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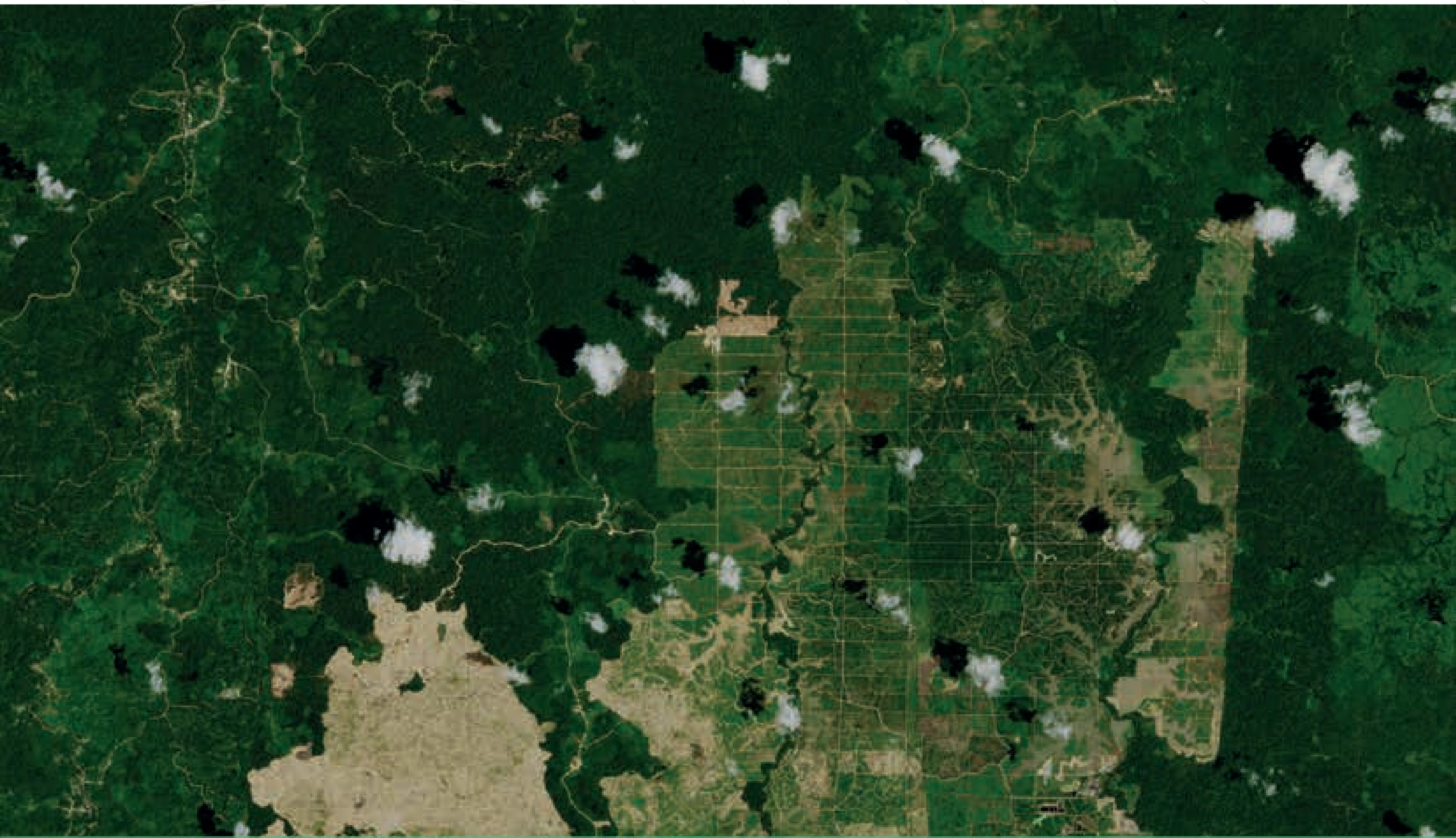
Securing land rights in Cameroon



Democratizing earth observation to improve transparency in land use governance

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Palm oil plantations in East Kalimantan, Indonesia, captured by the Copernicus Sentinel-2 satellite mission, 15 February 2019 (Photo credit: European Space Agency, CC BY-SA 3.0 IGO)

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List of acronyms and abbreviations

ASM	Artisanal and small-scale mining
AVHRR	Advanced very high-resolution radiometer
CSO	Civil society organisation
EO	Earth observation
ESA	European Space Agency
GFC	Global Forest Change
GFW	Global Forest Watch
ha	Hectare
JRC	European Commission's Joint Research Centre
km	Kilometer
LBI	Land-based investment
m	Meter
NGO	Non-governmental organisation
RGB	Red, green, blue
SAR	Synthetic-aperture radar
TMF	Tropical moist forest

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Executive summary

Rates of deforestation have increased in sub-Saharan Africa over the last decade, including in Cameroon, where historically rates were low. Growing interest from foreign investors, a shift in small-scale production to meet global demand for commodities like palm oil, and an increase in mining in primary forests is posing a serious threat to both communities and the environment.

Large international land deals often provide few quality jobs for locals and little economic gain for citizens, as elites tend to capture the benefits. Many such investments have proven highly damaging to both biodiversity and communities, who struggle to claim their land rights in the face of powerful multinational companies and vested national interests.

Cameroon's land regulations are lax and the government generally prioritises economic development over social and environmental concerns. This combined with a culture of secrecy surrounding the nature of mining and large agricultural operations leaves environmental non-governmental organisations (NGOs) and communities severely disadvantaged when challenging unjust concessions on communal lands or protected forest areas.

This paper looks at two case studies in Cameroon to demonstrate the value of earth observation (EO) – the use of satellite imagery and data – for tracking undisclosed commercial activities and generating evidence to advocate for justice and better regulation. The first case looks at small-scale artisanal mining in East Cameroon and the second at large-scale agricultural concessions in West Africa.

Earth observation

EO is emerging as a new tool for the monitoring and reporting of deforestation and land use change in tropical rainforests. Thanks to an increase in the resolution and frequency of publicly available images and free online tools that help users interpret the data, communities and organisations are now able to gather evidence on the social and environmental impact of land concessions.

Accessing information on the ground can be challenging due to ongoing violent conflicts related to land disputes and the inaccessibility of certain locations. EO using satellite imagery can contribute towards fill this data gap. In addition to photographing the landscape in a similar way to a normal camera, satellite sensors can also generate images using the entire electromagnetic spectrum. This can help analysts differentiate between vegetation, water and other types of land cover.

Active sensors on satellites can also be used to penetrate cloud cover by bouncing radio waves off the Earth's surface. This technology is essential for monitoring in Cameroon, where the rainy season means that much of the country is covered in cloud for months at a time. This study uses data from Global Forest Change (GFC) and the Joint Research Centre (JRC)'s tropical forest map (TFM) – both derived from optical Landsat images at a resolution of 30 metres (m) – to measure tree loss and regrowth in the study sites over time. This information was combined with visual interpretation of satellite imagery to assess the changes in land use that drive deforestation.

The impact of artisanal mining in East Cameroon

Mining activity has rapidly increased in the region over the last ten years, providing an ideal site to study the impact of mining on deforestation. A mix of EO, expert interpretation and proximity analysis revealed that small-scale mining activities along the Lom River and its tributaries have been associated with an increase in tree loss since 2014.

Satellite images showed the progression of pools along the region's riverbeds – a tell tale sign of mining activity. As most mineral mining takes place along rivers, we used proximity to these waterways as proxy for measuring mining-related deforestation. We found that intensive mining was driving deforestation in site 1 Betare Oya, tree loss in site 2 Meiganga was mostly driven by agricultural activities, and that limited mining activities had taken place at site 3 Batouri, although logging was observed at the site.

Deforestation started in these sites in 2013 and have continued every year since. Changes to small-scale agriculture is also driving tree loss at all three sites. In areas of open canopy cover, the GFC product classified mines as tree cover loss, whereas the TMF categorised these areas as an increase in water. We therefore relied on the GFC product to study these areas.

The impact of plantations in West Cameroon

An analysis of satellite imagery from the GCF and TMF databases dating back over 20 years provided new information on activities that until now not been disclosed by the companies involved or the government. We found significant deforestation in and around the official land concessions at both study sites. Forest loss has accelerated in recent years, with high rates of deforestation taking place from 2014 to 2018.

We also found that primary forest classified as high value conservation areas were cleared between 2011 and 2015 in a Sudcam concession. Deforestation in this area was halted in 2018 following pressure from environmental NGOs on the plantation's financing organisations. Satellite imagery could be employed to check that this suspension of activities remains in place.

Over different time periods, we observed the clearing of primary forest, and the subsequent regrowth of tree cover. The TMF map cannot differentiate between natural tree growth and planted oil palm or rubber trees. By cross checking these maps with satellites images, we were able to make out the geometric shape and specific colour of rubber trees and confirm that regrowth was not natural., Differentiating between deforestation and the clearing of planted trees cannot be done with certainty prior to 1990 using the TMF database due to the quality of images.

Outside the concessions, we observed disturbances in forest cover caused by shifting patterns of small-scale farming. However, one small patch of deforestation with a dynamic pattern similar to plantation activity was identified northwest of one concession and should be investigated.

Using earth observation to fight deforestation

This study demonstrates that EO can be successfully used to track and monitor land use change and deforestation associated with both artisanal mining operations and large agricultural concessions. Furthermore, it can detect activity taking place beyond concession borders and reveal the stages of plantation implementation and the degree of deforestation – information usually closely guarded by businesses and governments alike. It can also support the monitoring of environmental impacts of formal and informal artisanal mining, which can be difficult to regulate due to logistical challenges.

EO can therefore serve to increase transparency in large land deals and provide a powerful monitoring tool for organisations and affected communities to defend their rights and safeguard the environment. Governments could also make use of EO for policymaking and enforcement of regulations. The use of geo-information is relatively limited across Africa, but has been gaining traction in recent years. EO would require significant investment in new skills, but could have useful applications in disaster risk reduction, climate change and natural resource management, as in the land sector.

One barrier to the uptake of EO by governments is the vested interests of the political class, who may benefit from maintaining the status quo. Access to EO by communities and NGOs is therefore important for evidence gathering when challenging such powerful opponents. EO can be used to predict potential negative impacts, including environmental degradation and the loss of livelihoods in order to resist acquisition of community land. It can also be used to quantify the negative impact of existing concessions and help communities build a stronger case for fair compensation.

Three recommendations to scale up the use of EO:

1. **Combine EO with empirical evidence.** EO can provide evidence of changes, but does not reveal the causes of these changes. It must therefore be supplemented with field data and local knowledge on community land boundaries, land use patterns, and livelihood impacts to build a compelling evidence base. The digitalization of participatory community maps overlain with satellite imagery could be one effective way to accelerate advocacy efforts.
2. **Create non-technical platforms for analysis.** Analysing satellite imagery requires technical skills that are not always readily available in civil society organisations (CSOs) and governments. Cross-sector collaboration and greater investment in new, cost-free analytical products and platforms would make EO more accessible to non-specialist users. As the quality satellite imagery improves, so should the tools and interfaces that facilitate their access. For example, smartphone apps that make satellite data accessible and interactive could put the necessary evidence directly in the hands of activists.
3. **Improve public, private and civil society collaboration.** These innovations rest on long-term collaboration between remote sensing experts, practitioners and policymakers. Such partnerships should focus on capacity building of local and national actors and awareness raising on the availability and value of EO in preventing deforestation. Integrating such partnerships into government bodies would allow for a proactive rather than reactive approach to land allocation and regulations. Ultimately, greater transparency and better regulation would benefit all stakeholders – authorities, companies, communities and CSOs.

1 Introduction

Until the mid-2000s, deforestation rates in sub-Saharan Africa were lower than elsewhere in the tropics, driven largely by minor changes in rural population growth and smallholder agriculture (Curtis *et al.*, 2018; Rudel, 2013). Over the past two decades, a shift in driver dynamics has led to increased land use change and deforestation across the region (Ernst *et al.*, 2013; Tyukavina *et al.*, 2018). This is notably due to higher rates of rural population growth, growing urbanisation, and the expansion of agricultural land use – both from small-scale production and the rise in agro-industrial plantations (Ordway *et al.*, 2017).

Such trends are at play in Cameroon, which historically has had low deforestation rates but now faces a rapidly changing national landscape (Verhegghen *et al.*, 2016). The total area used for agricultural production is expanding, driven by foreign agro-industrial land-based investments (LBIs) and smaller-scale production linked to the global demand for export-oriented commodities, such as palm oil and cocoa (Ordway *et al.*, 2017; Schoneveld, 2014).

In parallel, increased investments in extractive industries have driven land use change in humid primary forests with rich mineral resources (Kamga et al., 2018). Despite national commitments to reduce greenhouse gas emissions linked to deforestation and forest degradation by 50% by 2025, and to reach zero net deforestation by 2035, forest cover continued to decline by an average of 1.1% each year between 2010-2015 (FAO, 2015). Projections show this rate could triple by 2035.

These dramatic changes in land use are often linked to national development agendas that push for economic liberalisation and growth. In theory, small and large-scale LBIs offer economic opportunity for countries and communities, providing local employment and investment in infrastructure and capacities (Cotula and Berger, 2017). However, the track record of LBIs to date points to serious negative consequences for communities and the environment, while national and international stakeholders reap the financial benefits (Behrman *et al.*, 2012; Ndi and Batterbury, 2017; Nguiffo and Sonkoue Watio, 2015).

Indeed, research has shown that the increasing prominence of exploitative investments is the route cause of significant social and environmental harms (Awang Ollong, 2015; Hamann and Sneyd, 2021; Ndi, 2017; Ordway *et al.*, 2017). Such land deals go against Cameroon's international commitments to reduce deforestation and protect human rights, including the Paris Agreement (UNFCCC); the REDD+ initiative; the voluntary guidelines on the responsible governance of tenure (VGGT); the African Union framework and guidelines on land; the African charter on human and peoples' rights; the international covenant on economic, social and cultural rights; and the convention on biological diversity. Yet, the pace and extent of land investment deals continue to be rapid and widespread, driven by the interests of powerful transnational and national economic actors (Borras *et al.*, 2011).

At the policy level, this is compounded by obsolete legislation and a lack of coordination between various agencies in charge of regulating land, natural resources and large infrastructure (Schwartz *et al.*, 2012). Often, the inconsistency between policy and implementation is easily exploited by elites with vested interests across scales (Keene *et al.*, 2015). A body of research points to the political economy of untransparent and unaccountable neopatrimonial governance of natural resource (Nguiffo, 2001; Oyono, 2004; Sneyd, 2014).

Democratizing earth observation to improve transparency

Many LBIs take place without local communities' knowledge, or at least without their meaningful consultation and associated consent, and without legally required social and environmental impact assessments. Even when the latter are performed, there are numerous limitations to their effective implementation, including a lack of baseline data on environmental conditions, weak institutional procedures, and ineffective participation in the process (Tamasang and Atanga, 2018).

In Cameroon, this is happening in a context where land laws fail to adequately secure the rights of rural communities and families. Loss of livelihoods, dispossession, food insecurity, pollution, conflict, migration and displacement are amongst the issues affecting local communities where high land use change and deforestation linked to commercial investments occur (Ngome *et al.*, 2019). The lack of transparency in investment procedures, from the land acquisition phase to investment operations, also prevents countries from optimising foreign direct investment in LBIs.

There is a need to engage in more systematic monitoring and assessments of the nature, location and impacts of land-based investments, and to generate evidence that can prevent widespread negative environmental and social impacts (Borras *et al.*, 2011; Keene *et al.*, 2015). In this study, we show how local and national actors can use earth observation (EO) as a tool to monitor and assess land-use changes around land investments, towards increasing the transparency of land governance. We focus our assessment on Cameroon, where negative impacts from land investments in agriculture and small-scale mining have considerably affected local communities and deforestation.

1.1 Objectives

In the context of land reforms in Cameroon, this study aims to support the LandCam project in improving the transparency of land decisions and access to EO information to support dialogues between communities, civil society, companies, and governments to resolve land conflicts.

In Cameroon, monitoring and tracking land use change resulting from small and large LBIs is difficult due to significant barriers to accessing information from the government and private investors. This includes the precise area investments cover, what agricultural or extractive activities are planned and when they will occur. Although public disclosure of information is increasing through online portals[2], this information is not always timely or accessible to rights' holders impacted by such investments.

Restricted physical access to certain areas due to remoteness, as well as the presence of armed guards around some plantations (WRM, 2018), and potential tenure rights conflicts mean obtaining accurate information on the ground is also difficult. Besides local participatory mapping of the area, which generally depends on timely, independent initiatives, few tools are available to communities and CSOs for the monitoring of land use changes. In this context, the use of remote sensing and EO to spatially map and detect changes in land use provides an opportunity to obtain information on these trends and fill a serious gap in data (GIZ GmbH, 2017; Hack *et al.*, 2016).

2 Both Cameroon's mining cadastre (https://portals.landfolio.com/Cameroon/FR/) and forestry atlas (https://bit.ly/3jXJ0dU) are available via online portals.

EO can be used in triangulation with data on community land boundaries to highlight overlaps that are often the cause of tension and conflict. Such evidence can in turn support advocacy efforts towards more robust policies and stronger legal, social and environmental protection of local community rights and habitats (Nagendra *et al.*, 2015; Qamer *et al.*, 2016; Rasmussen and Jepsen, 2018). Civil society actors in Cameroon have been vocal for years about the human rights abuses and environmental harms linked to the increasing number of concessions granted for commercial projects in various sectors (agribusiness, infrastructure, forestry). Advocates are calling for stronger regulation of mining activities to improve working conditions, the management of benefits and the monitoring of value chains (Bamenjo, 2016; Foumena and Bamenjo, 2013; Nelson, 2007; Nguiffo and Mbianda, 2013). Access to EO-generated evidence for selected geographies would support these calls for stronger, more transparent and accountable procedures for investments, land acquisitions and governance of land and natural resources.

This is a particularly prescient moment for EO tools, as reforms of the legal framework for land are ongoing and a coalition of civil society organisations is putting forward proposals based on solid evidence to strengthen the tenure rights of rural communities and reduce social and environmental impacts (Nguiffo, 2020). This initiative has been led by LandCam, a project funded by the European Union and jointly implemented by the Centre for Environment and Development (CED) in Cameroon, the Anti-Hunger Network (Réseau de lutte contre la faim, RELUFA) in Cameroon, and the International Institute for Environment and Development (IIED) in the UK. The project aims to improve land governance in Cameroon by facilitating dialogue between actors at the local level in selected sites and discussions on land reform options at the national level. The data generated by EO will assist this effort.

This study aims to demonstrate how EO can be used to monitor the expansion of unregulated land-based activities, such as mining, as well as LBIs and other economic activities that could harm the environment. In this paper, we use two cases studies to illustrate how EO can help identify land use changes driven by small- and large-scale activities. The first looks at small-scale extractive activities (small-scale mining) in East Cameroon to assess the level of deforestation associated with such sites. The second examines large-scale agricultural LBIs (agro-industrial concessions) in the South and Centre Regions of Cameroon, monitor the advancement of projects and bridge the gap in publically available information on company operations.

We first explain the process of acquiring satellite imagery and conducting analyses, allowing users not familiar with the subject to understand the approach (see "What is Earth observation?" section). In the subsequent section, we explain how to apply remote sensing methods to assess land use change and, in the two case studies, explain how to quantify forest cover changes. Detecting changes also includes identifying where activities are leading to increased deforestation. Finally, we discuss how EO could be better integrated in government land allocation processes to improve transparency, as well as in negotiations and dialogues to support local communities' interests in land decisions.

1.2 Earth observation data for land use change

EO is primarily based on the use of remote-sensing technologies, providing imagery and information about our planet, its systems and the changes occurring. Satellite imagery shows us things that the eye cannot see and enables us to explain more about the Earth's biophysical properties.

Until the early 2010s, the coarse spatial and temporal resolution of satellite products limited the detection of land use change; for example, it was difficult to differentiate between primary forests and mature oil palm plantations (Patarasuk and Fik, 2013). Thanks to the availability of open, high-resolution archives of Landsat satellite images, EO has evolved into one of the most promising means of mapping and monitoring land use change along with land cover change (Hansen *et al.*, 2013; Pekel *et al.*, 2016; Song *et al.*, 2018). Today, EO provides more granular, frequent and precise images. For example, Copernicus Sentinel 1 (SAR) and Sentinel 2 (optical) satellites provide coverage of Africa every 5-days at a 10m resolution (see Table a).

Tropical forest monitoring using satellite imagery has received growing attention in recent years. Specialised products designed to monitor forest cover now show accurate information in terms of spatial precision and time coverage. This in turn enables independent initiatives and users to create interfaces for others to access and analyse this information.

However, products that tell us about biophysical land cover do not automatically indicate whether a land use change is associated with tree cover loss. Indeed, images showing land cover require interpretation and analysis in order to assess land use changes and potential impacts (Curtis *et al.*, 2018). Accurate information on land use is critical to understanding the causes of forest cover change and for developing effective policies and strategies to slow and reverse forest loss (FAO and JRC, 2012).

Box 1. Definition of terms used in this paper to refer to changes in forest cover

Land cover and land use: land cover refers to the biophysical attributes of the Earth's surface which can be directly detected using satellite imagery. Land use implies a human dimension or purpose for the use of land (Lambin *et al.*, 2001), such as forestry, urban areas, and agriculture. Land use can be inferred from remotely sensed data, but should be verified by local experts or data collected in the field (FAO and JRC, 2012).

Tree cover change: tree cover change refers to the appearance or disappearance of trees. Tree cover loss specifically refers to the removal or mortality of trees and can be due to a variety of factors, including mechanical harvesting, fire, disease or storm damage. As such, 'tree cover loss' does not equate to human induced deforestation (source: GFC).

Deforestation: deforestation refers to a permanent change from forest to another land cover. This implies that the land use has changed, for example from forest to cropland.

Data from Global Forest Change (GFC) records the loss of tree cover on a yearly basis at a spatial resolution of 30 meters (m). In turn, the online platform Global Forest Watch (GFW) allows web users to combine GFC tree cover change maps with geospatial information on land use licensing, such as plans and maps of logging concessions, oil palm plantations, and mining permits (World Resource Institute, n.d.). Some of GFW's tailored applications review recent images of areas of interest, allowing users to receive notifications where forest loss is detected. Other organisations such as CIFOR (Centre for International Forestry Research) use remote sensing to empower communities engaged in forestry management using near real-time interactive online forest monitoring systems (Pratihast *et al.*, 2016).

Other initiatives related to land rights rely on geospatial data, but are at early stages of integrating the multi-year information provided by EO data. One such initiative is the Land Matrix, an independent global land monitoring initiative that provides maps and information about large-scale land acquisitions in low- and middle-income countries across the world to improve transparency and accountability in decisions. Due to difficulty accessing localised information, most initiatives provide poor coverage of community and communal lands, apart from specific exercises such as Landmark and the Rights and Resources Initiative's Tenure Tracking data.

EO data can also be used to develop practical tools that rely on expert interpretation of high-resolution imagery to monitor land use change, the compliance of large contractors and the implementation of large-scale land acquisitions (Lemoine and Rembold, 2016; Rembold *et al.*, 2019). This can provide more accountability and transparency in land use decisions, enable the participation of non-expert stakeholders such as local governments and communities, and provide evidence of unregulated land use changes that communities and CSOs can use to contest unfair land decisions. EO can also provide a research baseline to assess the impact of improvements to land governance and tenure systems on land use change (Fuller, 2006; Ordway *et al.*, 2019).

What is earth observation?

Earth observation[1] (EO) refers to the science and technology of acquiring information about the Earth's surface. EO is part of remote sensing; the science of obtaining information about an object through the analysis of data using a device that is not in contact with that object (Lillesand and Keifer, 1994). The terms EO and remote sensing are often used interchangeably to talk about the science of observing the Earth.

Remote sensing data can be gathered by different devices, for example sensors, film cameras, digital cameras and video recorders. In turn, these devices can be located on a variety of platforms, such as satellites, airplanes, unmanned aerial vehicles (UAVs or drones) and handheld radiometers. The main devices used for EO today are sensors located on satellites. While some devices only produce images of what is visible on Earth's surface from space, sensors can capture other types of information invisible to the human eye. The output of a remote sensing system is an image or digital picture, also referred to as satellite imagery, representing the objects and events being observed.

Satellite imagery requires analysis and interpretation to 'read' the data in the image, for example by overlaying and comparing different types of images. Data extracted from the image analysis is stored in different files type (shapefile, or raster file) that can be viewed and analysed by spatial software such as ArcGIS, and QGIS.

Satellite imagery was first used for land applications following the 1972 launch of the US civil EO satellite Landsat-1, designed for forestry and agricultural monitoring. In the early 1980s, the growing availability of low resolution satellite imagery from meteorological AVHRR (advanced very high resolution radiometer) satellites launched by the US agency NOAA (National Oceanic and Atmospheric Administration) proved useful for land observation, enabling the ongoing monitoring of large, frequently captured areas over time. Since then, the number of Earth observing satellites, launched by various countries, have consistently increased. Over the past decade, significant improvements have resulted in the technology being used for numerous purposes.

The main sensors currently available for operational use either under open or commercial licenses are presented in Table a.

A. Types of sensors

There are two main types of sensors that determine the type of information and quality of image that can be captured.

- ***Passive or 'multispectral' sensors:*** *capture images of the Earth using reflected sunlight (solar radiation) and operate on the visible and infrared spectrum. They are passive because they do not have their own source of radiation and are sensitive only to radiation from a natural origin. In this sense, they depend on sunlight and low cloud cover in order to capture images.*

1 Based on Weng, Q. Weng, Qihao. 2013. "Introduction to Remote Sensing Systems, Data, and Applications" and Davidson, A.M., Fisette, T., McNairn, Heather and Daneshfar, B. 2014. "Handbook on Remote Sensing for Agricultural Statistics"

- ***Active or 'synthetic-aperture radar' (SAR) sensors:*** *capture microwaves, firing pulses of radio waves at a target area and recording the echo as it bounces back. They are active because they operate according to their own source of radiation and energy. SAR sensors are indifferent to any atmospheric conditions.*

Because passive sensors measure reflected sunlight, they require sufficient solar illumination and clear skies to take a picture. In comparison, active sensors acquire consistent images in all conditions. This is especially important when producing a time series to monitor land use change and deforestation in countries which experience months of cloud cover during rainy seasons, such as Cameroon.

Satellites usually have one sensor, but can have more. Sensors have other attributes that define the quality of the imagery captured:

- ***Spatial resolution:*** *represents the measure of the smallest area that a sensor can capture, or in other words the dimension of the ground represented by each pixel. In the past, spatial resolution was low, capturing images around 300 square metres. More recently, frequent temporal coverage has become available at spatial resolutions of 10–20m, which has opened new frontiers in monitoring seasonal vegetation changes, including those linked to agricultural practices and urban environments.*
- ***Temporal resolution:*** *the temporal resolution of a sensor determines how much time passes between each time the sensor captures an image of the same point on the ground. Sensors today mostly capture images daily.*

B. Types of data and imagery

Sensors can capture different type of data. Passive sensors capture solar radiation reflected from the Earth back to the satellite. Light from the sun is emitted according to the electromagnetic spectrum. Sensors are sensitive to different portions of the solar light spectrum. For example, light that is visible to the human eye is only a small portion of that spectrum. Passive sensors used in land monitoring capture and record radiation reflected in different portions of the spectrum (the different bands of the satellite). Different surfaces show specific patterns through the electromagnetic spectrum (the way a surface is reflecting in different wavelengths) which allows us to differentiate them when processing satellite images.

In Figure a, the same image is displayed with different spectral bands. The images on the left and in the middle are displayed using the visible bands, the same as seen by the human eye. The image on the right is displayed using short wave and near infrared bands, in which vegetation is strongly reflected.

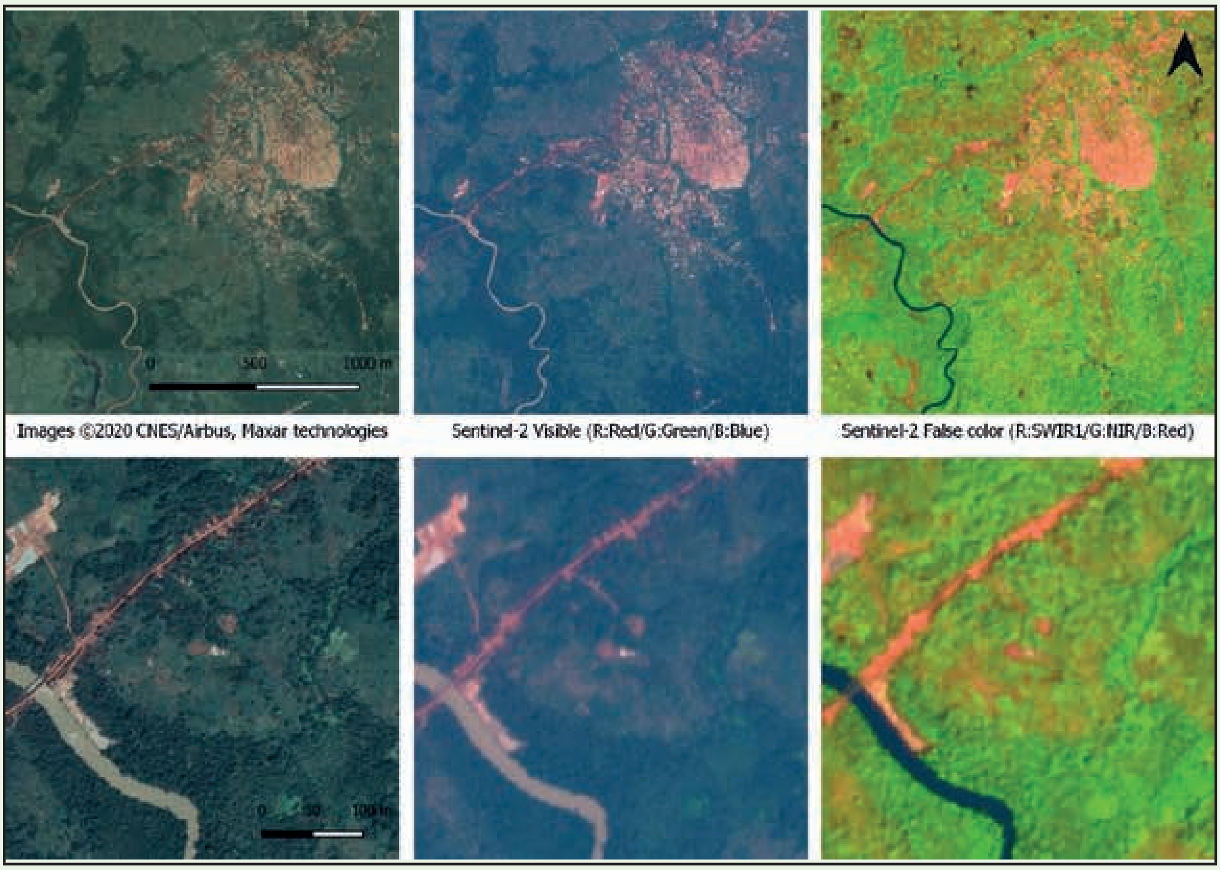

Figure A. Satellite images of the same area from different sensors. The Image on the left is a Very High Resolution (VHR) Image from Google Earth (passive sensor), which captures images on the visible spectrum. Colours captured are the same as seen by the human eye, with water in blue and forests in darker green. The images in the centre and on the right are from the Sentinel 2 satellite (also passive) and capture higher spectral resolution from infrared. The same image is displayed with two different band combinations. This image shows forest as dense vegetation in light green and water in dark blue.

Table A. Satellites generally used for land monitoring applications. Classification of satellite sensor categories, based on the European Space Agency (ESA) nomenclature used in the Copernicus programme (adapted)

Mission group	Spatial resolution	Sensors and agency (examples)	Access	First launch dates	Temporal frequency	Applications in the context of land cover and land use
OPTICAL MULTI-SPECTRAL	Low > 300m	AVHRR (EUMETSAT, NOAA) MODIS Infrared (NASA)	Open access	1978 1999	Daily	Global drought monitoring, vegetation monitoring, production estimation.
	Medium 30–300m	Modis Optical+near infrared (NASA) VIIRS (NASA, NOAA) Vegetation Proba-V (ESA, BELSPO) OLCI Sentinel-3 (ESA, COM)	Open access	1999 2011 2013 2016	1–3 days	Global to national drought monitoring, fire detection, forest monitoring. Monitoring of crop type and parcel level areas generally not possible, instead use at agricultural key areas level.
	High 10–30m	TM Landsat 5 ETM+ Landsat 7 OLI Landsat 8 (USGS/NASA) MSI Sentinel-2 (ESA, COM)	Open access	1984 2015	16 days 5 days	Agricultural mapping, crop type and parcel level. Crop area estimation and land cover/use classification.
	4–10m	Aster (METI,NASA) Spot 6-7, RapidEye, CBERS, IRS, LISS, DMC	Commercial per image			
	Very high 0.3–4m	World View3, Pleiades, Planet Labs, SkySAT, DMC-III	Commercial per image and by subscription	2007	Daily and on demand	Area measurement and parcel level applications. Precision farming, detailed mapping.

SAR (SYNTHETIC APERTURE RADAR)	High 4–30m	Sentinel 1 (ESA) Radarsat-2. ALOS-PALSAR2, RISAT	Open access Commercial	2015	6 days	Contribute to crop delineation, commonly used for rice crop mapping.
	Very high 1–4m	TerraSAR-X, CosmoSkyMed, Radarsat2(fine mode)	Commercial			Limited use

Sources: Global Strategy to improve Agricultural and Rural Statistics (GSARS). 2017. Handbook on Remote Sensing for Agricultural Statistics GSARS Handbook: Rome and http://database.eohandbook.com/database/missiontable.aspx

Satellite images were traditionally downloaded from national or international data portals (https://earthexplorer.usgs.gov/, https://scihub.copernicus.eu/dhus/#/home) but now images are frequently accessed via a cloud computing platform. In the land monitoring sector, the Google Earth Engine (GEE) platform (Gorelick et al., 2017) is intensively used to access and process images. For non-programming users, the full archive of Sentinel 1 and Sentinel 2 is accessible through applications such as the ASAP (anomaly hotspots of agricultural production) high resolution viewer (Rembold et al., 2018). The ASAP (https://mars.jrc.ec.europa.eu/asap/hresolution/?region=0) is a platform for agricultural monitoring at field level based on high resolution EO data that does not require programming on the user's side. Through the interface, it is possible to retrieve high-resolution imagery at a certain period of the year and compare images with the same period in a previous year. It is also possible to retrieve time series profiles.

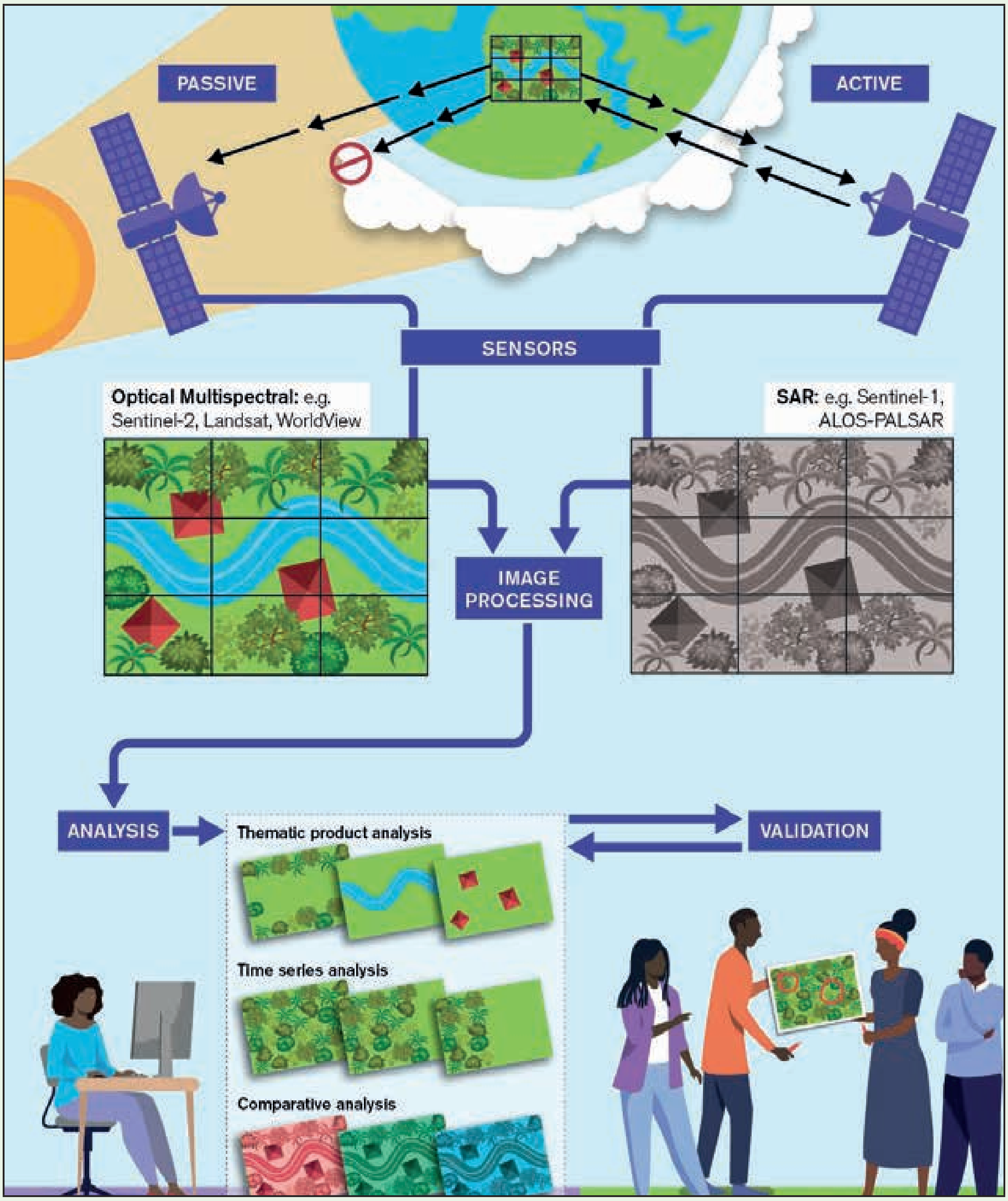

Figure B. From satellite imageries to analysis

C. Earth observation-based products for land cover and land use change applications

An image gives information at a certain moment in time. To monitor a location over a time period, a time series of images needs to be analysed. For land monitoring applications, time series are usually processed into thematic products. The following is a non-exhaustive list of products derived from EO which are useful for exploring land surface changes.

Land cover maps

The first global land cover maps derived from remote sensing were produced in the early nineties using the normalized difference vegetation index (NDVI) dataset from AVHRR at 1° and then 8 kilometers (km) spatial resolution (DeFries and Townshend, 1994; De Fries et al., 1998). In the 2000s, sensors dedicated to vegetation monitoring such as MODIS and SPOT-VEGETATION were launched (Bartholome et al., 2005; Friedl et al., 2002), resulting in a land cover spatial resolution of 1km. Since then, the spatial resolution has been increasing and most of the existing global land cover products have a resolution of 250–300m. The GlobeLand30 is even attempting to map the globe at 30m in the Landsat archive (Gong et al., 2013).

Land cover change

In recent years, some efforts have been made towards creating dynamic global land cover maps (Defourny and Bontemps, 2012) that show land cover over several years. However, these initiative are usually limited by the availability of reference data (Woodcock et al., 2020).

In parallel, targeted products are being developed to monitor specific classes of the Earth's surface (forests, croplands or water surfaces). Thanks to more than 20 years of Landsat data at 30m resolution, these products can achieve a finer spatial and temporal resolution than multi-class land cover maps.

Forest monitoring has witnessed a small revolution with the release of the Global Forest Change (GCF) product (Hansen et al., 2013), which identifies new tree cover loss annually at a 30m resolution.

The JRC TMF dataset (Vancutsem *et al.*, 2019) covers the tropical belt for the period 1984–2018. Every pixel in the product provides information about the dynamic of tree cover change.

Similarly, the JRC surface water occurrence product maps the location and temporal occurrence of water surfaces at the global scale at 30m spatial resolution (Pekel *et al.*, 2016). Products such as the multi-temporal global human settlement layer (GHSL) build up grid containing layers of information from four time periods: 1975, 1990, 2000 and 2014.

2 Materials and methods

2.1 Study sites

This paper looks at two cases in Cameroon to exemplify how EO can contribute to generating evidence on land use change driven primarily by extractive and agro-industrial activities. The study sites were selected by the LandCam consortium based on major recent land use changes that are not well documented. These activities are suspected to have had notable impacts on local communities, impacting livelihoods and subsistence activities, degrading the environment and violating people's land rights (Nguiffo and Sonkoue Watio, 2015). The two study sites are located in forested areas. The main land cover change assessed in this study is the loss of forest cover notably linked to the availability of reliable multi-temporal forest cover EO-based products.

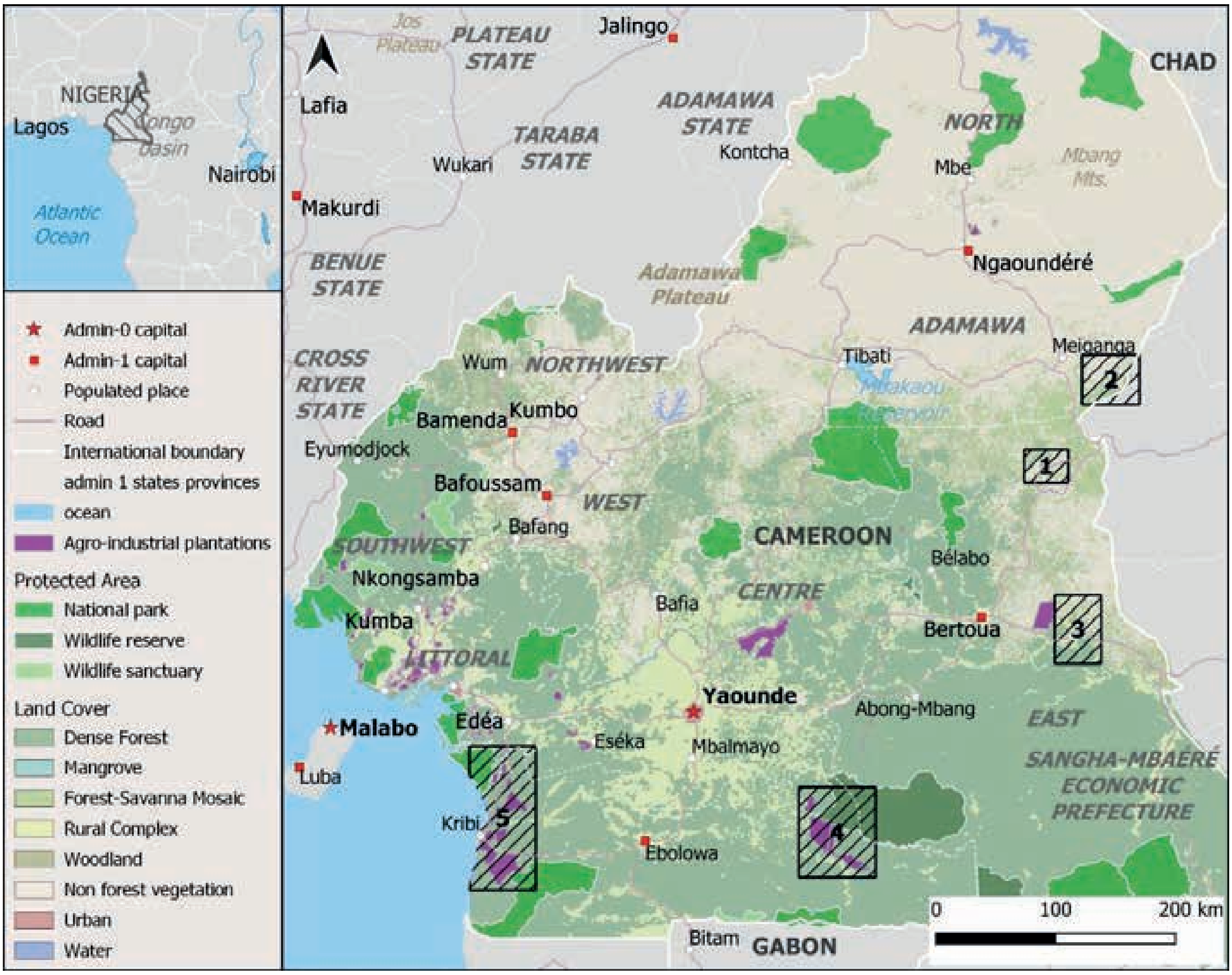

Figure 1. Location of the study sites

2.2 Mining in East Cameroon

The first case study focuses on the expansion of small-scale mining activities (mainly gold mining) and the corresponding impact on forest cover in alluvial plains in East Cameroon. Cameroon has abundant mineral resources of export value, including gold, diamonds, bauxite, and iron, amongst others. Large-scale mineral deposit mining requires significant capital expenditure to be technically feasible. Given Cameroon's governance and investment context, there is still a limited number of large-scale mining operations. However, artisanal and small-scale mining (ASM) has increased over the past decade.

A large proportion of artisanal mining takes place in unregulated value chains, due to the complexity of existing regulations governing mining activities and the environment (Bakia, 2014a, 2014b; Kouankap *et al.*, 2017). Due to the small-scale and ad hoc nature of these operations, ASM does not require an environmental impact assessment under the current permit process (Glass and Rakotoniary, 2021). However, artisanal mining has a number of negative environmental impacts, such as deforestation, land degradation, the creation of open pits that pose animal and human traps, health hazards, mercury and cyanide pollution, and dust and noise pollution (Kamga et al., 2018; Kouankap et al., 2017).

We focus on three sub-sites in East Cameroon (see shaded boxes 1, 2 and 3 in Figure 1) to assess the expansion of gold mining activities over the past 10 years and explore whether they have caused an increase in deforestation in the area. Site 1 is located close to the town of Bétaré-Oya in Cameroon's East Region and site 2 is close to the town of Meiganga in the Adamaoua Region. Both sites are located in environments dominated by savannah and gallery forests. Site 3, located close to the city of Batouri in the East Region, includes some dense humid forest.

2.3 Agro-industrial concessions in the Ocean division and Centre region

Agricultural expansion, whether smallholder-based or from agro-industrial plantations, remains one of the primary drivers of land use change globally, as is the case in Cameroon (DeFries *et al.*, 2010; Mertens and Lambin, 2000; Ndi and Batterbury, 2017). The second case study focuses on the operation of rubber and oil palm plantations in the Ocean division and Centre region. Since very little information is available to the public, the aim is to fill a gap in information concerning the level of advancement of operations within the concession boundaries.

These concessions have received a lot of attention from international and national civil society organisations, as they are associated with allegations of significant social and environmental harm, notably linked to the non-inclusive ways the concessions were allocated (Forest Peoples, 2019; Greenpeace and APIFED, 2019; Nguiffo and Sonkoue Watio, 2015; Sherpa *et al.*, 2010). The EO data enables us to monitor land use changes around the concessions as potential indicators of company breaches of concessions, displacement of populations, induced changes from inward migration and evolutions in livelihoods strategies.

For this study, we look at three main oil palm and rubber plantations owners in the area of interest (see shaded boxes 4 and 5 in Figure 1). The analysis considers one or several concessions for each of the following four companies: Biopalm, Socapalm (Kienké concession), Sudcam (North, Central and South concessions) and Hevecam (the main concession). Sudcam and Hevecam are owned by the same parent company (Halcyon).

2.4 Thematic products and satellite imagery

In the two study cases, a combination of EO-based thematic products and recent satellite imagery are used to map the past and current situation and provide independent spatial evidence of land use change. As explained in the "What is Earth observation?" section, information from satellite imagery can come from visual interpretation of images. However, the current common practice is to create EO-based thematic products using a time-series of images (several images) to extrapolate land cover change over time using specific algorithms.

2.5 Tree cover change products

The thematic products available in the area of interest are limited to tree cover change. We selected two different products to identify changes in forest cover over time in the mining and agro-industrial areas. The two datasets are very similar as they are both derived from Landsat images and provide information at a resolution of 30m. However, they are produced using a different methodology, cover different periods and have a different spatial focus.

The first product is the GFC dataset (Hansen *et al.*, 2013), which has been widely used by the EO community since its release in 2013. Based on Landsat data, the product provides yearly information on new areas of tree cover loss for the period 2000–2018. In addition, there is a binary layer which provides information on regrowth identified during the period 2000–2012. To provide a full picture of tree cover dynamics, the tree cover loss and gain information are combined with a layer representing the tree cover percentage in 2000.

The GFC does not distinguish permanent forest conversion associated with a change in land use and other changes that may be associated with subsequent regrowth. Nevertheless, it provides reliable information on when forest cover was cleared for the first time.

The second product is the European Commission's Joint Research Centre (JRC) tropical moist forest (TMF) map[3]. The map (Vancutsem *et al.*, 2021) exclusively covers the tropical belt during the period 1984–2018. The information is derived from all available single Landsat images and is therefore temporally very precise.

Relevant for our study, the TMF map provides information on subsequent regrowth for each pixel. The tree cover loss or regrowth observations are classified to inform the user of the timing and duration of the disturbance. Another added value is that agro-industrial plantations are also classified separately. This mainly includes the concessions registered in the World Resources Institute (WRI) spatial database of planted trees (Harris *et al.*, 2019). In addition, large-scale tree plantations were digitized using a visual inspection of very high-resolution satellite images.

2.6 Satellite imagery

Sentinel 2 (S2) images from 2016 to 2019 and Landsat images from 2010 to 2020 were used to further illustrate land use changes in the study sites. The visual interpretation of satellite imagery enables the assessment of forest cover change in terms of land use (mining, logging, shifting cultivation), as well as and other changes not related to forest cover.

3 The Tropical Moist Forest dataset was not publicly available when we conducted this analysis. We could access it in the framework of an institutional collaboration. The final product could present some modifications compared to the data presented here.

S2 images from the multispectral instrument (MSI) are available from 2016 to the present. Since the launch of S2 B in March 2017, the images have been available at a temporal resolution of five days and at a spatial resolution of 10m. The combined Landsat missions (with the succession of the TM 5, ETM+ 7 and OLI 8 sensors) have provided images every 16 days at a 30m resolution since 1984. However, the amount of Landsat data in the US Geological Survey archive is not consistent by year, geography, or type of sensor (Kovalskyy and Roy, 2013). For Cameroon, a 16-day temporal resolution was only achieved over the last few years.

2.7 Files and software

The spatial delimitation of agro-industrial concessions is available in shapefile (geospatial vector) format. The shapefiles for the four concessions were downloaded from the Forest Atlas of Cameroon website (MINFOF and World Resources Institute, 2017). The river network in mining sites 1, 2 and 3 was also downloaded from the same site. The GFC and TMF maps were reviewed alongside satellite images and shapefiles in QGIS (geographic information system software). The quantitative analysis based on GFC and TMF maps and shapefiles was conducted using R statistical software.

3 Methodology

3.1 Methods

The methodological approach can be detailed as follows: (i) exploring GFC and TMF thematic products to gain insights about an area, (ii) searching for recent satellite images for information on recent changes or land use change dynamics that are not represented in existing thematic products, (iii) interpreting the situation both visually and analytically, (iv) assessing if existing products are sufficient for reporting on the studied land use change dynamic, and where they are insufficient, identifying the need for ad-hoc mapping.

While different categories of land use change occur in the two case studies, we relied on thematic products designed to monitor forest cover change. However, the tree cover changes mapped in GFC and TMF datasets needed further interpretation to be attributed to a specific land use change. This was done using the visual interpretation of satellite images. Regarding small-scale mining activities, there is no existing EO-based product that reports on the extent of mining activities in Cameroon. Products reporting on tree cover loss provide the best information about land change dynamics in that area.

Another source of information is the visual interpretation of S2 and Landsat images. Our objective was to assess the extent of mining activities and their impact on forest cover between 2009 and 2019. We selected this time period because mining activities have intensified over the last 10 years and the evolution of tree cover has been stark. To complement this visual analysis, we used the proximity of tree cover loss activities to rivers as a proxy of deforestation caused by mining activities, as mining tends to take place in. We extracted the equivalent area of GFC tree cover loss pixels located within 500m of a river in the three sites. The GFC product was used for this analysis as it is more robust in areas with a low density of canopy cover, such as in site 1 and 2.

For the agro-industrial concessions, the general objective was to monitor the plantations' activities and check for any expansion outside the scope of the original concessions. To assess the activities of the plantations, we quantified the extent of tree cover loss and regrowth across the four concessions between 2001 and 2019 using the TMF and GFC products.

The TMF map focuses on changes in the dense tropical moist forests. Unlike the mining sites, the plantations are exclusively located in dense forest. The TMF map provides some valuable information about regrowth dynamics in these areas, indicating the date and intensity of forest disturbances and the presence of regrowth after the disturbance. For this analysis, we reclassified the TMF map's 48 categories into five main classes: (1) forest, (2) other land cover, (3) tree regrowth after clearing (1999–2015), (4) deforestation that started between 1999 and 2015, and (5) recent tree cover loss (period 2016–2018). Estimations of the area in 2018 of the different land use classes in each concession are derived from the intersection of the map and the spatial extent of the concession.

3.2 Limitations

Existing EO-based thematic datasets of tree cover loss have been used in combination with recent 10m resolution satellite images to show the extent and timing of deforestation linked to land use activities in Cameroon. While using only products or imagery, the combination of the two sets of information provides a basic toolkit for more accurate identification of land use changes. The high-resolution satellite images (10 to 30m spatial resolution) reviewed in this study allow for the monitoring of regional and local land use changes.

Nevertheless, identifying the accurate locations of small- and medium-scale agricultural plantations and other land uses, such as mining activities, requires robust 'ground-truth' data that was not accessible for this study. The images used are insufficient for measuring areas with a cadastre level accuracy of single parcels or to monitor tenure in terms of property. A mapping approach using orthoimages with a higher spatial accuracy is needed to assess overlaps between individually owned land in communities and other competing uses. Participatory community mapping would also be relevant in this context, but is not covered in this report.

4 Results

4.1 The expansion of mining activities in East Cameroon

In the three sub-sites of interest for mining activities, extended areas of tree cover loss were observed in both the GFC and TMF map in line with other studies on ASM impacts in these areas (Bakia, 2014b; Kamga *et al.*, 2020; Kouankap *et al.*, 2017). The correlation between mining and deforestation is strong, however, we acknowledge that the tree cover loss may not be exclusively linked to mining activities. It is necessary to differentiate deforestation linked to mining from other causes, such as shifting cultivation and logging activities.

Small-scale gold mining activities mostly take place along riverbeds where alluvial deposits tend to be easily accessible. In satellite images, mining activities are easily spotted as a series of pools of water along an existing river, as illustrated in Figure 4 and Figure 3.

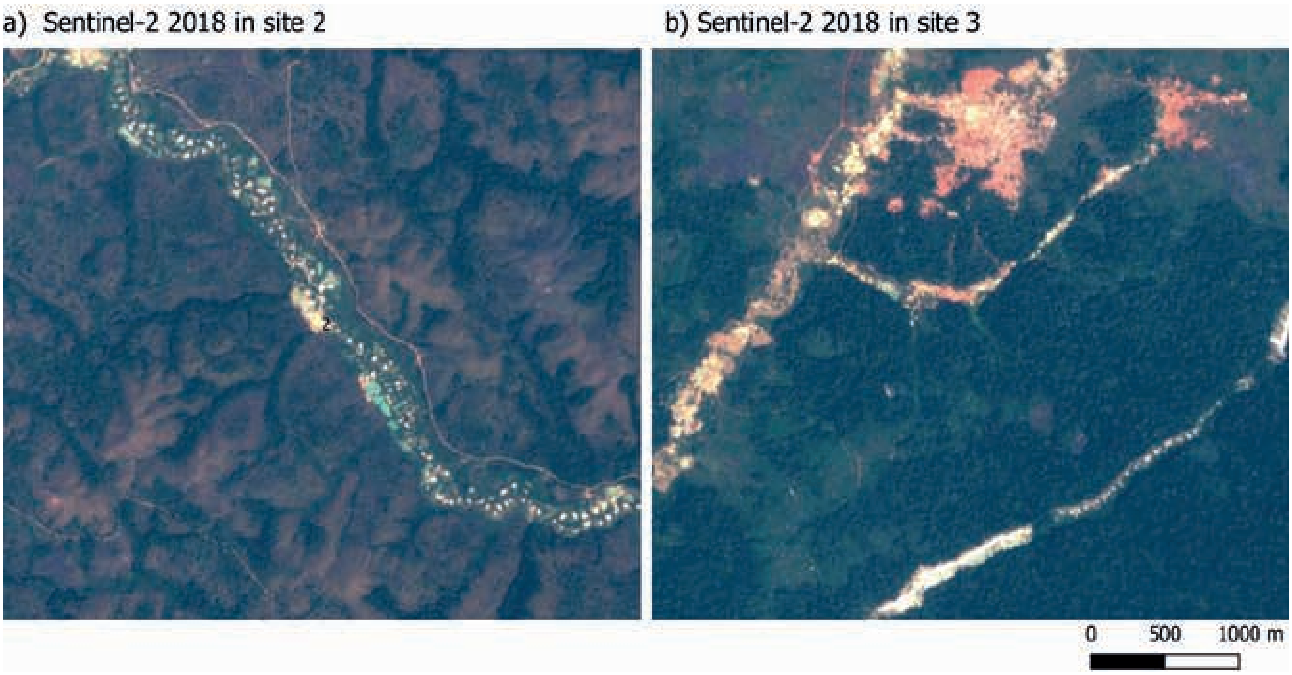

Figure 2. Mining activities in site 2 and 3 as seen in Sentinel-2 satellite images. S2 images are in an RGB composition (R: Red, G: Green, B: Blue) where forest appears in dark green, water in bright grey or blue and grass/savannah in light green and brown.

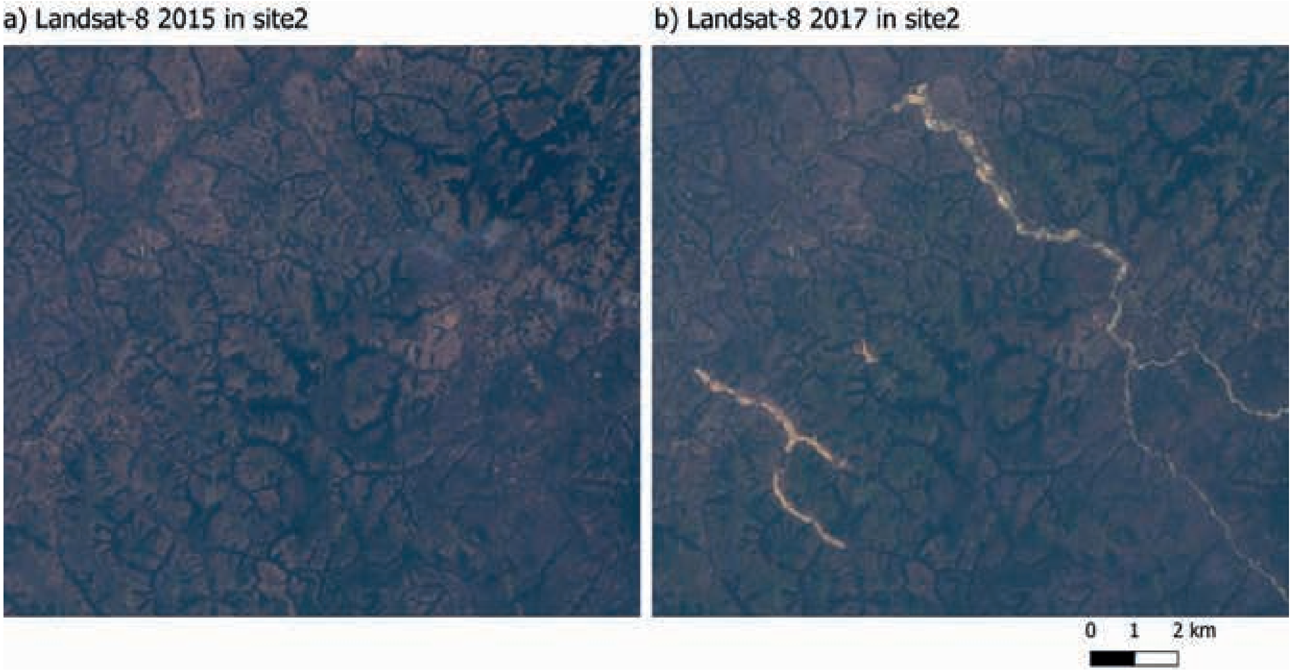

Figure 3. Start and increase of mining activities in site 2- Meiganga. Landsat images are displayed as a true RGB colour composite. The mining activities are the bright linear patches visible in the 2017 imagery.

Figure 4 shows site 1 Bétaré Oya using the GFC product and illustrates how mining activities appear in different data sources. The same analytical process was followed for each mining site, although this paper only displays site 1 in full. Using information on the pattern of mining activities spread across the main river and their tributaries, we note that the GFC and TMF datasets provide convergent information where mining activities occur in forests with a dense canopy cover. This is highlighted as tree cover loss reflecting deforestation. However, in areas with an open canopy cover, the TMF and the GFC products classify mining activities in a different way. As illustrated in Figure 4, the TMF, designed for tropical dense forest monitoring, presents the expansion of mining activities as an increase in water in the area. The GFC, designed for monitoring all types of tree cover density, pictures mining activity as tree cover loss. For the rest of the analysis, we use the GFC dataset and interpret tree cover loss occurring along rivers as deforestation caused by small-scale mining activities.

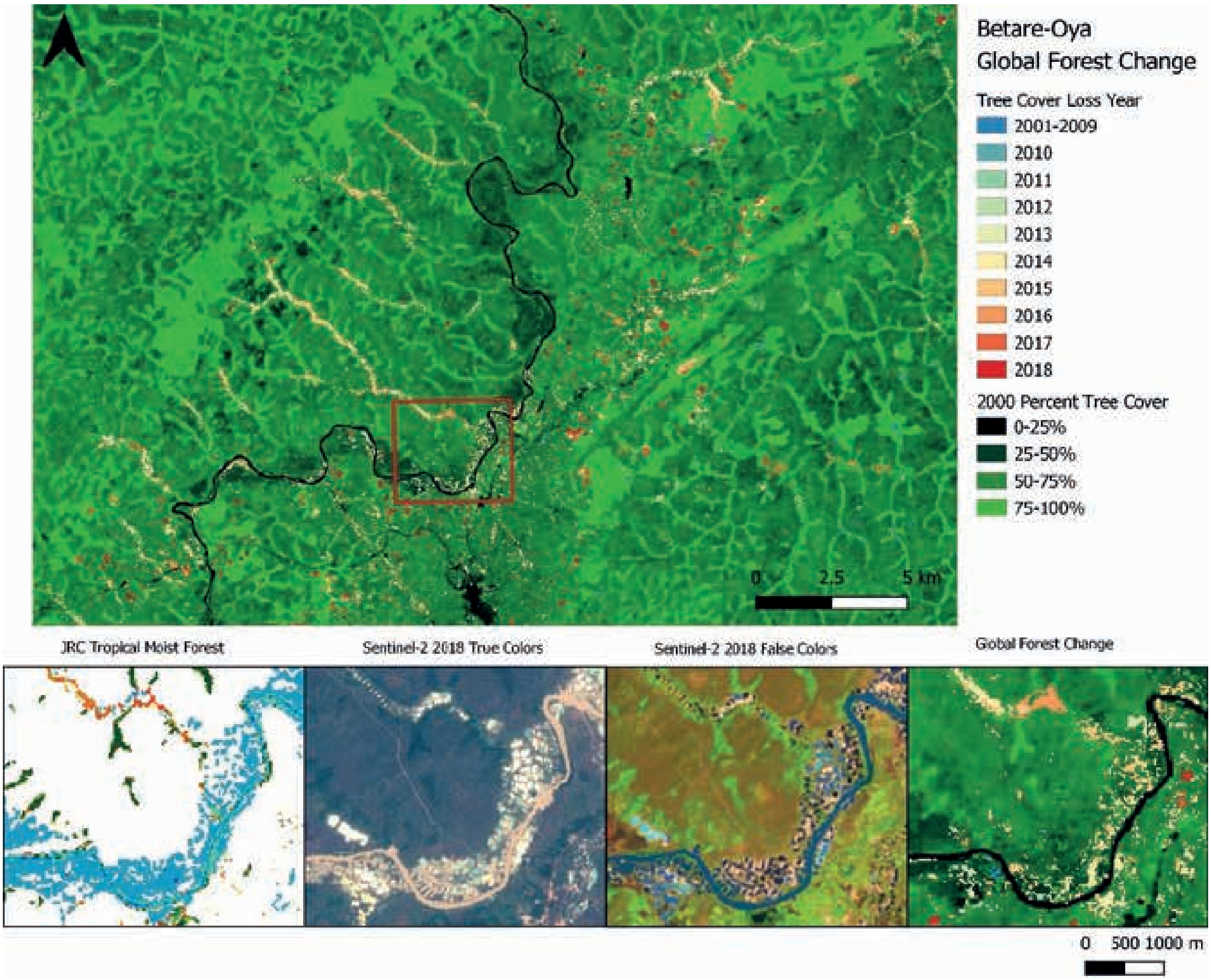

Figure 4. Site 1 Bétaré-Oya. Tree cover changes illustrated using the GFC product. Mining activities represented in three different ways: as water in the JRC TMF product (left), as blue water pools in a S2 image (middle), and as tree cover loss in the GFC (right). S2 image is in a RGB composition (R: SWIR 1, G: NIR, B: RED) where forest appears in green, water in blue and grass/savannah in pink.

An example of the progression of mining pools along a riverbed is visible in Figure 5, which shows that mining activities had already started at each end of the river by October 2016. One year later, a larger series of small pools was visible along the river. This corresponds to an observation of tree cover loss in the GFC product.

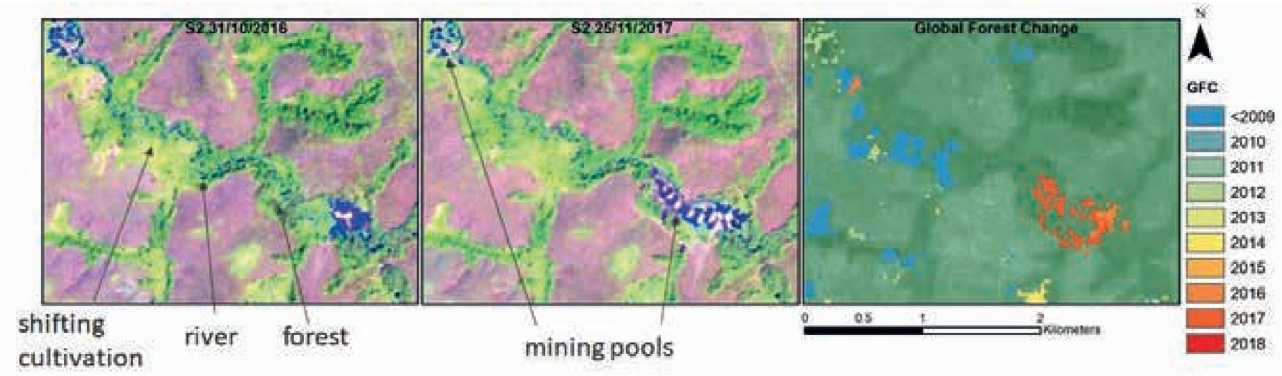

Figure 5. Expansion of mining activity in site 1 along the river in a gallery forest illustrated by two Sentinel 2 images 31/10/2016 (left) and 25/11/2017 (centre) and the GFC product (right).

In the three sites, we observed that deforestation along riverbeds started approximately in 2013 and increased each year since then. Patterns of tree cover loss corresponding to small-scale agriculture activities, probably shifting cultivation, are identified in the three sites as well. The activities related to agriculture were already present before these changes started in 2013. They are not restricted to riverbed areas. In site 3 Batouri, selective logging activities are visible, located in an area of dense moist forest.

We observed that the intensity of mining activities was highest in site 1 Betare Oya, with a high concentration of mining sites along the Lom River (Figure 4). Site 2 Meiganga presents extended mining activities in the centre of the area. An important area of tree cover loss is located close to the border of the Central African Republic. However, due to the pattern of tree cover loss patches and distances to rivers, we concluded this was mainly driven by agriculture activities. Site 3 Batouri presents limited mining activities. However, while mining activities are located in gallery forest or open savannah in the first two sites, the mining activities in site 3 are located at the fringe of dense forest (Figure 2). Any deforestation linked to the expansion of that activity should be closely monitored.

In order to relate deforestation to an increase in mining activities, we extracted GFC tree cover loss pixels located within 500m of a river over the period 2009–2018 in the three sites. Figure 6 illustrates the results of the extraction. The analysis highlights that site 1 Bétaré Oya presents a higher proportion of deforestation located near riverbeds. It coincides with observations based on the visual analysis of the thematic products and the S2 images.

Figure 8 shows the peak moments of increased deforestation in each site: 2014 in site 1 Bétaré Oya, 2017 in site 2 Maiganga and 2016 in site 3 Batouri. This allows us to pinpoint changes in the implementation of mining activities across time.

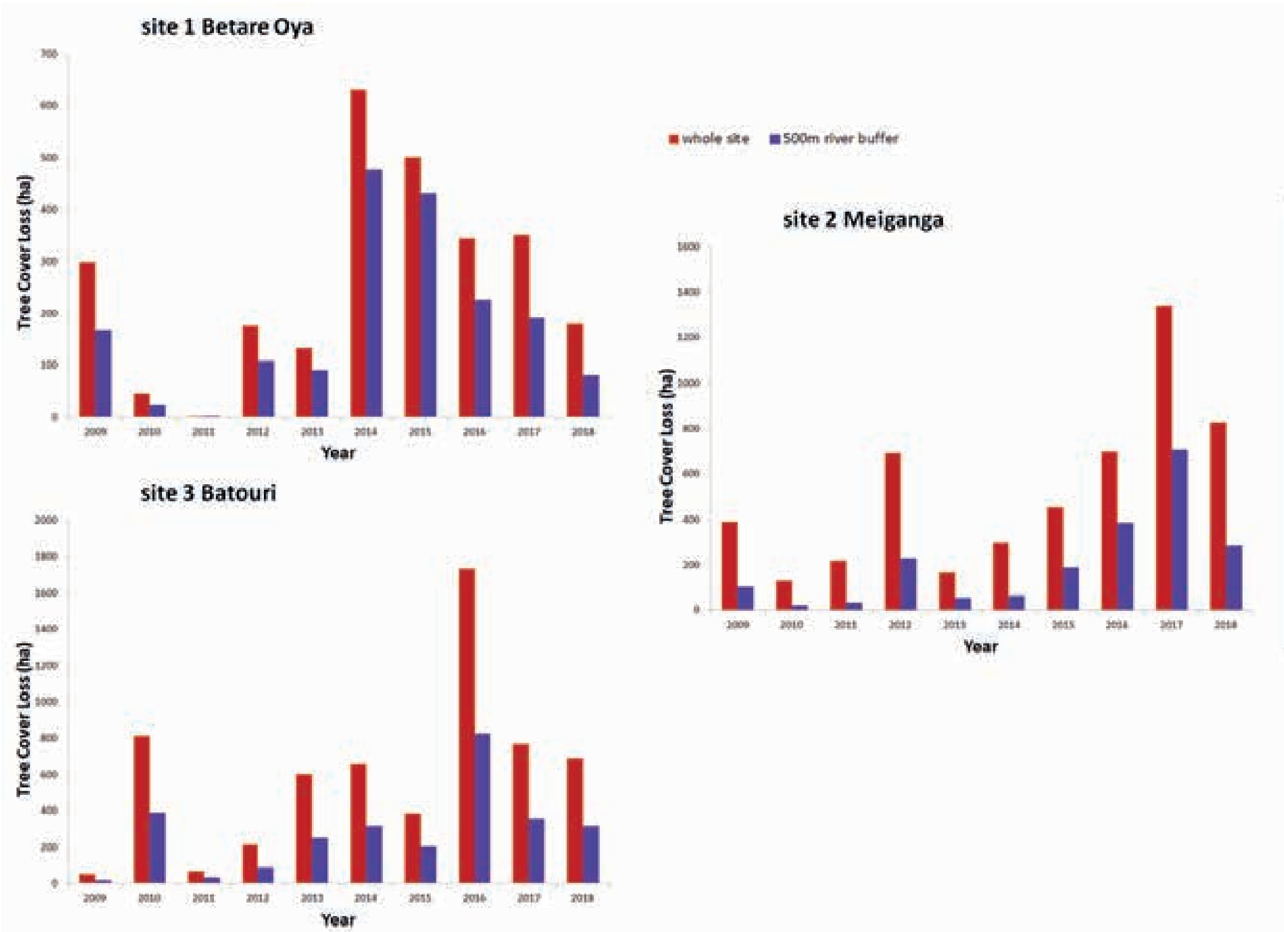

Figure 6. Area of tree cover loss in hectares (ha) by year observed using the GFC product over the period 2009–2018. In red, the total area of tree cover loss across the whole study site, and in purple, tree loss within 500m of a river.

This analysis provides a first glimpse of the expansion of small-scale mining activities and their impact on forests in East Cameroon. The extent of the area affected by mining should be more precisely quantified to report on their common impact on different forest biotopes (tree savannah, corridor forest etc.). Any future expansion of mining activities should be monitored, especially in densely forested areas. This could be achieved by developing specific algorithms to identify mining activity in satellite imagery, as done by Kamga et al., (2020) in three study areas of Cameroon for the years 1987, 2000 and 2017. The development of such algorithms relies, however, on the availability of field data or expert knowledge on the sites of interest, which extend far beyond the areas covered in this study.

4.2 Implementation status of agro-industrial tree plantations in West Cameroon

The TMF and GFC datasets give insight into forest cover changes over the last 20 years inside and close to the border of the three Sudcam concessions (site 4) and the selected concessions of the Socapalm, Biopalm and Hevecam plantations (site 5). This approach provides data that is usually not made available by operating companies or public agencies, and thus enables monitoring of company activities. We observed significant tree cover loss both inside and outside the agro-industrial plantations in the two datasets.

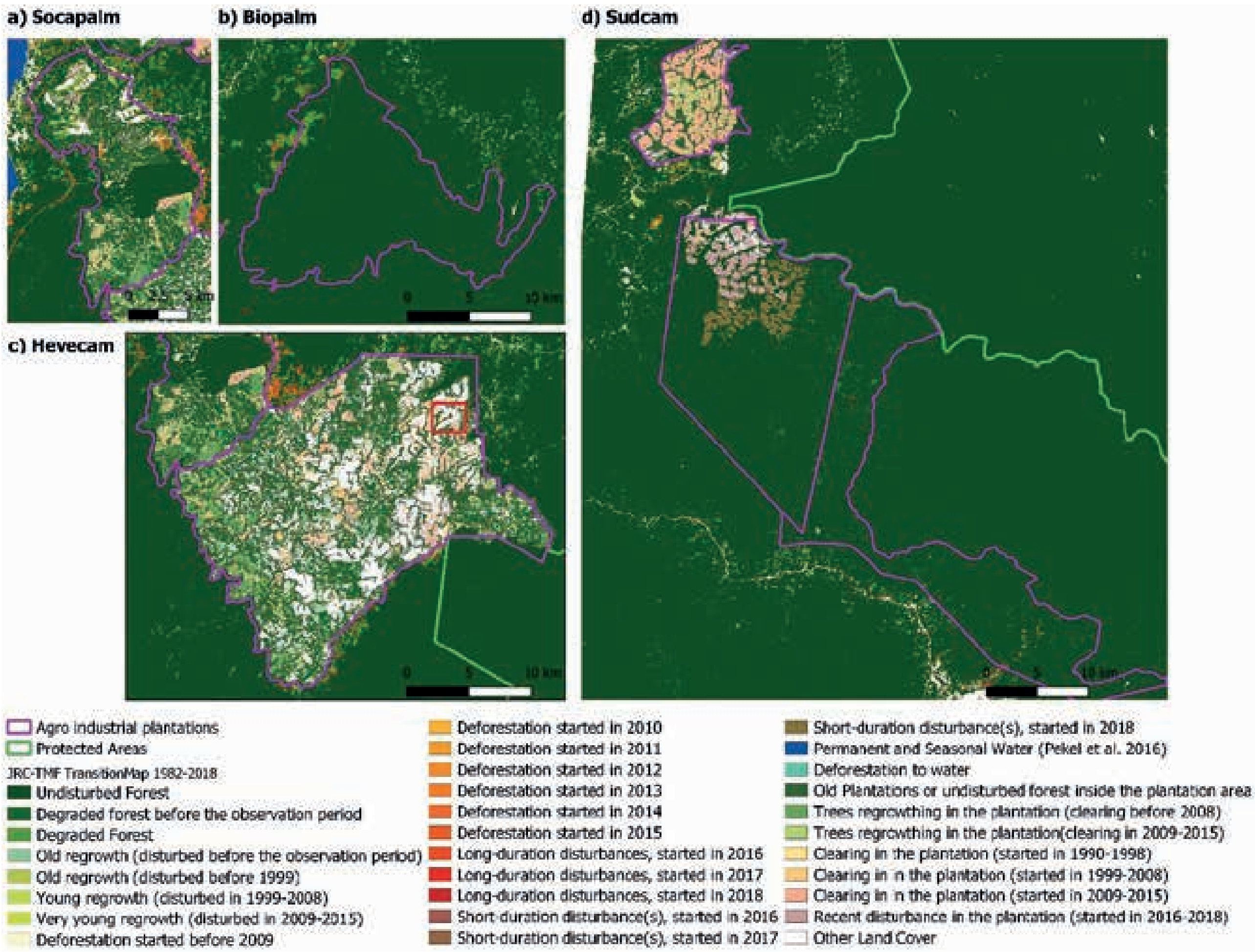

Figure 7. Tree cover changes in and around the four agro-industrial plantations of interest located in site 4 d) Sudcam and site 5 a) Socapalm, b) Biopalm and c) Hevecam (with zoom in Figure 8). The tree cover change dynamic from 1990 to 2018 is illustrated using the JRC TMF map.

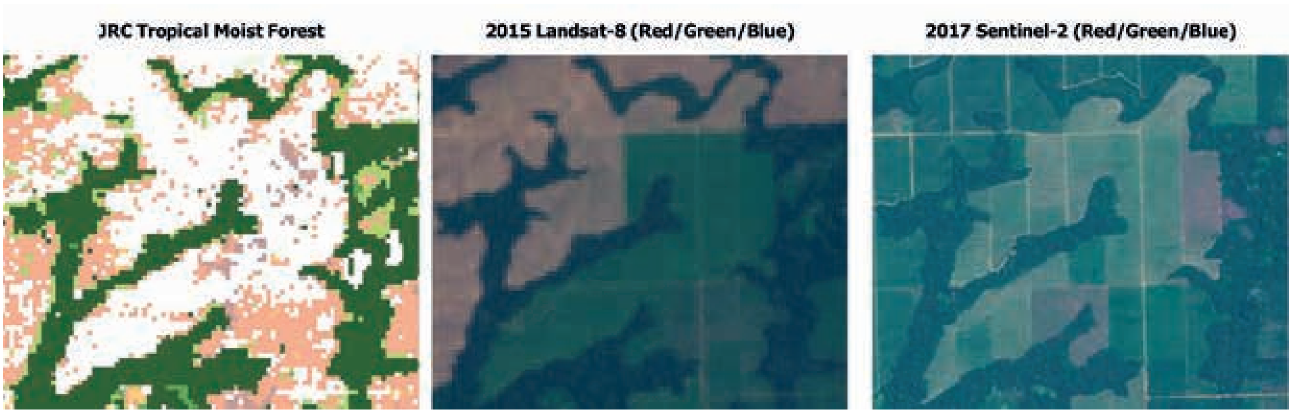

Figure 8. Different stages of rubber tree cultivation in the Hevecam concession (zoom of the location depicted in Figure 7 c) Hevecam).

In Figure 7, forest changes inside each concession are illustrated using the TMF map. The map is interpreted as follows: first, it captures the clearing of primary forest prior to rubber tree and oil palm plantation. Second, it captures the regrowth of tree cover. The map does not differentiate between the growth of oil palm or rubber trees (planted) or natural regrowth after logging. However, a specific class is attributed to any clearing or regrowth inside a known concession (see section 2). For the specific concession of interest, we see in Figure 7 that the TMF map and the geospatial location of the concession coincide in the Socapalm, Sudcam and Hevecam concessions. It is interesting to note that the tree cover loss in the Biopalm concession is not considered part of a plantation.

For the rest of the analysis, we hypothesise that regrowth inside the concession areas represents the planting or replanting of rubber trees (Hevecam and Sudcam) or oil palm (Socapalm). Such a hypothesis should be validated through ground observations or interpretation of very high resolution imagery (VHR) (see "What is Earth observation? '' section).

By reviewing Landsat and S2 imagery, we are confident that rubber trees are being cultivated in the Hevecam and northern concession of SudCam. For example, in Figure 8, the rubber tree patches planted in the Hevecam plantation are recognisable in the images due to their geometric shape. Rubber trees present a different colour and texture to primary forest. This also allows us to visually assess if rubber trees are present in areas classed as 'other land cover' in the Hevecam delimitation. This indicates that those areas were probably cleared and planted prior to 1990.

The TMF map also captures the clearing of planted trees. An ongoing issue when monitoring plantations is the challenge of differentiating between the clearing of natural forest (deforestation) and the harvesting of planted trees. For old plantations (implemented before 1990), information from the TMF map and the location of the concessions does not enable us to interpret with certainty whether recent clearings are the result of mature oil palm or rubber trees being harvested or natural forest clearing. Additional analysis on the ground or the use of additional imagery is needed to identify the specific species of trees.

However, in the case of the Sudcam concessions in site 4, new clearings of primary forest can be clearly spotted using the TMF and GFC maps and satellite images. Inside the 'North' Sudcam concession, the clearing of primary forest started in 2011 and continued until 2015, with trees planted in the centre of that area (light green in Figure 7). The 'Central' part has been more recently cut and planted. One block was cut in 2017, while the very latest clearing happened in 2018 (see Figure 9). Some of the areas cleared are classified as high-value conservation (HVC) areas (Council on Ethics, 2018). Such deforestation has been reported and contested by environmental NGOs. Halcyon Agri (Sudcam's parent company) responded by halting new clearings in Sudcam in December 2018 (Fritts, 2019). It is interesting to note that prior to clearing, selective logging activities were taking place (S2 of November 2017 – zoom of Figure 9). This is a common practice to retrieve high value trees before the forest is cleared, often by a specialist company.

Following a visual review of the forest cover change datasets (TMF and GFC), we spotted significant forest change both outside and inside the concessions (Figure 7). Outside the Sudcam concession, we observed small-scale disturbances linked to shifting cultivation activities along roadsides. Outside the concession to the northwest, we observed small patches of deforestation that represent a dynamic pattern similar to a plantation that would need more investigation. In the South, traces of old logging activities are visible. However, our analysis does not reveal any deforestation inside the Dja Faunal Reserve.

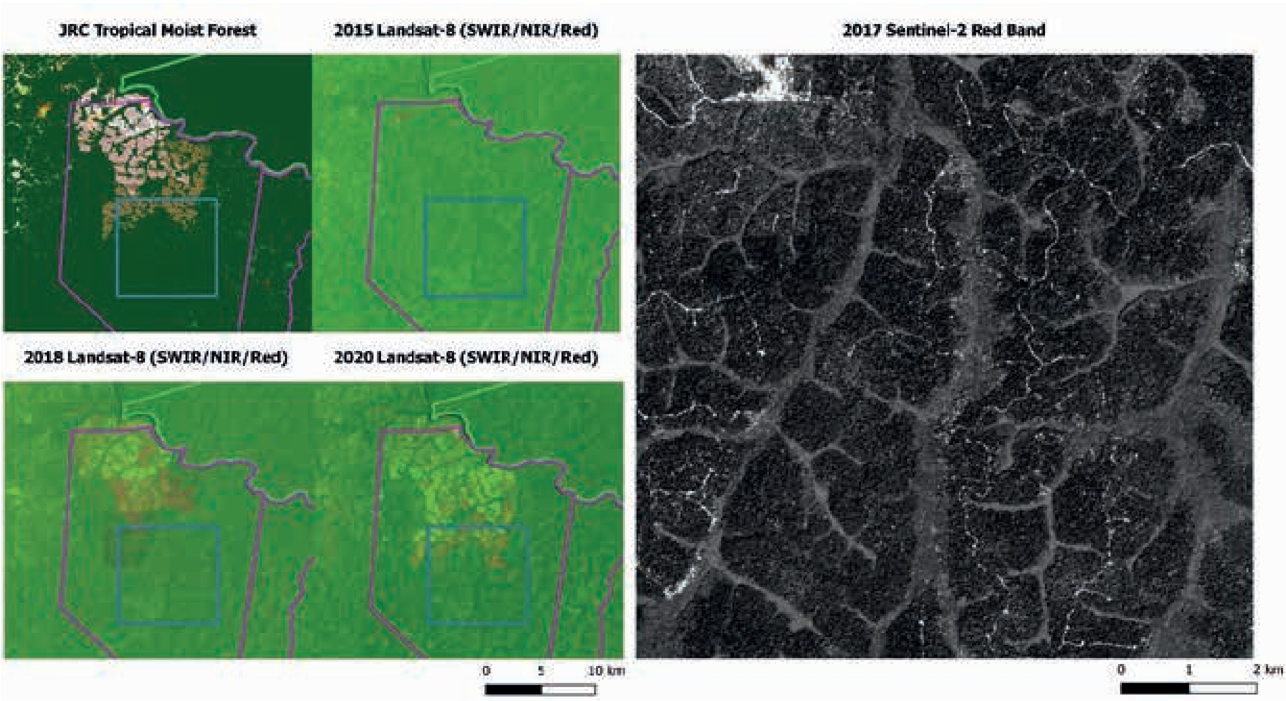

Figure 9. Implementation of the Sudcam rubber tree plantation in a zoomed-in area (see zoom location in Figure 7, image d) Sudcam). On the left: the JRC TMF map and Landsat–8 images from 2015, 2018 and 2020 (Landsat images are displayed with R: SWIR 1, G: NIR, B: RED showing the forest in green and grass or shrubs in pink). On the right: A Sentinel–2 image from 20/11/2017 for the zoomed in square in blue. The red band in the S2 image highlights selective logging activities.

The first analysis explores the proportion of land use change within each agro-industrial plantation, as an indication of their implementation status. The proportions of main land use change classifications retrieved from the TMF map are presented in Figure 10. It is important to keep in mind that the whole area affected by the plantation will not be converted into commodities. Indeed, some areas inside the concessions may be unsuitable for tree planting (due to soil conditions or steep slopes) and some forest areas are conserved for HVC reasons. Also, part of the Hevecam and Socapalm concessions classed as 'other land cover' could be old planted trees. Figure 10 is not a direct estimate of the degree of implementation of each concession, but gives an overview of what happened in the concessions over the last 20 years.

A visual analysis of TMF and GFC highlighted that the intensity of operations is more important in the Sudcam, Socapalm and Hevecam concessions and confirmed that the Biopalm area reveals no or very little implementation. Regarding Biopalm, the only forest cover change detected is located along the western and north-eastern borders. It would need further investigation, but one hypothesis is that it is related to logging activities – Biopalm being an old timber concession. On the other hand, the direct surroundings of the Biopalm plantation are very active in terms of forest disturbances. Along the road, there has been a shift in cultivation and a lot of small-scale deforestation over last few years.

In Hevecam and Socapalm, we observed areas being cleared over the period 1999–2008. The first activities detected in the Sudcam and Biopalm concessions are more recent, with clearing detected during the period 2009–2015.

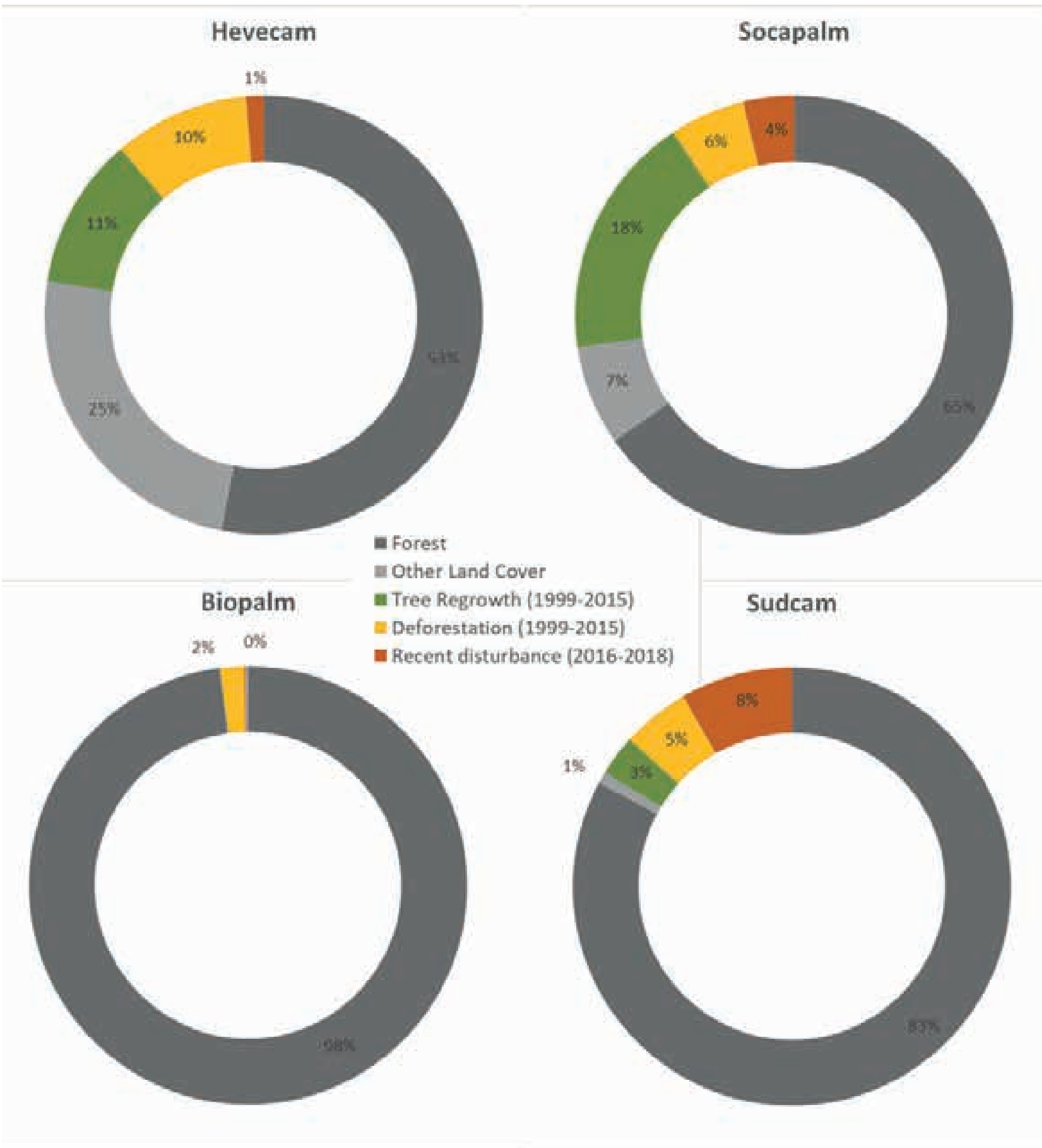

Figure 10. Proportion of the different classes of land use change within the Socapalm, Biopalm, Hevecam and Sudpalm agro-industrial concessions for the period 1999–2018. The proportion of forest, other land cover and tree cover change are extracted from the TMF map. The original legend is regrouped in five main classes.

In terms of the proportion of the total concession, half of the Hevecam concession has been cleared at some point in time, while the other half is covered by primary forest (riparian forests and other HVC areas). This assumes 'other land cover' partially represents rubber trees planted prior to 1990 (see Figure 8). About 35% of the concession is covered by rubber trees and the remaining area is either at an early stage of plantation or left as bare land.

In the Socapalm concession, the proportion of primary forest is slightly higher (about 64%) than in Hevecam. However, the proportion of regrown trees and bare land is similar. It is known that less than half of the original Socapalm concession has been clear-cut and planted. There were discussions on whether part of the concession should go back to the state.

In the three Sudcam concessions analysed together, the proportion of primary forest is about 80% and the area detected as tree regrowth is only 2% of the total area. The activities are more recent, as Sudcam's concessions were granted between 2008 and 2015. Thus, the rubber trees are only just beginning to be picked up as regrowth. Also, the three concessions were analysed together, while the northern concession seems to have been fully converted to a plantation. Deforestation started in the central concession around 2017–2018 and stopped following public pressure on the financing companies, as mentioned earlier. Since then, the deforestation activities have stopped in the Sudcam concessions. In the Biopalm concession, the majority of the area is covered by primary forest.

To illustrate the yearly tree loss over the last 20 years, we have quantified the extent of tree cover loss across the plantation areas using the GFC product. Figure 11 shows the intensification of tree cover loss in the four plantations over the period 2001–2018. The GFC product confirms the observations made using the TMF map. Tree cover loss has been detected in Hevecam and Socapalm since 2001, while tree cover loss started in 2011 and 2014 in Sudcam and Biopalm respectively. As already mentioned, some recent tree cover loss in the Hevecam plantation can be the result of harvesting of old planted trees.

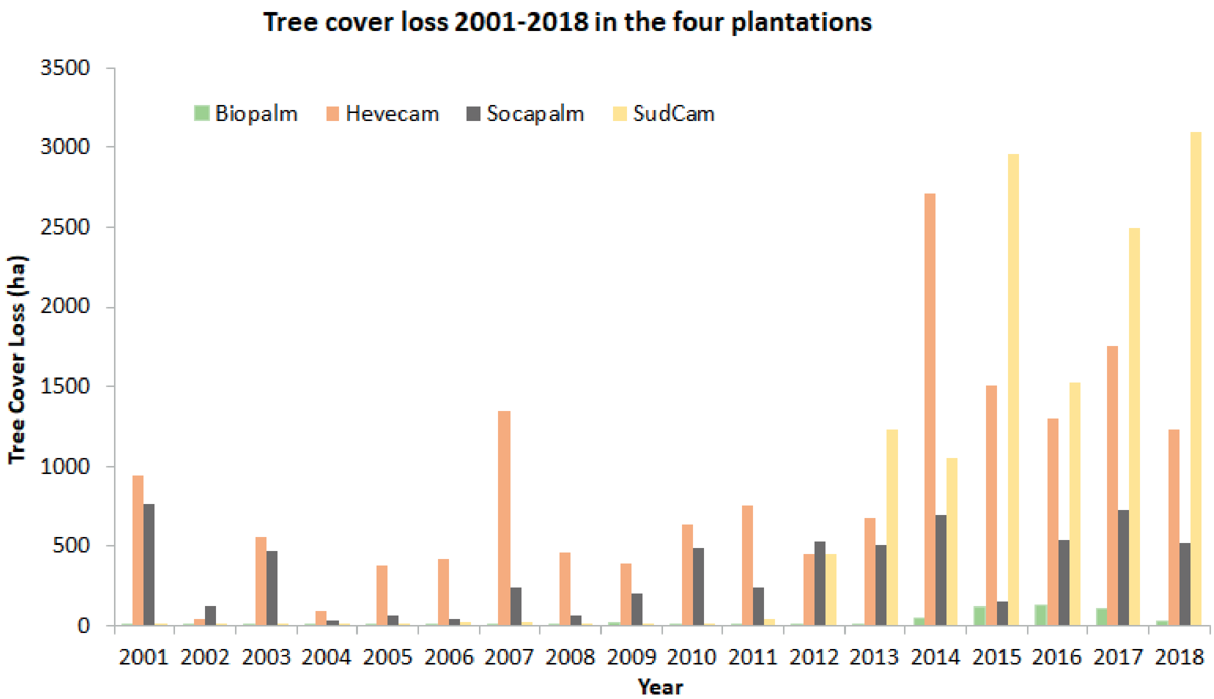

Figure 11. Tree cover loss (ha) derived from the GFC product for the four plantations. The bars represent yearly tree cover loss inside each agro-industrial plantation.

In summation, the older tree cover change activities are identified in the Hevecam concession, followed by the Socaplam and more recently the Sudcam. The effect of the moratorium on any new deforestation activities in the Sudcam concession is clearly visible in the data analysed. Satellite imagery can further be used to monitor adherence to the moratorium in future. The reviewed EO data for the Bioplam concession confirms an absence of implementation in that concession. In general, analyses differentiating natural regrowth, oil palm or rubber plantation conducted in recent studies could help refine the conclusions of this analysis (Descals *et al.*, 2020; Nomura *et al.*, 2019; Ordway *et al.*, 2019).

5 Potential applications of earth observation in Cameroon

In this study, we showed that the combination of existing EO-based products that report on tree cover changes can bring valuable information to support sustainable investment and policymaking related to two types of land-based activities.

The study showed that EO can be used to successfully identify land use change and deforestation associated with land investments, whether large-scale agricultural concessions or small-scale artisanal mining operations. Combining EO with calculations and proximity analysis further allows us to quantify specific changes, especially tree cover loss.

In East Cameroon, a mix of EO, expert interpretation and proximity analysis showed that small-scale mining activities spreading along the Lom River and its tributaries across time are associated with an increase in tree cover loss since 2014. Similarly, an analysis of EO datasets over and around agro-industrial plantations in the South of Cameroon provided an accurate assessment of the intensity of forest changes in and around the concessions. For agro-industrial plantations, EO data provides a way to follow what the companies are doing in terms of implementation and deforestation.

5.1 Earth observation can level power dynamics in land regulations

The evidence produced by EO can increase transparency in land governance, providing a powerful tool for monitoring and assessing land use change. EO can be used by governments to support a fairer and more regulated implementation of land policies, but also by civil society and community actors in the absence of publically available information. The use of EO by governmental actors is not new, however it remains limited in developing countries and sub-Saharan Africa. Over the past decade, Africa has seen a slow yet steady increase in the use of EO and geo-information systems (Woldai, 2020). Some African governments have invested in EO to support the land sector, but also in practical applications in areas of disaster risk reduction, climate change mitigation and natural resource management. In 2020, 11 African countries launched 36 satellites, pointing to an update of EO by governments (Woldai, 2020).

Based on our study, EO could be further used to regulate and monitor the development of ASM, which otherwise can prove difficult both administratively and logistically. The use of EO could support the monitoring of environmental impacts of formal and informal ASM, providing the necessary evidence to sanction certain small-scale mechanised mining companies. It could also support the strengthening of environmental regulations, compliance with conservation targets, and provide data on mining overlaps with community land to avoid and resolve conflicts (Tchindjang *et al.*, 2017).

However, the slow uptake of EO in Cameroon partly results from the lack of technical knowledge needed to run EO analyses, but also from the political economy of land investments which often benefits current power holders at the expanse of local communities (Ngeunga and Akana, 2018).

5.2 Leveraging evidence to support community rights

Due to poor government regulation and monitoring of investments that affect their land and livelihoods, communities are often faced with unequal power dynamics when trying to claim their rights against investors. By detecting changes in land use and tree cover loss, EO provides the opportunity to build strong evidence-based cases to support advocacy and legal reforms for the responsible governance of land-based investments. Both communities and CSOs can use EO as evidence to protect land rights and negotiate compensation for damages caused by land investments.

For example, we have shown that current EO products and maps provide valuable information for the analysis of the state of implementation of agro-industrial concessions – a type of information which is rarely communicated transparently by companies and governments. Where concessions have recently been allocated on community land, EO can help build a case to contest newly declared concessions by estimating the extent of future environmental damage, such as biodiversity loss, as well as the impacts on communities. EO represents an extra layer of information in participatory mapping initiatives.

In instances where investment activities are ongoing, EO can show how activities correlate to tree cover loss both inside and outside concession boundaries at specific times over years. Looking at tree cover loss around concessions can also show how, and to what extent, local communities have lost land and related livelihood activities. Both can support stronger cases for compensation against contested land-based investments.

5.3 Steps to democratizing earth observation

Evidence from EO can help build stronger cases for policies and laws that strengthen land and natural resource governance in effective, inclusive ways. Several EO products are openly available and free for any institution or CSO to use. However, three core challenges must be addressed to drive the use of EO in land governance.

Combining EO with empirical evidence. EO can provide transparent evidence on observable changes, but cannot shed light on the mechanisms that brought about these changes or show how they affect local communities. This type of information requires the collection of sufficient field data or local knowledge. In that sense, EO-generated data is most powerful when combined and triangulated with data from the field, for example, community land boundaries, land use patterns, and livelihood impacts. The combination of methods and the integration of spatial and socio-economic data remains an area for improvement in research, yet could bridge a significant gap around land-based activities. For example, the digitalization of participatory community maps overlaid with other EO products could accelerate the advocacy efforts of communities resisting concessions declared on communal or traditional land. Coupled with stories from the ground, EO-generated imagery creates a comprehensive picture of the implications of land-based activities on the landscape and on people.

Creating non-technical platforms for analysis. Technical barriers remain for the large-scale uptake of EO. For example, replicating the analysis presented here would require specialist skills in analysing EO products – skills that are not always readily available in CSOs and governments, both in developed and developing countries. Additionally, expanding the scale of the analysis would require the development of ad-hoc thematic products to automate the process over a large area. Thus, democratizing the use of EO for land governance requires investment to make products more accessible and improve cross-sector collaboration. An awareness about the limitations of the different sourced of EO-based products is also important in ensuring the quality of information.

Specific portals have already made access to maps and simple functionality, such as superposing different EO products, easily accessible for non-specialist users. As the quality of EO products improves, so should work on tools and interfaces to facilitate their access. For example, specific products can be designed to monitor changes over a large area using smartphone apps. This could make EO accessible to local CSOs with the push of a button, helping them hold governments and companies to account. The rise of citizen science can further mean that local communities with access to phones and the internet could upload and share geospatial information in real time.

Improving public, private and civil society collaboration. These innovations rest on the improvement of long-term collaborations between remote sensing experts, practitioners and policymakers. Collaborations that focus on the development of local and national capacities can raise awareness on the importance of transparency and negate the pervasive idea that such knowledge is difficult to obtain. Further embedding such collaborations into governmental agencies would allow for a proactive rather than reactive approach to land allocation and regulations, avoiding several costly conflicts. In the end, more transparent and clearer regulatory frameworks for land governance benefit all stakeholders – states, companies, communities and CSOs.

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Annex: JRC Tropical Moist Forest map legend

10. Undisturbed evergreen/semi-evergreen tropical forest (1982-2016)
11. Bamboo dominated forest
20. Degraded forest before the observation period
21. Degraded forest with short-duration disturbance (startedbefore 1999)
22. Degraded forest with short-duration disturbance (started in 1999-2008)
23. Degraded forest with short-duration disturbance (started in 2009-2015)
24. Degraded forest with long-duration disturbance (started before 1999)
25. Degraded forest with long-duration disturbance (started in 1999-2008)
26. Degraded forest with long-duration disturbance (started in 2009-2015)
27. Degraded forest with 2 degradation periods (started before 1999)
28. Degraded forest with 2 degradation periods (started in 1999-2008)
29. Degraded forest with 2 degradation periods (started in 2009-2015)
30. Old regrowth (disturbed before the observation period)
31. Old regrowth (disturbed before 1999)
32. Young regrowth (disturbed in 1999-2008)
33. Very young regrowth (disturbed in 2009-2015)
40. Deforestation started in (1990-1998)
41. Deforestation started in (1999-2008)
42. Deforestation started in 2009
43. Deforestation started in 2010
44. Deforestation started in 2011
45.Deforestation started in 2012
46.Deforestation started in 2013
47.Deforestation started in 2014
48.Deforestation started in 2015
51. Strong disturbances, started in 2016
52. Strong disturbances, started in 2017
53. Strong disturbances, started in 2018
61. Light disturbance(s), started in 2016
62. Light disturbance(s), started in 2017
63. Light disturbance(s), started in 2018
71. Permanent Water (Pekel et al. 2016 updates for years 2015-2018, January 2019)
72. Seasonal Water (Pekel et al. 2016 updates for years 2015-2018, January 2019)
73. Deforestation to Permanent Water
74. Deforestation to seasonal water
81. Old Plantations or undisturbed inside the plantation area
82. Plantation regrowthing (disturbed before 2008)
83. Plantation regrowthing (disturbed in 2009-2015)
84. Deforestation in the plantation (started in 1990-1998)
85. Deforestation in the plantation (started in 1999-2008)
86. Deforestation in the plantation (started in 2009-2015)
87. Recent disturbance in the plantation (started in 2016-2018)
90. Other LC (a regrouper avec 91)
91. Other LC
92. Other LC: Evergreen non-forest (shrubland, Grassland)
93. Other LC: Non-forest recently regrowthing
94. Other LC: From water to regrowth
95. Other LC: Semi-deciduous drying or deciduous forest (initially undisturbed)

About the project

LandCam: Securing land and resource rights and improving governance in the Cameroon
Timeline: February 2017 - January 2022

The LandCam project aims to develop innovative approaches to facilitate inclusive dialogue at the national level, based on lessons learned from past experiences, to improve land governance.

LandCam promotes learning, throughout the ongoing reform of Cameroon's land legislation and will contribute to building the capacity of actors at the local, regional and national levels. LandCam works with key stakeholders across Cameroon to improve customary and formal rights to land and natural resources by piloting innovations in land governance at the local level and contributing to sustainable policy reforms.

New spaces will be created for more informed, effective and inclusive dialogue and analysis, with the participation of stakeholders. LandCam will monitor changes on the ground, monitor legal reforms and share lessons learned nationally and internationally.

Who are we?

IIED, CED and RELUFA are the organisations implementing the LandCam project, working closely with a wide range of partners in Cameroon and internationally.

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International Institute for Environment and Development (IIED)

IIED promotes sustainable development by linking local priorities to global challenges. IIED supports some of the world's most vulnerable populations to make their voices heard in decision-making.

CED Centre pour l'Environnement et le Développement

Centre for Environment and Development (CED)

CED is an independent organisation working to promote environmental justice and protect the rights, interests, culture and aspirations of local and indigenous communities in Central Africa. As an active member of several networks, the CED has succeeded over the years to mobilise allies to influence positively legal frameworks, monitor natural resource exploitation activities, sustainably build the capacities of dozens of local communities, and produce important scientific and advocacy documentation.

Réseau de Lutte contre la Faim RELUFA

Réseau de Lutte contre la Faim (RELUFA)

RELUFA (Anti-hunger Network) is a platform of civil society and grassroots community actors created in 2001, which aims to address systemic problems that lead to poverty, hunger and social, economic and environmental injustices in Cameroon. The RELUFA's work is based on three programs: Equity in Extractive Industries; Land and Resource Justice; and Food and Commercial Justice.

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Democratizing earth observation to improve transparency in land use governance

Deforestation driven by international agricultural investments and mining operations are increasing in sub-Saharan Africa, often under a cloak of secrecy. Earth observation using satellite imagery and data allows us to track and report on rates of forest loss related to land concessions and empower communities and activists with evidence to resist unjust or harmful land deals. This paper looks at two case studies on artisanal mineral mining and rubber and oil palm plantations in Cameroon to demonstrate the value of satellite imagery in land governance. It finds that earth observation can serve to increase transparency in large land deals and provide a useful tool for organisations safeguarding the environment and communities defending their land rights.

LandCam Securing land rights in Cameroon

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