Distribution of drivers of peat forest disturbances in the Cuvette Centrale by peat forest type (hardwood, palm dominated) from 2019 to 2021.

The peat forests were categorized into palm dominated, hardwood dominated, and other types. For the ‘other’ category, vegetation type information was unavailable. Our calculations of the total disturbance area across these three peat forest types revealed that the ratio between palm dominated and hardwood dominated peat swamp forests aligns closely with the approximately 1:3 ratio observed in the sample disturbance areas, validating the representativeness of our sampling approach.

	Palm dominated peat forests				Hardwood dominated peat forests			
Drivers	Number of events	Events area (ha)	Area (%) relative to events in palm forests	Area (%) relative to events in both forests	Number of events	Events area (ha)	Area (%) relative to events in hardwood forests	Area (%) relative to events in both forests
Agriculture	442	204.8	85.4	22.2	1085	609.1	89.1	65.9
Logging	32	8.9	3.7	1.0	162	64.8	9.5	7.0
Flood	42	22.0	9.2	2.4	5	2.3	0.3	0.3
Roads	0	0.0	0.0	0.0	4	2.0	0.3	0.2
Settlements	5	1.4	0.6	0.2	2	0.6	0.1	0.1
Unidentified	7	2.8	1.2	0.3	8	5.2	0.8	0.6
	528	239.8	100.0	26.0	1266	684.0	100.0	74.0

Appendix L

Distribution of direct drivers in agreement vs non-agreement peat forests in Cuvette Centrale from 2019 to 2021.

More than two-thirds of the areas were cleared for smallholder agriculture in the non-agreement peat forests, which is around 3.2 times higher than those in the agreement forests. Logging related disturbances were roughly 5 times higher in non-agreement forests.

	Events in agreement peat forests				Events in non-agreement peat forests			
Drivers	Number of events	Events area (ha)	Area (%) relative to events in agreement forests	Area (%) relative to events in both forests	Number of events	Events area (ha)	Area (%) relative to events in non-agreement forests	Area (%) relative to events in both forests
Agriculture	428	252.1	88.4	20.9	1505	808.2	88.0	67.1
Logging	51	14.5	5.1	1.2	175	72.8	7.9	6.0
Flood	34	16.0	5.6	1.3	39	21.3	2.3	1.8
Roads	3	0.9	0.3	0.1	1	1.1	0.1	0.1
Settlements	1	0.1[a]	0.0	0.0	11	4.3	0.5	0.4
Unidentified	5	1.8	0.6	0.2	14	11.1	1.2	0.9
Total	522	285.2	100.0	23.7	1745	918.7	100.0	76.3

[a] Events smaller than the MMU of 0.1 ha in the RADD alert forest disturbances data have been rounded up to 0.1 ha. We intersected the peat forest disturbance data in space and time, resulting in events having areas smaller than the MMU. This can be observed in the table, where one settlement event in agreement peat forests was notably smaller (0.04 ha).

It is important to note that the RADD alerts are generated for humid tropical forests without further distinguishing between forest types. In the Cuvette Centrale region, where peat forests are interspersed with other forest types, intersecting the RADD alerts with the peat forest layer and for our study period (2019–2021) produced disturbance areas smaller than 0.1 ha. Additionally, we have segregated the peat forest disturbances data based on hardwood and palm dominated peat forests, as well as agreement and non-agreement peat forests. This segregation has also contributed to the creation of smaller areas.

Appendix M

Distribution of direct drivers by area size of the events in peat forests of Cuvette Centrale from 2019 to 2021: small (<0.5 ha), medium (0.5–2 ha), and large events (>2 ha).

Notably, agriculture events exhibited an upward trend relating to event sizes: area proportion continually increased from 84% in small events to 95% in large events (appendix M). Logging events showed a contrasting pattern, as area proportion decreased from 12% in small events to a mere 4% in large events. Floods, roads and settlements were relatively small events with large events being non-existent.

Drivers	Small events (< 0.5 ha)				Medium events (0.5–2 ha)				Large events (>2 ha)			
	Number of events	Events area (ha)	Area (%) relative to small events	Area (%) relative to all events	Number of events	Events area (ha)	Area (%) relative to medium events	Area (%) relative to all events	Number of events	Events area (ha)	Area (%) relative to large events	Area (%) relative to all events
Agriculture	1269	274.2	84.1	22.8	605	562.4	87.5	46.7	59	223.6	95.1	18.6
Logging	174	37.8	11.6	3.1	48	40.5	6.3	3.4	4	8.9	3.8	0.7
Flood	43	10.0	3.1	0.8	30	27.2	4.2	2.3	0	0.0	0.0	0.0
Roads	3	0.6	0.2	0.1	1	1.4	0.2	0.1	0	0.0	0.0	0.0
Settlements	8	1.8	0.6	0.2	4	2.5	0.4	0.2	0	0.0	0.0	0.0
Unidentified	7	1.6	0.5	0.1	11	8.7	1.4	0.7	1	2.6	1.1	0.2
Total	1504	326.1	100.0	27.1	699	642.7	100.0	53.4	64	235.1	100.0	19.5

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