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Monitoring and quantifying forest degradation: remote sensing approaches for applied conservation in the Congo Basin

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Summary

Global forests play a crucial role in regulating global climate by actively storing and sequestering carbon. Despite efforts to mitigate climate through international efforts, human-caused forest disturbance and forest-related greenhouse gas emissions continue to rise.

Deforestation and forest degradation are two different processes affecting global forests. Deforestation is a clearly defined conversion or removal of forest cover, while degradation can be more subtle, temporary, variable, and therefore difficult to detect. Forest degradation is generally identified as a functional reduction in the capacity of forests to provide ecosystem services, that does not qualify as a change in land cover or forest clearing. That means no clear reduction of the forest area, but rather a decrease in quality and condition. This change, like deforestation can still be associated with significant reductions in above-ground biomass and therefore considerable greenhouse gas emissions.

Estimates of carbon emissions from forest degradation and disturbance range anywhere from 12-20% of all emissions emitted globally with values varying widely because of a lack of uniform definition or method for quantifying degradation, the broad number of influencing factors, and uncertainty in biomass estimates. The area affected by forest degradation could in fact be much larger than that of deforestation, which is already estimated to be an area about the size of Iceland every year.

The REDD+ mechanisms of financing emissions reductions to mitigate climate change require robust, transparent and scalable methods for quantifying degradation, along with a quantification of associated direct drivers. Furthermore, as degradation often precedes deforestation, timely monitoring and assessment of forest degradation and changes in drivers can provide crucial early warning to engage interventions to keep forests intact, benefitting nature and biodiversity as well as the livelihoods, health and well-being of millions of people around the world.

This research proposes methods for consistent, repeatable and scalable satellite-derived indicators for identifying and quantifying different types of forest degradation and its causes to inform future risk and policy scenarios.

Zusammenfassung

Wälder spielen global eine entscheidende Rolle bei der Regulierung des Weltklimas, da sie aktiv Kohlenstoff speichern und binden. Trotz der Bemühungen durch internationale Programme nehmen die Waldschäden weiter zu.

Entwaldung und Walddegradierung sind zwei unterschiedliche Prozesse, die sich auf die globalen Wälder auswirken. Entwaldung ist eine klar definierte Umwandlung oder Abholzung der Waldflächen, während Degradierung subtiler, vorübergehend und variabel sein kann und daher schwer zu detektieren ist. Walddegradierung wird im Allgemeinen als eine funktionale Verringerung der Fähigkeit von Wäldern Ökosystemleistungen zu erbringen identifiziert. Sie wird nicht als Veränderung der Landbedeckung oder Entwaldung klassifiziert. Daraus folgt keine deutliche Verringerung der Waldfläche, sondern eher eine Abnahme der Qualität und des Zustands. Diese Veränderung kann, wie die Entwaldung dennoch mit einer signifikanten Verringerung der oberirdischen Biomasse und damit miterheblichen Treibhausgasemissionen verbunden sein.

Die Schätzungen der Kohlenstoffemissionen aus Waldstörungen liegen zwischen 12 und 20 % aller weltweit emittierten Emissionen. Durch eine fehlende einheitliche Definition oder Methode zur Quantifizierung der Degradation, der Vielzahl an Einflussfaktoren und der Unsicherheit bei der Schätzung der Biomasse variieren die Werte stark. Die von der Walddegradierung betroffene Fläche könnte in der Tat viel größer sein als die der Entwaldung, die ohnehin jedes Jahr auf eine Fläche von etwa der Größe Islands geschätzt wird.

Die REDD+-Mechanismen zur Finanzierung von Emissionsreduktionen zur Minderung des Klimawandels erfordern robuste, transparente und skalierbare Methoden zur Quantifizierung der Walddegradierung, zusammen mit der Erfassung der damit verbundenen Treibern. Da die Degradierung oft der Entwaldung vorausgeht, kann ein schnelles Monitoring mit einer Beurteilung der Waldschäden und ihren Treibern ein wichtiges Frühwarnsystem sein. Nur so können Maßnahmen frühzeitig ergriffen werden, die die Wälder schützen und sowohl der Natur und der Biodiversität als auch dem Lebensunterhalt, der Gesundheit und dem Wohlbefinden von Millionen von Menschen auf der ganzen Welt zugute kommen.

In dieser Arbeit werden Methoden für konsistente, reproduzierbare, skalierbare und satellitengestützte Indikatoren zur Identifizierung und Quantifizierung verschiedener Arten von Walddegradation um zukünftige Risiko- und Politikszenarien zu unterstützen.

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Declarations

"I declare that I have completed the thesis independently using only the aids and tools specified. I have not applied for a doctor's degree in the doctoral subject elsewhere and do not hold a corresponding doctor's degree. I have taken due note of the Faculty of Mathematics and Natural Sciences PhD Regulations, published in the Official Gazette of Humboldt-Universität zu Berlin no. 42/2018 on 11/07/2018."

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List of publications

Chapter I: **Aurélie Shapiro**, Naikoa Aguilar-Amuchastegui, Patrick Hostert, Jean-Francois Bastin. 2016. Using fragmentation to assess degradation of forest edges in Democratic Republic of Congo. *Carbon Balance and Management* (11). https://doi.org/10.1186/s13021-016-0054-9

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AGB – Above Ground Biomass

BFAST – Breaks For Additive Season and Trend

CCDC – Continuous Change Detection and Classification

DRC – Democratic Republic of the Congo

EO - Earth Observation

FAO – Food and Agriculture Organization of the United Nations

FC – Forest Condition

FLR – Forest Landscape Restoration

FSC - Forestry Stewardship Council

HCV – High Conservation Value

HFLD – High Forest Low Deforestation

IFL – Intact Forest Landscape

IUCN – International Union for the Conservation of Nature

LiDAR – Light Detection and Ranging

NBR – Normalized Burn Ratio

NFI – National Forest Inventory

PES – Payments for Ecosystem Services

PFM – Participatory Forest Management

REDD+ - Reducing Emissions from Deforestation and Degradation

REL – Relative Emissions Level

SAR – Synthetic Aperture Radar

WWF – World Wide Fund for Nature

Chapter 1: Introduction

Research background and presentation of general concepts on forest degradation, causes, monitoring approaches and information on the study region.

1.1. Background

Tropical forests have been drastically deforested and degraded in recent decades, resulting in significant consequences for climate, biodiversity, human health and water as well as reduced resilience to face future threats (Seymour & Harris, 2019; Thompson, 2009). These ecosystems, despite covering only a third of the global land surface are crucial to human well-being by providing various goods and services to over a billion people around the world, as well as harbouring a majority of the earth's biodiversity (Grace et al., 2014; Newton et al., 2020). More recently the benefits provided by forests have been increasingly valued and quantified for their role in mitigating climate by sequestering greenhouse gas emissions. The urgency to safeguard forests is now growing, and conservation of land and forests has been identified as the most urgent climate policy intervention of our time by a majority of the global population (UNDP, 2021).

Tropical forest loss, driven primarily by agriculture and land conversion for commodity production (Curtis et al., 2018) has continued in recent decades at a rate of about 0.4 %/year (Hansen et al., 2013) while degradation is estimated to affect even more area, so that less than half of remaining forests are considered healthy, intact or untouched by human impacts (Grantham, Duncan, et al., 2020; Lewis et al., 2015). These remaining tropical forests, despite this situation still act as important carbon sinks, storing more carbon than other land ecosystems (Harris et al., 2021; Pan et al., 2011). Understanding the magnitude, spatial distribution and nature of drivers of forest related changes and associated emissions is essential for informing management to avoid deforestation, reduce emissions, enhance sequestration and drive climate relevant policies including nature-based solutions (Griscom et al., 2020). This effort is however hindered by many complexities related to data sources, definitions, scopes, assumptions, and uncertainties related to mapping and quantifying deforestation, degradation, and associated carbon stocks. This research explores the patterns and changes in forest degradation disturbance in the Congo Basin which can be correlated to degradation, along with the direct causes.

1.2. Key concepts

This research is built on several key concepts and definitions:

Deforestation is universally recognized as a permanent conversion of forest to other uses (GOFC-GOLD, 2014). Monitoring of forest loss from space is generally reliable and in recent years has become available in near real-time using a variety of earth observation (EO) technologies (DeFries et al., 2007; Hansen et al., 2013; Reiche et al., 2021). Despite these advancements, consistent estimates of forest loss are nevertheless hindered by differences in forest definitions, methodologies and data sources (Chazdon et al., 2016; Pacheco et al., 2021).

Forest degradation on the other hand, suffers from the lack of a globally accepted definition, due to biophysical differences, perceptions or values (Ghazoul et al., 2015). Generally, degradation is known as a reduction in the delivery of ecosystem services – which have no defined criteria or assessment. There are varying definitions applied around the world (Lund, 2009; Simula, 2009) resulting in the quantification of degradation, already difficult to detect being further complicated by its perception, lack of permanence, or varying effects and extent, and confounded by natural degradation. For this research I used above ground biomass as an estimator of forest ecosystem function (Karjalainen et al., 2003). As forest degradation is temporal in nature (Thompson et al., 2013), I establish that degradation should not be detected by one static observation in time.

Forest fragmentation is the definition of the spatial pattern of forest extent. Fragmentation is the process of change from larger, intact forest pieces to smaller, disconnected ones. Over time these fragments suffer from greater edge effects and are less able to sustain the same ecosystem functions of larger patches, resulting in decreased biodiversity, biomass, resilience.

Forest integrity, condition or health refers to the anthropogenic modification of forests, affecting the delivery of ecosystem services (Grantham, Duncan, et al., 2020) and is defined by the degree to which humans have impacted structure, composition and function (Parrish et al., 2009). This operational definition is technically similar to forest degradation and has been used to measure the extent of degradation a forest ecosystem has already undergone.

Resilience is an intrinsic trait of an ecosystem to return to its original state following a disturbance, while maintaining its essential characteristics and functions(Holling, 1973). A resilient forest ecosystem can withstand and respond to disturbances over long periods of time, notably climate change (Watson et al., 2018).

1.3. What is forest degradation?

There is no universal accepted definition of forest degradation, and there are hundreds of interpretations and concepts to assess it in various contexts (Karjalainen et al., 2003; Simula, 2009). The definitions are varied, and can include changes in structure, resilience, species composition, or its causes. More broadly it is considered an accumulation of human-caused disturbances which affect forest function and the delivery of ecosystem services, but don't alter the forest enough that it falls below the definition of forest: these are changes in forests that aren't severe enough to be called deforestation.

Forest degradation may be short term or long term, subtle or severe, multi-dimensional and multi-faceted. The variety of causes, impacts, temporal and spatial variation and lack of specific criteria make forest degradation a particularly complicated factor to monitor and evaluate in clear terms, especially when forests themselves are inherently dynamic. Ecologically speaking, a degraded forest means a potential loss of resilience to future events, future disturbances and future drivers of degradation which might be difficult to recover (Mueller et al., 2005). Degradation is not always permanent, and does not need be defined as such – as natural regeneration is in fact possible or can be aided with sylvicultural or management approaches (FAO, 2019).

For the purposes of monitoring and management, the degradation definition must be conceptually and functionally clear as well as practical, and avoid generic descriptions (FAO, 2011; Ghazoul et al., 2015). One area of contention is the aspect of short-term changes in forests due to sustainable forest management or exploitation, which in theory, when adequately implemented should allow a forest to quickly recover to its intact state. The Food and Agriculture Organization of the United Nations (FAO) defines forest degradation to include the effects of management or exploitation, while others do not (Heymell et al., 2011; Thompson et al., 2013; Vásquez-Grandón et al., 2018). The reality, however, is that sustainable forest management can have permanent consequences through the creation of skid trails or landing areas, or can have unexpected impacts by allowing increased access to forests for other unassociated uses, such as small-scale timber harvesting or extraction, bushmeat hunting, or the introduction of invasive species which are all causes of degradation (Boston, 2016).

Another complicating aspect of defining forest degradation is discerning a human cause. Are the impacts of natural disasters, events including blowouts or tree mortalities, or extended drought, which are a result of human-caused climate change included in the definition of forest degradation? In more concrete terms, when working with satellite imagery and earth observation, the discrimination between direct causes or drivers may not be possible. But the underlying cause is nevertheless important to consider in the context of drivers, risk mapping and early warning.

1.4. Causes of Forest Degradation

The causes of forest deforestation and degradation can be grouped into direct and underlying causes (**Figure** 1). Geist and Lambin (2002) organize direct drivers into four major categories: agriculture, infrastructure and timber and other factors. However, it does not mean that these drivers act alone – there are synergistic, complex processes at work that interact to drive changes that vary in time and space. This section describes the major causes of forest degradation in the central African Congo Basin considered in this research.

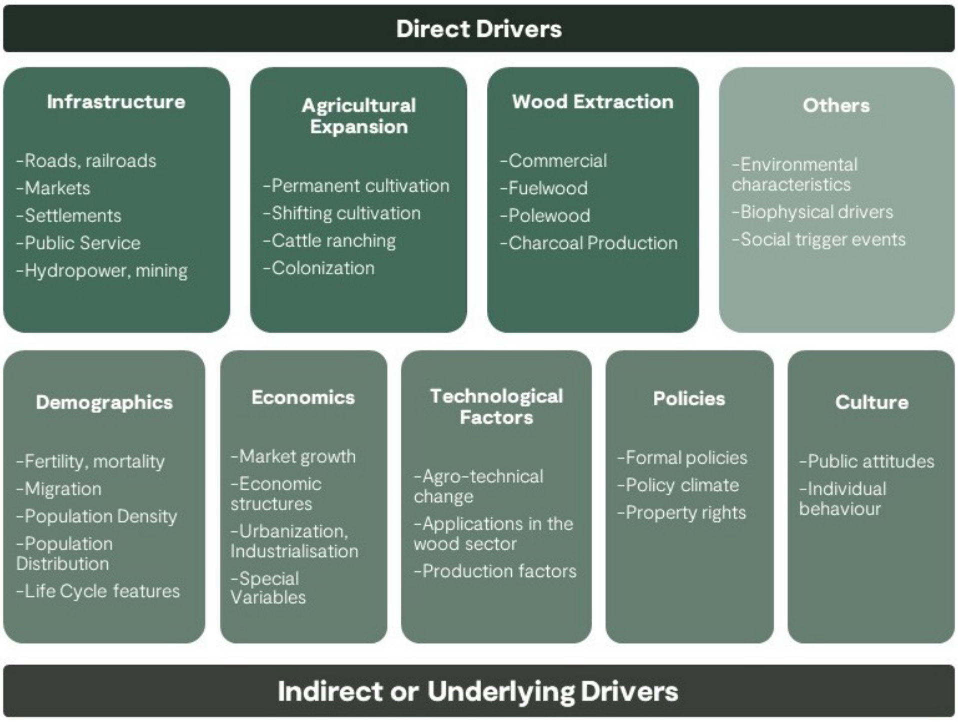

Figure 1. Proximal causes of forest decline (Geist & Lambin, 2002)

1.4.1. Agricultural Expansion

Agriculture is considered to be the most important global driver causing the large majority of forest loss (Kissinger et al., 2012). The demand for agricultural products is intrinsically linked with population growth, development and wealth or poverty. Slash and burn approaches, mostly by poor subsistence farmers is the process of clearing vegetated land, and burning the field before establishing agriculture for a few years until yields decline, and the land is left to fallow (Hauser & Norgrove, 2013; Molinario et al., 2017). In many cases these activities can cause fires to spread out of controlled areas and into edges of clearings, resulting in even more forest disturbance.

In other cases, areas can either re-used eventually or left to regenerate to become forest again, which could mean becoming more or less carbon neutral (Tinker et al., 1996). As populations increase along with the demand for more yield however, more land is cleared or fallow times reduced resulting in permanent land cover change (Hauser & Norgrove, 2013). In central Africa, the combination of rural developing areas and associated agricultural exploitation around forests has been named the "rural complex" which has expanded over time and is a cultural norm (Mayaux et al., 1999; Molinario et al., 2015; Molinario et al., 2017). Slash and burn is not scalable for large populations, and in these situations agricultural intensification, commercialization, or cattle ranching are established, preventing natural regeneration as seen for example in South America (van Vliet et al., 2012). The agricultural frontier and smallholder clearing in Central Africa has been expanding as population and associated demand grows while mechanization, infrastructure, and business climate are limiting great advancements in efficiency or productivity (Hourticq et al., 2013; Tyukavina et al., 2018).

1.4.2. Accessibility

Human accessibility is a large encompassing factor for human interference and disturbance in forests and is associated with many of the causes described in this section. The opening of logging roads for industrial exploitation often invites other actors to use these access routes for further resource extraction, in areas where population growth and greater demand result in more deforestation (Southworth et al., 2011). Roads are also a direct driver of habitat fragmentation, by increasing edge effects, reducing water quality, allowing the invasion by exotic species and incurring local changes in micro-climate (Trombulak & Frissell, 2000).

Enabled accessibility into forests is also a vector for the further exploitation of non-timber forest products such as fruits, honey, small fuelwood or bushmeat (Wilkie et al., 2000). While many populations rely on bushmeat for essential proteins, unsustainable hunting and the resulting elimination of key herbivore and seed dispersing species have devastating effects on forest composition, regeneration and resilience and can lead to further degradation (Harrison, 2011; Nasi et al., 2011; Stokstad, 2014).

1.4.3. Wood Extraction

Timber extraction from forests includes industrial activities, which can range from clear-cutting to selective harvesting, as well as small-scale, subsistence activities including fuelwood collection, all of which can have implications on carbon emissions and ecosystem health (Hosonuma et al., 2012). Timber extraction and exploitation can cause direct disturbance through harvesting, as well as associated impacts of logging roads, skid trails and associated infrastructure (Pearson et al., 2014).

Industrial exploitation in the Congo Basin, notably of processed timber is very low compared to other regions, with only a small contribution to the global market, and imports of wood exceed imports (Megevand, 2013). Of all Congo Basin countries, the Democratic Republic of Congo (DRC) has the lowest timber volume, despite having the most forests (de Wasseige et al., 2012), which is attributed to political instability, lack of access and means of transport (Tchatchou et al., 2015). The impacts on forests are more related to exploitation for national demand which is profitable at small scales and contributes to local infrastructure development (Lescuyer et al., 2014). Many of these enterprises, however, are unregulated or do not follow sustainable practices or can be illegal, resulting in additional impacts and emissions than planned. The impacts of industrial wood extraction in DRC are limited by selective logging practices, and mostly related to the development of logging roads and skid trails, which can quickly recover when not used, although they still threaten pristine forests by encouraging access and additional destructive activities (Pearson et al., 2014; Samndong et al., 2018).

In Congo Basin countries, and even more in the DRC, the local population relies primarily on low-priced wood fuel and charcoal for cooking as there is little access to electricity. The use of fossil fuels is extremely low and is not expected to change in the near future (Megevand, 2013). Fuelwood consumption on the other hand is expected to grow dramatically with increasing population and few investments in infrastructure. The supply chain feeding urban areas is largely unregulated, unsustainable, or illegal and the volume of wood removal from forests is steadily increasing and expanding. Whereas in rural areas, wood fuel collection is primarily focused on dead branches and logs which has minimal impacts, charcoal can provide a source of income for local communities who are meeting a growing demand from urban centers, which can eventually have more wider reaching effects (Samndong et al., 2018).

The Democratic Republic of the Congo (DRC) has potentially the greatest natural wealth on earth, estimated to be potentially more than $24 Trillion, yet continues to be at the bottom of the lists of the UN Human Development Index, plagued by instability, low education, low life expectancy. This “resource curse” is inevitably driven by corruption, where the elite divert resources for private gain, virtually eliminating any state investments into education, health, sanitation, development. This is compounded by political decentralization of a massive land mass. The DRC is the epicenter of conflict minerals, with an industry thriving on instability and child labor. The momentum for change needs to come from transparent, responsible sourcing, and a needed civil rights movement or motivation from inside for change.

1.4.4. Infrastructure

Major development corridors which aim to boost agricultural production, exports and economies include large scale expansion of infrastructure which bisect some of the most intact forests in central Africa and are expected to incur drastic irreversible impacts (Laurance et al., 2015). These infrastructure projects comprising roads, railways and power structures are often responsible for not only causing forest loss and degradation, but are effectively opening up remote areas to further access and disturbance.

The DRC has the lowest per capita electricity consumption of all Congo basin countries (Megevand, 2013). This under-developed sector could respond to growing energy demand with quick growth in coming years, resulting in expanded infrastructure for power plants, dams, electricity transmission networks (International Energy Agency, 2019).

Linear infrastructure such as roads and power lines which cross natural ecosystems have major ecological effects including forest fragmentation and associated degradation, as well as impacts on water flow, introduction of chemicals, noise and visual disturbances (Seiler, 2003). Roads are also associated with increased hunting pressure on African wildlife which can alter mammal communities who play an important role in seed dispersal, therefore affecting forest regeneration (Osuri et al., 2020).

1.4.5. Conflicts

Violent conflicts have significant ecological and socio-economic consequences (Machlis & Hanson, 2008) and would likely fall in the "Other" category of drivers from **Figure 1**. Conflicts can have both positive and negative impacts on forests, from restricting access to natural areas which can reduce disturbances, to increased pressure and unsustainable use of natural resources due to displaced people. In addition, conflicts can have negative impacts on protected area effectiveness through limiting enforcement or may incur decreased economic activity and impact resource pressure (de Merode et al., 2007). More generally, conflicts cause political and socio-economic instability which hinders sustainable development, good governance, and management. Furthermore, conflicts can arise over mineral or forest resources, which tend to encourage additional unsustainable exploitation through illegal or illicit activities.

The eastern DRC, on the border of Rwanda, Uganda and Burundi is an area with a simultaneous presence of high biodiversity, carbon stocks and mineral resources – which would under normal conditions provide opportunities for productive and economically successful activities. However, this area has experienced one of the most prolonged violent conflicts in the world, resulting in significant changes in forest cover and suffering local populations. This is emblematic of the "resource curse," a paradox of wealth and natural resources coupled with low economic growth and status (Matti, 2010).

1.5. Impacts of forest degradation

Intact and healthy forests typically provide more ecosystem services and benefits than degraded ones (Watson et al., 2018). Forest degradation events can be slow or fast, resulting in changes in structure, light regime, species richness, and biodiversity, impacts on biodiversity and livelihoods. The consequences are numerous and wide ranging, including a reduction of carbon sequestration and storage, reduced water retention and regulation, lower quality habitat and associated biodiversity, and a lower resilience to climate change and other disturbances. Degradation is directly responsible for reductions in habitat and associated biodiversity, which are part of natural functioning ecosystems and provide benefits in terms of genetic diversity, resilience and productivity (Pearce, 2001).

Fragmentation is the process of reducing forest cover into smaller patches, causing an increase in forest edges, incurring a number of impacts connected to ecosystem function and biodiversity (Chaplin-Kramer, Ramler, et al., 2015; Haddad et al., 2015; Silva Junior et al., 2020). Conservation biology theory and the concept of species-area relationships mean that larger habitats can support greater species richness (McGuinness, 1984). The increase in isolation between forest patches can reduce faunal species richness, limit the available gene pool and incur species extinction (Pfeifer et al., 2017; Watling & Donnelly, 2006). Reductions in faunal diversity have important consequences on forest regeneration and resilience (Gardner et al., 2019). Fragmentation is also shown to decrease biomass which can have persistent effects on carbon sequestration (Chaplin-Kramer, Ramler, et al., 2015; Chaplin-Kramer, Sharp, et al., 2015; Silva Junior et al., 2020).

Degradation via selective logging, which most often targets larger, valuable trees will affect species composition, light regimes and structure (Blanc et al., 2009). Loss of tree cover, even when incomplete results in soil erosion, which may have the effect of further decreasing forest resilience to changing climates (Flores et al., 2020). Fires, associated with slash and burn agriculture or hunting practices will negatively affect cover, density, structure, composition, diversity, and productivity, as well as community structure (Cochrane & Laurance, 2002; Juárez-Orozco et al., 2017; Morton et al., 2011).

Forest loss and degradation are the second global cause of greenhouse gas emissions after burning fossil fuels (Simula & Mansur, 2011). The quantification of these contributions is the main focus of most emissions reduction initiatives, while those associated specifically with degradation – the second D in REDD+ - are poorly understood. While the area associated with forest degradation are estimated to be larger than those of deforestation, the associated estimates of degradation vary widely (Baccini et al., 2017; Bucki et al., 2012; Miettinen et al., 2014; Pearson et al., 2014). Degradation emissions might be higher than deforestation, or they might be lower – this variation can be attributed to differences in forest types, the magnitude of degradation, or the method of estimation (Goetz et al., 2015). Additionally, forests may be repeatedly degraded, which can result in large cumulative emissions over time. This is important when considering full carbon accounting and the concept of foregone removals, the preservation of intact forests avoids future degradation and could actually have a larger impact on potential carbon emissions than simply accounting for one-time carbon storage removal (Maxwell et al., 2019).

1.6. Approaches for assessing forest degradation

Remote sensing provides a consistent, holistic and efficient method to monitor forests over time. Satellite earth observation is possible through a number of freely available or commercial sensors, both optical and cloud-penetrating active radar so that practically any forest on earth can be imaged at least once a week.

A number of new remote sensing based approaches have been developed in recent years based on these data streams. These can generally be categorized into indirect approaches, which include the use of metrics or proxies, or direct methods, which are derived from direct remotely sensed measurements (Herold et al., 2011). A summary of commonly used approaches is shown in Figure 2.

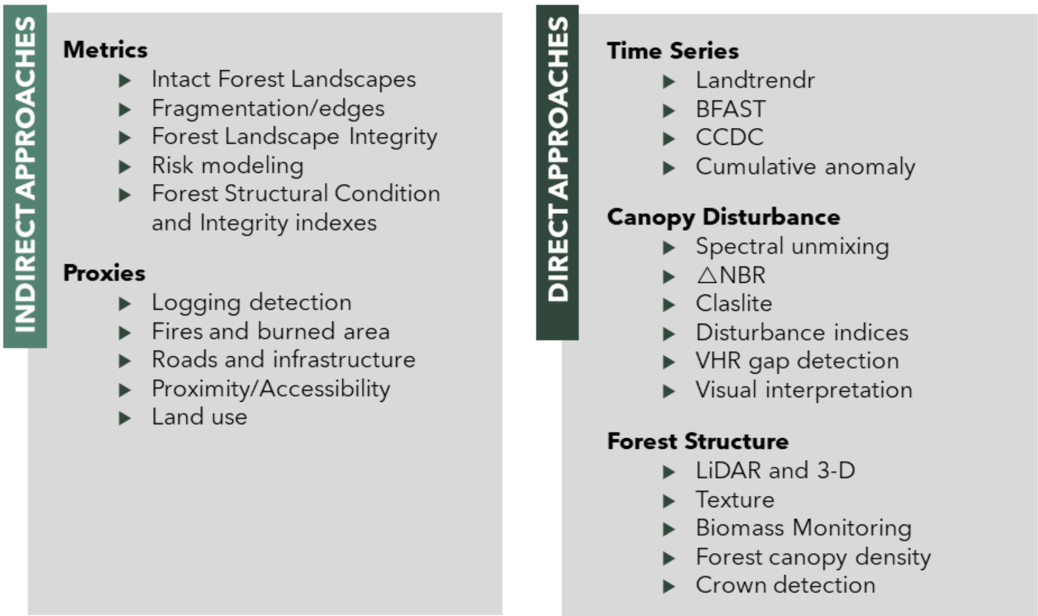

Figure 2. Direct and indirect approaches to assess forest degradation via remote sensing

Indirect measurements can comprise mapping a driver or an indicator such as the presence of fires, roads or other direct threats (Brandão & Souza, 2006; Grantham, Duncan, et al., 2020; Morton et al., 2011; Souza et al., 2005) or fragmentation indices, or spatial pattern to identify degraded forests from intact ones (Chaplin-Kramer, Ramler, et al., 2015; Potapov et al., 2008; Riitters et al., 2015; Tyukavina et al., 2016). These result in the identification of intact vs. degraded forests based on buffering, proximity or risk, which are consistent methods which can be assessed over time. Other approaches measure threats through a human footprint approach (Venter et al., 2016), or accessibility associated with potential biomass loss (Dons et al., 2016). The advantage of indirect methods is that they can be simple to calculate, easy to understand and replicate, and therefore a benefit to those with low resources or capacities for monitoring (Bucki et al., 2012). The disadvantage is that they can be too coarse or generalized and might not be sensitive enough to subtle changes in forests which might be degradation.

Direct measurements are spectral or structural assessments in time and space, related to canopy cover, productivity, forest structure or texture. These include identifying degradation delineated from visual assessments of high-resolution images, or expert knowledge from field data (Peres et al., 2006; Schepaschenko et al., 2019). Texture analysis and spatial autocorrelation assessments can be used to estimate spectral heterogeneity at multiple scales to determine hotspots of variations in the canopy (Bastin et al., 2014). Automatic segmentation algorithms group similar pixels based on size, spectral properties and edges, identifying homogenous forest types at one time period, and degradation at a later date can be through the variety or standard deviation within a segment (Conchedda et al., 2008). Spectral mixing analysis, fractional canopy density (Asner et al., 2005; Souza, 2003; Wang et al., 2005) can be used to separate percentages of pure elements such as soil, vegetation within a pixel can be characterized for degradation. Lacunarity indices (Malhi & Román-Cuesta, 2008) and fractal algorithms are used to identify heterogeneity and automatically distinguish gaps. Others have developed automated canopy identification or crown edge detection algorithms (Palace et al., 2008). Changes in phenology detected from high temporal resolution time series can provide information on disturbances (Verbesselt et al., 2010). The most robust methods for direct detection of degradation include monitoring of changes in biomass (Ryan et al., 2012), or canopy disturbance (Reiche et al., 2015; Reiche et al., 2021; Vancutsem et al., 2021) which is also successful with synthetic aperture radar (SAR) data which has the added advantage of being cloud-free, although the sensitivity to biomass is known to saturate, which is a particular problem in high biomass tropical forests (Imhoff, 1995). Direct measurements are beneficial in that they detect measurable changes in forests but have the disadvantage in that they may require more resources and processing for complicated approaches, can be sensitive to natural dynamics, or in the case of optical remote sensing, affected by clouds.

1.7. Monitoring needs

There is an increasing need to monitor, understand and promptly react to forest disturbances, notably degradation in forests before they permanently disappear, and the impacts are too extensive to reverse, or restoration too costly. Whether part of a framework to reduce forest related carbon emissions, or a prioritization for conservation interventions, there is an increasing reliance on accurate and reliable scientific data derived from satellite Earth Observation (EO) to improve our knowledge of these dynamics of natural forest systems.

Countries are actively getting involved in international initiatives to mitigate climate change and financing of results-based payments and associated carbon accounting, which needs to be as transparent, robust and cost effective as possible. Given the need to monitor and quantify forest degradation over long time periods consistently, repeatedly and at large scales, remote sensing and EO are providing the most efficient solutions (GOFC-GOLD, 2014). Satellite imagery is an effective tool to monitor forest ecosystems at many scales bringing many advantages, including consistency, transparency, accuracy and timeliness (Herold et al., 2011).

Remote sensing plays a critical role in climate change projects through monitoring, reporting and verification (MRV), and the establishment of reference levels, which are the baselines through which deforestation reduction success is evaluated (De Sy et al., 2012; Mitchell et al., 2017). The bold commitments by the international community and results-based finance to encourage countries to reduce and slow deforestation need to be supported by accessible, credible technology to inform forest policies (Neeff & Piazza, 2020). The selection of appropriate data to meet these challenges is very important (Sandker et al., 2021), as are repeatable, understandable and transferrable technologies which will function over long enough time periods.

The timely detection of degradation plays an important role in early warning. As degradation has been shown to be a precursor for deforestation (between 17 and 45% of degradation ends up deforested in Congo Basin countries, according to Vancutsem et al., 2021), it should be logical that the detection of degradation can serve as a warning system to prevent further, more permanent impacts. Detecting degradation could be an effective method to reduce investments in restoration or promotion of regeneration, which is more difficult and expensive after deforestation. Therefore, if we can detect degradation quickly after it happens, along with the causes, we could sensibly address it efficiently before a forest is converted to another land use that is more difficult to return to its original state.

In order to reward activities in the context of result-based payments for emissions reduction, an approach to conservativeness is realistic and recommended (Grassi et al., 2013). One simple approach is the intactness matrix (Table 1) where general categories or forest types can be evaluated and tracked over time (Bucki et al., 2012). This has the advantage of being clear, understandable, and repeatable, and particularly relevant when expensive carbon monitoring systems are not in place or not available. These represent meaningful performance indicators that can be measured and rewarded in the context of a REDD+ program.

Table 1. REDD+ activity matrix describing forest transitions (from Bucki et al., 2012)

	TO		
FROM	Natural/ intact	Non-intact	Other land
Natural/ intact	Forest Conservation	Forest Degradation	Deforestation
Non-intact	Afforestation/Reforestation	Sustainable Management	Deforestation
Other land	Conversion to non-intact	Afforestation/Reforestation	

However, more robust approaches should be integrated into monitoring approaches which include direct carbon monitoring, and associated uncertainty estimates to keep confidence and robustness of an international marketing scheme high (Yanai et al., 2020). As the impacts of degradation can vary widely, it would be beneficial to include at a minimum categories of degradation, or continuous estimations related to intactness (Grantham, Duncan, et al., 2020; Venter et al., 2016), or timing of disturbances (Vancutsem et al., 2021) which can provide finer granularity and more in accordance with the temporal definition of degradation.

1.8. Potential Solutions

While forest degradation is described here as having significant, long-term impacts, there are nevertheless potential solutions. For one, restoration of degraded forests is much more efficient and cost-effective and successful than the restoration of completely deforested ecosystems. The most ambitious efforts to slow deforestation and degradation are international emissions reduction efforts such as REDD+, which allow countries to invest in approaches to reduce forest disturbance value standing forests. These approaches implemented through international financing mechanisms come with the added benefit to encourage sustainable development, biodiversity and social safeguards which support forest-dependent communities.

Payments for ecosystem services (PES) and rewards-based economies to reward proven benefits or good practices are a direct way to encourage positive behaviors (Neeff & Piazza, 2020; Schomers & Matzdorf, 2013), for example, developing a scheme for local communities to manage and protect the forests in their vicinity. These approaches require robust and transparent methods for monitoring changes in forest cover, disturbance and ways to verify positive outcomes and avoid leakage (Sandker et al., 2021). These interventions also require good and stable governance. Strong governance in concert with incentives such as payments for ecosystem services and enabling measures can ensure long term positive change that is mainstreamed embedded into the economic system (Börner et al., 2011).

The identification of drivers of forest degradation is essential for context-relevant mitigation, notably successful land use policies, zoning and planning. A detailed understanding of these proximal causes can increase the effectiveness of strategies when they are addressing the correct actors, stakeholders and processes and use the proper data sources and methods (Kissinger et al., 2012). A current drivers analysis can inform site specific interventions to mitigate destructive activities via reforestation, promotion of alternative livelihoods, sustainable agro-forestry or cash crops and the establishment of community woodlots in support of the production of fuel wood and charcoal, which can reduce pressures on remaining natural forest. By addressing the underlying factors and the interactions of threats that are causing forest degradation, decision-makers can reduce or tackle certain pressures on forests and in successful cases provide alternatives to destructive activities.

Nature-based solutions encompass approaches that use natural processes to increase carbon sequestration, reduce carbon emissions and mitigate climate change (Griscom et al., 2017). For forests, these include better practices such as restoration and replanting or conservation efforts to enhance natural processes. Forest protection, particularly in the tropics can have long term benefits in terms of biodiversity, maintaining ecosystem processes and in terms of climate, through avoided forest conversion – essentially preventing forest loss and associated emissions (Griscom et al., 2020). Reforestation, avoided forest conversion and natural forest management have the largest potential mitigation potential respectively in terms of overall amounts of carbon (Griscom et al., 2017) which has associated benefits of improved biodiversity and resilience.

Global efforts to restore forest landscapes (Forest Landscape Restoration – FLR) are being developed in many countries by establishing commitments to plant trees and improve land management to enhance and promote natural regeneration. The approach operates on the concept to restore ecosystem functionality at the landscape scale, while integrating benefits to multiple stakeholders to ensure long term success (Maginnis et al., 2012).

Meanwhile, the carbon uptake in restored ecosystems is higher (Bernal et al., 2018) along with other co benefits of improved biodiversity, connectivity, agricultural productivity (César et al., 2020).

The involvement of local communities in these decisions concerning land use is extremely important to any approach. The establishment of participatory forest management (PFM) arrangements have been increasing in recent years and include a wide range of activities including co-management, community-based natural resource management (CBNRM) and community forestry (Schreckenberg et al., 2006). Studies have shown that community managed forests experience lower forest loss than areas with strict protection (Porter-Bolland et al., 2012). Community concessions grant rights to local people, including indigenous people for sustainable use forest resources (Yeung, 2021); this positive engagement derives many benefits while ensuring that resources are maintained in the long term.

Addressing larger scale forces such as international demand and trade which place additional pressure on forests is being achieved through voluntary agreements, measures, and regulatory frameworks. For example, Voluntary Partnership Agreements (VPAs) are bilateral trade agreements between the EU and other nations to ensure that wood exported from countries and into Europe complies with local laws and is not illegally harvested. This approach not only seeks to reduce illegal activities, which can diminish the value of legally harvested wood, but supports improved forest governance and stakeholder involvement. Other market based approaches label or certify forest products, for example the Forestry Stewardship Council (FSC) ensures that products are sourced responsibly managed forests providing environmental, social and economic benefits (Forest Stewardship Council, 2021). This approach can reward companies who comply to these standards by fostering access to exclusive markets or demanding a higher price than traditionally harvested products which can encourage the uptake of better, sustainable practices.

1.9. Study Area

1.9.1. The Congo Basin

The forests of central Africa are the largest intact tract on the continent comprising over 90% of Africa's tropical forests, second to the Amazon. These ecosystems provide a critical role effectively regulating regional as well as global climate, and providing important cultural, social and natural resources to more than 60 million people living in or around these ecosystems (de Wasseige et al., 2015). Compared to the Amazon, the Congo Basin has a relatively lower annual deforestation rate (Tchatchou et al., 2015), which suggests that African forests are overall more intact. However a recent assessment of forest integrity shows that the Amazon has a larger proportion of healthy forests than Africa (Grantham, Duncan, et al., 2020) which is more likely due to the more gradual and subtle impacts of forest degradation, versus concentrated, large-scale deforestation in South America. More critically, the degradation rate in the Congo Basin has been shown to be sharply increasing in recent years which is a cause for concern (de Wasseige et al., 2015; Tchatchou et al., 2015).

The Congo Basin countries (Figure 3) are home to a rich biodiversity, including over 10,000 species of tropical plants, one third of which are endemic to the region, over 1000 species of birds, 450 mammal species, 700 kinds of fish and almost 300 unique reptiles (de Wasseige et al., 2012). The freshwater ecosystems are also incredibly rich, with new species being discovered by nearly every new expedition. The region is mostly known for its unique great apes, including the Bonobo endemic to the DRC, and species of lowland and western gorillas, African chimpanzees, and forest elephants. This biodiversity is a crucial component of the forest ecosystem, as mammals are important seed dispersers which keep the forest diverse and regenerating.

There are many international efforts to conserve and secure central African forests, as Congo Basin countries have been addressed via regional initiatives to address the tropical forest belt. CAFI, the Central African Forest Initiative[1] is a collaborative partnership between international donors supporting strategic, country-level REDD+ and Low Emission Development investments in the six central African high-forest cover countries. Its objective is to recognize and preserve the value of the forests in the region to mitigate climate change, reduce poverty and contribute to sustainable development. COMIFAC[2], the Commission des Forêts d'Afrique Centrale was borne out of the Yaoundé declaration which unites forest conservation activities in 10 central African countries (Tchad, Sao Tomé and Principé, Rwanda, Burundi in addition to the six countries presented in Figure 3). This regional body is tasked with addressing political harmonisation between countries to address sustainable forest use, financing the development of the forestry sector, reduction of illegal wildlife trade and poaching. The United States Agency for International Development (USAID) has a Central Africa Regional Program for the Environment (CARPE)[3] which supports similar efforts related to conservation of forests and biodiversity and capacity building. All these regional approaches provide a lot of support to transboundary efforts and themes common to all countries, fostering south-south exchange and collaboration.

[1] https://www.cafi.org/
[2] https://comifac.org/
[3] https://carpe.umd.edu/

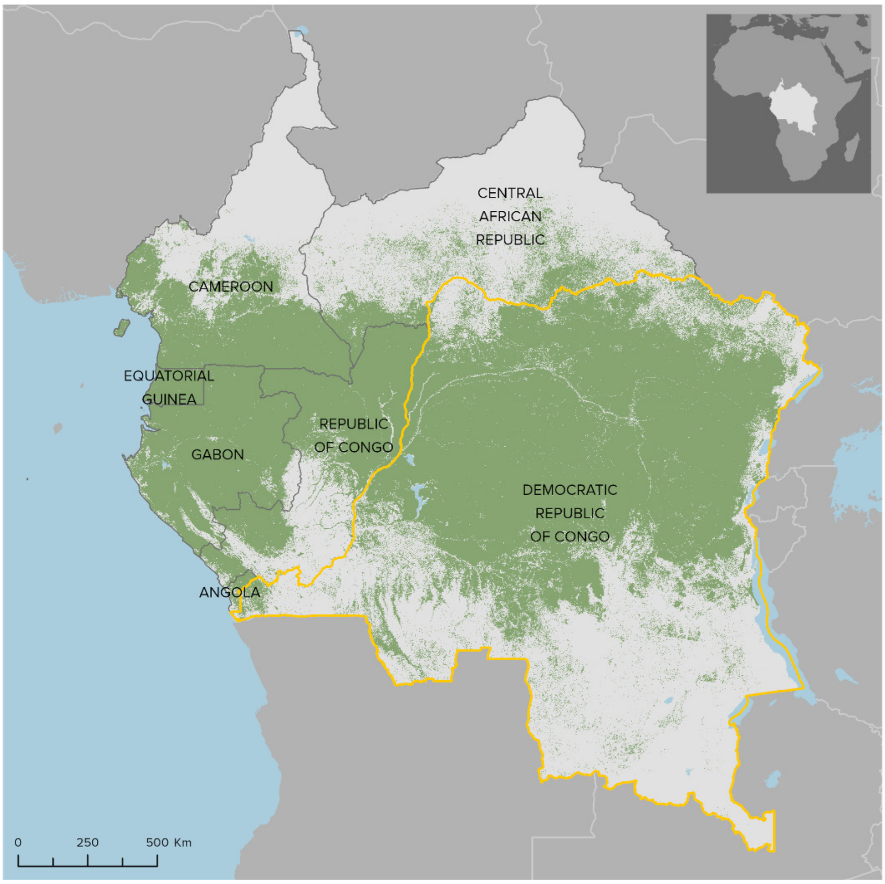

Figure 3. The six counties of the Congo Basin, of which the Democratic Republic of the Congo (DRC – in yellow) holds the largest continuous tract of tropical forest in Africa

1.9.2. Democratic Republic of the Congo (DRC)

The Democratic Republic of Congo (DRC) possesses the largest contiguous tract of remaining tropical forest in Africa, is surrounded by savannas, grasslands and human-dominated landscapes (**Figure 4**). It is known for its remarkable natural resources and outstanding biodiversity (Strassburg et al., 2010; WWF, 2006) while ranking 175 of 189 on the United National Development Programme Human Development index (UNDP, 2020). Poor governance has allowed extensive unregulated resource exploitation such as mining, timber harvesting, charcoal production, resulting in one of the highest deforestation and degradation rates in central African countries (Zhuravleva et al., 2013). The DRC is also among the most prominent REDD+ enabled nations, which is highly engaged in the UNFCCC process (Herold, 2009) as a high forest/low deforestation country (HFLD; (Griscom & Cortez, 2011) recognizing its potential for sustainable and economic development through emerging governance structures, as well as technical instruments such as the national Emissions Reduction Programme (CN-REDD, 2014).

The expansion of agricultural activities has been determined to be the greatest driver of forest disturbance in the DRC (Molinario et al., 2020; Molinario et al., 2015; Samndong et al., 2018) where the population is predominantly rural, with 70% of the employed engaged in agricultural activities, which are a significant contributor to GDP (Hourticq et al., 2013; USAID, 2016).

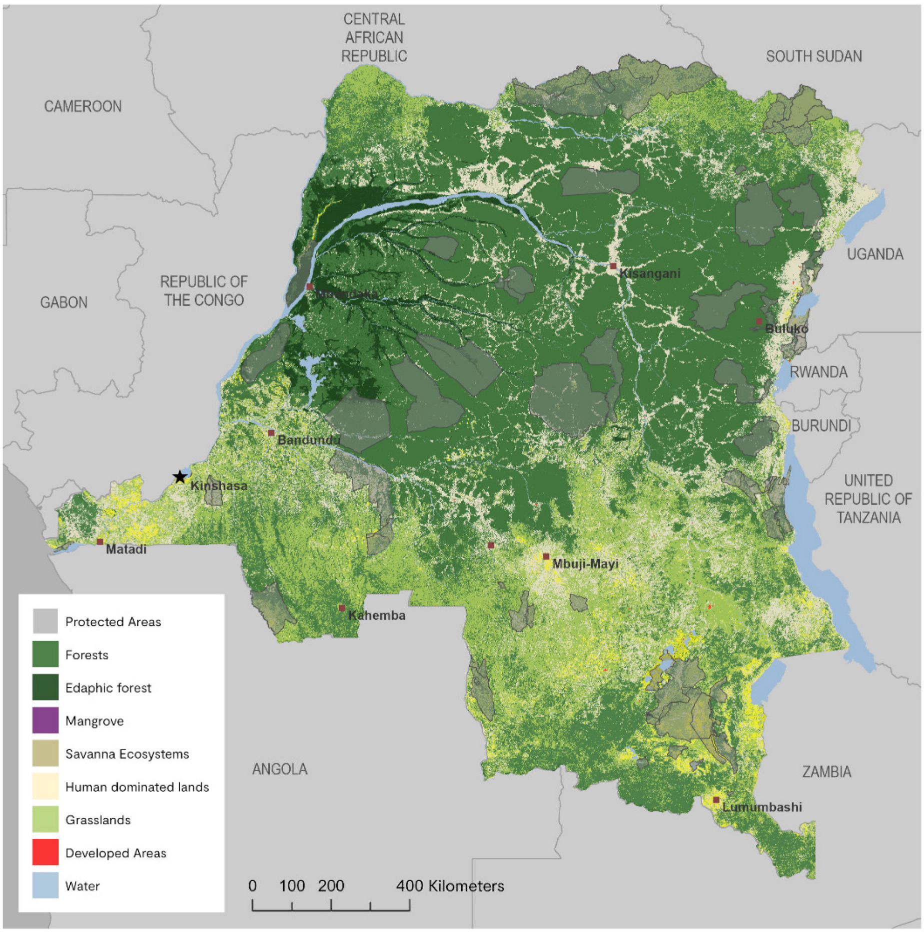

Figure 4. DRC land cover in 2010 (Verhegghen et al., 2012)

In response, the DRC has been building up political REDD+ capacity, albeit with limited resources and capacity for such a vast area. The country has been increasing efforts to monitor forest with satellite imagery, and mapping forest carbon at the national scale using airborne LiDAR and satellite imagery (Aquino & Guay, 2013; Mpoyi et al., 2013; Tollefson, 2013). The proposed field plot methodology to support the DRC National Forest Inventory (NFI) is a necessary component of any national REDD+ strategy but has been greatly hindered by low resources and capacity, as direct carbon monitoring on the ground through permanent field plots remains difficult due to human resources, cost, logistics, and security. A proposal for a pre-inventory amounted to well over 600 field plots in the pre-sampling phase came with estimated costs of over several million € and required years until completion. All these efforts represent massive mobilization of international organizations, various ministries, extensive, long-term training and capacity development via large collaborations of many international and local institutions.

Given the need for an accurate, robust carbon assessments to ground international climate arrangements, WWF-Germany, through the support of the German Federal Ministry of the Environment, Nature Conservation and Nuclear Safety (BMUB) International Climate Initiative (IKI) and the KfW Development bank endeavored to create Africa's first wall-to-wall carbon map developed through airborne LiDAR, satellite data and field observations. The Carbon Map and Model Project (CM&M)[4] was implemented to establish the basis for receiving REDD+ payments, by proposing model emissions reduction projects and livelihood alternatives, while efficiently estimating the carbon stock

4 https://wwf.panda.org/?211033/Carbon-Map-and-Model-Project-launched-in-support-of-REDD-initiatives-in-DRC

of all of DRC's tropical moist forests to support national monitoring efforts and carbon emissions assessments. The national airborne data collection campaign was executed between June 2014 and February 2015, collecting LiDAR measurements in 216 plots located in a stratified random fashion (**Figure 5**), totaling more than 430,000 hectares of data and very high-resolution airborne imagery. Additionally, ferry data collected in between plots increased the LiDAR data extent to 580,000 ha. This data collection was used to evaluate the distribution and patterns of above-ground biomass (AGB) in DRC (**Figure 6**) in relation to a number of biophysical variables (Xu et al., 2017), while providing a comprehensive dataset for a number of other research activities.

The application of advanced technology such as airborne LiDAR to estimate forest stocks in DRC was long debated, but was ultimately implemented mostly to overcome uncertainties, biases and limited resources for field inventories in a vast, remote forest areas. A national carbon inventory from field plots alone is likely to be very costly and take a long time to establish and implement, as explained above. The proposed pre-inventory for the IFN relied mostly on field plots that would be accessible by field teams – close to roads or forest edges and within days of an airport meaning it was inherently biased to sample edge forests which are different in terms of structure and biomass than continuous intact forests (Chaplin-Kramer, Ramler, et al., 2015). The use of airplane-based LiDAR meant that no stretch of forest was inaccessible, and the sampling method could be completely random and unbiased. Field plots are not indispensable, they are essential for calibration and validation of LiDAR metrics. But the overall number of field plots needed for robust carbon estimation can be reduced with the consistent structure metrics obtained from airplane-based remote sensing. For this reason, an investment of 3 million € for the LiDAR campaign and map development, (about half the budget for a full field inventory), amounting to a little over 2€/hectare of dense forest was considered a worthwhile investment – especially if it enables the DRC to realize the financial benefits from emissions payments sooner than having to wait for a full field plot inventory.

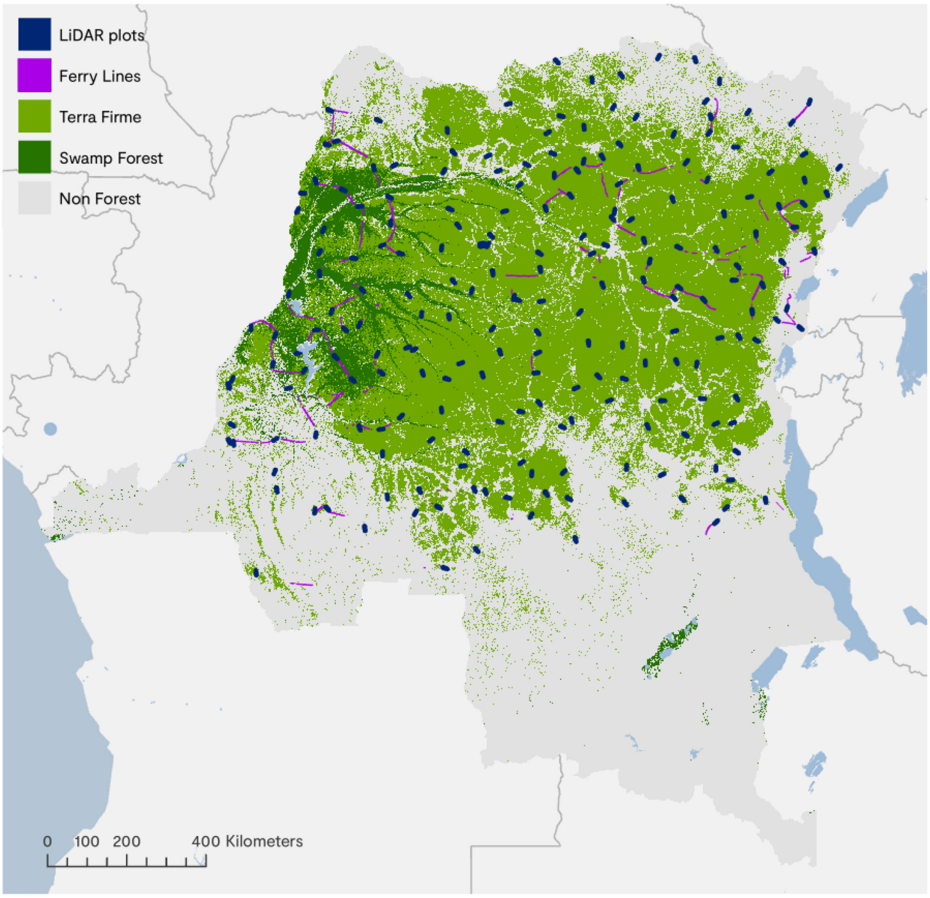

Figure 5. The LiDAR sampling strategy is an unbiased stratified random sample which extends over the tropical forest belt of the DRC covering more than 1 million km²

The results from this national carbon mapping initiative included a validated forest biomass map with uncertainty estimates allowing for detailed evaluations of biomass with topography, forest type, and climate. The areas with highest AGB density are located in the northeastern part of the tropical forest extent which is also associated with the greatest uncertainty. These data are the first of their kind for the African continent, and are accompanied by high resolution airborne data that are freely available, and have provided useful for a variety of other projects and applications and were fundamental for this research.

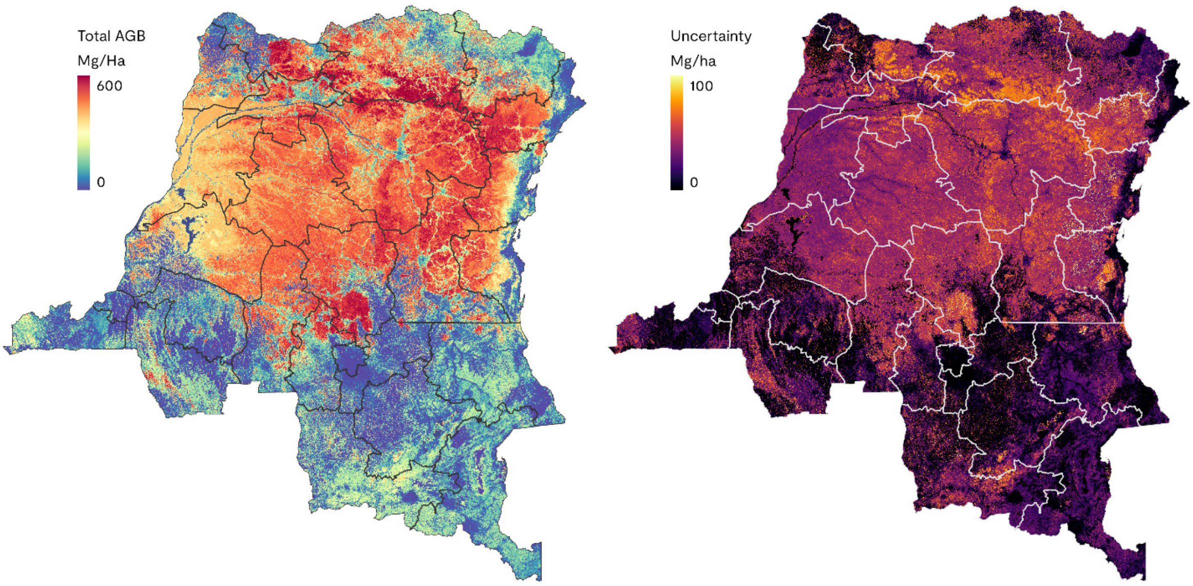

Figure 6. Total Above Ground Biomass (AGB) and uncertainty were mapped for the DRC, wall-to-wall covering over 2.2 million km^2

1.10. Objectives

The goal of this research is to derive methods to accurately map, understand and quantify forest degradation and its associated drivers in the Congo Basin. The methods are developed using a combination of satellite remote sensing, calibrated biomass information and spatial pattern and statistics. Clear indicators, proxies, metrics at the appropriate resolution and scale for quantifying degradation are urgently needed in this region to locate and estimate forest degradation in the context of REDD+, as well support landscape planning and restoration and targeted conservation interventions.

This research provides components and approaches for estimating greenhouse gas emissions from degradation vs. deforestation and establishing methods for assessing the condition of standing forest. Furthermore, identifying and quantifying the direct drivers of degradation, and how they differ from what is causing deforestation, will provide crucial insight into the pressures on forests of the region, potential early warning systems and how to plan low carbon pathways to sustainable development.

The following **research questions** have been addressed in three chapters:

- **Research question 1:** How can forest degradation be defined and mapped using indirect remote sensing or proxy techniques?
  Hypothesis: Forest degradation can be adequately quantified using spatial pattern, the disturbance history and above ground biomass as an indicator for ecosystem service over time. The relative emissions from deforestation and degradation can be calculated from this model.

- **Research question 2:** How can forest degradation or status be quantified and monitored on a continuous scale? How can these data be used for conservation planning?
  Hypothesis: Forest degradation can be estimated from 0 (intact) to 100% (deforested) by integrating the biomass lost due to previous disturbance, calculated as the proportion of the maximum potential biomass of intact forest. This metric can be used to infer the risk of ecological collapse and used to prioritize conservation interventions in the most intact and connected forests.

- **Research question 3:** What are the different anthropogenic drivers affecting forest degradation and how do they influence forest degradation in space and time?
  Hypothesis: Increased access, conflicts, built-up area, fires directly affect forest condition, and these impacts are additionally influenced by specific land uses and biophysical properties of forests. These drivers of degradation are not static in time or space, and their dynamics understood in order to implement appropriate policies.

1.11. Dissertation Structure

This thesis is organized in five chapters, structured around three peer-reviewed publications (chapters 2, 3, 4) which are tied together with connecting sections entitled "further consideration" which follow the progress and development built between successive stages of the research. The final chapter summarizes the research and my personal perspectives on the subject and future trends.

In **Chapter 2** I address research question 1 with an approach to defining forest degradation as a temporal process defined principally by the change in AGB over time. This component of the research relies on data collected from an extensive airborne LiDAR campaign over the Democratic Republic of the Congo for a detailed forest carbon stock estimation. Coupled with field data, this provides an ideal testing ground for comparing high resolution data with the known structure of forests under varying levels of fragmentation and answering questions regarding patterns of forest degradation and the extent compared to deforestation. It is found that AGB is significantly different between forest edge types, and increases with decreasing fragmentation, showing that we can apply the fragmentation for stratification and its relation to AGB, while also quantifying the associated carbon emissions from degradation vs deforestation.

This is the basis for the next **Chapter 3**, which addresses research question 2 and further refines the forest degradation assessment according to a continuous metric, Forest Condition (FC). In this chapter FC is validated with canopy gaps detected from airborne LiDAR data and direct remote sensing methods to validate the theoretical framework of FC. FC is used in an applied conservation prioritization workflow, more specifically criterion D of the IUCN Red List for Ecosystems workflow to estimate the risk of ecosystem collapse. FC was also used in a regional analysis of High Conservation Value (HCV) in the Congo Basin to support forest concession management.

In Chapter 4 I answer research question 3, with an assessment of drivers of forest degradation through a spatial panel analysis of FC in relation to independent spatial variables in the DRC. I demonstrate how biophysical variables, human access, land use, conflict, fires are driving decreases in forest condition and how these variables change in space and time. I assess the spatial divergence of two key variables and note the importance in understanding proximal drivers to assess future risk and derive context-specific policy and conservation interventions.

In Chapter 5 I summarize the final conclusions and the general discussion and synthesis, with my own comments on the trends and future perspectives of new research in this topic.

Chapter 2: Using fragmentation to assess degradation of forest edges in Democratic Republic of Congo

Spatial pattern analysis is used to identify forest fragmentation (core, inner and outer edge and patch forests) overtime in the DRC. We demonstrate that above ground biomass (AGB) estimated from airborne LiDAR and satellite imagery is statistically different between classes and decreases with increasing fragmentation. This establishes the basis for using spatial pattern and proxy approaches to quantify degradation at forest edges and the associated carbon emissions.

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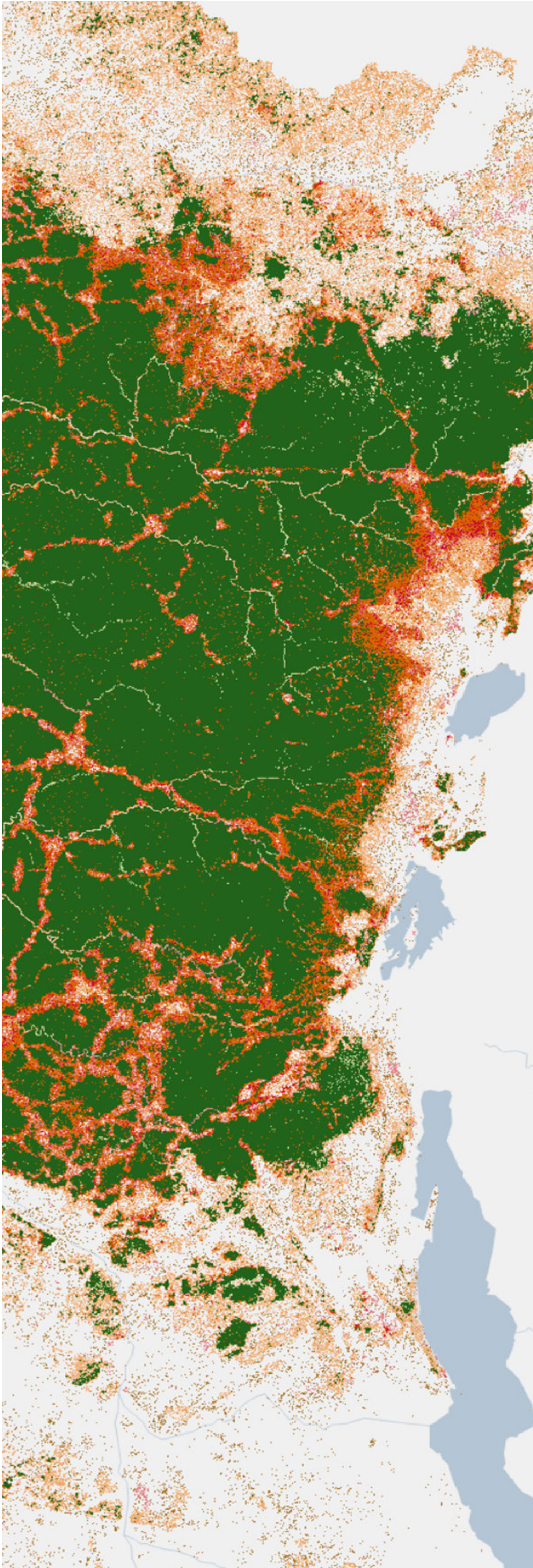

Background

Recent studies have shown that fragmentation is an increasing threat to global forests, which has major impacts on biodiversity and the important ecosystem services provided by forested landscapes. Several tools have been developed to evaluate global patterns of fragmentation, which have potential applications for REDD+. We study how canopy height and above ground biomass (AGB) change across several categories of forest edges determined by fragmentation analysis. We use Democratic Republic of Congo (DRC) as an example.

Results

An analysis of variance of different edge widths and airborne estimated canopy height found that canopy heights were significantly different in forest edges at a distance of 100 m from the nonforest edge. Biomass was significantly different between fragmentation classes at an edge distance of 300 m. Core forest types were found to have significantly higher canopy height and greater AGB than forest edges and patches, where height and biomass decrease significantly as the level of fragmentation increases. A change analysis shows that deforestation and degradation are increasing over time and biomass loss associated with degradation account for at least one quarter of total loss. We estimate that about 80 % of primary forests are intact, which decreases 3.5 % over the 15 year study period, as primary forest is either deforested or transitioned to forest edge. While the carbon loss per hectare is lower than that of deforestation, degradation potentially affects up to three times more area than deforestation alone.

Conclusions

When defining forest degradation by decreased biomass without any loss in forest area, assessing transitions of core forest to edges over time can contribute an important element to REDD+MRV systems. The estimation of changes between different forest fragmentation types and their associated biomass loss can provide an estimate of degradation carbon emission factors. Forest degradation and emissions due to fragmentation are often underestimated and should comprise an essential component of MRV systems.

2.1. Background

Deforestation and forest degradation are global problems, significantly altering ecosystems, the services they provide, while contributing to carbon emissions and affecting regulation of global climate and terrestrial carbon storage (Foley et al., 2005; Harris et al., 2012; van der Werf et al., 2009). International mechanisms such as the reduction of emissions from deforestation and degradation (REDD+) require complete, repeatable, conservative and transparent assessment and quantification of changes in forest biomass which emit greenhouse gases in order to mitigate impacts and develop robust measurement, reporting and verification (MRV) systems (Agrawal et al., 2011; Gibbs et al., 2007; Houghton, 2005; Pelletier et al., 2013).

Deforestation is defined by a long term loss of canopy cover and area, notably a conversion to another non-forest use, which been monitored effectively over time at multiple scales effectively for tropical forests using remote sensing technologies (Asner et al., 2006; DeFries et al., 2007; FAO, 2006; Hansen et al., 2013; Lambin et al., 2003; Mayaux et al., 2005; Skole & Tucker, 1993). In contrast, forest degradation is a more poorly understood process which involves partial canopy loss with no clear reduction in forest area, but a reduction in ecosystem services, more often described by a decrease in above ground biomass (Lund, 2009; Schoene et al., 2007; Simula, 2009; Thompson et al., 2013; UNFCCC, 2008), and is the definition applied in this study. The associated decrease in carbon stock and biomass are key to forest degradation assessments with respect to climate change mitigation in the context of REDD+ and thus of essential importance for determining baseline rates of degradation, in the same manner baseline deforestation is assessed (UNFCCC, 2008).

The main drivers of forest degradation are related to urban expansion, extraction of forest products for both industrial and subsistence markets and associated infrastructure and accidental or deliberate fires for small-scale clearing (Hosonuma et al., 2012; Kissinger et al., 2012). Most remote sensing studies focusing on forest degradation are driver specific and aim to detect canopy gaps and clearings through direct approaches such as spectral mixing (Souza, 2003; Souza & Roberts, 2005), or indirect methods such as mapping roads or human settlements (Brandão & Souza, 2006; Wasseige et al., 2004) or fire monitoring (Morton et al., 2011). Still, many nations are unable to effectively monitor forest degradation at large scale over time to meet their REDD+ goals. This is more often due to the lack of a consistent definition, few robust and transparent methods for general degradation monitoring, data deficiencies, low technical capacity and limited funding (Böttcher et al., 2009; Herold, 2009; Thompson et al., 2013). No accurate estimates of global degradation exist to date for the reasons stated above, yet the actual extent of degraded tropical forests and associated emissions could in fact be comparable to, or larger than actual deforestation, particularly in high forest/low deforestation (HFLD) countries (Achard et al., 2004; Asner et al., 2005; Foley et al., 2005; Gaston et al., 1998; ITTO, 2002; Souza, 2003; Souza et al., 2005; Souza et al., 2013).

Recent studies have addressed the impact of human activity on the fragmentation of forests through various analyses (Broadbent et al., 2008; Chaplin-Kramer, Ramler, et al., 2015; Haddad et al., 2015; Laurance et al., 2000; Molinario et al., 2015; Numata et al., 2011; Riitters et al., 2015; Riitters et al., 2000; Wade et al., 2003) possible with the increase in available forest cover data and satellite imagery (Chaplin-Kramer, Ramler, et al., 2015; Hansen et al., 2013; Rose et al., 2015). More recently, analyses have shown that core forests are more likely to be intact, providing greater ecosystem services than those exposed to edges and fragmentation. The intact forest landscapes (IFL) approach differentiates potentially intact and degraded forests worldwide (Potapov et al., 2009a; Potapov et al., 2008; Zhuravleva et al., 2013) and has determined that forests are in fact structurally different outside the hinterland area (Tyukavina et al., 2016). Haddad et al. (2015) identified fragmented forests globally as all forests within 1 km of forest edge and assessed the long term ecological consequences, including degraded ecosystem processes and declines in species richness. Riitters et al. (2015) report significant deforestation of interior core forests worldwide and the resulting transitions from core forest to edge types was shown to impact twice the area affected by deforestation alone. Chaplin-Kramer, Ramler, et al. (2015) assessed a reduction of 25 % of forest biomass in edges which shows that fragmentation may indeed be a key driver of forest degradation and often lacking from forest carbon emissions accounting.

In this study we use forest cover spatial pattern to classify several types of forest fragmentation, using the optimal edge distance for which degradation is affecting forest structure and biomass. We then identify degraded forests by their transition between core and fragmentation types and use mean AGB estimates per fragmentation class to determine the associated emissions, using the Democratic Republic of the Congo as an example.

We classify primary forest into four fragmentation classes defined by pattern: core (intact forest), inner edge (or perforation), outer edge (bordering large non-forest areas) and small forest patches, derived from the methods published by (Vogt et al., 2007). The method involves a series of moving window analyses and union and intersection operations which determine the edge width, connectivity and holes of data in a binary forest/non forest image (Soille & Vogt, 2009; Vogt et al., 2007). The derivation of multiple types of edges, notably interior and exterior edge are an improvement over buffer methods which only define forests as either intact or edge, as we conclude that different types of fragmentation are demonstrated to be fundamentally and functionally different. The interior and exterior edges are in fact differentiated by the size of neighboring non-forest or forest. This analysis enables to differentiate between the impact of a small perforation within an area of intact forest which differs from for example, the edges created by a large non-forest patch which could be encroaching field or pasture. The fragmentation analysis provides insight into different patterns or drivers of degradation at forest edges, as interior holes are likely to be less accessible by anthropogenic impacts. Equally important is the appropriate distance used to assess forest edges. We use mean canopy height and AGB estimates to address this.

Assessing transitions between fragmentation classes over time allows to identification of degraded forests by the dynamic process of degradation, supporting a simple matrix approach to forest monitoring as recommended by Bucki et al. 2012. This proxy assessment is important to identify degradation by its dynamic process, which supports monitoring of forests as dynamic systems defined by their trajectories (Chazdon et al., 2016). This analysis is also useful to identify degraded areas which still meet the forest criteria and using AGB estimates to quantify the ability to provide ecosystems services, which are key functions of intact forests (Chazdon, 2008). Here we propose to use the transition between different initial fragmentation classes in order to differentiate between primary and secondary degradation and regeneration, which demonstrates the typical pathways of forest degradation and can inform forest condition.

2.2. Methods

2.2.1. The DRC Context

The Democratic Republic of the Congo (DRC) possesses the largest continuous tract of remaining tropical forest in Central Africa (**Figure 7**). It is known for its remarkable natural resources and high biodiversity (Strassburg et al., 2010; WWF, 2006) while ranking nearly last on the United National Development Programme Human Development index **(UN, 2013)**. Poor governance has allowed extensive resource exploitation such as mining, timber harvesting, charcoal production, resulting in one of the highest deforestation and degradation rates in central African countries (Zhuravleva et al., 2013). Compared to other countries, the DRC remains a high forest/low deforestation country (HFLD; (Griscom & Cortez, 2011) and recognizes the potential for sustainable and economic development through emerging governance structures and significant engagement in the United Nations Framework Convention on Climate Change (UNFCCC) process (CN-REDD, 2014; Herold, 2009). The DRC has been building up political REDD+ capacity while increasing efforts to monitor and mitigate forest loss with satellite imagery, in addition to mapping forest carbon at the national scale using airborne LiDAR and satellite imagery (Aquino & Guay, 2013; Mpoyi et al., 2013; Tollefson, 2013). Current emissions reduction activities are focused in the Mai Ndombe region northwest of the capital, Kinshasa, which is used as a local scale test site in this study (**Figure 7**).

Figure 7. The Democratic Republic of the Congo possesses the largest tract of continuous tropical forest in Africa (forest cover data from Verhegghen et al. (2012). The new Mai Ndombe province region is a target site for implementation of new REDD+ activities

2.2.2. Datasets used

The fragmentation algorithm was executed first at the local scale in Mai Ndombe to evaluate the effect of edge distance on biomass and canopy height available from airborne LiDAR in order to select the scale for the national analysis (**Figure 8**). The local scale study encompasses LiDAR plots collected Mai Ndombe province, which are part of a collection of LiDAR collected in a stratified random manner throughout the DRC, producing an unbiased sampling of forest areas. LiDAR data were collected between October 2014 and 2015 in a series of 216 10× 2 km rectangular plots, with a mean point density of $2/m^2$. All pixels with a LiDAR mean canopy height greater than 3 m according to the national definition were classified as forest and resampled to 10 m resolution as input for the local scale fragmentation analysis. AGB estimates derived from LiDAR in Mai Ndombe were produced for the Mai Ndombe Emissions Reduction program by the University of California, Los Angeles, using the VCS VT0005 method (Tittmann et al., 2015) along with field data calibrated LiDAR, while the national LiDAR biomass map is still being developed for DRC.

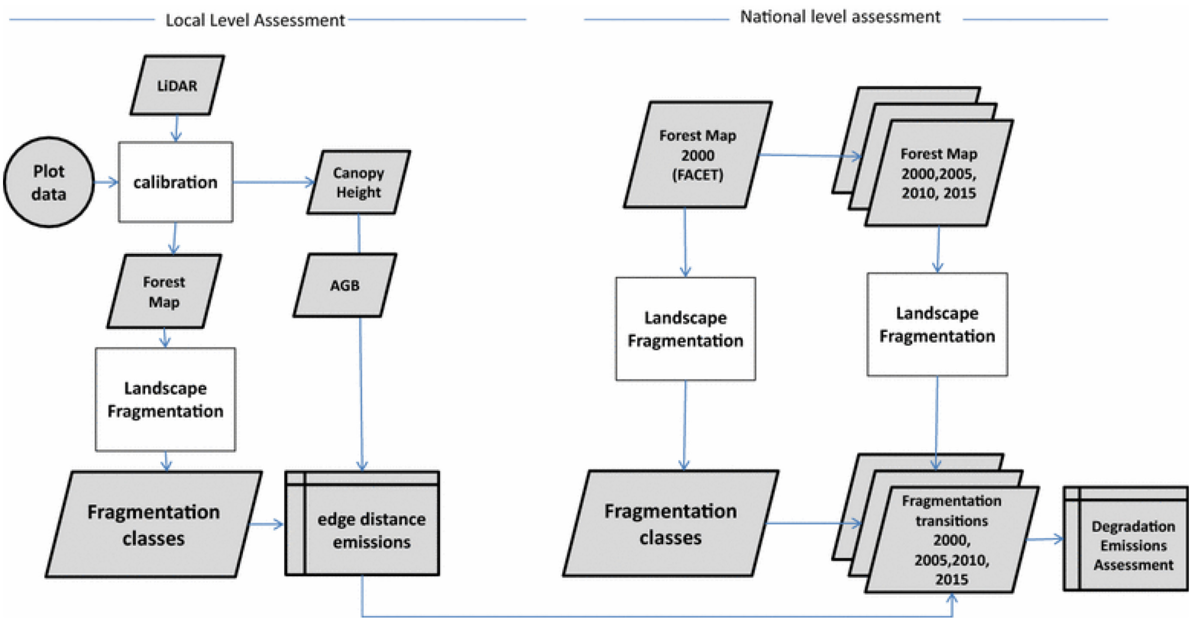

Figure 8. Flowchart of national scale analysis to develop fragmentation statistics and change in DRC from 2000 to 2005 and 2010 and 2015

Primary forest cover for the entire DRC for the year 2000 was derived from Landsat imagery by the University of South Dakota, the Observatoire Satellital des Forêts d'Afrique Centrale (OSFAC) and University of Maryland producing a dataset identified as Forêts d'Afrique Centrale Evaluées par Télédétection (FACET; (Potapov et al., 2012). This data is a pre-cursor to the Global Forest Cover Change product and uses similar techniques (Hansen et al., 2013) producing forest maps as a resolution of 60 m and identifying primary, secondary and woodland dominated forest from 2000 to 2005 and 2010. Forest cover in the primary humid tropical forest category for 2000 was used for this analysis, as this class correlates best with moist tropical forest as defined by IPCC, while other FACET forest types mix secondary and dry forest (Potapov et al., 2012). Annual forest loss data for 2000–2014 from Global Forest Cover Change product from the University of Maryland (Hansen et al., 2013) were then used to determine forest cover for 3 additional time intervals, 2005, 2010, 2015, which were combined based on the uncertainties of annual assessments of this data (Tyukavina et al., 2015). The gain data provided do not have a date of detection and about 20 % of gain pixels were also identified as loss, which could be due to changes in planted forests or agroforestry. In order to integrate areas of gain into the analysis, all areas of gain which overlapped with areas of loss were removed and the remaining pixels of gain were added to the final transition map to assess regeneration.

2.2.3. Forest fragmentation algorithm

We used modified outputs from the Landscape Fragmentation Tool (LFT; (Parent et al., 2007) derived from the research of Vogt et al. (2007) to identify and evaluate four forest fragmentation classes: core, inner edge, outer edge and patch forest which have varying degrees of fragmentation (**Table 2**).

Table 2. Main fragmentation classes derived from Vogt et al. (2007)

Fragmentation class	Description	Level of fragmentation
Core	Interior forest pixels far from forest edge	low
Inner Edge	Forest pixel on edge of small interior non-forest	
Outer edge	Pixels that are between forest and large non-forest areas	
Patch	forest regions too small to contain core forest	high

The LFT processes a forest image using a defined edge width, which determines the edge effect distance between non-forest and intact core forest. A specific definition of edge effect for a particular locale can be used to adjust the analysis according to local information or expert knowledge on the forest of interest. We tested several window sizes and determined the statistical difference between LiDAR estimated canopy height and AGB within fragmentation classes to identify the appropriate window sizes. With smaller window sizes, a greater percentage of in the landscape is classified as core than other types; and with larger sizes a greater estimate of edge occurs (Pelletier et al., 2013). The fragmentation classes produced by edge distances of 50, 100, 150, 200, 250, 300, 350 and 500 m were evaluated for statistical differences in canopy height and AGB. A set 5000 points located randomly within the LiDAR footprints in Mai Ndombe were selected to assess canopy height and estimated AGB within each fragmentation class produced with varying edge distances. The mean canopy height difference between samples in each fragmentation class was determined using an analysis of variance ANOVA for all sample points. A Tukey honest significant difference and Mann–Whitney pairwise tests for non-parametric data were performed to determine a significant of difference in mean canopy height and biomass between each fragmentation category pair. Statistics were performed using the R statistical package version 2.14.0 and Past Version 3.10 (Hammer et al., 2001).

Additionally, a semi-variogram analysis was used to assess heterogeneity in canopy heights to determine the best minimum mapping unit for forest cover data by estimating semi-variance over progressively larger window sizes. Thus, forest cover at the national scale was rescaled to 1 ha resolution, informed from the LiDAR data analysis.

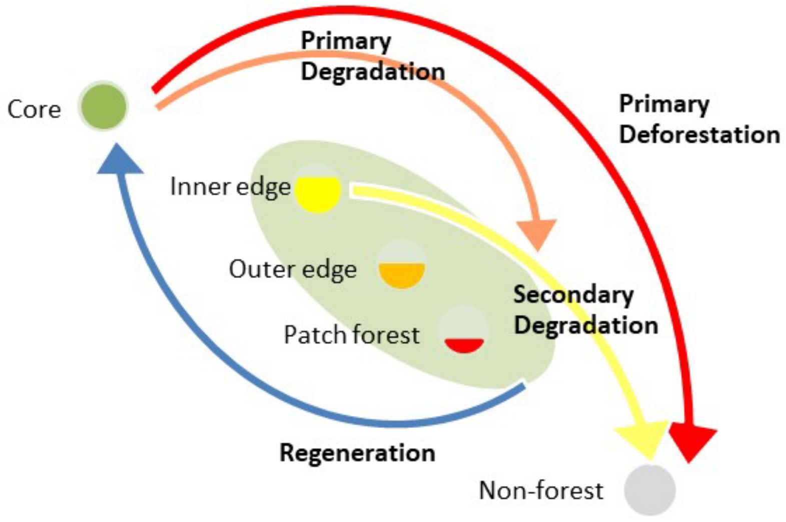

Figure 9. Transition pathways between forest fragmentation types, using fragmentation classes to differentiate between primary and secondary deforestation and degradation. Reverse trends (from more degraded categories towards core) are recovering forests. Forests that remain in the same class over time are named "stable"

2.2.4. National scale analysis

The primary forest data were resampled to 100 m based on results from semi-variography analysis of the LiDAR canopy height data. Fragmentation classes were assessed for each forest cover map and the transitions between fragmentation categories over time were identified as in **Figure 9**. Mean AGB for each class of new degradation was used to provide the estimated biomass loss (emission factor) for all degradation transitions to calculate emissions from forest fragmentation at the national scale, based on a tier I stock difference approach, using biomass estimates and the area of forest cover lost at each time period (Bird et al., 2010; Bucki et al., 2012; Murdiyarso et al., 2008).

2.3. Results

2.3.1. Local scale assessment

Semi-variogram spherical modelling parameters with better fit averaged in the 110 ± 7 m range, which was used as a metric to estimate the spatial dimension of forest structural heterogeneity. Thus, a minimum mapping unit (MMU) of 100 m was used for mapping forest cover at national scale (**Figure 10**).

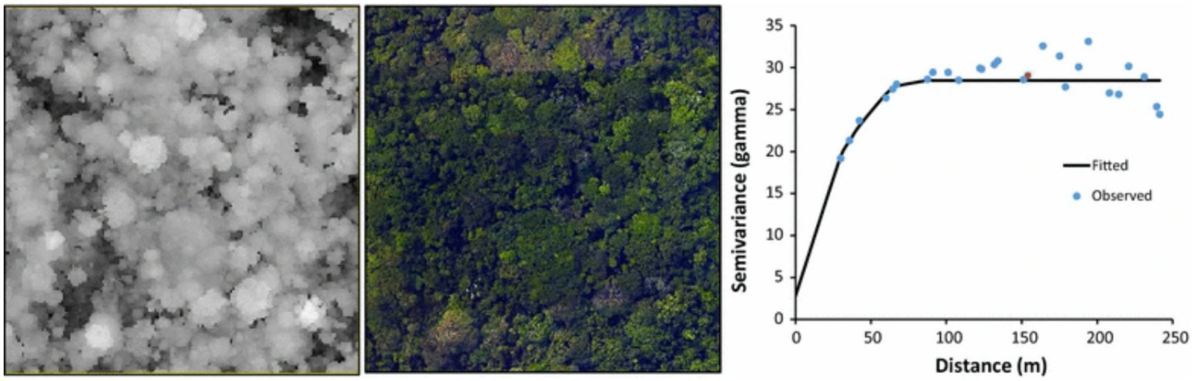

Figure 10. One of the 12 ha areas assessed with semi-variography, showing the true-color image (left), mean canopy height (center), and corresponding semi-variogram (right). Semi-variogram symbol indicates semi-variance frequency with blue dot indicating highest frequency at 154 m

Forest fragmentation classes generated for the high resolution/small spatial scale analysis from LIDAR data collected in 2014 are shown in **Figure 11**, with canopy height, forest cover and AGB derived from airborne LiDAR acquired during the study period. A subset of the FACET Landsat data and derived fragmentation classes show how forest edges occur around villages (**Figure 12**). Forest heights were highest in core forest areas and decrease into significantly lower averages as fragmentation increased.

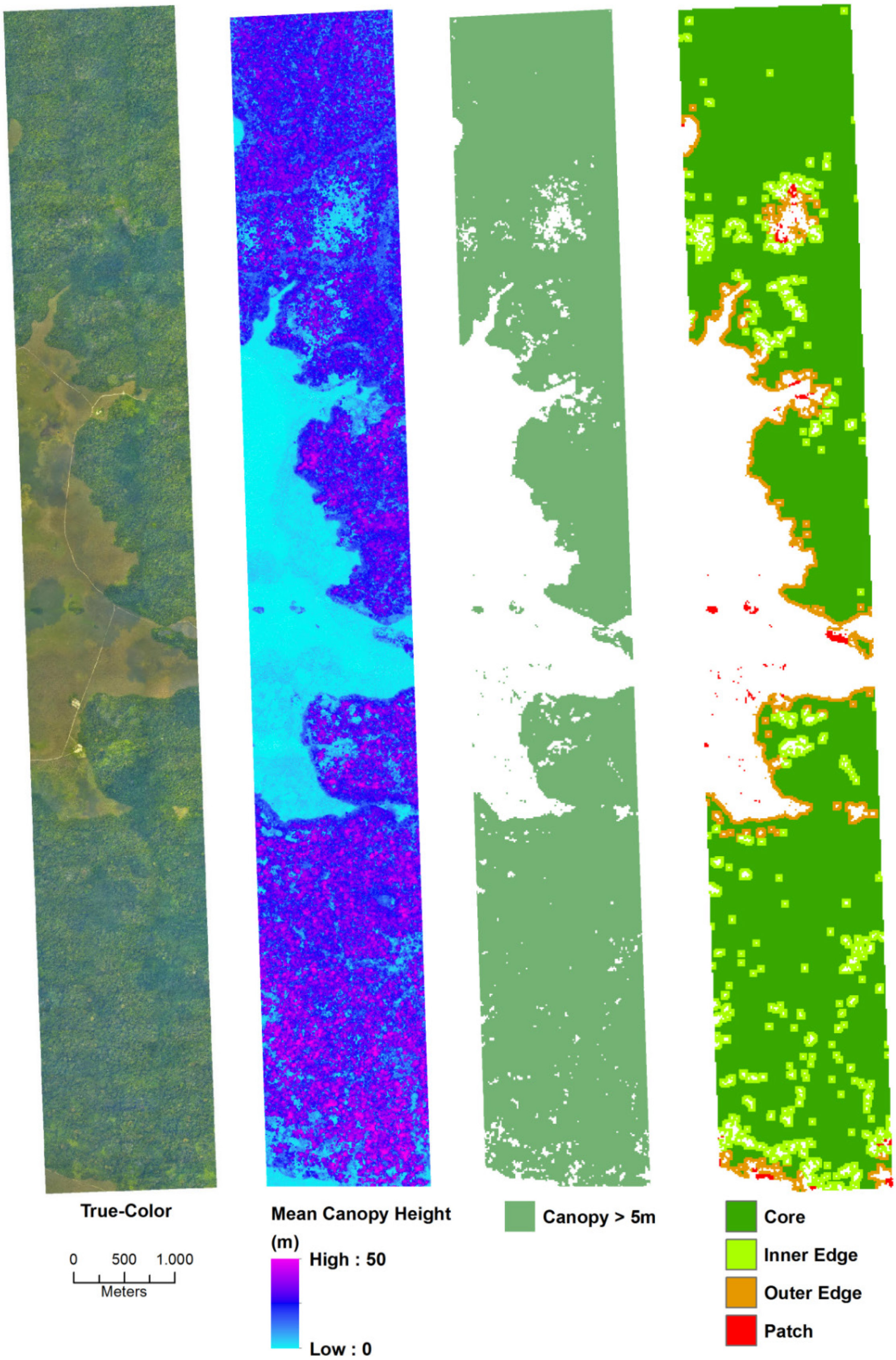

Figure 11. Sample 10 km x 2 km LiDAR plot used in the local scale analysis. From left to right: 10 cm aerial photo; mean canopy height from LiDAR returns at 15 m resolution; forest/non-forest map obtained by filtering mean canopy heights below 5 m (per country forest definition); Fragmentation classification

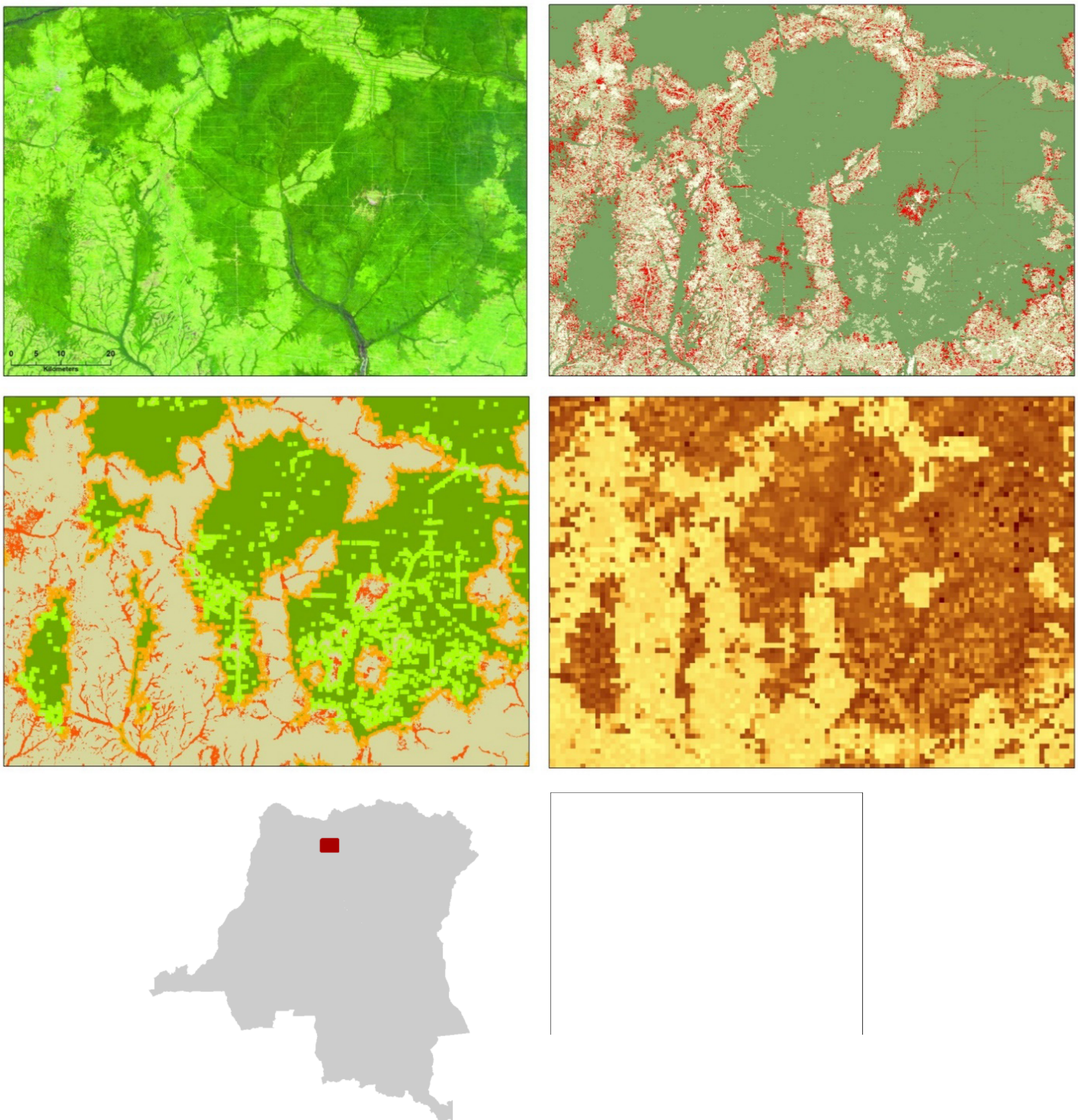

Figure 12. Example of MSPA in northern DRC. Upper left: True-color Red, Green, Blue Landsat 2005-2010 composite from FACET; Upper right: Forest cover change 2000-2005-2010 from FACET (green: primary forest; light green: secondary forest; red: forest loss); Lower left: Forest fragmentation s calculated for 2010 (green: core forest, light green: inner edge; orange: outer edge; red: patch). Lower right: AGB map from Saatchi et al. (2011)

Mean canopy height within forest fragmentation classes derived from LiDAR heights were found to be significantly different at all scales in the ANOVA, however, the non-parametric tests for the differences between paired categories varied. Only at the scale of 100 m was the difference in canopy height between all fragmentation classes significant (Mann–Whitney $p \ll 0.005$).

AGB estimates showed differences on a different spatial scale than canopy height. While all edge distances showed significant differences, only an edge distance of 300 m produced significantly different differences of AGB between each fragmentation class pair (Mann–Whitney $p \ll 0.005$; **Figure 13**).

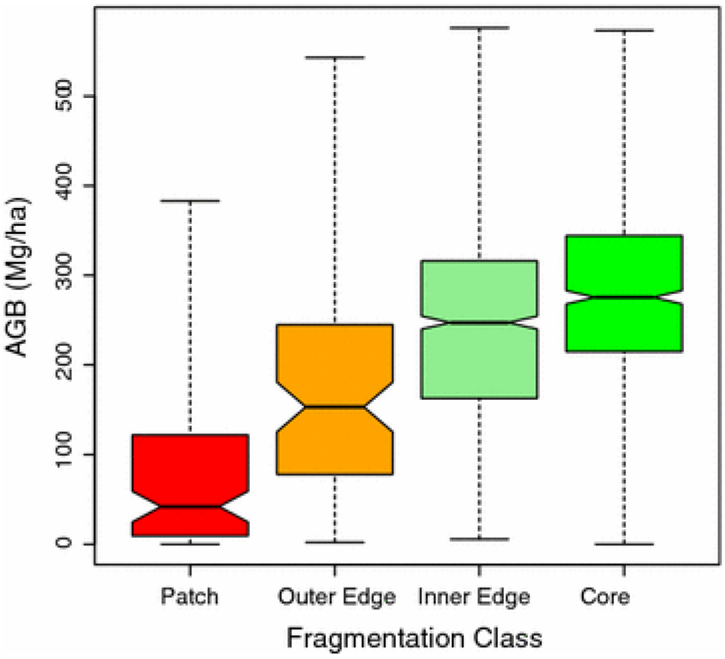

Figure 13. Distribution of AGB estimated from airborne LiDAR for fragmentation classes derived with an edge distance of 300 m; model $p \ll 0.005$

2.3.2. National scale temporal changes

Overall forest cover decreases over the study period. Core forest decreases 3.5 % over the study period, inner and outer edge increase and patch forest remains about the same (Table 3). The transitions between fragmentation classes on a 1 ha pixel basis from 2000–2005–2010–2015 are reported in

Table 4 and mapped for the entire DRC primary forest belt in **Figure 14**. Core forest is most often transitioned to inner edge and outer edge is more often deforested than other fragmentation classes.

Table 3. Total core and degraded forest types for 2000, 2005, 2010 and 2015, with percent of total forest area. Forest gain is included to the 2015 forest cover

	2000		2005		2010	
Fragmentation class	Km^2	% of total forest area	Km^2	% of total area	Km^2	% of total area
Core	735,807	70.44	723,489	69.51	705,065	68.20
Inner edge	148,611	14.23	155,019	14.89	163,326	15.80
Outer edge	92,311	8.84	92,564	8.89	90,563	8.76
Patch Forest	67,823	6.49	69,809	6.71	74,921	7.25
Total forest	1,044,552		1,040,881		1,033,875	

Table 4. Transition matrices estimating change between fragmentation classes in km2 from 2000 to 2005 (top) and from 2005 to 2010 (middle) and 2010 to 2015 (bottom)

	TRANSITION TO (2005)					
Transition from (2000)	core	inner edge	outer edge	patch	non-forest	TOTAL
core	814,298	11,339	1,425	11	751	827,824
inner edge		79,574	1,348	54	807	81,783
outer edge			94,698	979	1,670	97,347
patch				34,539	604	35,143
non-forest					1,305,354	
	TRANSITION TO (2010)					
Transition from (2005)	core	inner edge	outer edge	patch	non-forest	TOTAL
core	798,605	12,405	2,196	40	666	814,319
inner edge		85,764	3,100	216	1,875	90,945
outer edge			92,656	1,874	2,764	97,482
patch				85,764	1,085	86,849
non-forest					1,309,186	
	TRANSITION TO (2015)					
Transition from (2010)	core	inner edge	outer edge	patch	non-forest	TOTAL
core	775,753	17,833	3,087	61	1,870	798,604
inner edge		90,176	4,765	460	2,765	98,166
outer edge			90,822	3,065	4,063	97,950
patch				35,418	1,209	36,627
non-forest					1,316,162	

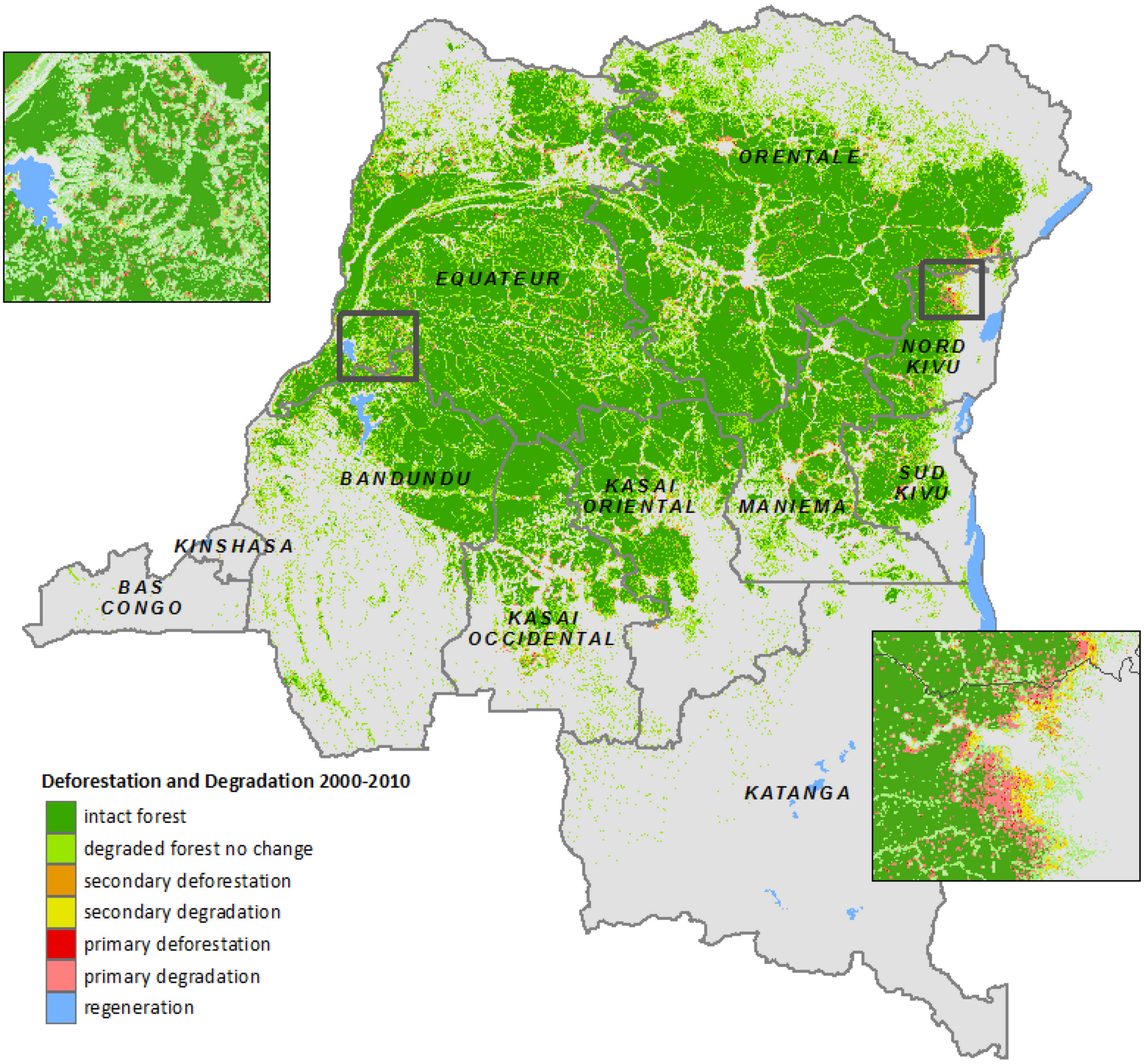

Figure 14. Forest fragmentation change from 2000–2010, showing transitions between fragmentation classes. Insets show areas of significant degradation in North Kivu Province around Beni, and more diffuse degraded forest edges in the forest mosaic of Mai Ndombe around Mbandaka. Primary and secondary degradation appear to be concentrated around cities and access routes. The largest areas of forest undergoing degradation are in North Kivu province, with the most fragmented forests occurring in the transition to savanna landscapes in western DRC. Small recovery areas were observed where forest patterns areas change from outer edge to inner edge (less than 1000 km2 overall, not visible at the national scale map) which are due to consolidation of forest areas into more uniform shapes

The largest transition in fragmentation classes observed from 2000 to 2015 was primary degradation, notably in the transition from core forest to inner edges, followed by degradation of inner to outer edges. The most significant observation at the national scale is that overall area of degradation increased nearly by 50 % in the time period and when associated with biomass estimates, resulted in a quarter of total forest related emissions (**Table 5**)

Inner edge increases much larger than the other classes, more than 40,000 km2. The total degraded area increases from 2000 to 2015, with a much greater increase in the 2010 to 2015 time period. Primary forest loss increases over time and was highest in the 2010–2015 time period than the previous 5-year intervals.

Area calculations show increases in degradation in 2005–2010, 2010–2015 compared with the first 5-year span, with the greatest transition occurring between core and edge classes. This results in more than double the area affected by degradation as deforestation in the second 5-year span; and a far greater proportion of associated emissions. There is a larger increase in inner edge throughout the analysis. Several examples of this have been found, indicating that clearings may be increasingly further in the forest. Of the total 6295 km^2 of primary deforestation, 2603 km^2, or nearly a third transition to a degraded state before deforestation. As for secondary deforestation, which was overall greater than primary deforestation (14,420 km^2), only 834 km^2 transition to a degraded state before deforestation.

2.3.2. Emissions estimates

Table 5 shows the biomass losses estimated for the 5-year intervals from 2000 to 2015. Deforestation is steadily increasing, as is degradation. The overall area affected by degradation is shown to be much larger than that affected by deforestation, however, emission per hectare are lower, thus degradation contributes to a lower proportion of emissions, as most primary degradation is within inner edge and results in lower emissions.

Table 5. Contribution of deforestation and degradation of primary forests to total forest emissions

	2000-2005		2005-2010		2010-2015	
	Def.	Deg.	Def.	Deg.	Def.	Deg.
Area (km2)	3382	15,157	6,975	19,832	9908	29,272
Biomass Loss (MgC)	63,709,538	33,235,831	116,081,439	39,374,186	168,515,864	54,426,709
Tons CO_2 equivelent	233,176,909	121,643,141	424,858,067	144,109,521	616,768,062	206,521,755
% of total CO_2 emissions	65.7	34.3	74.7	25.3	74.9	25.1

2.4. Discussion

Bucki et al. (2012) recommend the development of a matrix approach (i.e. the gross calculation of transitions from intact to non-intact forest lands) for forest monitoring to help countries with limited resources monitor and reduce emissions from degradation. Indirect approaches, including the use of proxies applied over time may be useful and accurate for estimating areas of forest degradation and decreased carbon stocks, especially when direct detection by high resolution satellite imagery is problematic due to data costs, presence of clouds, or the area of interest is large (Herold et al., 2011). The assessment of forest fragmentation in the temporal domain by the detection of new forest edges can be useful in this respect, because forest edges have greater human access and associated anthropogenic effects and have been shown to have significantly less biomass, increased tree mortality and lower biodiversity, all characteristics of degradation (Cayuela et al., 2009; Chaplin-Kramer, Ramler, et al., 2015; Haddad et al., 2015; Laurance, 2004; Nepstad et al., 1999; Vieira et al., 2004). Regardless of human intervention, forest edges will always have different properties and structure associated with edge environments, but the detection of new edges occurring next to deforested areas is essential to differentiating degradation from secondary forests, which may be stable, or regenerating. In addition, as nearly one-third of primary degradation ends up as deforestation eventually, the fragmentation analysis presents an important assessment of potential future deforestation. A spatial assessment of edge and core forests and their transitions allow the assessment of forest dynamics, which should constitute a good proxy for forest degradation (Riitters et al., 2000).

This research has shown how fragmentation classes defined by forest patterns have significantly different canopy height and biomass allowing their potential use as strata to discern or monitor forest uses or biomass dynamics required for national forest inventories, when other information on land use may be lacking (Maniatis & Mollicone, 2010). Using forest cover maps from multiple time periods and deriving the associated transitions between fragmentation classes over time can be used to derive major forest cover changes and dynamics, such as primary and secondary deforestation, primary and secondary degradation and regeneration which provide more information on forest dynamics and uses than simply estimating forest cover (Chazdon, 2008; Chazdon et al., 2016; Riitters et al., 2015). Most importantly we show here that degradation at forest edges affects more area than deforestation. Combining this information with available AGB data allows for the estimation of biomass loss from these changes which is one of the required carbon pools for REDD+ reporting.

The selection of edge distance is important to determine before the analysis and affects the estimation of area defined as degraded edge. Canopy height was shown to be different within fragmentation classes, which is evidence of structural differences at forest edges. However, if we look at forest height alone, we see that secondary forests can quickly reach similar heights as intact forests, which complicates optical remote sensing of degradation. Thus, biomass is the important measure and essential to defining forest degradation. The resolution of the biomass estimates is also important as it would be difficult to discern edge effects at the sub-pixel scale, for this reason Chaplin-Kramer, Ramler, et al. (2015) suggest an edge distance that is much larger. Pelletier et al. (2013) however, showed that edge distance is actually the lowest source of uncertainty compared to other factors when estimating emissions. Here we suggest a window size which effectively stratifies forests based on the available accurate estimates of biomass.

The fragmentation analysis employed is straightforward, repeatable and easily executed. A simple proxy indicator does not necessarily mean higher uncertainty, and this can be informed by field data, which are always needed to improve algorithms to assess edge forest structure and transitions, also for biodiversity indices to inform comprehensive biodiversity safeguard monitoring. Additionally, determination of appropriate analysis window size and resolution to define minimum mapping units (MMUs) by applying geospatial statistics approaches such as semi-variography of carbon estimates or field data can inform the most suitable resolution for forest and biomass mapping.

Our results support the findings of Zhuravleva et al. (2013) and Molinario et al. (2015). Both studies estimate a greater area of forest that is affected by degradation than deforestation, with an increase in degradation observed in 2005 to 2010, compared to the previous 5 years. However, the areal estimates are different and difficult to compare directly, because Zhuravleva et al. (2013) combined degradation with deforestation, estimating that 40 % of primary forests are degraded. On the other hand, Molinario et al. (2015) present very similar results for changes in fragmentation, but they do not specifically refer to degradation. Zhuravleva et al. (2013) did observe a decrease in fragmentation rate in the 2005–2010 time period than 5 years prior, while we observe an increase in the second 5-year span, due to the fact that we assess changes between successively degraded classes as degradation, whereas with IFL degraded forests remain in the same class and thus secondary degradation is not entirely accounted for. This is an important distinction, as degradation is a process, resulting in various levels of degradation and further degradation of secondary forests can still result in further loss of ecosystem services and emissions. Small perforations within intact forest have been shown to increase. These create interior edges which have a higher AGB than outer edges, which demonstrate how fragmentation and associated degradation can vary in degree (Laurance, 2004; Numata et al., 2011). Many examples of this phenomenon have been observed (**Figure 15**), showing that people may be entering deeper in the forest to either clear forests with better timber or perhaps to evade detection.

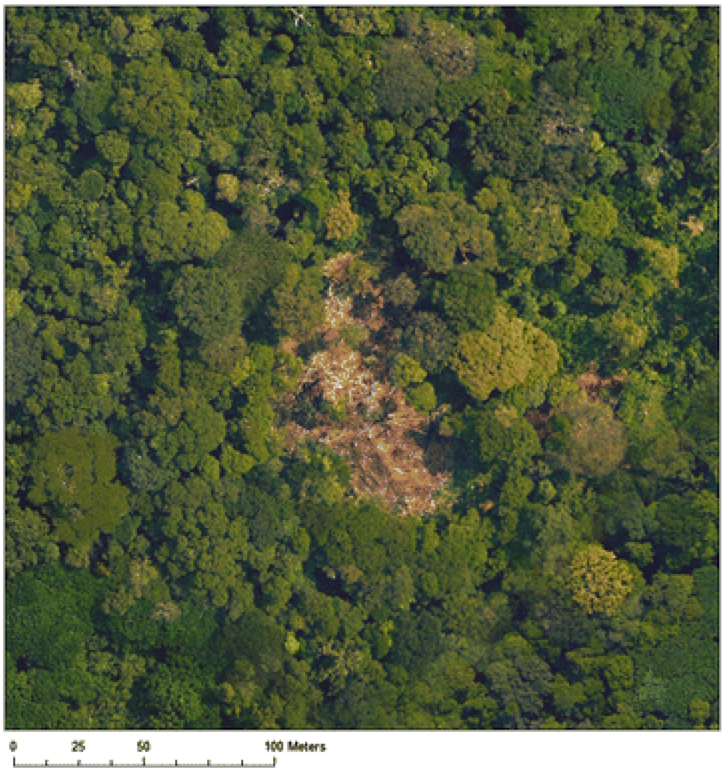

Figure 15. An example of a conversion of core forest to a perforation with inner edge

Given the significant difference in biomass between fragmentation classes and the observed transitions and associated emissions, this method shows a distinct advantage over other approaches which lump degradation into one class, define degradation at one point in time, or identify fragmentation as deforestation or shifting cultivation (Chaplin-Kramer, Ramler, et al., 2015; Haddad et al., 2015; Molinario et al., 2015; Tyukavina et al., 2016). The assessments which assess only intact and edge forest may ignore the different possible degraded states and prevent differentiating forests which are being degraded from those which may be regenerating. It is clear in this example that forests are experiencing several degraded states in the degradation, deforestation or regeneration process and the forest fragmentation method applied to subsequent forests maps allows one to distinguish, or even stratify forests by these transitions, which is an important element for monitoring of dynamic forest systems (Chazdon et al., 2016).

It is also important to consider the aspects of spatial scale, especially given the common misconception that higher resolution is necessarily better. The aggregation of data to a 1 ha MMU for canopy height, and 300 m scale for AGB is an important consideration here, as studies have shown how forest biomass estimates change with scale (Mascaro et al., 2011). Degradation has a spatial dimension which must be considered at a scale of the forest, rather than trees and in this case, biomass is being used as the definition for degradation. The difference in DRC degradation estimates between other published results demonstrate the importance of a universal definition of degradation including the element of spatial scale.

2.4.1. Sources of uncertainty

The main limiting factor to this method is ultimately the quality of the forest cover map. In this example we use data from FACET (Potapov et al., 2012), which was considered best available at the time and considered a benchmark product for DRC and was derived specifically for DRC. Higher resolution, global algorithms which use temporal mosaics to reduce cloud cover may contribute to improve the quality of the analyses. Hansen et al. (2013), however this annual data has been found to suffer from low accuracy in some key locations (Tropek et al., 2014; Tyukavina et al., 2015) which is why the Global Forest Cover change products were merged to 5 year intervals. The element of forest gain may be underrepresented here, due to the lack of date associated with this information. As a result, regeneration overall was found to be negligible compared to other transitions. Lastly, persistent forests, which may act as carbon sinks and potentially offset carbon emissions (Pan et al., 2011) are another unknown contribution to the carbon accounting in DRC.

There are several potential sources of error at many scales, particularly when measuring proxies which need to be considered. Errors from LiDAR derived estimates are identified as outliers and easily corrected. However, there remain uncertainties, in both the LiDAR derived biomass and the global biomass map. In the LiDAR data, errors were found to be similar to errors in field plots, which can be as high as 20 %. The global biomass map is accompanied by an uncertainty map, which can be used to estimate confidence intervals in emissions estimates. Pelletier et al. (2013) provided a thorough review of the large potential errors and uncertainties in estimating emissions using the matrix method in Panama. Of particular attention are the sensitivities and uncertainties related to buffer width in determining area of degradation and the biomass estimates. The latter will be significantly reduced in DRC with the production of a new national LIDAR-derived biomass map with a resolution of 1 ha, which will allow detection of biomass changes in more detail and more conservative estimates of degradation. The authors also recommend increasing tier level with more localized information, accuracy assessment of proxy results and adhering to principles of consistency and conservativeness which should also apply for DRC and including a critical assessment of model uncertainties and how to apply them conservatively and consistently over time.

2.4.2. Biodiversity safeguards

Carbon emissions aside, what is potentially a more useful application of forest fragmentation analysis is the impacts of increased forest degradation on habitats. As the additional requirements to operationalize biodiversity safeguards are implemented, this degradation proxy can be used in combination with biodiversity information to assess ecosystem services and risks to biodiversity, which are based on the principles of landscape ecology, which have demonstrated important relationships between habitat area, quality, with biodiversity. The effects of fragmentation have been shown to critically impair the ability of an ecosystem to provide viable habitat through decreased area, increased isolation and edges (Haddad et al., 2015). These are propagated throughout the ecosystem, affecting species richness, persistence, community composition among other effects and along with an increase in anthropogenic access can provide a solid basis to use fragmentation to evaluate essential habitat indicators for biodiversity safeguards in REDD+ projects. An intact forest can then support not only increased biomass for climate mitigation, but the ecosystem services that local communities require—pollination, non-timber forest products, water regulation etc.... which will improve livelihoods and reduce pressure to deforest and degrade forest resources.

2.5. Conclusion

As global deforestation and degradation increase, there is an even greater need for accurate data for assessing forest cover change and associated emissions (Baccini et al., 2012). The results of this forest pattern analysis show extensive forest fragmentation and degradation of forest edges in DRC, which is greater than the area affected by deforestation alone. This can result in adverse and long-lasting effects on biodiversity and ecosystem services (Haddad et al., 2015). Many attempts to develop subjurisdictional REDD+ programs and define baselines for relative emissions levels have opted to avoid estimates or calculations of unplanned degradation from their baselines and reductions targets. This research demonstrates a transparent, repeatable and simple method for including degradation in MRV systems for a matrix method approach to forest monitoring, using any available forest cover map, which should support countries with limited resources and vast forests (Bucki et al., 2012).

This analysis has allowed a more detailed look at a fragmentation algorithm and the correlation between degraded forests and above ground biomass. Degradation is an especially relevant and important aspect of emissions reduction and conservation activities and when little information is available for mapping forest condition, this proxy can serve as a cost-effective tool in assessing degradation over time. Using forest cover maps derived for

different years, the analysis enables one to assess reference condition, change over time and the trajectory which is a required component for monitoring degradation for REDD+ (Thompson et al., 2013). The benefit of the approach proposed here is the ability to separate degrading or regenerating forests by their trajectories between degraded classes. This helps assess potential hotspots of degradation, as well as the existence of secondary forest carbon sinks to drive management interventions to promote regeneration.

The effect of carbon map resolution may have an important role here. The DRC is currently mapping national forest carbon stocks via integrated field, satellite and airborne LiDAR, an initiative funded by the German Ministry of Environment and Nuclear Safety (BMU) International Climate Initiative and the KFW Development Bank (Tollefson, 2013). This work has included the collection of more than 400,000 ha of airborne LiDAR throughout the country, enabling a more detailed look at canopy structure, biomass, degradation and producing better estimates of forest carbon in areas with little available data to data, or areas with particularly high error. This data will greatly improve access to reliable and unbiased biomass data.

Future steps for quantification of forest degradation will include an assessment of causes, notably from the addition of information on drivers of degradation (Mpoyi et al., 2013) and higher resolution biomass. This will enable correlation of auxiliary data to model degradation based on human factors such as infrastructure, fire, distance to population centres which can support the development of future baselines of forest degradation for REDD+ in DRC.

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2.7. Further Consideration

This research has provided an important insight into the trends and consequences of degradation, notably that almost a third of observed primary forest loss was first degraded before being converted to non-forest land. This is important in defining the anthropogenic causes of degradation, and the processes that lead to forest loss and a potential opportunity to use degradation as warning or prevention for future deforestation.

This approach was built on the matrix concept provides a proxy design to assess degradation as per recommendations from Bucki et al., 2021 for countries with low monitoring resources, particularly related to carbon monitoring, and also at a time where data volume and access, adequate computing power or access to cloud technologies were relatively limited compared to the present. This application also appropriately responds to the conservativeness implementation in REDD+ (Grassi et al., 2013). In a large country like the DRC, direct carbon monitoring through field plots is difficult and expensive, not only due to travel to remote locations and lack of infrastructure, the need for extensive training of staff, but also serious security issues. Therefore, a simple and conservative proxy approach can meet the basic requirements for the development of a FREL and quality the DRC for international climate payments.

The method has been further implemented in practice, notably in the national REDD+ strategy of Nepal (Forest Carbon Partnership Facility, 2018). The same four fragmentation classes were derived from national forest cover maps from 2004 and 2014. Transitions between time periods including both gains and losses were used to identify activity data and the associated emissions factors with Monte Carlo simulated uncertainty estimates derived from detailed biomass inventories from field and LiDAR. Similar differences were found where core forests contained higher biomass than edges and emissions factors were considered for core deforestation and edge deforestation and degradation which satisfied requirements for integrating forest degradation into national emissions reference levels. More importantly this approach has relied entirely on Nepalese capacities with no need for specialized software or hardware. The ability to assess forest gains and reductions in fragmentation is also highlighted as valuable, as well as the simplicity, repeatability of the approach.

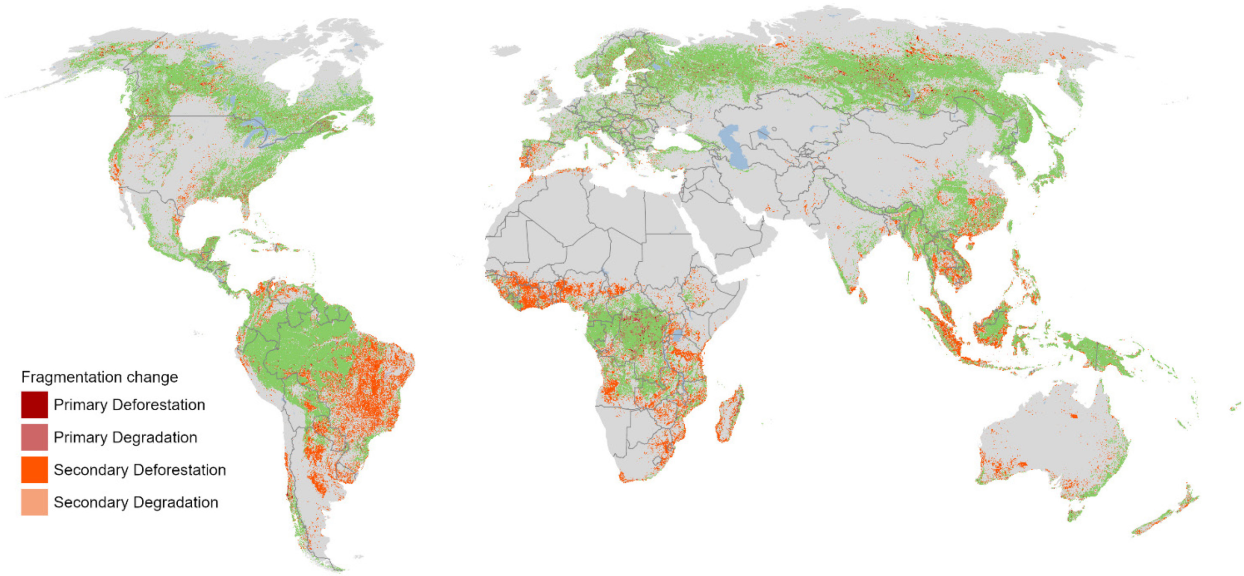
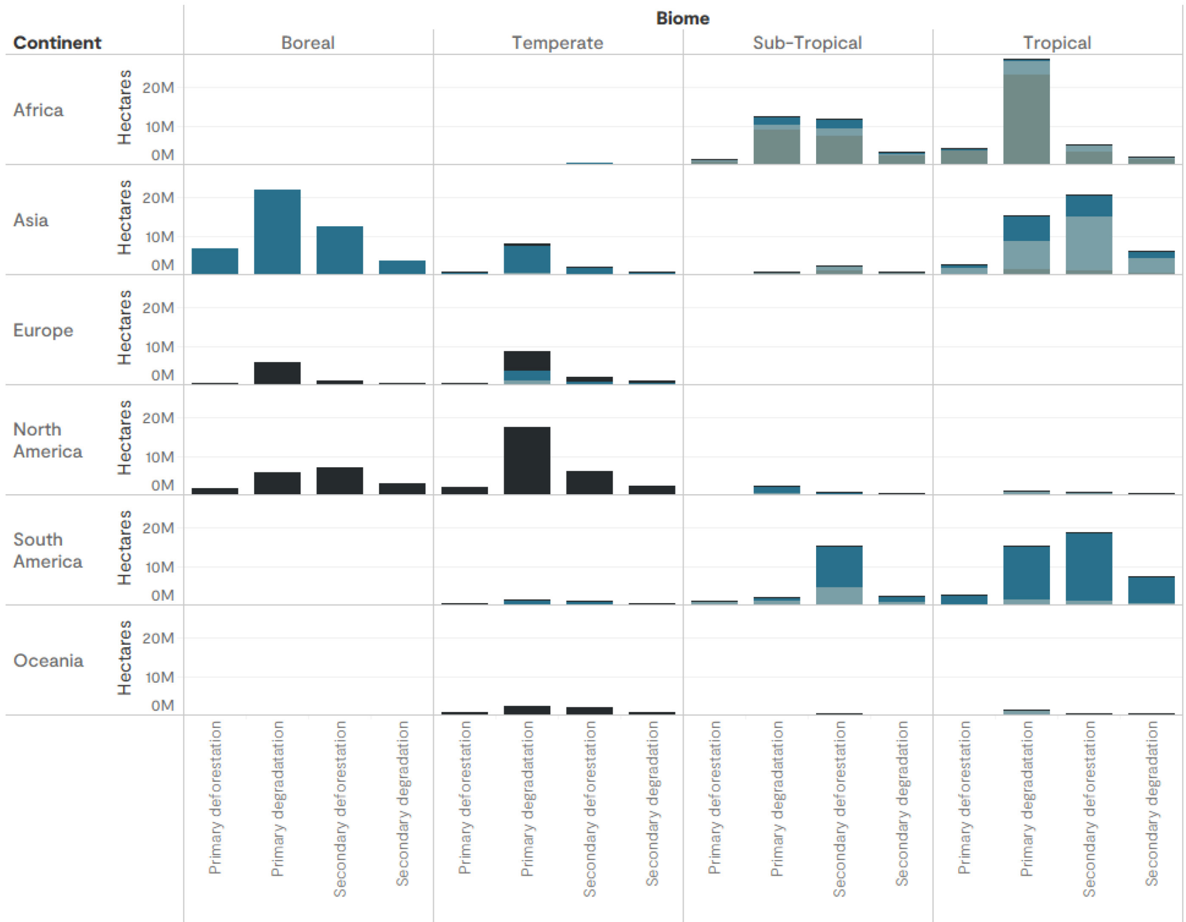


Figure 16. Global forest fragmentation change 2000-2018

The method is also very scalable. I applied the same fragmentation transition analysis to a global forest cover dataset for 2000 and 2018 (see Pacheco et al., 2021), to assess primary and secondary deforestation and degradation (**Figure 16**). I quantify the transitions in all countries and biomes of the world using multi-evidence forest maps (**Figure 17**), and overlaid with burned forest area to identify areas of fire-driven deforestation and degradation (**Figure 18**).



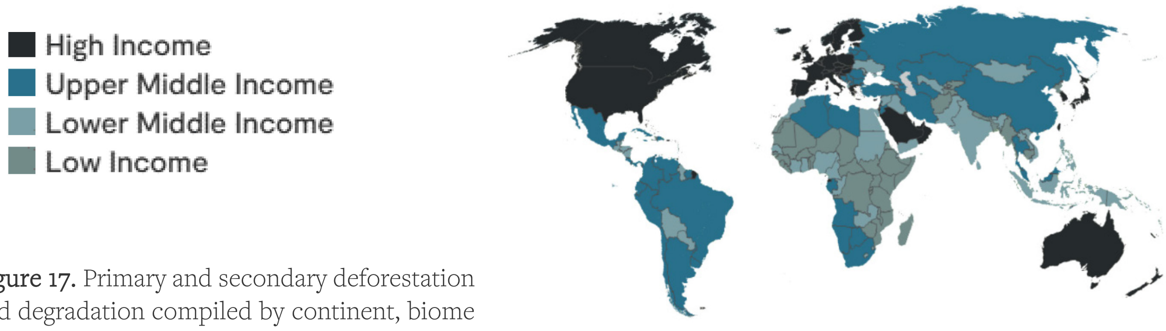


Figure 17. Primary and secondary deforestation and degradation compiled by continent, biome and economic status

While much of the blame for forest loss is cast on poor countries with tropical forests, but extensive degradation is nevertheless present in high income countries with temperate forests. Primary deforestation is in fact observed to be highest in upper middle income boreal and tropical countries, while primary degradation is highest in high income temperate forests, and low-income tropical nations. For secondary forests, they are being cleared in upper middle income tropical countries.

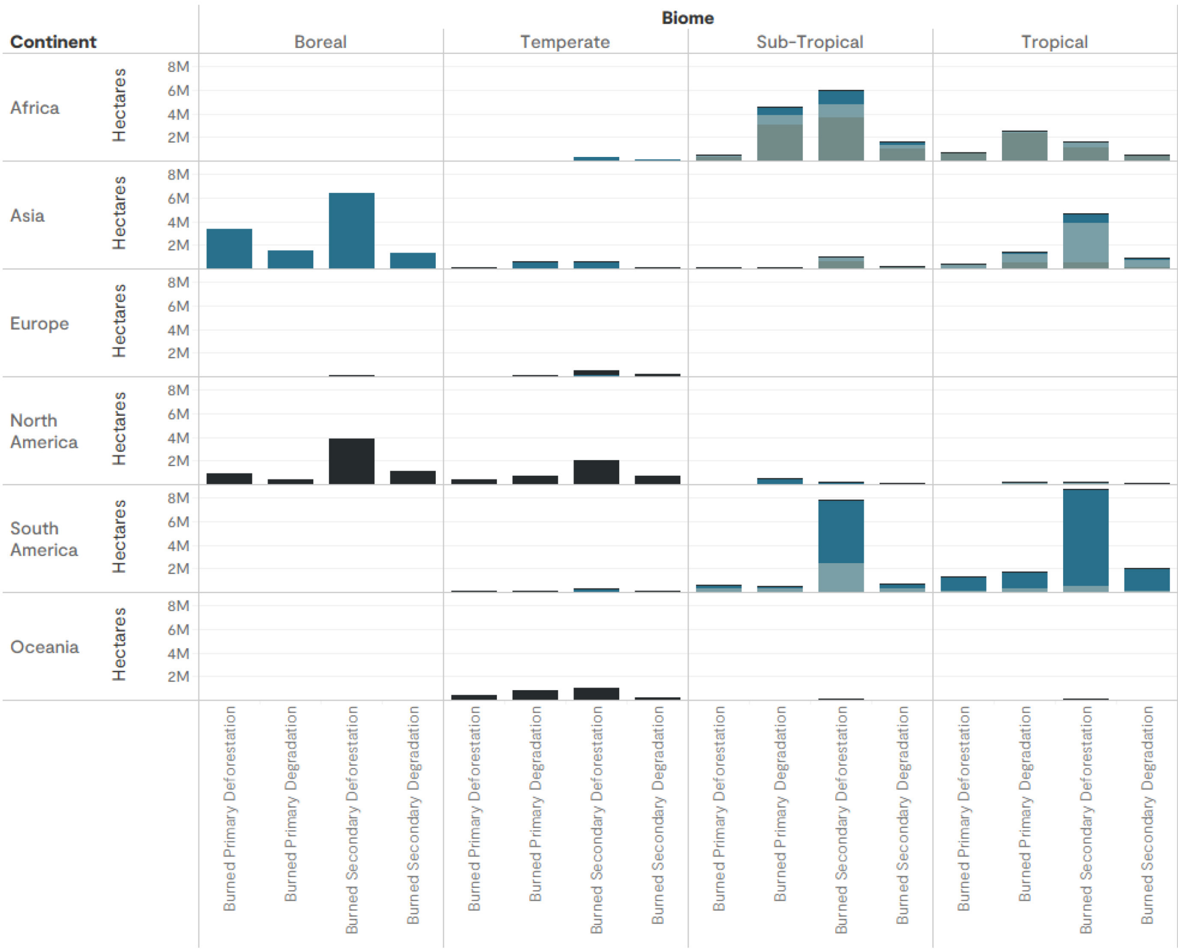


Figure 18. Fire associated deforestation and degradation by continent, biome and economic status (same colors for income level as the previous figure)

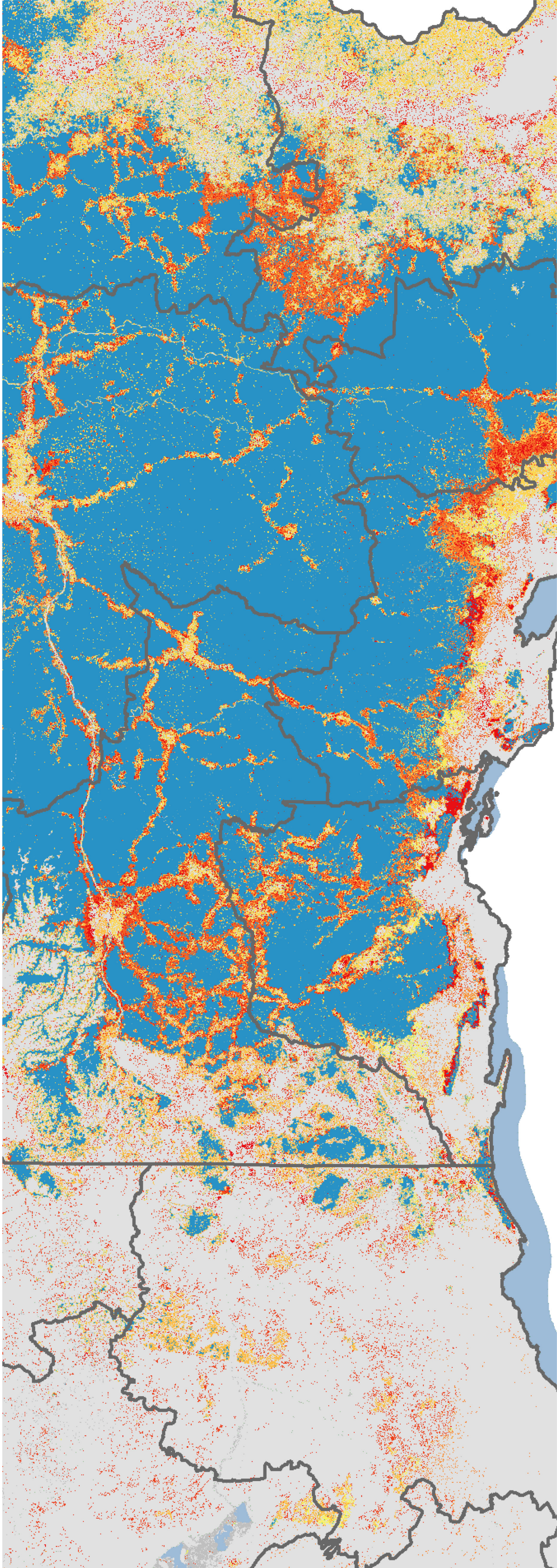
I used the MODIS burned area product (Roy et al., 2008) in combination with the global map of forest changes (2000-2018) to determine how much of these changes in primary and secondary forests are associated with fire. Across all regions, secondary forests are being burned and cleared, although in Boreal Asia, fire is also present in areas of primary forest clearing. Upper middle-income countries in South America are seeing the most forest related clearing and low-income nations have the highest rates of burning in areas identified as primary degradation.

An analysis at global scale can support wider policies and international efforts such as the New Deal for Nature and People[5], or policies that aim to shift patterns of food consumption, production and demand, or even to help determine where international organisations or corporations should focus commitments or resources. As forests progressively get reduced to small islands or patches, a consistent analysis that includes fragmentation can help mobilize the needed resources for restoration and fire suppression efforts.

5 https://explore.panda.org/newdeal

Nevertheless, a categorical approach can have its limitations, namely that fragmentation classes may be a coarse oversimplification of degradation into specific types, whereas degradation can consist of subtle ranges of change in canopy density or cover. Moreover, the estimation of biomass within fragmentation strata could be variable in time and space or by ecosystem, and currently this approach of classifying transitions does not differentiate between forest types, or forests with larger ranges of AGB. Therefore, there is a need for the estimation of a continuous metric, one which uses biomass in the degradation definition, and is applied specifically to different forest ecosystems, but is also not affected by a natural tendency of high or low biomass. It is important to be able to measure degradation on a continuous, relative scale, regardless of the forest type or biomass and use this information for appropriate spatial planning and conservation prioritization. The next chapter identifies a new continuous metric to estimate forest degradation to evaluate the risk of ecosystem collapse.

Chapter 3: Forest condition in the Congo Basin for the assessment of ecosystem conservation status



Building upon the previous chapter a continuous metric to define forest condition (FC) is developed as a function of fragmentation and above ground biomass lost, incorporating the temporal history of each pixel to define its status.

This indicator is applied to a conservation prioritization framework, the IUCN Redlist for Ecosystems in order to assess the risk of ecosystem collapse.

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Abstract

Quantifying ecological condition, notably the extent of forest degradation is important for understanding and designing measures to protect biodiversity and enhancing the capacity of forests to deliver ecosystem services. Conservation planning, particularly the prioritization of management interventions for forests, is often lacking spatial data on forest degradation, and it is often overlooked within decision-making processes. We develop a continuous metric termed Forest Condition (FC) which aims to measure the degree of forest degradation on a scale from 0 to 100, incorporating the temporal history of forest change over any spatial extent. We parameterize this metric based on estimated changes in above ground biomass in the context of forest fragmentation over time to estimate a continuous measure of forest degradation for Congo Basin countries. We estimate that just <70% of Congo Basin forests remain fully intact, a decrease from 78% in the year 2000. FC was validated by direct remote sensing measurements from Landsat imagery for DRC. Results showed that FC was significantly positively correlated with forest canopy cover, gap area per hectare, and magnitude of temporal change in Normalized Burn Ratio. We tested the ability of FC to distinguish primary and secondary degradation and deforestation and found significant differences in gap area and spectral anomalies to validate our theoretical model. We apply the IUCN Red List of Ecosystems criteria to demonstrate the integration of forest condition to assess the risk of ecosystem collapse. Based on this assessment, we found that without including FC in the assessment of biotic disruption, 12 ecosystems representing over 11% of forested area in 2015 would not have been assigned a threat status, and an additional 9 ecosystems would have a lower threat status. Our overall assessment of ecosystems found about half of all Congo Basin ecosystem types, accounting for 20% of all forest area are threatened to some degree, including 4 ecosystems (<1% of total area) which are critically engendered. FC is a transferrable and scalable assessment to support forest monitoring, planning, and management.

3.1. Introduction

Forest ecosystems provide essential ecosystem services to people, such as provision of food and materials, hydrological functions for clean supply of water, and home to numerous indigenous peoples (Díaz et al., 2019). They are also at the forefront of global initiatives for the mitigation of greenhouse gas emissions, as conserving remaining intact forests is important for carbon sequestration and avoidance of future potential emissions (Jantz et al., 2014; Maxwell et al., 2019; Mitchell et al., 2017). Forests harbour unique and important biodiversity which underpins many of these functions, aligning with conservation efforts (Feeley & Terborgh, 2005; Stokstad, 2014) and intact forest ecosystems are shown to have greater conservation benefits than degraded ones of similar ecological type (Betts & et al., 2019; Haddad et al., 2015), making strong arguments for prioritizing them for conservation management (Watson et al., 2018).

Despite this value, forests are increasingly threatened by expanding human activities (Thompson et al., 2011; Venter et al., 2016). The degradation of forest can occur through a process of fragmentation, which in turn impacts biodiversity, biomass, and therefore the ability of forest to provide many ecosystem services (Betts & et al., 2019; Chaplin-Kramer, Ramler, et al., 2015; Haddad et al., 2015; Potapov et al., 2012). Although there is no standard definition of forest degradation (Ghazoul et al., 2015; Potapov et al., 2009b), it has been acknowledged that declines in forest intactness result in environmental and social problems which impact forest health, affecting human livelihoods and economic development (Foley et al., 2005; Pereira et al., 2010). Understanding and quantifying changes in forest fragmentation related to ecological condition is therefore crucial to monitor, manage and protect intact forests over time to prevent such problems (Brooks et al., 2006; Mittermeier et al., 2003). We define degradation via the term forest “condition” between a state of maximum intactness and completely deforested using a combination of spatial patterns of fragmentation and ecosystem services, notably above ground biomass (AGB) as described in Shapiro et al., 2016.

Remote sensing can provide affordable, efficient, consistent multi-temporal measurements for forest monitoring, and assessment of forest condition when appropriately defined (Mitchell et al., 2017). The recent increases in the reliable use of satellite technology, as well as improved access to data and enhanced processing capabilities, are promoting analyses of higher temporal resolution which enable improved assessments of forest degradation over time. Remote sensing approaches for forest degradation are generally grouped into direct and indirect approaches (Herold et al., 2011). There are advantages and disadvantages to each approach which will vary by geography, resources available, and specific needs. Direct remote sensing methods estimate parameters such as spectral indices related to canopy gaps and structure, changes in forest canopies, or productivity in time series (DeVries et al., 2015; Mitchell et al., 2017; Souza et al., 2005; Spruce et al., 2011; Verbesselt et al., 2010; Verbesselt et al., 2012), although the implementation over a large area can be limited by image resolution or availability of time series or consistency between sensor types or climate effects (Cohen et al., 2010; Kennedy et al., 2010; Zhu, 2017) which can hinder the ability to compare variables in different geographies or climate regimes. Direct satellite measurements can also be affected by the complexity of defining degradation according to specific remote sensing indicators, and are more sensitive to forest dynamics, changes in vegetation, climate or even extreme events such as droughts, which may represent shorter term events which may be confused with degradation. In contrast, indirect methods employ the mapping of proxies, for example presence of roads, fires, forest edges or pattern (Broadbent et al., 2008; Chaplin-Kramer, Ramler, et al., 2015; Haddad et al., 2015; Potapov et al., 2008; Riitters et al., 2015; Shapiro et al., 2016; Tyukavina et al., 2016). These methods are particularly suitable for planning and monitoring, reporting and verification in developing countries with low field monitoring resources (Bucki et al., 2012). Fragmentation and spatial pattern approaches are conceptually simpler, and being increasingly used in the development of reference levels and targets for emissions reduction programs, for example in Nepal (Forest Carbon Partnership Facility, 2018). Indirect methods do however have their own limitations, which include of oversimplifying degradation processes, may not be sensitive to small-scale changes, and relies heavily on the quality of underlying datasets such as forest cover (Herold et al., 2011; Miettinen et al., 2014).

There is a need for simple approaches for assessing and monitoring forest condition to provide a repeatable, transferrable and understandable indicator for regional conservation planning and prioritization for conservation, for example the intact forest landscape approach (Potapov et al., 2008), hinterland forests (Tyukavina et al., 2016), or the stratification approach from Bucki et al., 2012. These binary assessments are based on the application of hard thresholds (which may vary by geography or landscape) to discern degraded forests from intact, although forest degradation is in reality, a gradient of disturbance or impacts over time (Sasaki & Putz, 2009). An indicator that provides a continuous estimation forest condition could therefore provide a finer representation of this temporal, cumulative process.

In this study, we build on previous research (Shapiro et al., 2016), to assess forest condition (FC) by developing analyses of key forest fragmentation and structure indicators over time. We first assess changes in forest spatial pattern, and then use available estimates of above-ground biomass (AGB) in strata defined by these spatial patterns to assign a continuous estimation of FC. FC is calculated by effects of fragmentation and increase in forest edges and associated impacts over time using relative changes in AGB. We apply a theoretical model to discern primary and secondary degradation from deforestation, and demonstrate how the results -- a new forest condition metric – enable evaluations of the extent and severity of ecosystem degradation to assess forest ecosystem collapse under the IUCN Red List of Ecosystems categories and criteria (Bland et al., 2015; IUCN, 2016; Rodríguez et al., 2015).

3.2. Materials and Methods

3.2.1. Study Area

The Congo Basin forest ecoregion (Olson et al., 2002) is comprised of tropical forests in the Democratic Republic of the Congo (DRC), Republic of Congo (ROC), Equatorial Guinea, Gabon, Cameroon, Central Africa Republic and a small portion of Angola (Figure 19. The regional study area encompasses 6 countries in the Congo Basin. A national scale assessment focuses on the Democratic Republic of the Congo (DRC). Major biogeographic boundaries are defined by the Ubangi and Congo Rivers. Green shows the primary tropical forest cover for 2016 This represents the largest connected tract of forest in Africa, and the single largest peatland complex in the world, storing a significant amount of forest carbon (Dargie et al., 2017). The basin is highly biodiverse and is a focus of recent species discovery(Dargie et al., 2019; Hart et al., 2012);, while more than 30 million people inhabit the basin, including indigenous communities with a long and intricate relationship to natural ecosystems (Riddell, 2013). Together these characteristics represent a unique ecological opportunity to mitigate climate, while supporting the livelihoods of the many communities who depend on essential natural resources. The relative lack of current geo-spatial information on forests, and few validation information from the ground due to lack of access or security, political instability; or widely distributed studies on land-use related impacts on forests and associated species biodiversity, for example in compared to the Amazon basin or Asian forests currently hinders successful management and conservation efforts in the context of needed sustainable development (Malhi et al., 2013).

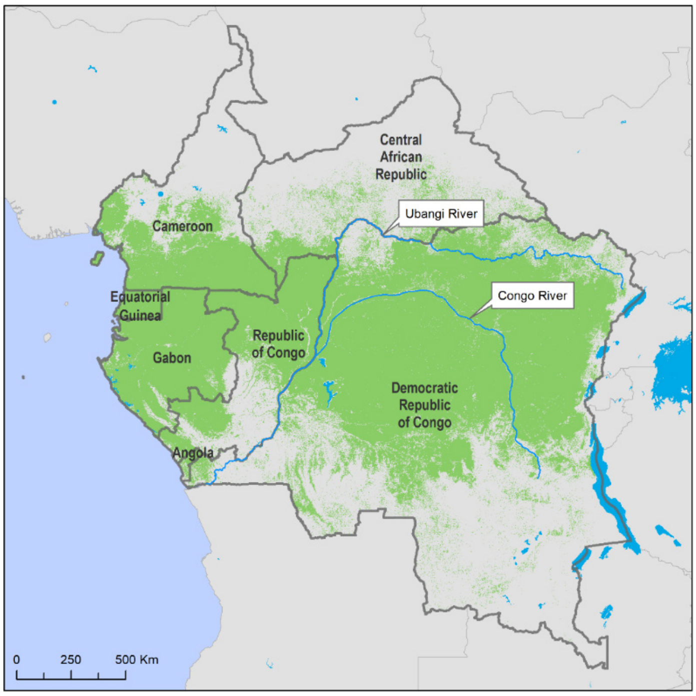

Figure 19. The regional study area encompasses 6 countries in the Congo Basin. A national scale assessment focuses on the Democratic Republic of the Congo (DRC). Major biogeographic boundaries are defined by the Ubangi and Congo Rivers. Green shows the primary tropical forest cover for 2016

3.2.2. Data Sources

We developed a comprehensive dataset of relevant ecological, physical and forest data layers to evaluate FC for Congo Basin forests, explained in **Table 6**. This includes the assessment of biogeographically distinct forest ecosystems, best available data on AGB, and validation data such as canopy height, gap area and fractional cover derived from LiDAR, and Landsat derived normalized burn ratio (NBR).

Table 6. Datasets and descriptions and relevant article section

DATA	SOURCE	DESCRIPTION	SECTION
Forest Ecosystems	(Betbeder et al., 2014 ; Dargie et al., 2017 ; Giri et al., 2011; Hansen et al., 2013 ; Philippon et al., 2018)	64 unique forest types determined by phenology, climate regime, flooding dynamics and bio-geographical zone	3.2.3.
Above Ground Biomass (AGB)	(Xu et al., 2017)	National forest biomass dataset derived from LiDAR and satellite imagery for the DRC	3.2.4
Canopy height	(Xu et al., 2017)	National airborne LiDAR dataset for the DRC	3.4.1.
Forest gap area	(Xu et al., 2017)	Derived from LiDAR canopy height following method of Betts et al., 2005	3.4.2.
Fractional cover	(Xu et al., 2017)	Derived from LiDAR forest canopy height	3.4.3.
Normalized Burn Ratio (NBR)	(Key & Benson, 2005)	Index derived from Landsat Tier 1 imagery	3.4.4.

3.2.3. Congo Basin Forest Ecosystems

To develop the forest ecosystem map we applied a number of processing steps. First, we used forest cover data for *terra firme* forests from (Philippon et al., 2018), which assessed phenology patterns and light regimes derived from MODIS (Moderate Resolution Imaging Spectrometer) to identify eight distinct forest types at 500m resolution. To complete coverage of all forests in our study area we then identified open forests using data from Hansen et al., 2013, which were identified from tree cover greater than 60% (in 2000) and outside the MODIS derived map. We integrated mangroves mapped by Giri et al., 2011 and lastly, swamp forest types by overlaying data from two sources, (Betbeder et al., 2014) and (Dargie et al., 2017) which together identified 14 unique swamp forest types by flooding dynamics and dominant species (see supplemental material). We resampled our forest types data to a common pixel resolution of 1 ha (100 m x 100m).

To better represent biogeographic patterns in forest types, we split our combined maps into regions defined by important bio-physical barriers which are known to have isolated distinct species (e.g. great apes) over many generations (Olson & Dinerstein, 2001; Takemoto et al., 2015). To represent these regions, we split areas east and west of the Congo River, and north and south of Ubangi river. We further distinguish sub-montane and montane vegetation according to elevations above 1100m and 1750m respectively (Verhegghen et al., 2012). Finally, we identified an area of Maranthaceae dominated forests in the Republic of Congo based on expert input. The final product was a map of 64 unique forest ecosystem classes for the year 2000 (see supplemental material for a list of all forest ecosystem types), which was updated to a second epoch of 2016 by removing all areas identified as tree cover loss by Hansen et al., 2013. The forest ecosystem maps for both epochs were used to create binary forest/non-forest masks for 2000 and 2016.

3.2.4. Above Ground Biomass (AGB)

Spatially explicit AGB (Mg/ha) at the Congo Basin scale was sourced from the *integrated pan-tropical dataset* developed by (Avitabile et al., 2015) at 1km resolution. We further tested the index in the DRC using a finer scale national dataset calibrated by airborne LiDAR (Light Detection and Ranging; Section 2.2.3) and field data, extrapolated to the all DRC forests using wall-to-wall Landsat, ALOS PALSAR active radar and topography datasets as described in Xu et al., (2017).

3.3. Developing a forest condition metric

We estimated FC by combining forest fragmentation change and the relative loss in AGB for each transition between fragmentation classes. This process of anthropogenic deforestation encroaching on forest stands results in greater edges (Broadbent et al., 2008; Gascon et al., 2000), and relative AGB (in the absence of real-time carbon monitoring) of each of these fragmentation classes allows us to assess an indicator of forest structure from a maximum theoretical intact state to completely deforested. To achieve this we assigned the forest/non-forest mask from the two time periods (2000 and 2016) into fragmentation classes using Morphological Spatial Pattern Analysis (MSPA) from the GUIDOS toolbox (Soille & Vogt, 2009; Vogt & Riitters, 2017). The edge distance has a significant impact on the resulting metric, and we use an edge distance of 300m, which we consider an appropriate distance of satellite measurable impact into intact tropical forests (Harper et al., 2005; Shapiro et al., 2016). We reclassed bridges and loops to inner and outer edges based on their location on the boundary of interior or exterior non-forest patches respectively. Thus, forest cover in each time period is assigned into one of four fragmentation classes: core, inner edge, outer edge and patch forest. We calculate the mean AGB in each fragmentation class of each ecosystem type.

We then assess transitions in fragmentation classes from 2000 to 2016 as a result of change in forest cover pattern, identified as areas that change from core forest to other fragmentation classes, identifying which forest pixels remain in the same class, versus transitions between different classes, which are assigned primary and secondary deforestation, primary and secondary degradation, as shown in **Figure 20**. We discern two types of edges, inner perforations and outer edges bordering non-forest, as these have significantly different biomass (Shapiro et al., 2016), and have also been shown to be a result of different anthropogenic land uses (Molinario et al., 2020). Similar subsequent categories of core and edge forest according to canopy height have been described in Brazilian rainforests (Silva Junior et al., 2020).

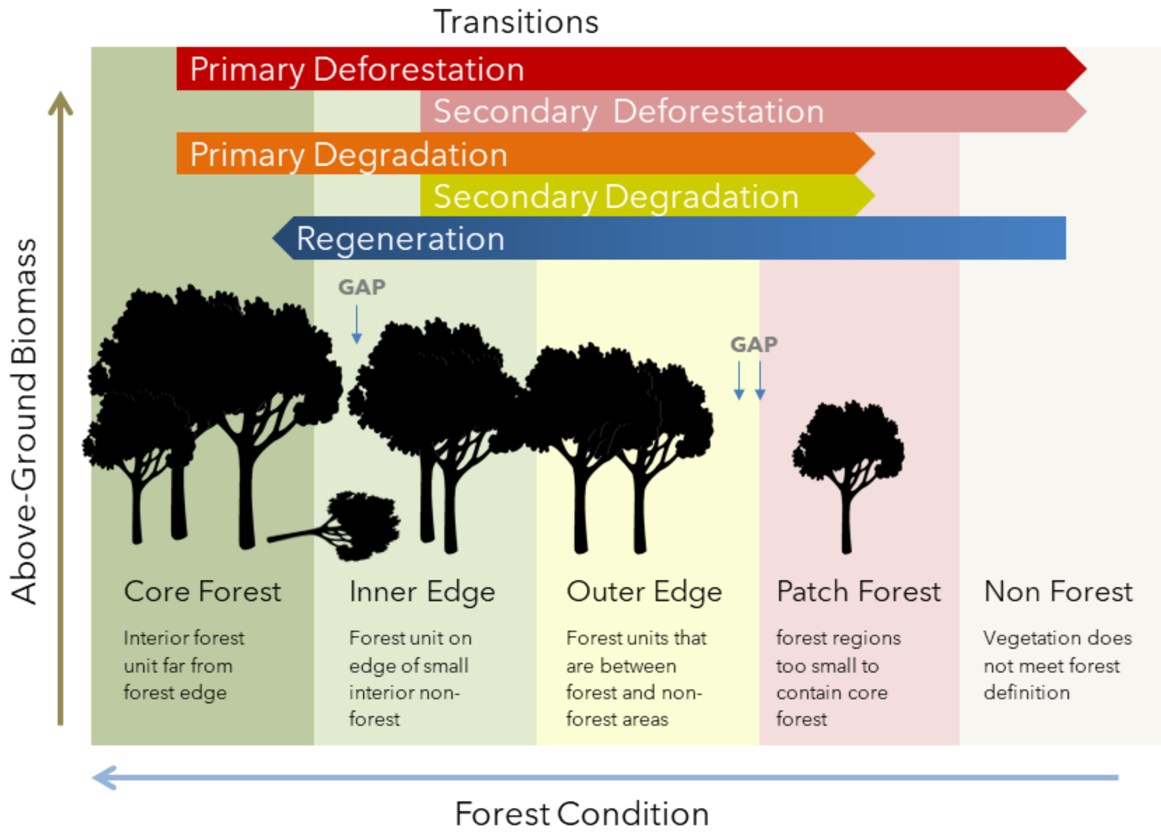

Figure 20. Theoretical concept of forest condition (FC) as a combination of AGB, deforestation and degradation transitions via fragmentation. A forest/non-forest map is classified into 5 fragmentation types (core, inner edge, outer edge, patch forest) which have decreasing levels of above-ground biomass (AGB) respectively and a greater presence of canopy gaps. The transitions between classes from one time period to the next are described in the top of the figure with an arrow that has a beginning point and an end, e.g. a change in core forest to outer edge is primary degradation. An inner edge forest that becomes non-forest is secondary deforestation. Stable forest types are primary forest (core forest with no change) and secondary forest (inner and outer edges, patch forests with no change)

The change in above-ground biomass between two time periods (2000 to 2016) was calculated from using a process analogous to the gain-loss method for carbon stock monitoring using the mean AGB of each fragmentation class of each forest ecosystem (Murdiyarso et al., 2008). Gains and losses in AGB are calculated according to differences between fragmentation/forest ecosystem strata means (Shapiro et al., 2016).

We compute FC as a continuous metric from 0-100, based on the percentage change in biomass between classes as a proportion of the maximum potential AGB, thereby integrating the temporal dynamics of a forest area that is an indication of not only present state (one snapshot: degraded or not) but the state in a trajectory from intact to deforested. This transition is determined according to the proportion of AGB remaining in comparison to the mean AGB of the core forest class (maximum intactness). Relative FC was then estimated on a continuous scale from fully intact (100) to completely lost (0), based on the proportional loss of biomass between fragmentation classes for two time periods.

The FC of the second time period j for each forest ecosystem is calculated using the following **Equation 1**:

Equation 1: $C_{tj} = 100 * (AGB_{tj} / AGB_{ti})$

Where C is the condition of that specific forest ecosystem fragmentation strata at any time t (denoted by t_j), based on the AGB of the previous and current fragmentation category.

To differentiate an ecosystem that has changed to a new state versus one that is stable, we assess overall Forest Condition (FC) using **Equation 2**:

Equation 2: $FC_{tj} = C_{tj} - (\frac{AGB_{tj}}{AGB_{ti}}) * C_{tj}$

3.4. Testing the FC metric in DRC

3.4.1. Forest canopy height

Forest canopy height was estimated using the airborne LiDAR dataset collected in 2014 and 2015 throughout the DRC following a systematic random sampling pattern, as described by the VCS VT0005 methodology (Tittmann et al., 2015; Xu et al., 2017). In total, 216 random plots of 2,000 ha each were distributed over a 1°×1°grid laid over the national primary dense forest cover dataset for DRC (Potapov et al., 2012). LiDAR data were collected with a mean point density of $2/m^2$ from which digital surface models and mean canopy height were derived at 2m meter resolution (Xu et al., 2017). All canopy heights above 3m (national forest definition) were used to create a detailed forest cover map for these LiDAR sampling areas, and further used to develop the variables described in the following two sections.

3.4.2. Forest Gap Area

Forest gap area was estimated using the difference between the LIDAR canopy height and a maximum estimated within a 50-cell window (or 1 hectare, following Betts et al. (2005)). Gaps were identified using a threshold of 21m less than the canopy maximum, which located all gap areas within continuous forest, verified by the very high resolution (10cm) airborne imagery collected by the same airborne data collection campaign. The gap area was then summed for each hectare in the LiDAR footprints and sampled using the random sample of 100 points per LiDAR plot.

3.4.3. Fractional Cover

Forest fractional cover was estimated from the 2m LiDAR-derived forest canopy height by summing the total number of cells in a 50x50 window and calculating the proportion of 2500 cells covered by forest to produce % forest cover at the 1ha scale.

3.4.4. Normalized Burn Ratio (NBR)

We used the normalized burn ratio index (NBR; (Key & Benson, 2005) as a direct remote sensing indicator of canopy disturbance associated with encroachment and illegal logging (Langner et al., 2018). We calculated NBR from Landsat surface reflectance imagery from the USGS Tier 1 collection from 1984 to 2016 processed in Google Earth Engine (Gorelick et al., 2017). All available Landsat data since 1984 were compiled, filtered by cloud cover (less than 90%), poor quality pixels were masked according to pixel quality (Foga et al., 2017), and the image collected was sorted by acquisition date. We use a cumulative anomaly analysis to assess NBR in a monitoring period (2000-2016) compared to a baseline historical period (all previously available imagery from 1984-1999), where all Landsat images are sorted in time, and the differences with the mean are sequentially summed and divided by the number of available images. From 2000 onward, coinciding with the first year of forest condition transition assessment, the difference between calculated NBR for each cloud-free pixel and the historical mean was calculated, summed, and normalized by the number of non-null observations as in Lagomasino et al. (2018). An area with a time period of high positive anomalies (higher NBR than historical mean) followed by subsequently larger negative anomalies, will have an overall high negative accumulated anomaly.

We assessed the performance of FC and the theoretical framework in several ways for the DRC, for which we have detailed validation data (Table 6). We correlated FC with fractional forest cover and canopy gap area, along with the estimate of biomass lost and the NBR cumulative anomalies. This was done using a random sample of 50 points distributed inside the fragmentation classes inside each LiDAR plot (n=10,800) from Xu et al., 2017 in order to assess forest structure variables of fractional cover and gap area, biomass lost and anomaly using a Pearson correlation matrix executed in R software (version 3.5.1). Negative cumulative anomalies of NBR (Section 2.7) were evaluated within each degradation class using analysis of variance (ANOVA) of the same random sample of points as above. These were further evaluated using the Tukey honest significant difference pairwise test (Bland & Altman, 1995) to determine significant differences between paired fragmentation transition classes.

3.5. IUCN Red List of Ecosystems assessment

To estimate the risk of ecosystem collapse for each of the forest ecosystem types, we applied the IUCN Red List of Ecosystem criteria A2b, B1 and B2 and D (Bland et al., 2017) summarized in **Table 7**. The Red List of Ecosystems employ a rule-based protocol that utilises information on spatial change, range size, and biotic and abiotic variables for each ecosystem to identify ecosystems at risk of ecosystem collapse.

Table 7. Summary of relevant IUCN Red List for ecosystems criteria applied in this assessment

Criterion	Description	Red List category		Thresholds	
A2b	Reduction in geographic distribution in any 50-year period including the past, present and future:	CR		≥80 %	
		EN		≥50 %	
		VU		≥30 %	
B1	Extent of a minimum convex polygon enclosing all occurrences (extent of occurrence, EOO) is no larger than:	CR		2000 km^2	+ sub criteria (see Bland et al. 2015)
		EN		20,000 km^2	
		VU		50,000 km^2	
B2	The number of 10x10km grid cells occupied (are of occupancy, AOO) is no more than: 1% rule: grid cells with patches of the ecosystem type accounting for less than 1% of grid cell area are excluded	CR		2	+ sub-criteria
		EN		20	
		VU		50	
D2 a	Disruption of biotic processes or interactions over any 50-year period, based on a change affecting a fraction of the extent of the ecosystem with an estimate of relative severity		Relative severity (%)		
		Extent (%)	≥80	≥50	≥30
		≥80	CR	EN	VU
		≥50	EN	VU	
		≥30	VU		
D3	Disruption of biotic processes or interactions since 1750, based on a change affecting a fraction of the extent of the ecosystem with an estimate of relative severity	Extent (%)	Relative severity (%)		
			≥80	≥70	≥50
		≥90	CR	EN	VU
		≥70	EN	VU	
		≥50	VU		

Criterion A2b was applied to assess the reduction in geographic extent of each ecosystem over a 50-year period. We used the adjusted proportional rate of decline based on the extent data for two time periods, 2000 and 2016 (**Figure 21**). To assess the range size criterion B, we computed extent of occurrence as a minimum convex polygon encompassing all occurrences of each ecosystem (criterion B1) and area of occupancy using the 1% occupancy rule (criterion B2) and appropriate sub-criteria as described in Bland et al., 2015.

Criterion D focusses on the disruption of biotic processes (Bland et al., 2017), for which we applied the area of primary degradation (see **Figure 20**) as the extent of the disruption, and the mean forest condition to indicate severity. Forest edges are known for their detrimental effects on ecosystems services and vertebrate habitats (Pfeifer et al., 2017), thus, making a fragmentation approach relevant for conservation prioritization applications. Instead of the recommended 1750, we use the year 1850 as the historical reference because prior to then forests in the Congo Basin were considered largely free of human disturbances and industrial development (Morin-Rivat et al., 2017). Both sub-criteria D2 and D3 were evaluated to determine the validity of these assumptions.

The change in FC over the 16 year study period was used as an indicator of biotic disruption, as reduced AGB affects the delivery of ecosystem services such as climate change mitigation over time (Heymell et al., 2011; Pettorelli et al., 2017; Shvidenko et al., 2005). The change in amount of core forest versus edge classes determined the extent of the ecosystem affected by fragmentation, edge effects (Haddad et al., 2015) for criterion D3, while the changes in mean forest condition per ecosystem were used to assess relative severity of degradation for the severity.

FC by definition assumes that at some initial point in time, all forests were intact ecosystems with 100% condition, thus providing the information needed to assess two of the sub-criteria D2a and D3. For D2a, we presume the rates of change of core versus edges determine the fraction of the extent of the ecosystem affected since 2000; and these are projected to 2050 using the proportional annual rate of decline (PRD; (Rodríguez et al., 2015). For D3, we assessed the proportional rates of decline over the actual annual rates of decline (ARD) in mean FC by ecosystem which were modelled using the changes from 1850-2016, with the assumption that in 1850, all forest ecosystems were core intact forest with maximum potential biomass (**Figure 21**). The final ecosystem status was assigned as the highest assessment outcome between all three criteria evaluated, A, B and D.

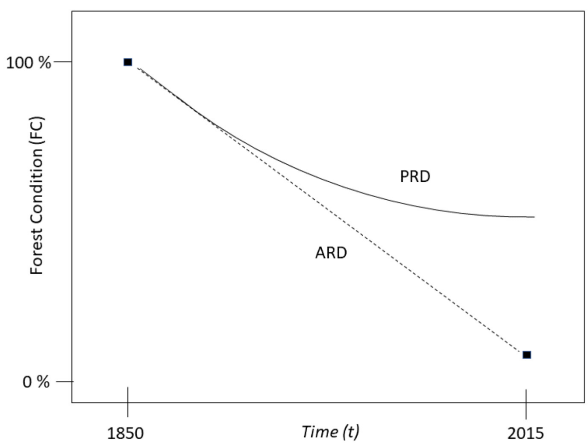

Figure 21. The correlation between forest condition estimated in 2015, and the assumed 100% condition in 1850, can be calculated using either annual rates of decline (ARD) or proportional rate of decline (PRD, adapted from Rodríguez et al., 2015

3.6. Results

3.6.1. Condition of Congo Basin Ecosystems

Our forest ecosystem map shows the Congo Basin forests cover more than 210 million ha in 2000 and are predominantly lowland, equatorial semi-deciduous forests with a significant swamp forest ecosystem in the central region covering more than 29 million hectares (**Figure 22**).

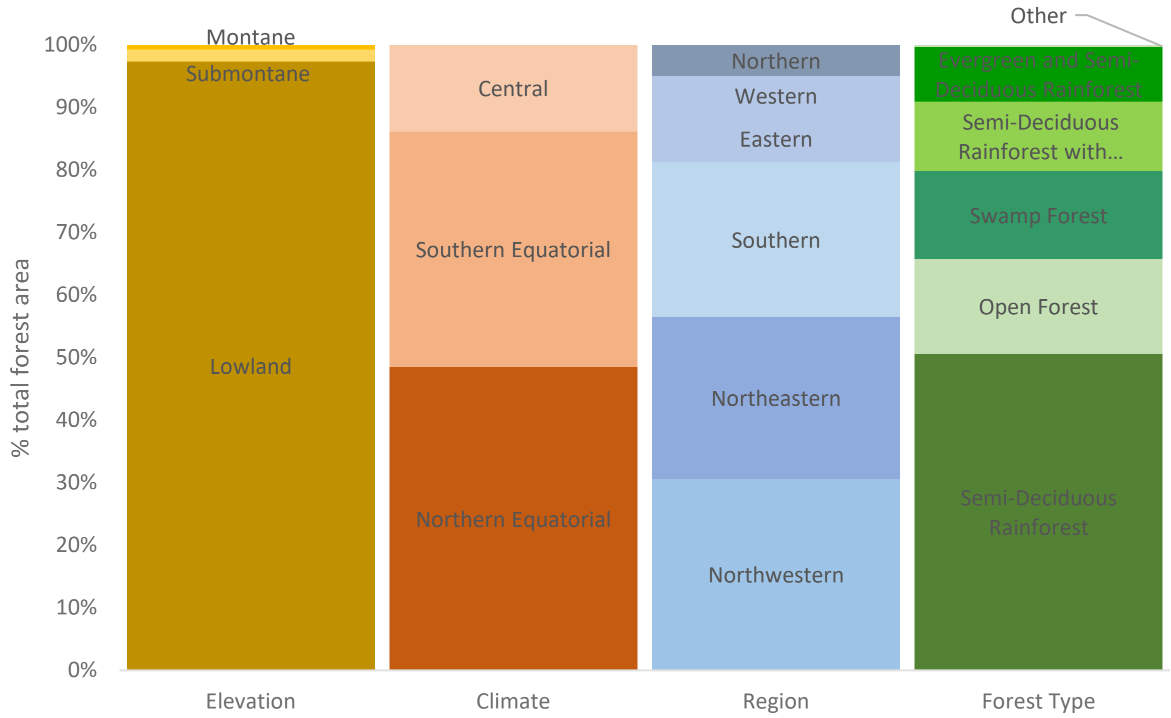

Figure 22. Congo Basin forest composition by region, forest type, elevation and climate. (Other forest types include mangrove and Maranthaceae)

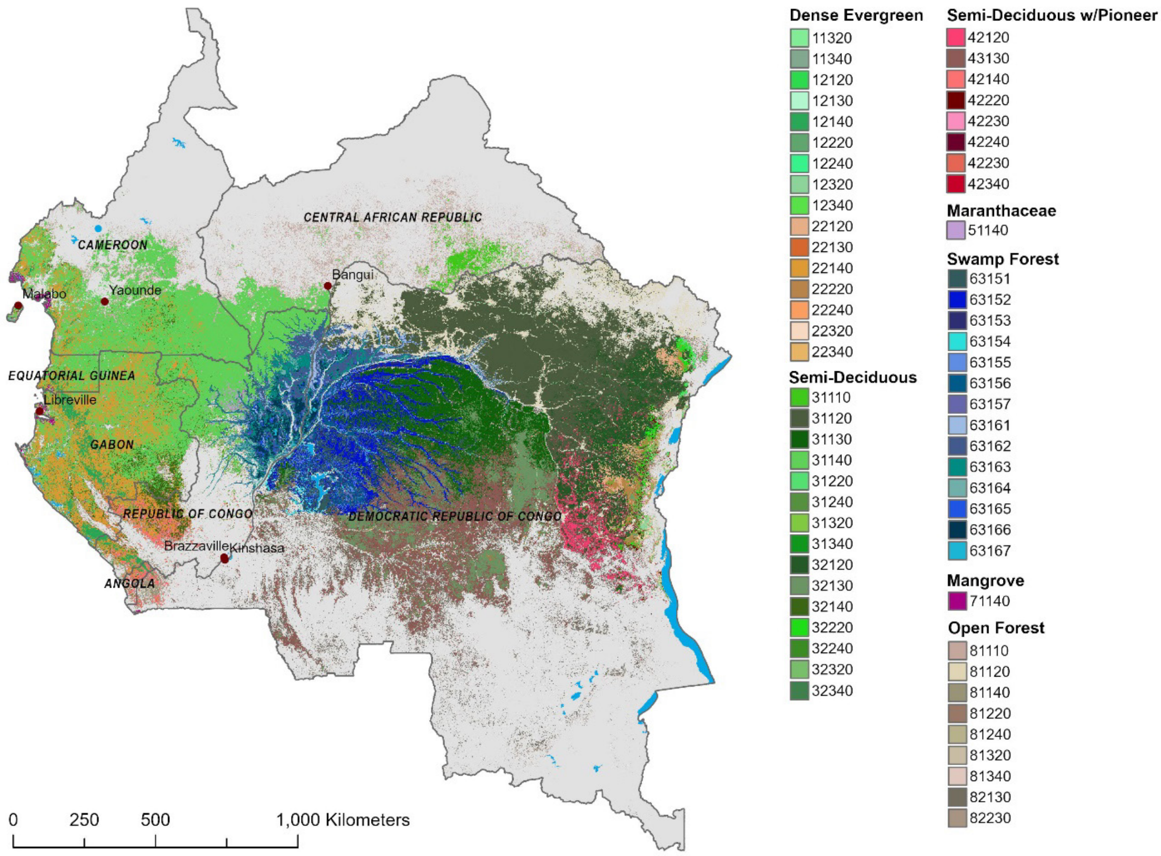

Figure 23. Distribution of forest ecosystem types of the Congo Basin. The codes indicate the hierarchical classification scheme and are explained in the supplemental material

The condition of these 64 forest ecosystems vary widely across the region. Overall we estimate that in 2000, 78% of all forest area was intact, core forest, decreasing to 67% in 2016 (intact forests shown in blue, **Figure 24.** F) where more than 23 million hectares of core forest transitioned to edge classes. For broad forest types, open forests and mangroves have the lowest mean FC, while swamp forests and the mixed evergreen and semi-deciduous rainforests have the highest mean FC (**Table 8**). The localized Maranthaceae forests have the highest mean condition. High condition forest (>80) is generally present in the dense forest ecosystems in Gabon, which have the highest mean forest condition, followed by Republic of Congo (**Table 9**). Large areas of lower condition (<50) are present in eastern DRC, along the Congo River and in the southwest corner of DRC, and south central Cameroon, while fragmented, low condition forests are predominant in the Central African Republic.

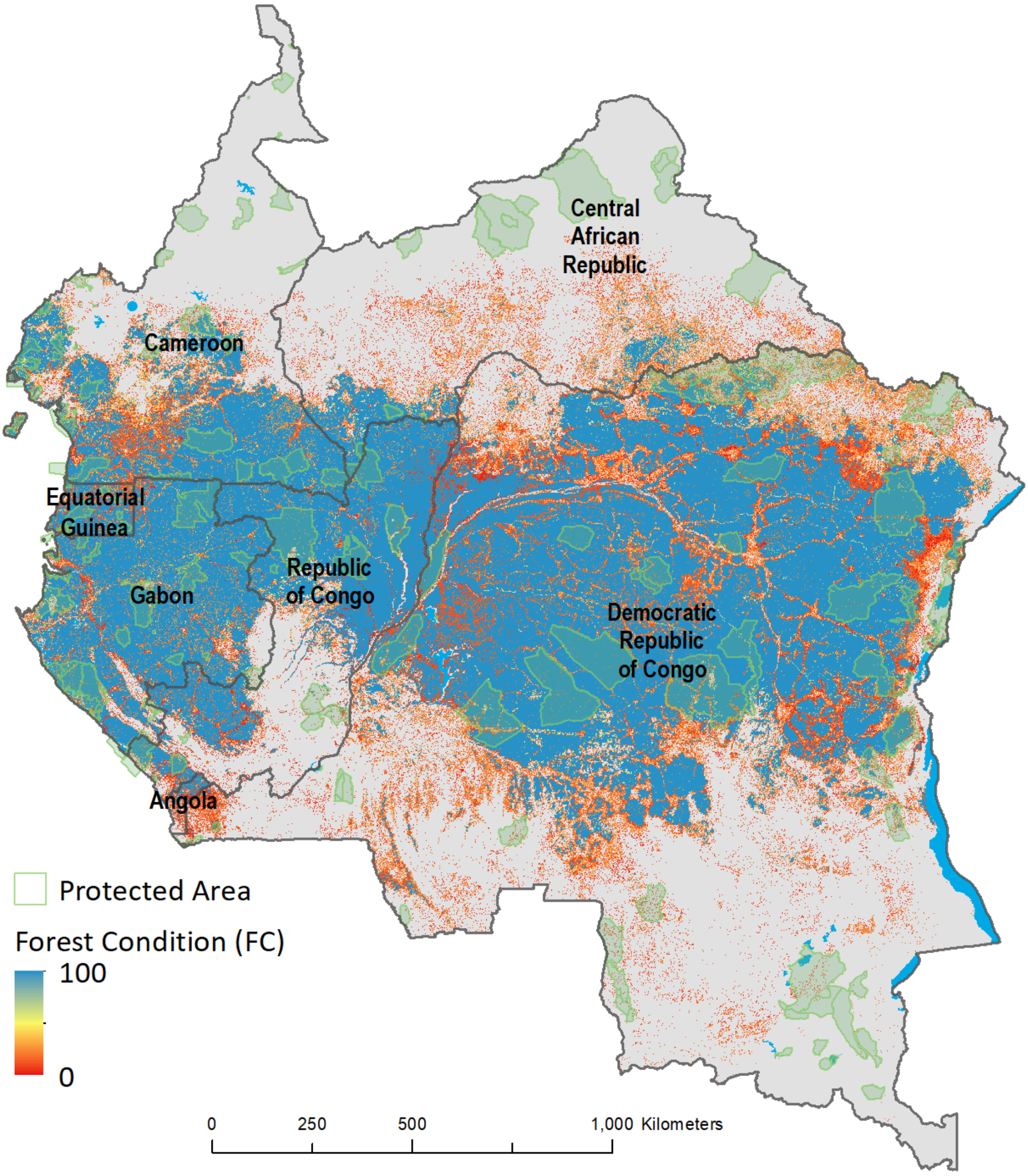

Figure 24. Forest Condition for Congo Basin forests (2015). Protected areas data from Pélissier et al., 2019 and WRI Forest Atlases (World Resources Institute, 2018)

Table 8. Mean FC by broad forest type.

Broad Forest Type	Total Area (ha)	Mean FC	Std. Dev.
Dense Evergreen Rainforest	4,457,859	82.13	32.24
Evergreen and Semi-Deciduous Rainforest	18,177,916	89.92	25.99
Semi-Deciduous Rainforest	104,332,094	85.24	30.38
Semi-Deciduous Rainforest with Pioneer	22,453,096	75.14	38.05
Maranthaceae	267,717	91.71	20.81
Swamp Forest	28,928,944	85.88	32.02
Mangrove	402,780	64.71	40.51
Open Forest	31,239,177	18.93	15.22

Table 9. Mean FC by Congo Basin country

Country	Total Area (ha)	Forest area 2015 (ha)	Mean FC	Std. Dev.
Cameroon	47,177,546	21,686,790	75.21	36.41
Central African Republic	62,889,075	11,385,949	45.47	39.32
Republic of Congo	34,220,955	23,701,530	84.91	31.97
Equatorial Guinea	2,701,407	2,594,197	77.27	35.99
Gabon	26,489,820	23,939,932	85.94	29.98
Democratic Republic of the Congo	234,751,788	126,437,088	73.25	38.58
Angola	712,269	514,097	52.46	43.05

3.6.2. Validating FC in the DRC

Using the detailed LiDAR dataset and random sample plots in the DRC, (n = 21,600) FC was shown to be significantly, yet weakly correlated with fractional cover, gaps, biomass loss and NBR anomalies, with the greatest negative correlation with gaps and biomass loss (**Figure 25**). The NBR anomalies also show the highest positive correlation with fractional cover, where greater negative anomalies are correlated with lower fractional cover.

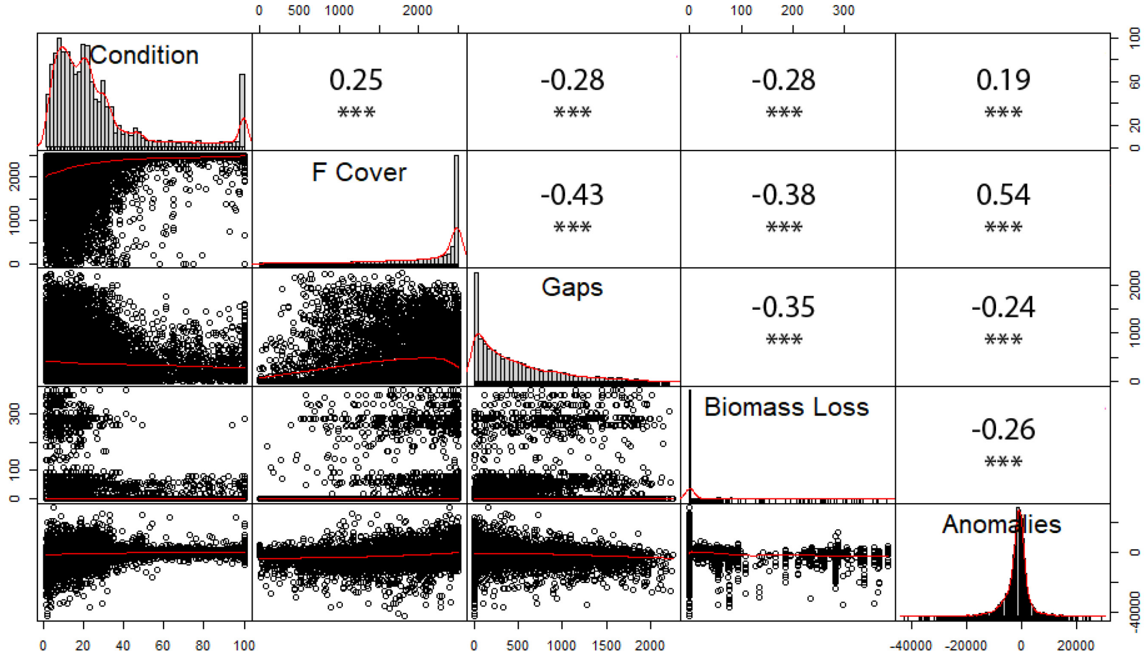

Figure 25. Correlation matrix of sampled variables including ecosystem condition, fractional cover at 1 ha (F Cover, Section 2.2.5), Biomass loss (Mg/ha, Section 2.2.2) and the NBR Anomalies Section (2.2.6). The distribution of each variable is shown on the diagonal, bivariate scatter plots on the lower left, and the correlation coefficient shown as a value. Significance levels are denoted by red stars (3 stars: p<0.001; 1 star: p<0.05)

When assessing gap area by transition type, gap area decreases significantly for stable classes (primary and secondary forest), with the highest gap area observed in areas which were identified as primary deforestation **Figure 26**). Gap area was significantly different deforestation and degradation, but not statistically different to discern changes in primary or secondary types of forest.

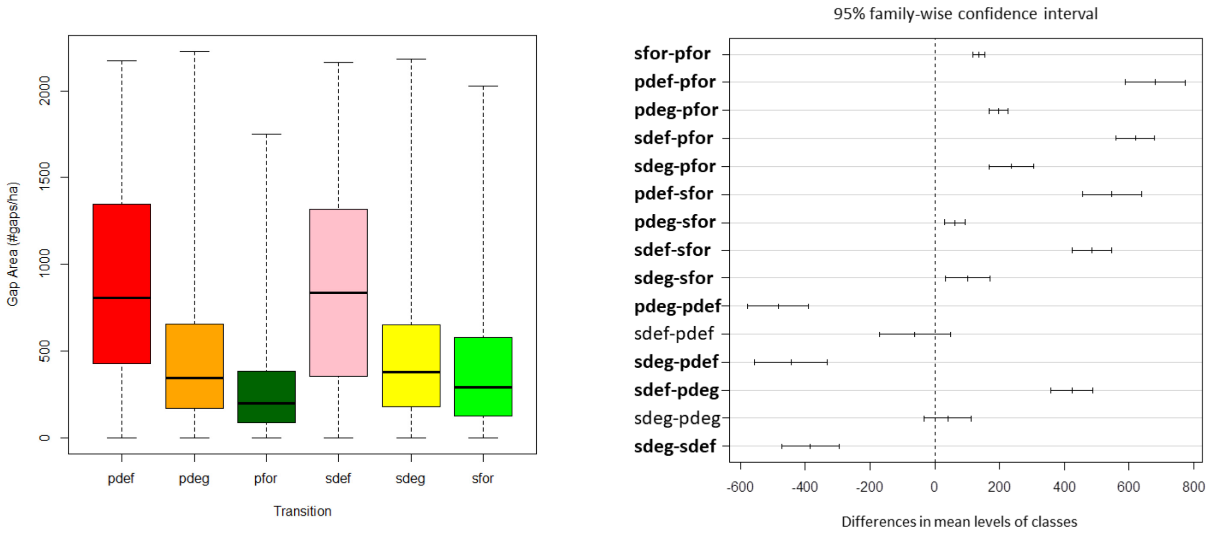

Figure 26. The relationship between gap area per hectare and transition type (left), and Tukey's HSD comparison of means, (right). Bold indicates significant difference between pairs. The color scheme matches the transitions in figure 2, and from Shapiro et al., 2016. (pdef = primary deforestation; pdeg = primary degradation; pfor = primary forest; sdef = secondary deforestation; sdeg = secondary degradation; sfor = secondary forest)

Mean cumulative negative anomalies were observed to be lowest overall in areas defined as primary or secondary deforestation, and less in degraded areas, and closest to zero in stable forest types with no change (**Figure 27**). All paired combinations were significantly different, with the exception of primary and secondary deforestation.

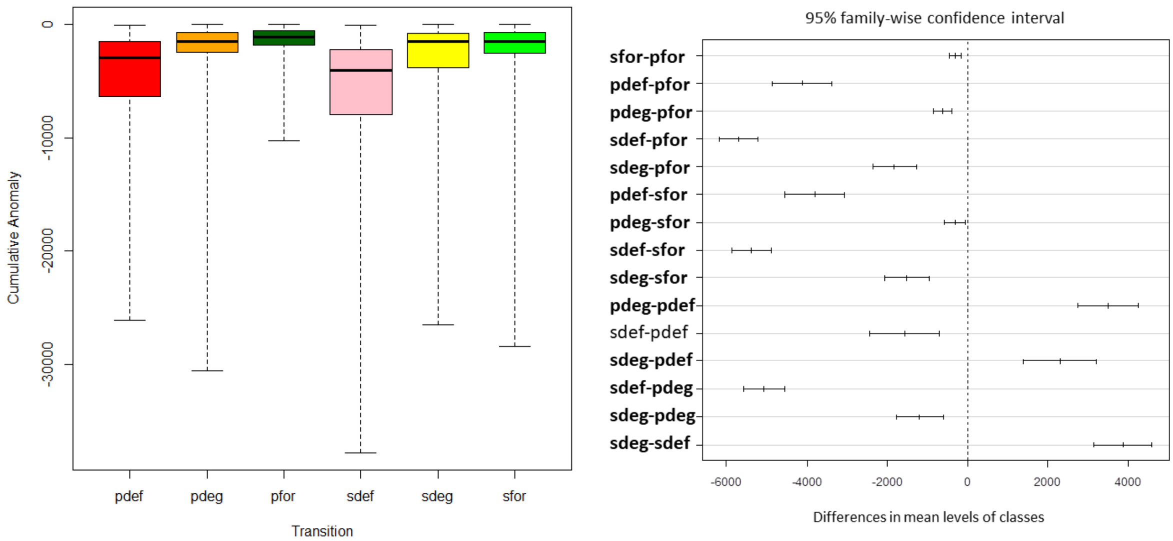

Figure 27. Magnitude of cumulative anomaly by transition type (left), and Tukey's HSD (right). Bold indicates significant difference between pairs. The color scheme matches the transitions in figure 2, and from Shapiro et al., 2016. (pdef = primary deforestation; pdeg = primary degradation; pfor = primary forest; sdef = secondary deforestation; sdeg = secondary degradation; sfor = secondary forest)

3.6.3. Red List of Ecosystems Assessment

Our assessment of the Red List of Ecosystem criteria indicates that 4 ecosystems are critically endangered, 15 endangered, and 14 vulnerable (**Table 10**; **Figure 28**). The remaining did not meet any of the category thresholds and are therefore listed as least concern. The full table of ecosystems and criteria are presented in the supplementary material, showing that criterion D, which was based on FC was also triggered when criterions A and B were, however, additional ecosystems met criterion D alone.

The four critically endangered ecosystems are located in DRC, notably in and around the Virunga and Kahuzi-Biega National Parks (**Figure 28**) are shown to have low condition, and experienced significant biomass loss and forest cover loss. DRC also hosts the majority of the endangered ecosystems, along the Congo River and in the west near Angola, along with the northern open forests. Central African Republic is dominated by fragmented, endangered open forests, and the Republic of Congo has large areas of vulnerable ecosystems. In the central cuvette, swamp forests are vulnerable in DRC and Republic of Congo. Several dense, evergreen and semi-deciduous forests in the northeast and northwest regions fall in the endangered categories, while three types of swamp forest ecosystems fall in the vulnerable category.

Table 10. Redlist of Ecosystem summary for 64 Congo Basin Forest Ecosystems

Final Status	Number of ecosystems	Total Area (ha)	% of Congo Basin Forest Area
CR	4	311,832	0.15
EN	15	32,756,664	15.25
VU	14	14,042,047	6.54
LC	31	167,636,697	78.06
Total	64	214,747,240	100.00

Of the 33 ecosystems qualified as above least concern, 21 qualified for ranking in a category above Least Concern for criterion A or B as well as D, indicating general agreement between the criteria (**Table 11**). An additional 12 ecosystems were assigned a threat ranking according to criterion D alone, meaning they did not undergo a significant change in extent, but rather extensive and significantly decreasing condition. These means that 11.6% of present forest ecosystems would have been missed as being categorized without applying FC. These ecosystems included several categories of open forests, which were assigned the higher threat class of endangered due to the extent and severity thresholds for criterion D, while all four critically endangered ecosystems were assigned a higher risk class due to criterion D than A or D. In contrast, no ecosystems were assigned a threat status according to A or B alone, which is expected as reduced area is associated with a reduced core area.

Table 11. Ecosystem Red List assessment for 64 Congo Basin Forest Ecosystems based on criterion A2b, B1 and B2 and D

General Forest Type	Code	Forest Type Extent 2000 (ha)	Forest Type Extent 2016 (ha)	Mean FC	A2b (adjusted % PRD)	B1 Extent (km2)	B2 Area (1% rule)	D2a affected extent (% PRD core forest in 2050)	D2a severity (% PRD forest condition 2050)	D3 extent (% core forest loss since 1850)	D3 Severity (condition lost since 1850)	Final Threat Status
Dense Evergreen	11320	1,414	1,332	28.06	28.27	117,779	6	87.37	90.44	84.79	71.94	CR
	11340	64,235	63,176	72.37	9.08	31,391	44	61.73	51.95	40.31	27.63	VU
	12120	127,724	115,908	64.84	39.05	1,252,571	401	48.35	48.72	64.66	35.16	VU
	12130	293,166	271,207	42.66	31.97	1,226,900	939	55.08	68.77	79.15	57.34	VU
	12140	3,683,258	3,652,941	85.91	3.84	1,805,672	2,523	25.36	25.99	19.49	14.09	LC
	12220	114,911	113,699	91.76	4.25	453,124	135	20.03	18.00	11.15	8.24	LC
	12240	26,543	26,321	84.10	4.70	107,017	46	39.95	38.58	19.36	15.90	VU
	12320	185,738	180,869	76.07	11.85	167,546	121	45.80	46.44	29.46	23.93	LC
	12340	3,012	2,980	66.67	6.01	22,156	9	48.99	54.95	41.70	33.33	EN
Evergren and Semi-Deciduous	22120	1,662,006	1,650,651	95.67	3.21	1,219,257	1,318	9.13	8.85	7.31	4.33	LC
	22130	385,836	369,374	65.22	19.48	1,200,163	1,059	42.08	51.35	48.55	34.78	LC
	22140	14,915,844	14,765,946	89.80	5.04	1,886,996	5,450	31.47	26.16	14.40	10.20	LC
	22220	1,029,960	1,023,036	96.01	2.77	287,906	467	15.59	11.97	5.92	3.99	LC
	22240	33,597	33,319	83.98	4.44	235,436	69	36.85	33.29	23.31	16.02	LC
	22320	258,645	247,788	72.36	19.49	111,203	197	60.09	58.63	33.33	27.64	VU
	22340	5,138	5,109	59.92	2.52	35,930	14	31.30	48.28	50.04	40.08	EN
Semi-Deciduous	31110	1,577,743	1,549,357	71.65	7.84	193,021	701	27.20	38.61	41.60	28.35	LC
	31120	29,266,061	27,585,817	80.90	24.46	1,279,272	5,896	44.44	42.17	26.97	19.10	LC
	31130	13,376,916	12,696,521	84.12	23.18	961,081	3,664	44.45	38.95	22.86	15.88	LC
	31140	37,851,190	37,051,712	85.30	10.24	1,924,336	7,737	41.80	35.57	21.42	14.70	LC
	31220	498,705	454,093	61.88	34.18	369,112	392	80.45	72.88	53.28	38.12	EN
	31240	75,450	74,388	73.36	7.09	252,923	89	55.07	47.77	41.55	26.64	LC
	31320	129,090	116,523	46.47	41.88	111,092	142	88.86	87.53	61.91	53.53	CR
	31340	14,949	14,806	62.51	4.96	39,374	27	39.95	54.97	45.78	37.49	VU

General Forest Type	Code	Forest Type Extent 2000 (ha)	Forest Type Extent 2016 (ha)	Mean FC	A2b (adjusted % PRD)	B1 Extent (km2)	B2 Area (1% rule)	D2a affected extent (% PRD core forest in 2050)	D2a severity (% PRD forest condition 2050)	D3 extent (% core forest loss since 1850)	D3 Severity (condition lost since 1850)	Final Threat Status
Semi-Deciduous	32120	8,740,924	8,627,203	95.31	6.48	911,114	2,573	19.21	14.07	7.64	4.69	LC
	32130	10,705,279	10,592,702	94.12	5.23	1,166,921	4,396	14.98	14.22	8.27	5.88	LC
	32140	3,190,203	3,136,105	83.83	7.68	1,019,159	3,006	44.24	38.61	22.30	16.17	LC
	32220	810,449	783,165	85.19	14.73	428,420	560	48.36	39.39	21.77	14.81	LC
	32240	10,654	10,557	82.60	5.10	200,429	35	47.46	36.06	29.31	17.40	VU
	32320	208,448	192,664	63.42	33.72	110,475	197	76.22	73.76	43.57	36.58	VU
	32340	2,116	2,103	72.88	3.45	18,753	5	49.69	48.41	36.81	27.12	EN
Semi-Deciduous with Pioneer	42120	3,213,222	2,949,922	74.20	34.01	489,205	1,677	60.99	57.02	34.68	25.80	VU
	42130	17,198,872	16,027,875	78.18	28.97	1,194,308	5,693	43.40	43.08	30.27	21.82	LC
	42140	2,467,033	2,342,183	59.96	22.49	869,131	1,485	73.78	72.83	47.95	40.04	VU
	42220	349,164	316,814	58.47	35.93	300,419	410	83.70	77.44	55.43	41.53	EN
	42230	922	901	80.32	12.73	10,118	1	39.35	21.75	81.24	19.68	CR
	42240	6,468	6,351	71.81	9.67	41,384	20	62.28	59.80	34.52	28.19	VU
	42320	180,406	160,827	42.89	45.23	167,140	208	89.20	88.59	66.03	57.11	CR
	42340	2,334	2,291	76.70	9.58	6,542	3	67.44	54.46	33.85	23.30	EN
Maranthacae	51140	270,382	265,991	91.71	8.00	33,354	188	33.88	22.58	15.40	8.29	LC
Swamp Forest	63151	4,537,018	4,068,227	70.64	42.14	376,553	2,433	74.67	67.72	38.91	29.36	VU
	63152	6,036,564	5,945,728	92.42	7.41	369,866	2,447	25.52	22.60	9.63	7.58	LC
	63153	1,783,496	1,753,679	89.16	8.00	380,728	1,571	32.24	28.34	14.52	10.84	LC
	63154	817,340	801,088	69.32	9.29	368,573	909	49.86	50.93	39.79	30.68	LC
	63155	1,033,979	1,023,902	91.32	5.11	266,923	896	29.38	25.94	10.55	8.68	LC
	63156	1,548,171	1,540,305	94.45	2.72	266,485	824	19.38	16.73	6.97	5.55	LC
	63157	311,196	307,660	86.97	5.92	251,245	386	33.06	30.52	18.05	13.03	LC

General Forest Type	Code	Forest Type Extent 2000 (ha)	Forest Type Extent 2016 (ha)	Mean FC	A2b (adjusted % PRD)	B1 Extent (km2)	B2 Area (1% rule)	D2a affected extent (% PRD core forest in 2050)	D2a severity (% PRD forest condition 2050)	D3 extent (% core forest loss since 1850)	D3 Severity (condition lost since 1850)	Final Threat Status
	63161	1,671,255	1,498,735	70.73	41.92	480,285	1190	72.39	65.72	39.41	29.27	VU
	63162	4,642,848	4,541,822	89.57	10.07	490,315	1842	32.90	29.59	13.29	10.43	LC
	63163	3,205,778	3,164,469	91.21	5.84	490,983	1652	25.38	22.87	11.41	8.79	LC
	63164	1,142,687	1,124,208	68.33	7.22	457,531	959	51.62	49.48	40.53	31.67	VU
	63165	554,484	546,680	92.41	6.44	288,024	691	25.78	22.84	9.53	7.59	LC
	63166	2,014,147	2,003,064	96.19	2.72	292,569	870	13.08	11.65	4.73	3.81	LC
	63167	209,992	206,923	83.96	6.59	292,902	396	35.04	33.51	21.01	16.04	LC
	81110	9,077,498	8,912,775	19.40	8.12	1,623,726	6243	55.48	88.32	96.92	80.60	EN
Mangrove	71140	404,083	401,897	64.71	2.54	224,232	174	29.77	43.69	45.02	35.29	LC
Open Forest	81120	7,915,813	7,287,374	21.79	31.61	1,051,266	4280	66.17	76.39	97.38	78.21	EN
	81140	2,752,083	2,585,455	19.26	26.52	2,773,294	2570	56.22	85.19	95.00	80.74	EN
	81220	577,782	544,560	22.52	23.91	205,313	431	64.98	82.46	97.06	77.48	EN
	81240	85,797	85,004	21.58	4.39	261,394	136	51.30	81.04	96.18	78.42	EN
	81320	282,233	263,227	14.00	28.64	80,439	229	70.74	88.77	98.32	86.00	EN
	81340	38,659	38,139	18.41	5.67	90,736	62	30.56	82.49	95.91	81.59	EN
	82130	10,614,508	9,686,379	16.25	34.14	1,967,561	8913	70.42	86.99	98.92	83.75	EN
	82230	551,822	540,422	18.26	9.61	908,869	846	35.67	82.29	99.56	81.74	EN

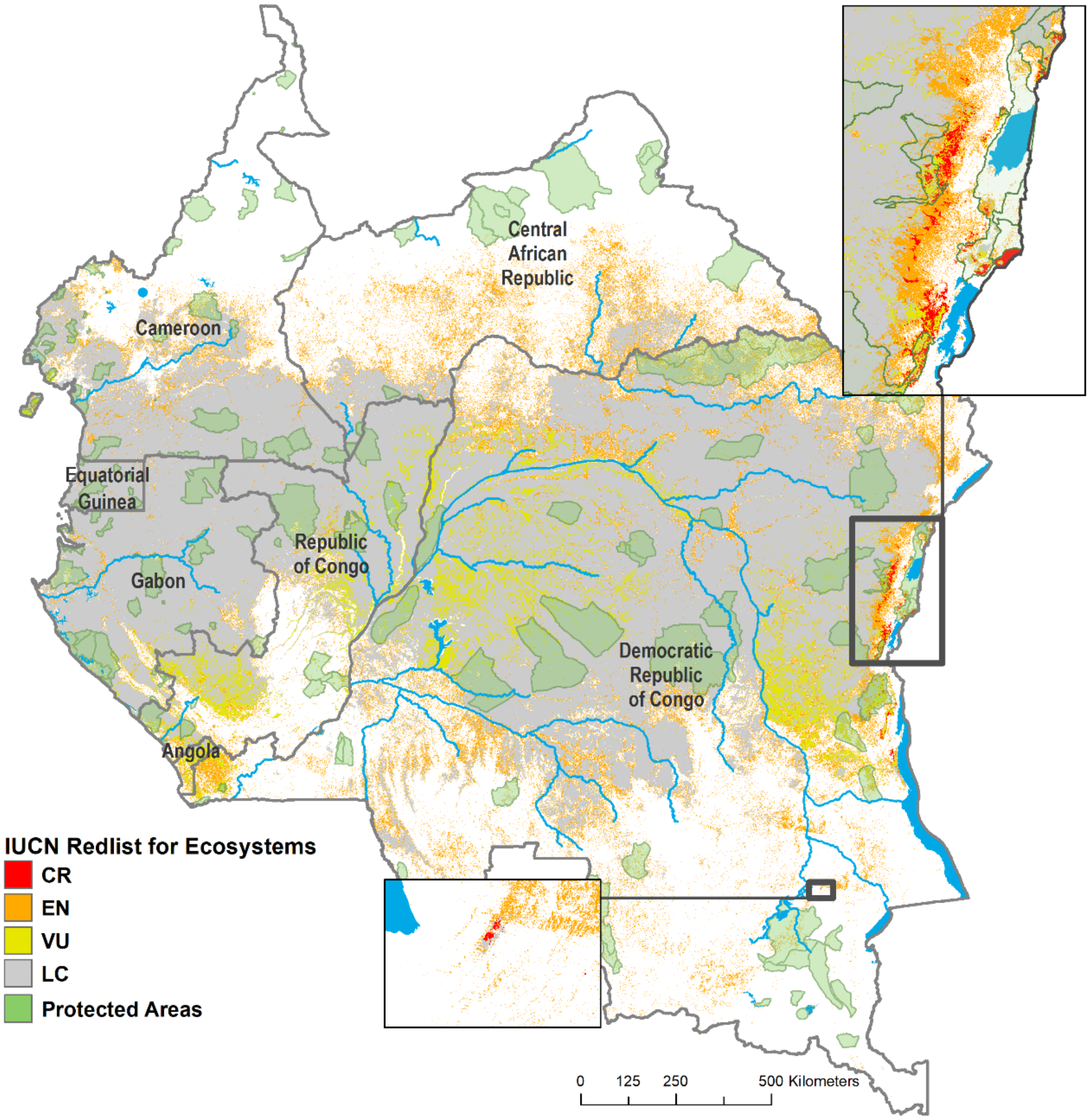

Figure 28. IUCN Red List assessment for Congo Basin forest ecosystems

The trajectory of FC over time assessed differs for each ecosystem and Red List category (**Figure 29**). The critically endangered ecosystems are shown to decrease more rapidly after 2012, except for the evergreen/semi-deciduous ecosystem (upper most red line) which has a slower decline in FC over time, and its threat status mostly due to limited extent. The lowest lines represent the open forests which overall lower condition compared to other ecosystem types, as they are greatly fragmented and as a result have a much lower than the maximum potential AGB.

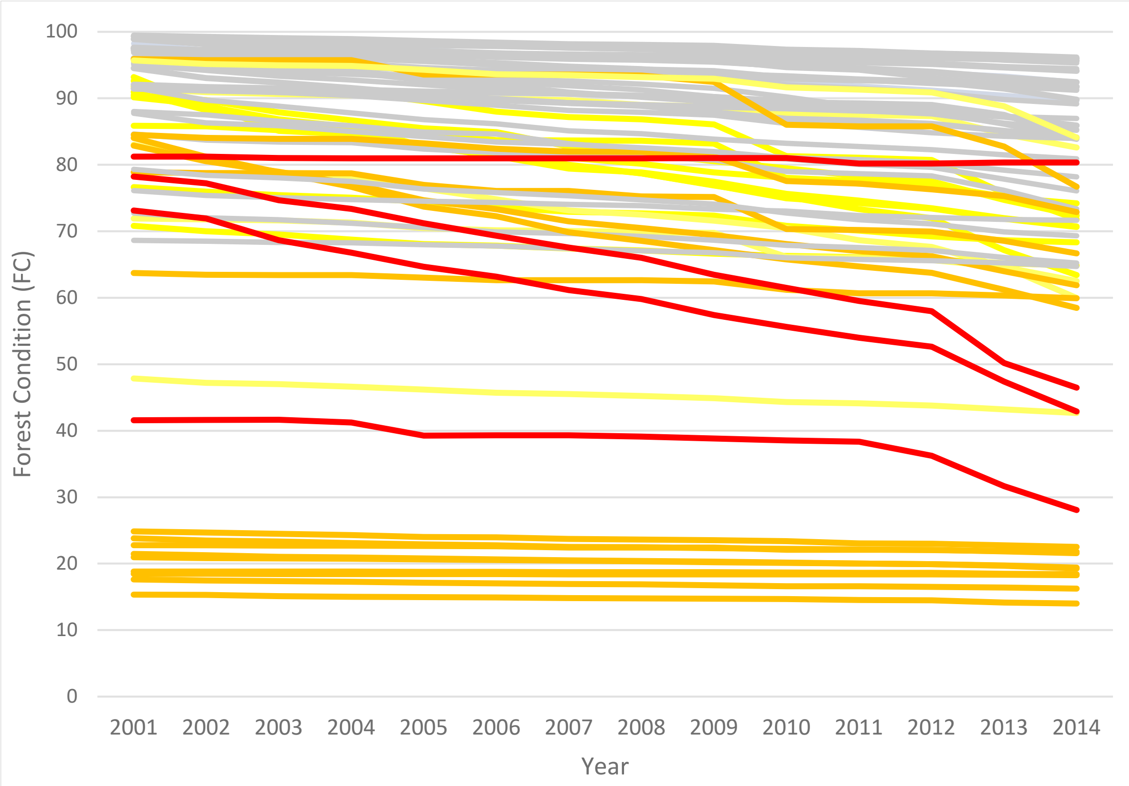

Figure 29. Annual FC of each forest type; grouped into colors according to red list classification (**Figure 28**)

3.7. Discussion

We identified 64 unique forest ecosystems that provide a fundamental basis for representative and comprehensive conservation planning in the Congo Basin region. Although forest cover is still quite extensive, the impacts of forest degradation and fragmentation are high (33% of overall forest area), reducing the capacity of forests to support biodiversity and ecosystem services. We found notable areas of degradation in eastern mountains of DRC and southern, northern peripheries of semi-deciduous forests stands; the open forests of Central African Republic and southern Cameroon. Our forest condition index assesses the extent of degradation, which can be used within the Red List for Ecosystems risk classification framework. Through our analysis we have developed functional tools to support the RLE by defining ecosystems with reduced extent and significantly reduced condition. The application of FC to evaluate potential ecosystem collapse has provided additional information than extent or size alone (criterions A and B) and 18% of forest area would not have been identified as threatened if it were not applied.

We characterize FC as a combination of biomass lost and fragmentation over time to produce a metric on a continuous scale from 0-100%. In contrast with indicators that provide a single snapshot in time, binary assessments of intact versus not (Potapov et al., 2008; Tyukavina et al., 2016) or classifications of forest intactness (Molinario et al., 2015) , FC has the unique element of incorporating a temporal dimension of biomass loss to produce a relative index of degradation on a continuous scale. This output allows an end user to decide their own classification or thresholding approach which could be specific to their geography. The integration of temporal information is an important requirement for accurately identifying the forest degradation process, and differentiating a regenerating secondary forest from one which is stable, or from one which may have previously been intact (Thompson et al., 2013). The overall approach to developing this metric lies in a specific definition of forest degradation based on AGB, related to the climate regulating services of intact forest ecosystems (Pan et al., 2011). Therefore, the assessment of FC over time provides an important metric for monitoring forests capacity to either sequester or emit forest carbon over time, but is not limited to such use as it can be used to prioritize restoration efforts.

FC was positively correlated with forest canopy fractional cover, biomass lost over time, and negatively associated gap area at 1 hectare scale, validating the theoretical model of subsequent states of degradation presented in **Figure 20**. The assessment of forest transitions (primary and secondary deforestation and degradation) gap area and cumulative anomalies of direct assessments of long-term changes in NBR provide more context in describing the successive forest states which lead to deforestation. The incremental significant differences point to an indicator which can accurately discern deforestation from degradation, and the combination of temporal data with biomass allows for more information than any of these variables alone. FC and transitions together provide an informative stratification for cost-effective conservation planning, monitoring and climate change interventions, as direct measures of forest gaps, fractional cover or direct remote sensing metrics alone do not inform the prior status of a forest ecosystem. High resolution forest structure and gap area require significant investments into very high resolution airborne or drone data which are not always feasible. While fractional cover remains highly correlated with the other validation variables, fractional tree cover from satellite cannot adequately discern different forest heights or high or low biomass ecosystems. Additionally, a forest with a continuous canopy will have the same fractional cover regardless of its biomass, structure, making it inadequate to independently assess relative degradation state.

The Landsat observation frequency is not always ideal for wall-to-wall degradation detection, particularly before Sentinel-2, and higher resolution sensors such as Planet data have cost barriers and are less spectrally consistent than lower resolution sensors. While the methodology we developed for measuring forest degradation is an indirect method, incurring greater assumptions and over-simplification of processes, they can be adapted and flexible to rapid monitoring assessments. Indirect methods are generally simpler, but can provide the necessary information for conservation planning or targeting of interventions (Grantham, Shapiro, et al., 2020; Pelletier et al., 2013). We have demonstrated that the integration of temporal information can differentiate primary from secondary deforestation where a direct spectral measure or estimation of fractional cover cannot.

Our validation shows that FC is correlated with decreasing gap area, increasing canopy height and cumulative NBR anomalies, supporting the theoretical framework and transition definitions proposed in **Figure 20**. Tukey HSD pairings of differences in mean canopy gap, and anomalies are significantly different, with the exception of primary and secondary deforestation, which were not significant in the paired variable tests. This is not entirely unexpected, as a deforested ecosystems are similar whether it was previously intact or already degraded. For this reason, FC provides important contextual information, to differentiate the differences in subsequent degradation transitions from stable secondary or degraded forests and provides a suitable indirect method to meet most monitoring needs.

For direct remote sensing approaches to degradation, indicators directly related to canopy changes are necessary (Mitchell et al., 2017). To validate our approach, we chose NBR as a suitable index to detect pixel components of bare soil within tropical forests, an indicator of canopy closure and does not suffer from the saturation effects of NDVI, or the calibration required for spectral mixing approaches (Langner et al., 2018). The presence of bamboo understories or deciduous species in the forest community, however, could falsely detect canopy openings, however a long-term cumulative anomaly approach, in which increases in NBR cancel out decreases should effectively remove seasonality and discern long term changes. Despite a suitable direct indicator, cumulative NBR anomalies alone cannot discern degradation events which may be followed by quick regeneration, nor does it differentiate between different types of forest dynamics. An assessment of trends, for example using LandTrendr (Kennedy et al., 2010), might be required to investigate various transitions, but still aren't designed to assess the relative changes occurring in primary or secondary forest types, or elements correlated to AGB, as these require consistent long term cloud-free time series data and calibration information that remain sensitive to short term dynamics.

FC can also support conservation prioritization and planning in many ways. Our approach can integrate a flexible number of time steps (minimum of two to incorporate the temporal dimension) but can be calculated over subsequent annual time series (**Figure 29**) which can support adaptive monitoring or alert approaches, for example, identifying when an ecosystem FC dips below a certain threshold. This method has also supported the prioritization of forest areas for high conservation value assessments (Grantham, Shapiro, et al., 2020) or via the ecosystem Red List addressed in further detail in the next section. We observed varying estimates of FC for individual ecosystems, where areas with lower condition may be prioritized for restoration activities, while those with high overall condition could be managed for conservation and carbon stock maintenance.

In comparison with binary indices such as Intact Forest Landscapes (Potapov et al., 2008), hinterland forests (Tyukavina et al., 2016), methods identifying core and edge (Haddad et al., 2015; Riitters et al., 2015), or approaches classifying post-deforestation changes and land use (Molinario et al., 2020; Molinario et al., 2015), FC provides a continuous index which has parameters which can be adjusted and applied according to specific needs or geographies. This is important for adapting the method to different context or forest types – although we do note that our metric might be biased towards continuous forest types, for example dense forest stands, as opposed to naturally open forests which are patchy in nature.

Our results are supported by analyses such as Molinario et al., (2020) who have defined different land cover trajectories and impacts for different edge types (inner versus outer). In particular in the Congo basin, FC identified many forests which happen to fall outside the IFL definition yet are the locations of essential corridors, valuable species habitats, or are identified as Key Biodiversity Areas (KBA; (Birdlife International, 2018; IUCN, 2016). In addition, a continuous metric integrating the temporal history supports conservation prioritization and methods to rank areas by FC for different interventions – such as active restoration or mitigation activities to promote regeneration.

3.7.1. Application to IUCN Red List of Ecosystems

The application of FC for Criterion D of the IUCN Red List enabled us to assess the disruption of biotic processes over a large region, assessing both spatial extent of impact and the severity, which could be otherwise difficult to measure or estimate, for example biotic processes related to the loss of species richness, or changes in trophic diversity (see supplementary material of Bland et al., 2015). We found that we would have under-estimated ecosystem risk by assigning the Red List category based only on the geographic extent and area of occupancy by applying criterion A and B only. The additional element of FC is necessary to assess ecosystem status independent of spatial extent. As our analysis has shown, 12 of the 64 ecosystems, representing more than 11% of total forest area in 2015 did not meet the risk criteria for A or B, but were triggered by criterion D, while no ecosystems were classified at risk with only A or B. This was observed in all open forest categories in dryland ecosystems which despite their very fragmented state can still potentially harbour high AGB (Bastin et al., 2017). This high potential AGB in a very fragmented forests results in low FC and triggers extent and severity of criterion D, while their large geographic distribution do not trigger criterion A or B. This shows that A and B do not adequately integrate fragmentation and pattern to assess ecosystems. It is also possible that these naturally fragmented forests are under-estimated by our metric focused on connectivity, meriting further attention. We do ultimately demonstrate that criterion D captures the ranking of several criteria and is an effective indicator for the ecosystem risk assessment, in both extent (calculated as % core forest) and severity (measured by mean condition), as opposed to A and B which are focused primarily on extent. As ecosystem functioning, notably species biodiversity greatly affected by fragmentation (Haddad et al., 2015), it is logical and necessary to include spatial pattern metrics in an ecosystem risk assessment designed for conservation. The FC estimate directly addresses the concept of the endpoint (FC=0) of ecosystem decline, supporting the scientific underpinning of the ecosystem red list process (Keith et al., 2013) and can also be applied to other ecosystem prioritization efforts for conservation. Finally, this assessment has shown that that the principal driver of ecosystem collapse in Congolese forest systems are related to fragmentation and degradation, and while deforestation overall may remain low, there are significant pressures that can affect forest health and associated biodiversity (Grantham, Duncan, et al., 2020).

The availability of temporal data and trends over annual time steps enables a forward and backward modelling to fit the criteria requirements of estimating changes in FC over 50 years past or future predictions. Most importantly, the method has enabled the identification of critically endangered ecosystems among the large extensive forests in the Congo Basin. In particular, the montane and sub-montane forests identified as critically endangered are already limited in extent and have suffered deforestation and degradation, and are home to the Eastern Chimpanzee and Eastern Gorilla habitat, which are endangered and critically endangered species on the IUCN Red List respectively (IUCN, 2019). These habitats are presently within iconic protected areas such as Virungas National Park, which have undergone recent forest loss and threats from oil development, demonstrating the limits of formal protection and World Heritage status in a situation of political instability, high levels of poverty, and conflict (Hochleithner, 2017; United Nations Economic Commission for Africa, 2015). The other critically endangered habitat identified is currently unprotected and lies between several mining concessions which might present acute threats in the future (Pélissier et al., 2019). Additionally, particular consideration should be given to ecosystems in endangered and vulnerable categories which lie along southern edge of the dense forest ranges. These are likely naturally more fragmented open forests, making them more susceptible to encroachment by humans and are present among mixed agricultural landscapes and could be sites to focus restoration activities.

3.8. Limitations

All metrics or approximations such as indirect methods or proxies come with the risk of oversimplifying or missing crucial detail that one might observe with direct methods, or for example observing forest degradation events with very high-resolution imagery. FC relies on accurate forest cover maps, which are not always possible with limited validation or available quality data, or at regional scales that can be affected by varying forest definitions. For example, the global forest cover maps from Hansen et al. (2013), which are most often used due to access, consistency, resolution, can be difficult to harmonize at the regional global scale because the forest cover threshold varies by latitude, along with different country definitions of forest (Romijn et al., 2013). For this reason, we developed forest ecosystem maps integrating data from various sources and validated with expert opinion to limit bias from one dataset.

FC is a relative index based on biomass estimations, which will always include an element of uncertainty. We overcome this by not using AGB data directly, but rather averaged over forest strata, which should minimize any large errors or inconsistencies, unless most of the ecosystem is already degraded. We base our assessment on the assumption that the maximum potential biomass is present in intact, core forest – this can be hindered by the quality of the AGB map, or ecosystems that are so severely degraded that no core forest area exist. Additionally, as the changes in biomass are relative, the actual biomass estimates do not necessarily bias the final condition estimate to a great extent – if biomass is generally over or under-estimated the condition value is not affected. Next, the estimate of maximum potential FC depends on the biomass of forest types at an initial, presumably intact state. For forest types which are already degraded or have low biomass initially based, subsequent condition estimates will be related. For this reason, we recommend that the forest condition index in tandem with the transition classes to adequately identify the current state in the potential degradation time series.

3.8.1. Future Work/Implications

Detecting changes in forest cover condition and degradation alone does not meet all the needs for management in the face of increasing population and threats, and new drivers of changing climate. A further step in the analysis is to undertake a geo-spatial assessment of drivers of degradation, to support better land planning and mitigation strategies. An assessment of shifting cultivation drivers and change is provided by (Molinario et al., 2015) which adds a further relevant level of refinement to assign types of transitions to drivers or assess post deforestation land covers. A more in-depth analysis of the complex interactions and changes in drivers over time could provide a finer assessment to manage the causes of deforestation in DRC and define and project future risks and scenario assessment.

3.9. Conclusions

The outlined approach to assessing FC has provided a consistent and repeatable tool for evaluating forest over time allowing us to distinguish stable, degenerating and regenerating forest via a continuous metric, according to a biomass definition of forest degradation. We have shown that the amount of intact forest in the Congo Basin has decreased from 78% in 2000 to 67% in 2016 with over 24 million hectares of forest degraded in that time period. FC is inversely correlated with canopy gap density, and positively correlated with cumulative NBR anomalies. We demonstrate the application for ecosystem Red Listing, using FC to identify potential ecosystem collapse, and found 4 critically endangered forest ecosystems in the DRC. We demonstrate that for understanding the threatened status of ecosystems, quantifying condition can be just as important as understanding its change in extent or rarity. We propose to integrate FC into future conservation assessment and prioritization approaches.

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3.10. Supplementary Material

All geo-spatial data are available via GLOBIL.panda.org: https://arcg.is/LvqvD

The Google earth engine script used to run assess the NBR cumulative anomaly is here: https://code.earthengine.google.com/c921aea08a693caaedd2414425744f6e

Table 12. Forest Ecosystem Types of the Congo Basin are coded according to 5 groupings and data sources.

BROAD ECOSYSTEM TYPE	CODE
Evergreen Rainforest (Philippon et al., 2018)	10000
Evergreen and semi-deciduous Rainforest (Philippon et al., 2018)	20000
Semi-deciduous Rainforest (Philippon et al., 2018)	30000
Semi-deciduous Rainforest with pioneer (Philippon et al., 2018)	40000
Maranthaceae (zone defined from expert input)	50000
Swamp Forest (Betbeder et al., 2014)	60000
Mangrove (Giri et al., 2011)	70000
Open forest(Hansen et al., 2013)	80000
CLIMATE	
northern equatorial (Philippon et al., 2018)	1000
southern equatorial (Philippon et al., 2018)	2000
(Betbeder et al., 2014)	3000
ELEVATION	
lowland (0-1100m above sea level)	100
submontane (1100-1750m)	200
montane (>1750m)	300
BIOGEOGRAPHICAL	
northern (north of Equator)	10
northern eastern - North and east of Congo River	20
southern - south of Congo River	30
northwestern - north and west of Ubangi river	40
eastern - east of Congo River	50
western - West of Ubangi and Congo rivers	60

FLOODED AND SWAMP FORESTS	
Irregularly Flooded Swamp Forest (Betbeder et al., 2014)	1
Seasonal Short-Lasting Flood Pulse Swamp (Betbeder et al., 2014)	2
Stable Water Level Swamp Forest (Betbeder et al., 2014)	3
Seasonal Flood Pulse Swamp Forest (Betbeder et al., 2014)	4
Palm-Dominated Seasonal Short-Lasting Flood Pulse Swamp Forest (Betbeder et al., 2014; Dargie et al., 2017)	5
Palm-Dominated Stable Water Level Swamp Forest (Betbeder et al., 2014; Dargie et al., 2017)	6
Palm-Dominated Seasonal Flood Pulse Swamp Forest (Betbeder et al., 2014; Dargie et al., 2017)	7

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3.12. Further Consideration

Given limited resources for conservation and sustainable management, there is an urgent need to locate the most valuable areas are to focus conservation effort and maximize potential benefits. The FC metric was integrated into a regional scale prioritization assessment to identify and rank the most intact, functional forest ecosystems that are the most likely to harbor biodiversity and resilience to face future threats. Systematic conservation planning is urgently needed in the Congo Basin to identify important areas for biodiversity conservation, while also maximizing areas with the highest forest intactness using multiple indicators. This planning effort is not only to identify new protected areas, but plays a role in other management regimes, for example for protection of high conservation value (HCV) areas in sustainable timber concessions. For this reason, the Forestry Stewardship Council (FSC) requested a regional HCV assessment which ranked connected, intact, lowest threat and high biodiversity forests over the entire Congo Basin. FC played a central role in defining intact forests, through its unique ability to integrate a long-term history into the variable rather than a single snapshot in time. FC was combined with human threat to create a Forest Intactness Index which was used within Zonation software to run successive iterations to produce the best scenario to maximize all variables. In this study, it was found that conservation value ranking based on FC alone was not enough to ensure ecosystem representation – as that some ecosystem types are far more degraded than others. A prioritization based on biodiversity or representation alone without taking FC into consideration runs the risk of selecting low quality or degraded forests when intact ecosystems might be present.

The requirements for HCVs include intact, connected habitats with high biodiversity that most represent the diversity in forest ecosystem types – therefore including the FC metric as well as biodiversity and threat indicators. The final prioritization is shown in **Figure 30**. In this scenario protected areas were "locked" into the selection, and the remaining forest area was selected to maximize the variables described above. The dark blue areas show the locations of ranked HCVs, which are considered forests of maximum value both ecologically and functionally.

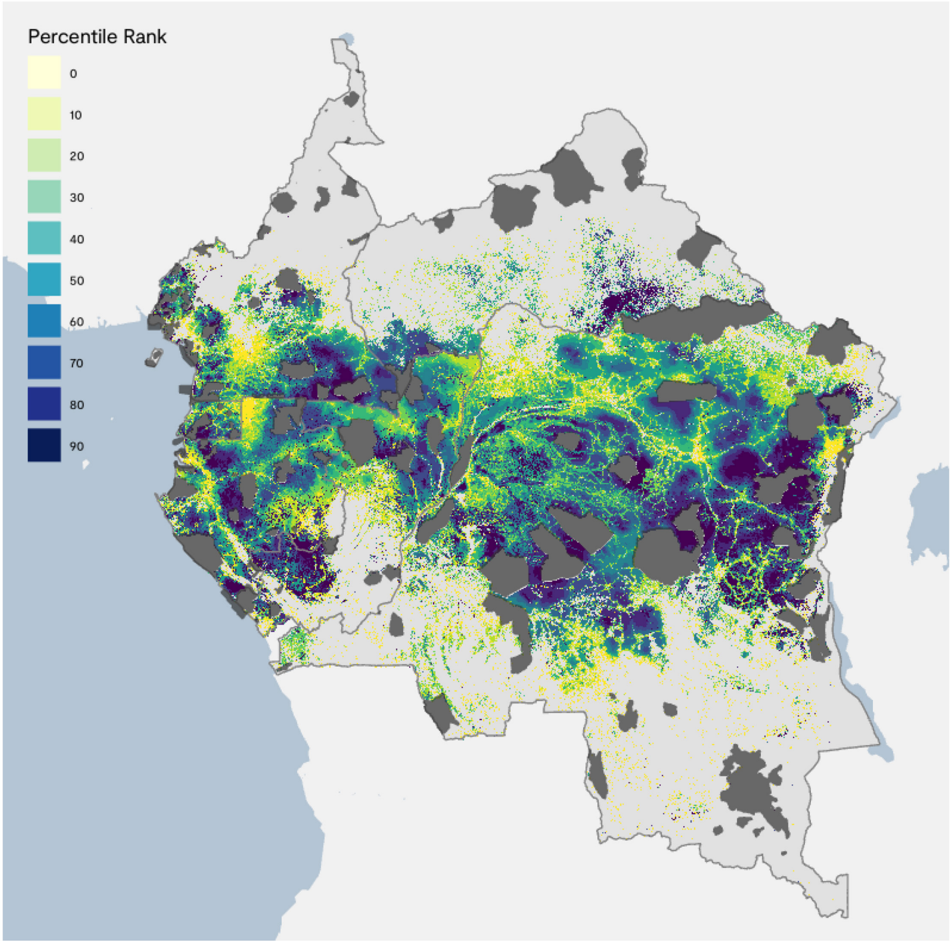

Figure 30. Regional prioritization of HCV areas for the Congo Basin (Grantham, Shapiro, et al., 2020)

The FC metric concept was also applied to assess forest integrity, quality at large scales. The forest landscape integrity assessment (Grantham, Shapiro, et al., 2020) integrates the concept of fragmentation and change from this doctoral research as one of the metrics on anthropogenic modification of forests. Meanwhile the forest structural condition index (Hansen et al., 2019) relies primarily on tree cover loss and canopy height combined with the human footprint and disturbance history to assess forest quality.

While these efforts make inroads into assessing the human impact on forests, they mostly consider that drivers, threats are static in time. Yet we know that change in time and space, and are even more likely to under future climate scenarios. These also fail to separate the relative impacts of drivers in favor of their combined combinations, without addressing relative impact, potential interactions, or spatial and temporal dynamics. For this reason, an up-to-date assessment of drivers or spatial determinants of forest disturbance is needed to determine where the proximal causes of forest disturbance or changing, how far the impacts can reach and where they are most pertinent for context-specific interventions.

Chapter 4: Proximal causes of forest degradation in the Democratic Republic of the Congo vary in space and time

This chapter uses econometric statistics to evaluate the relative impact of various drivers – land use, accessibility, fires and conflict – on forest condition.

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Abstract

Forest degradation, generally defined as a reduction in the delivery of forest ecosystem services, can have long-term impacts on biodiversity, climate, and local livelihoods. The quantification of forest degradation, its dynamics and proximate causes can help prompt early action to mitigate carbon emissions and inform relevant land use policies. The Democratic Republic of the Congo is largely forested with a relatively low deforestation rate, but anthropogenic degradation has been increasing in recent years. In this study we assess the impact of eight independent variables related to land cover, land use, infrastructure, armed conflicts, and accessibility on forest degradation, measured by the Forest Condition (FC) index, from 2002 to 2016. We employ spatial panel models with fixed effects using regular 25 km x 25 km units over five 3-year intervals. The regression results suggest that the presence of swamp ecosystems, low access (defined by high travel time), and forest concessions are associated with decreased forest degradation, while built up area, fire frequency, armed conflicts are associated with more forest degradation. The effects of protected areas and mining depend on the inclusion of a spatial neighborhood. We assess the impact of neighboring units on FC and find that all variables within the 50km spatial neighborhood have a greater effect on FC than the on-site spatial determinants, indicating the wider influence of drivers beyond the 25km square unit. In the case of protected areas, we unexpectedly find that protection in neighboring locations leads to higher forest degradation, suggesting a potential leakage effect, while the local protected area variable has a positive influence on FC. We evaluate the trends of fires and conflicts after the analysis period until 2020, and using Kendall-Mann trend statistic determine that significant increases in conflicts and fires are spatially divergent. Overall, our results highlight how assessing the proximate causes of forest degradation with spatiotemporal analysis can support targeted interventions and policies to reduce forest degradation while accounting for effects of variables in neighboring areas.

4.1. Introduction

The degradation of natural forests is a serious problem with resonating impacts around the world, from significantly contributing to greenhouse gas emissions (Simula & Mansur, 2011), biodiversity loss (Foley et al., 2007), reductions in water regulation (Lele, 2009), and ultimately reducing the ability of forests to provide ecosystem services linked to food and goods which sustain local livelihoods (Lambin & Meyfroidt, 2011). Successful implementation of actions to reduce forest degradation, such as climate-relevant policies for emissions reduction and nature-based solutions requires prompt, well-informed, and appropriate actions (Griscom et al., 2017). The policy decisions based on available information, resources, socioeconomic conditions, and economic risk play important roles in how humans manage forests (Angelsen & Kaimowitz, 1999). A thorough understanding and quantification of the proximate causes and spatial determinants of the degradation, their magnitude, and spatial extent are needed to prevent degradation from eventually turning into deforestation (Griscom et al., 2020).

Deforestation is the result of forest loss or conversion to alternative land use, while degradation can fundamentally alter a forest without reducing its area or definition as a forest (Vásquez-Grandón et al., 2018). The identification of the proximate causes and spatial determinants of degradation is complicated by varied temporal time scales, dynamics, extent, definitions, and perceptions. Although deforestation and degradation can be closely correlated (Defourny et al., 2011), they differ fundamentally in terms of definition and impacts on ecosystem services. The quantification of drivers of deforestation and degradation is not only important for targeting national strategies to reduce the emissions from deforestation and degradation (REDD+), but have wide applications to sustainable development initiatives supporting local economies as well as conservation efforts seeking to reverse or slow the significant downward trends in forest cover and quality (Bernhard et al., 2020). A proper understanding of the proximate causes and determinants of degradation is essential for aligning policies with the appropriate actors (Tegegne et al., 2016), but available quantitative information on degradation drivers and how they interact at various scales is still quite limited. Degradation is often a precursor to deforestation in tropical areas (Gerwing, 2002; Vancutsem et al., 2021). This means that timely and accurate assessment of degradation risk is of utmost importance to prevent deforestation before it happens, and to improve and target mitigation activities.

The causes of forest disturbance are driven by multiple synergistic factors acting together, rather than single variables alone (Geist & Lambin, 2002; Megevand, 2013), meaning that policies and responses need to address a variety of factors and their interactions. In this study we use spatial panel regressions to assess the impact of multiple proximate causes and spatial determinants of forest degradation over time and space in the Democratic Republic of the Congo (DRC) using a novel forest condition (FC) metric (Shapiro et al., 2016). The DRC holds the largest intact tract of tropical forest in Africa, hosting a wealth of biodiversity in a globally important carbon sink to mitigate climate change, while also supporting the livelihoods of millions of people (Molua, 2019). National rates of deforestation are relatively low, but in the last ten years has nearly doubled to about 0.5% per year (FAO, 2020); this trend could continue with an increasing population dependent on natural resources, unregulated timber and mineral exploitation, and conflicts over these resources (Kengoum et al., 2020). The DRC is vast, with large variations in the rates of forest loss, which are due to different demographics, threats, political frameworks, that require tailored policies and management. Unfortunately, the extent of forest degradation is still poorly understood in the DRC but can potentially result in more emissions than deforestation (Pearson et al., 2014; Pearson et al., 2017), particularly under the high prevalence of resource-based livelihood activities, such as harvesting for fuelwood, unsustainable bushmeat hunting which affects natural forest regeneration (Harrison, 2011), and expansion of small-scale agricultural activities. The lack of understanding of the causes and determinants of forest degradation in the DRC is relevant because nearly 30% of total loss of primary forest between 2000 and 2015 was degraded before being deforested (Shapiro et al., 2016).

Direct or proximate causes of degradation have been identified as occupying five main themes: the expansion of commercial and subsistence agriculture, mining and infrastructure development, and urban expansion (Hosonuma et al., 2012). A major indirect cause of forest disturbance in the DRC is extreme poverty, which affects a majority of the population (World Bank, 2020), is closely linked to forest dependent behaviors, and is an additional contributing factor to forest degradation (Nerfa et al., 2020). This situation is compounded by political instability and an ongoing humanitarian crisis due to decades of armed conflict that pushes human activities deeper into the forests (Butsic et al., 2015; Nackoney et al., 2014; OCHA, 2021). The DRC's population is predominantly rural, with a strong reliance on the informal agricultural sector, which mostly comprises of informal slash and burn practices (Molinario et al., 2020; Tyukavina et al., 2018) associated with increased fire frequency on managed lands, new clearings and forest edges (Jiang et al., 2020; Morton et al., 2008). The high reliance on natural resources will likely increase further due to the rapidly growing population along with urbanization; the overall population of the DRC is expected to exceed 100 million by 2035 (Tchatchou et al., 2015). We approximate the human impacts on DRC forests using covariates on built-up area, fire frequency, accessibility, and presence of armed conflicts.

As forest degradation is dynamic, so must be the proximate causes and spatial determinants to capture the variations in time and space. Spatial econometrics techniques and their application to conservation and development enable research controlling spatial and temporal components via spatial panel data, which are a spatial cross-section of observation repeated over time (Baylis et al., 2011; Bernhard et al., 2020). The observations in a spatial panel can be correlated in time (repeated observations that may be dependent on a previous date) but also in space (neighborhood interaction;(Molinario et al., 2020)). Here, we assess eight independent covariates over time within a grid of square of 25 km x 25 km units. We control for fixed individual site differences and capture both time variant and time-invariant factors at unit level to isolate site-specific trends from neighboring or national trends, hence controlling for characteristics which might be auto-correlated in space and time. We evaluate the spatial panel models from 2002 to 2016 with the overall aim to provide a key understanding of the dynamic proximate causes and spatial determinants of forest disturbance to inform conservation, spatial planning, and climate mitigation initiatives. We answer two major research questions:

- What are the spatial determinants of changes in forest condition?
- How do these determinants interact and change over time?

4.2. Methodology

4.2.1. Study area

This study assesses proximal causes of degradation in the Democratic Republic of the Congo (DRC), the largest country in the Congo Basin (Figure 31), which is characterized by having high forest area and low deforestation (da Fonseca et al., 2007; de Wasseige et al., 2015), with 60 % forest cover and a deforestation rate of about 0.5% since 2010 (FAO, 2020). The known distribution of forest biomass and its potential carbon sinks support new economic opportunities for sustainable development under REDD+ (Xu et al., 2017). While deforestation is generally low, degradation however has been estimated to affect large areas (Shapiro et al., 2016) which are increasing over time (Figure 32;(Shapiro et al., 2021). The forest transition model (Mather, 1992) shows that as countries develop, the related economic and population growth will likely elevate pressure on forest resources, notably intensification of agriculture and urbanization resulting in the increased threat of accelerating deforestation and forest degradation (DeFries et al., 2004; Hosonuma et al., 2012).

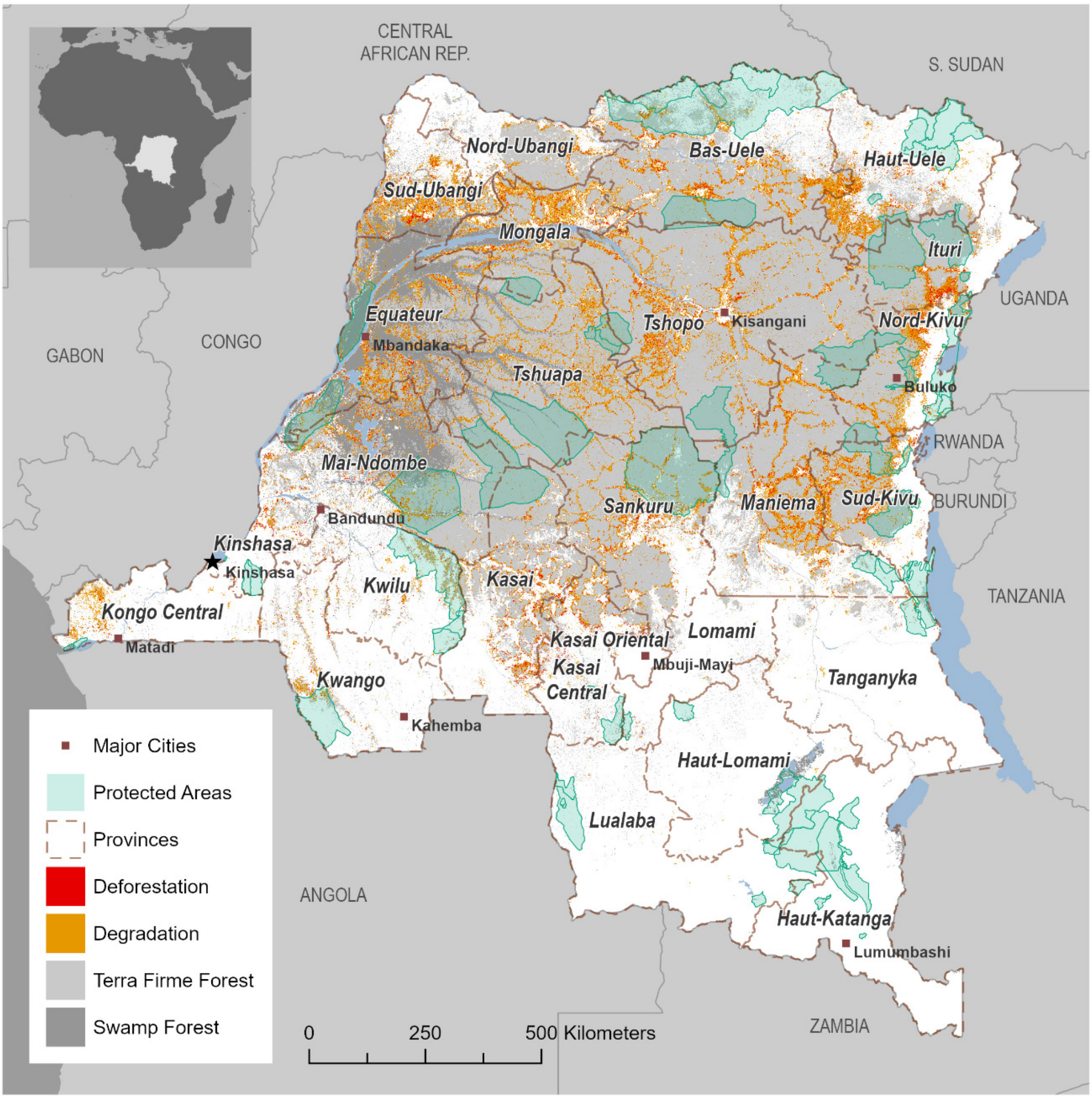

Figure 31. The Democratic Republic of the Congo (DRC), with the capital Kinshasa, divided into 26 provinces, possesses over 100 million ha of tropical forest, of which about 11 million are swamp forest. Deforestation and degradation data from Shapiro et al. (2015).

4.2.2. Data Sources

To quantify and understand human impacts on forests and the associated determinants of degradation, context and location is important. The literature regarding deforestation and forest degradation are often addressed together, citing slash-and-burn agriculture, collection of charcoal, mining and forest exploitation, and infrastructure development as key proximate causes in DRC (Defourny et al., 2011; Tchatchou et al., 2015). In the following section, we discuss these key proximate causes of forest degradation addressed in this study (**Table 13.** Variables evaluated for each forest grid and relevant literature. We assign the expected effect of each independent variable.). These are evaluated for each grid unit for each time period, which is a 3- year interval between 2002 and 2016. We then apply spatial panel regression techniques to identify the correlates for degradation and build on the concepts in published literature (Bernhard et al., 2021).

Table 13. Variables evaluated for each forest grid and relevant literature. We assign the expected effect of each independent variable.

Type	Variable	Expected Effect	Temporal Resolution	Data Source	Relevant Literature
Forest Degradation	Forest Condition (FC)	Dependent Variable	annual	(Giri et al., 2011 ; Hansen et al., 2013; Philippon et al., 2018 ; Xu et al., 2017)	(Grantham, Shapiro, et al., 2020 ; Shapiro et al., 2021)
Human pressure	Total number of fires	+	daily	MODIS Fire Data Giglio et al. (2016)	(Barlow et al., 2012; Ramo et al., 2021)
	Built-up area in 2000 and 2015 (km^2)	+	decadal	GHS Human Population Grid, JRC (Pesaresi et al., 2016)	(Corbane et al., 2017)
	Total number of conflicts observed	+	daily	ACLED (Clionadh et al., 2010)	(Butsic et al., 2015 ; Draulans & Van Krunkelsven, 2002 ; Negret et al., 2019)
	Travel time (hours)	+	time invariant	Data derived from slope, elevation, land cover, roads, and populated area using methods from Grantham et al., 2020)	(Aguilar-Amuchastegui et al., 2014; Grantham, Shapiro, et al., 2020)
Land use	Protected Areas (km^2)	-	annual	WWF (Pélissier et al., 2019)	(Butsic et al., 2015 ; Leberger et al., 2020)
	Forest Concessions (km^2)	+	Time invariant	World Resources Institute/ Direction Inventaire et Aménagement Forestiers (DIAF); (World Resources Institute, 2018)	(Zhuravleva et al., 2013)
	Mining concessions	+	Time invariant	WRI/CAMI	(Butsic et al., 2015 ; Hund et al., 2013)
Biophysical	Swamp Forest	-	Time invariant	Swamp Forest Extent (Dargie et al., 2017)	(Dargie et al., 2019 ; Miles et al., 2017)

4.2.3. Forest Condition

Forest condition (FC; from Shapiro et al. (2021)) is estimated as a relative index of forest degradation related to the loss of living biomass where core, intact, and connected forest areas have an FC of 100; deforested areas have an FC = 0, and degraded or fragmented forests have an FC proportional to the total potential above ground biomass of intact forest. FC of all tropical dense forest area is used as the dependent variable to assess the proximate causes and spatial determinants of degradation over time. Shapiro et al. (2021) estimated about 27 million ha of degraded forests in DRC, with the total degraded area increasing over time (**Figure 32**).

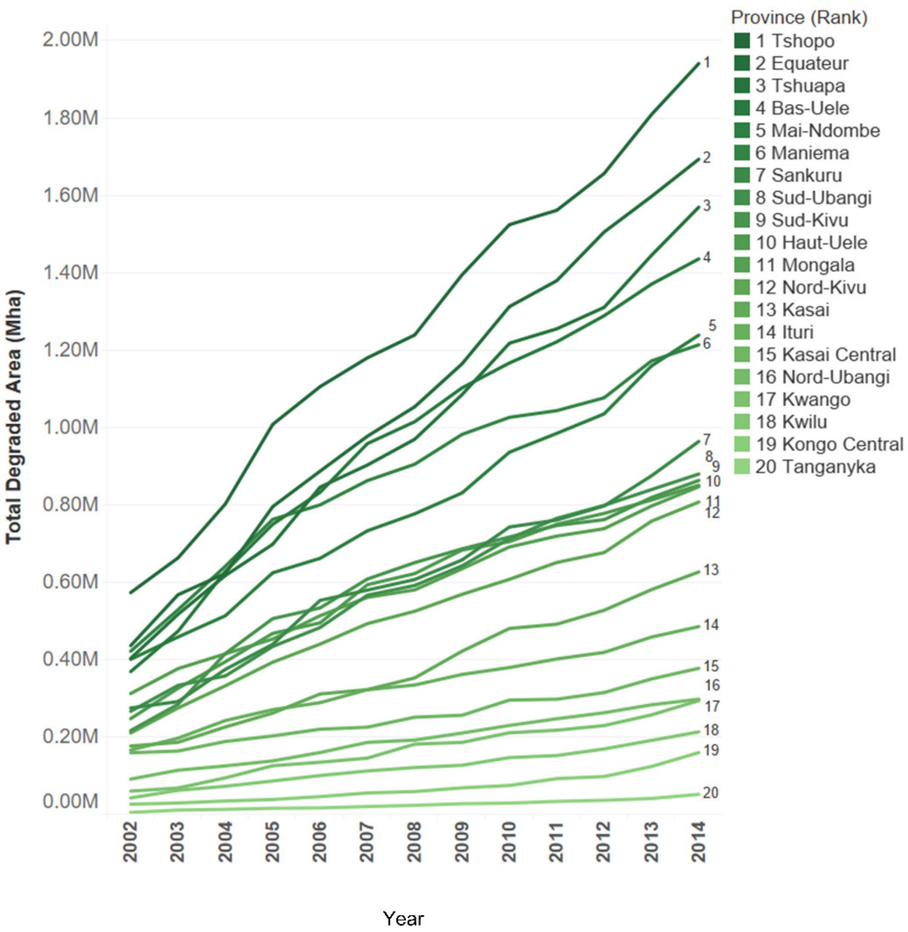

Figure 32. Total degraded forest area of the 20 provinces with highest degradation rates (data from Shapiro et al. (2021).

4.2.3. Fire

Fires are typically infrequent in tropical forests, and most observations outside of any typical fire season have a human cause (Bowman et al., 2011; Morton et al., 2008). Anthropogenic fires occur more often in forest edges (Benali et al., 2017; Cochrane, 2001) and are a major cause of forest degradation and deforestation in tropical biomes, which are not adapted to fire regimes and as a result experience reduced ecosystem resilience, with higher impacts on biodiversity as well as large greenhouse gas emissions (Juárez-Orozco et al., 2017; Ramo et al., 2021). These impacts can potentially increase with warming, drier climate (Malhi et al., 2009; Siegert et al., 2001). Fires, and especially multiple burns per year, are associated with agricultural expansion, especially slash and burn cultivation, which is cited as the greatest cause of forest disturbance in DRC (Molinario et al., 2020; Tyukavina et al., 2018), and is also increasing (Cochrane, 2001; Lewis et al., 2015). Fires are therefore a crucial variable for degradation monitoring and emissions reduction interventions (Barlow et al., 2012). We use the latest Fire Information for Resource Management System (FIRMS; (Giglio et al., 2018) dataset, which is the near real time active fire location product derived from the Moderate Resolution Imaging Spectrometer (MODIS) sensor thermal anomalies. We use Google Earth Engine (Gorelick et al., 2017) to sum all fire detections with a confidence flag greater than 30 at a resolution of 1 km.

4.2.4. Accessibility and Infrastructure

Physical access by humans into forests ecosystems is also an important driver of forest disturbance (Ferretti-Gallon & Busch, 2014). In the DRC, the means of access include both roads and rivers used to access forest areas for bushmeat, logging and fuelwood collection, the latter being an essential resource for local communities and large cities alike and a significant cause of forest degradation (Chidumayo & Gumbo, 2013). An estimated 90% of wood harvested in the Congo Basin is destined for fuelwood, a trend exacerbated by poverty, population growth, and urbanization (Marien, 2009). Meanwhile, the extirpation of wild species by unsustainable hunting practices results in forests devoid of keystone, seed dispersing wildlife which can affect natural regeneration and resilience while also having significant social consequences to local human populations (Harrison, 2011; Nasi et al., 2011). We use a travel time dataset, which is the cost surface model from a source layer of human settlements from the Global Human Settlement BUILT dataset (Corbane et al., 2018) for the year 2000, combined with a cost surface using roads, rivers, elevation, and slope, as described in the development of the forest pressure index (FPI) described in Grantham, Shapiro, et al. (2020). The cost surface estimates driving speed over roads and walking speed over various land cover surfaces, which are decreased with increasing slope and elevation; a navigation speed approximates travel on waterways as a function of their flow. As no temporally explicit data are available for road infrastructure, we can only develop accessibility for a single reference period of 2000, deriving the mean travel time in hours for all grid units. The BUILT dataset was also used to define the extent of built-up area per grid unit, using data for 2000 for the first four time steps and 2015 for the final time step.

4.2.5. Conflicts

Another determinant of degradation is armed conflict, which can have far-reaching ecological impacts (Machlis & Hanson, 2008). Violent conflicts can result in significant deforestation and degradation due to movements of refugees and internally displaced people (IDPs) into forests to escape violence (McNeely, 2003). Furthermore, conflicts in the region tend to be in areas of rich natural resources, such as minerals or forest; these areas are often inhabited by indigenous groups, which can result in further conflicts over land rights and acquisitions for resource extraction (Humphreys et al., 2007). The total number of conflicts recorded in DRC has been increasing in recent years, notably the violence against civilians (Figure 33). Conflicts in DRC are persistent in transboundary regions, which overlap with heavily forested and protected areas. For example, in the eastern DRC, conflicts have been a constant issue, especially in the Greater Virunga Landscape (GVL), which covers a network of thirteen protected areas between DRC, Rwanda, and Uganda. The GVL has seen protracted conflicts, with periodic spikes over the last three decades, including ongoing armed rebel group activity based out of forests and remote areas.

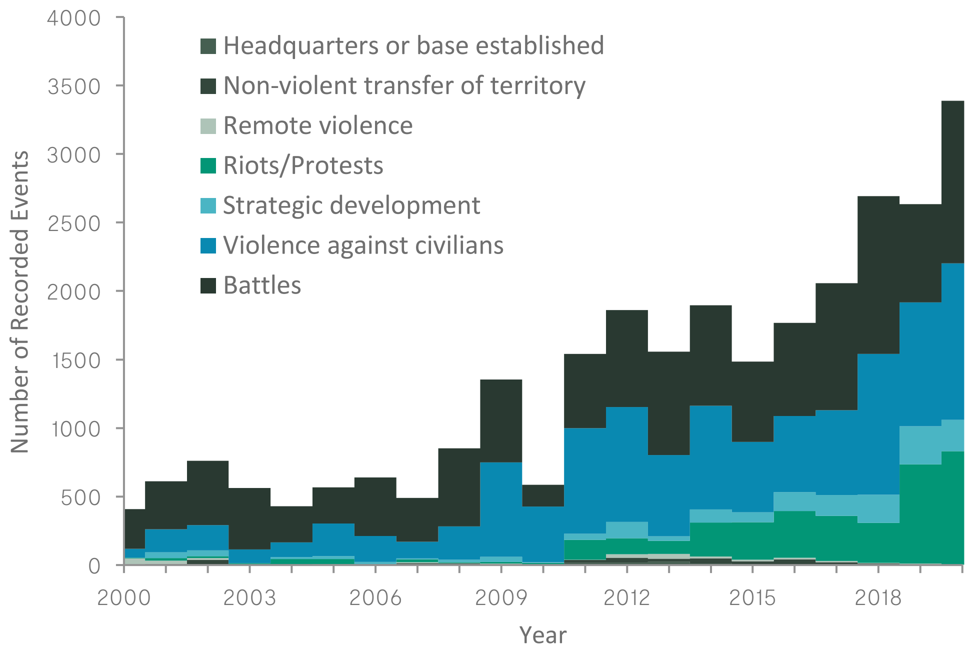

Figure 33. Recorded conflict events in DRC, broken down by event type. From Clionadh et al. (2010).

We calculated the conflict variable using the Armed Conflict Location & Event Data Project (ACLED) database (Clionadh et al., 2010) which is a collection of real-time data on the locations, dates, actors, fatalities, and types of reported political violence and protest events across the world. We use the total sum of conflicts in each grid unit as our variable, and do not discern between the number of fatalities or types of conflicts, as even non-fatal activities can have the effect of terrorizing and destabilizing local communities and their livelihood activities (Draulans & Van Krunkelsven, 2002) and the presence of protests can indicate civil unrest or political conflicts. Various rebel and armed groups use systematic and strategic sexual violence as a weapon of war (van Wieringen, 2020), increasing pressure on local resources through non-lethal threats and terror, as they depend on local communities, raid villages and fields, and force local residents to provide food, payments, or other income to armed groups (Laudati, 2013). On the other hand, some studies show that conflict could reduce or prevent deforestation by, at least temporarily, limiting private sector or extractives sector activity (Burgess et al., 2015). The armed conflicts caused by the long-term unrest in eastern DRC are an important variable to consider in the assessment of the causes and determinants of forest degradation.

4.2.6. Land Use

The attribution of land use and its change over time is directly affecting activities on land. The DRC is extremely rich in minerals, and efforts to extract these are exerting increasing pressure on unprotected forest and savanna ecosystems (Edwards et al., 2014). However, recent studies show the impacts on forests is generally low (Tyukavina et al., 2018). We use available data on protected areas, legal mining and forest concessions to assess the potential impacts from attributed land use management. Although there has been a moratorium on forest concessions and a legal conversion process in 2002, the impact has been questionable, with extractive activities occurring regardless (Lawson, 2014). For this reason, we do not incorporate temporal information into the forest concessions as data can also be unreliable and may not be correlated with actual forestry activities.

While date information is available for some mining concessions, the information was also incomplete for many, or considered to be unreliable due to differences between different official and commercial data sources. Additionally, the timing of a particular type of legal mining license might not preclude illegal or artisanal activities, which may occur before or after the establishment or end of a legal permissions. Therefore, we do not account for temporal information of the mining concessions.

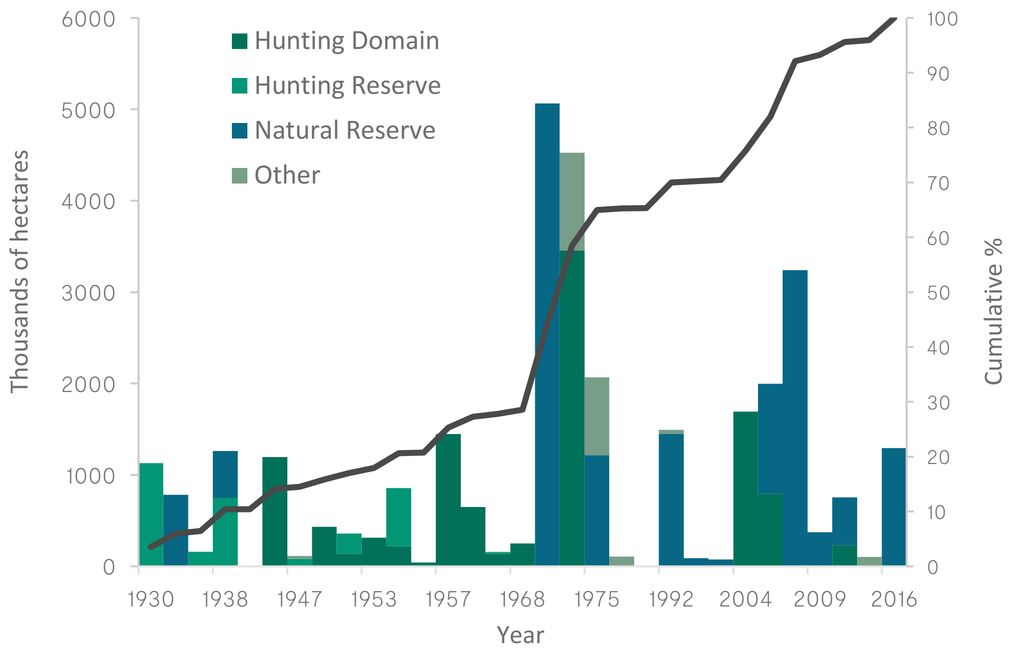

Figure 34. Protected areas in DRC have been established since the 1930s, which significant increases in the 70s and early 2000s (Pélissier et al., 2019). Most protected areas are hunting reserves and domains (names are translated to English). Other category includes scientific, zoological and forestry reserves, as well as annexes.

We incorporate protected areas, which were recently re-evaluated in DRC and include the year of establishment (Pélissier et al., 2019). Several new protected areas were established during the study period which allows us to assess their potential impacts (**Figure 34**). Protected areas downgrading, downsizing, and degazettement (PADDD) is present, but occurred mostly in the late 1950s, prior to our analysis (Forrest et al., 2014).

4.2.7. Spatial Statistics

We estimated spatial panel regressions for the period from 2002 to 2016, separated into 3-year intervals to evaluate the impact of drivers in affecting degradation over time, spatial panel regression models were developed for the study period of 2002-2016, divided into five intervals of three years. Panel datasets effectively have two dimensions: a spatial dimension, with multiple temporal panels to assess effects over time(Vijayamohanan, 2016). The summary statistics of all variables is presented in **Table 14**.

.

Table 14. Summary of variables

Name	Min	Max	Mean	Std. Dev.
Forest Condition (FC)	0.10905	100	62.9939	32.1467
swamp ecosystem area (km^2)	0	621.5	37.4072	103.8042
travel time (hours)	0.1924	57.4116	7.9027	7.6073
forest concession area (km^2)	0	625	38.1795	127.5848
mining concession area (km^2)	0	625	47.7687	118.7354
protected areas (km^2)	0	625	77.3228	184.0276
built-up area (km^2)	0	381.82	3.3940	16.4991
total # of fires	0	40402	4371.864	5593.546
total # of conflicts	0	322	0.8893	8.6468

The areal units were selected within the primary dense forested area of DRC, which was divided into 25 km x 25 km grid squares (**Figure 35**), with data assessed over all 3-year time intervals between 2002 and 2016, resulting in 2,996 observations in each panel for a total of 14,980 observations. The decision to use equal-size grid cells as opposed to administrative boundaries was due to several reasons. First, some of the administrative boundaries changed substantially over time, in part due to instability and inconsistency in governance at both central and local government levels throughout DRC. This can adversely affect a panel model with the same units over time and, furthermore, these changes could be associated with deforestation (Alesina et al., 2015). Additionally, the availability of forest resources (timber products, bushmeat) is directly related to the amount of available forest to degrade, therefore different sized units cannot be adequately accounted for simply by normalizing area. A consistent grid avoids these pitfalls but may lessen any potential impacts in differing governance or power structures, and therefore addresses the patterns independent of small administrative units. Given the small size of the grid in relation to other variables related to land use larger polygons such as forest concessions or protected areas are likely to cross neighbor boundaries, which could result in a source of endogeneity between units.

For each grid cell, the dependent variable, mean FC, and all independent variables (**Table 14**) were estimated for each 3-year time interval. We used zonal statistics to calculate the mean value for continuous variables, such as accessibility; for area estimates, such as mining concession area, protected area, forest concession area, built-up area, and swamp ecosystem area, we calculated the percent of the grid cell occupied by the respective variable. All temporally explicit data, such as protected area and built-up area, were calculated for the relevant time interval. A Pearson correlation matrix was assessed for all independent variables to identify multicollinearity. We assess significance at the 0.005 level using a correlation threshold of 0.5 to identify correlated variables.

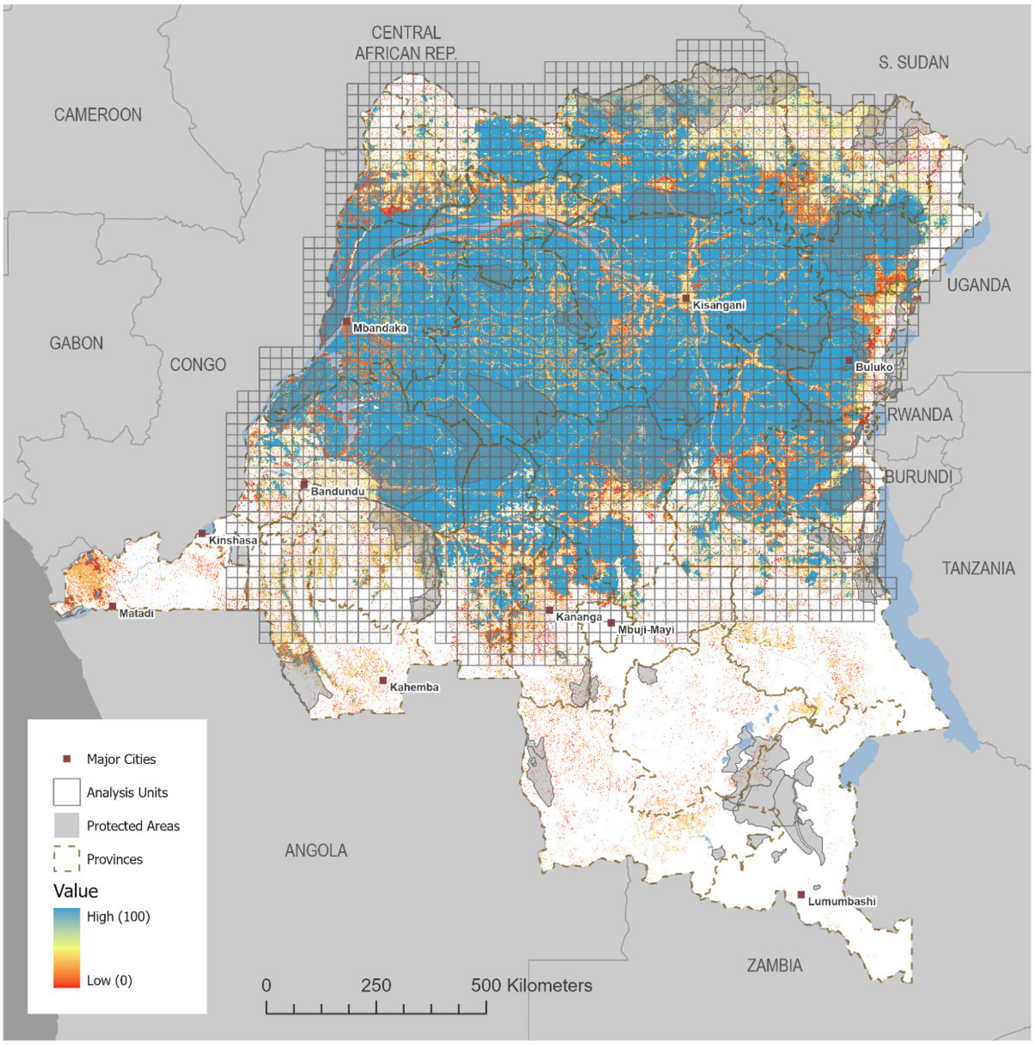

Figure 35. The analysis units shown over forest condition (FC) from Shapiro et al. (2021). About 70% of DRC forests remain intact, with an FC of 100.

4.3. Spatial Panel Regression

We evaluate spatial autocorrelation of the dependent variable through a non-parametric spatial correlogram of Moran's I using GeoDa version 1.18 (Anselin et al., 2005), where a local regression is used to evaluate correlations for all pairs of observations as a function of the distance between them (Bjørnstad & Falck, 2001). This provided the information to select the appropriate structure of the spatial neighborhood that has an influence on each observation. The spatial weights matrix is defined as a N x N matrix that identifies spatial dependence among the observations (i.e., the grid cells) across the study area.

The availability of repeated observations on the same units of a panel model allows the capture of individual-specific, time-invariant factors affecting the dependent variable in addition to unobserved effects (Baltagi, 2005). The rationale behind random effects models is that static differences across entities are presumed to have influence on the dependent variable; while a fixed effects model controls for all time-invariant differences between the individuals (Greene, 2019). We apply spatial considerations to these models by adding using spatially lagged independent variables to our models.

These spatial lags are the average of the neighborhood according to the spatial weights matrix, without the central cell, in order to evaluate the local grid and the effect of its neighbors separately.

We explored the different model specifications based on data constraint considerations (e.g., some spatial variables having only one reference period) and also in an effort (1) to illustrate the robustness of results to different model specifications; and (2) to provide complementary results where one model type has weaknesses. For example, fixed effects regression cannot include spatial variables without temporal variation (four out of eight independent variables). Therefore, we use the random effects to evaluate time and time invariant variables together. We describe each of the three model types through equations 3 and 4.

Random effects models incorporate parameters, which are random and uncorrelated (Equation 3).

Equation 3: $y_{it} = \beta x_{it} + \alpha_i + u_{it} + \varepsilon_{it}$

Where $\boldsymbol{y_{it}}$ is the dependent variable of entity *i* at time *t*. $\boldsymbol{\beta_1}$ is the coefficient of variable *x*, the vector of independent variables, $\boldsymbol{\alpha_i}$ is the individual specific effect potentially correlated with the independent variables, $\boldsymbol{u_{it}}$ is the between entity error term, and $\boldsymbol{\varepsilon_{it}}$ is the within entity error term. Random effects models are typically fitted using generalized least squares (GLS) which is efficient and unbiased for situations with heterogeneous variance (Baltagi, 2005). Fixed effects models fix variables across observations rather than time, as some variables do not vary over time, or only have few time periods (Equation 4).

Equation 4: $y_{it} = \beta_{it} * x_{it} + \alpha_i + u_{it}$

Where y_{it} is the dependent variable of entity *i* at time *t*, $\alpha_i (i = 1 \ldots n)$ is the unknown intercept for each entity (n entity-specific intercepts) , x_{it} represents one independent variable, and β_{it} is the coefficient for independent variable *x*.

We evaluate the random and fixed effects model with and without spatial lags. All regression analyses were executed in Stata (StataCorp, 2019) . We assess all four models via their coefficients and significance, overall, R^2, and estimation of rho, the ratio of individual specific error variance in relation the entire error variance. We employ the Hausman statistic to select the preferred model, random effects or fixed effects.

4.3.1. Trend analysis of time variant drivers

Based on the outputs of the random effects panel model, we enrich the analysis by evaluating fires and conflicts over time, key dynamic determinants with high temporal resolution to highlight their impacts on forest condition in space and time. We provide two analyses to demonstrate approaches to support management efforts such as targeting fire suppression activities or where resources could be allocated to reduce armed conflicts.

We assess trends over time using the Mann Kendall trend (M-K test) statistic (Kendall, 1975; Mann, 1945) to identify areas where frequency of fires and conflicts are significantly increasing or decreasing. We apply the space-time modelling tools available within ArcGIS Pro 2.7 (ESRI, 2020) using the same units as the panel data. For the case of fires, we use daily data acquired from 2002 to 2020 from FIRMS, summarized within each unit over 4 month time bins, and assess trend using the M-K test statistic. We perform the same analysis with the ACLED database of conflict locations from 2000-2020, applying the same temporal window of 4 months and hexagon spatial unit.

4.4. Results

The spatial correlogram indicated that spatial autocorrelation of the dependent variable approaches zero at approximately 50 km. Thus, we settled on the second order rook contiguity neighborhood as the structure for the spatial weights matrix (in analogy to a chess board, all grid cells that share a common border are considered neighbors, as well as the neighbors of the neighbors). Models using queen contiguity (common borders and common vertices) case did not significantly change model outputs. We did not detect substantial multicollinearity with all Pearson correlations below 0.4 (Table 15).

Table 15. Pearson correlation matrix of independent variables

	swamp ecosystem area (km^2)	travel time (hours)	forest concession area (km^2)	mining concession area (km^2)	protected areas (km^2)	built-up area (km^2)	total # of fires
swamp ecosystem area (km^2)	1						
travel time (hours)	0.1165***	1					
forest concession area (km^2)	0.1764***	-0.0063	1				
mining concession area (km^2)	-0.1425***	-0.0300***	-0.1133***	1			
protected areas (km^2)	-0.0556***	-0.3320***	-0.0101	-0.0804***	1		
built-up area (km^2)	-0.0246***	-0.1582***	-0.0267***	0.0855***	-0.0431***	1	
total # of fires	-0.2078***	-0.4388***	-0.1738***	-0.0885***	-0.0358***	-0.1422***	1
total # of conflicts	-0.0323***	-0.0705***	-0.0278***	0.1125***	-0.0127	0.2029***	-0.0088

The results of the random and fixed effects models without and with spatial lags are presented in Table 16. Because we use a linear model with no interactions and FC is measured in percentage, the coefficients can effectively be interpreted as margins, meaning that for a unit increase in the independent variable, the coefficient informs the associated % change in mean FC of the unit. In all models the estimate for rho approaches one, meaning that nearly all the variance is described by differences across time, the highest rho is observed in the fixed effects model with spatial lags. The coefficient directions are mostly consistent between models, with the exception of protected areas and mining, which have opposite coefficients in the models with spatial lags. R^2 are higher for random effects models than fixed effects.

In the random effects models, a greater presence of swamp forest, higher travel time (lower accessibility) and greater coverage of forest concessions are associated with increases in mean FC. Mining concessions are negatively correlated when assessed without its spatial lag; when the lag is included the coefficient is positive, and the lag has a larger, negative coefficient indicating that mining concessions in the neighboring areas are reducing FC more than those in the local neighborhood. Protected areas have an unexpected negative effect on mean FC in models without include spatial lags, however when the spatial lag is present the locally estimated variable is positively correlated with FC while the effect of the neighborhood is negative, indicating potential displacement of disturbances. The increase in built-up area, number of fires, and conflicts all are associated with lower forest condition, along with their spatial lags which all have higher impact on FC. The % built-up variable is associated with the largest per unit decrease in FC.

Table 16. Results of OLS, random effects (RE), RE with lags, and fixed effects (FE), FE with lags. (*** p<0.005, **p<0.05).

	MODEL			
Variable	RE	RE lags	FE	FE lags
swamp ecosystem area (km^2)	0.0347*** (0.0027)	0.0193*** (0.0063)		
swamp ecosystem area (km^2) – spatially lagged		-0.0034 (0.0076)		
travel time (hours)	1.913*** (0.0617)	0.6760*** (0.0771)		
travel time (hours) – spatially lagged		1.6352*** (0.1087)		
forest concession area (km^2)	0.0334*** (0.0019)	0.0018 (0.0031)		
forest concession area (km^2 – spatially lagged		0.0567*** (0.0049)		
mining concession area (km^2)	-0.0140*** (0.0033)	0.0019*** (0.0070)		
mining concession area (km^2) – spatially lagged		-0.0197*** (0.0070)		
protected areas (km^2)	-0.0066*** (0.0006)	0.0116*** (0.0015)	-0.0422** (0.0047)	0.0720*** (0.0082)
protected areas (km^2) – spatially lagged		-0.0289*** (0.0025)		-0.1755*** (0.0112)
built-up area (km^2)	-0.2991*** (0.0616)	-0.1239*** (0.0629)	-3.8986*** (0.1918)	-0.3038** (0.2047)
built-up area (km^2) – spatially lagged		-0.9644*** (0.0629)		-12.0822*** (0.3761)
total number of fires	-0.0013*** (0.00005)	-0.0006*** (0.00006)	-0.0009*** (0.00003)	-0.0005*** (0.0006)
total number of fires – spatially lagged		-0.0009*** (0.00007)		-0.0007*** (0.00005)
total number of conflicts	-0.0357** (0.0156)	-0.0128 (0.0143)	-0.0196*** (0.0068)	-0.0073 (0.0006)
total number of conflicts – spatially lagged		-0.2928*** (0.0363)		-0.2231*** (0.0154)
constant	53.0854*** (0.8470)	54.8350*** (1.0310)	69.4510*** (0.7011)	76.4417*** (0.2544)
R^2	0.5688	0.6228	0.2142	0.3057
rho	0.9504	0.9507	0.9799	0.9995

For the fixed effects models, all variable coefficients are significant at the 0.05% significance level. Once again, the protected variable has an opposite sign as expected, and a reverse coefficient when the spatial lag is considered. Built-up area, fires and conflicts have significant negative correlation with mean FC and built-up area has the highest per area unit effect. With the inclusion of the spatial lag, the coefficient for conflicts lower, while conflicts in the neighboring area have a stronger negative effect on FC. In the model with spatial lags, an increase in fires results in lower FC, and neighboring cells have a smaller relative impact. The total conflicts in the neighborhood have a greater influence on FC than the non-spatially lagged variable, indicating that an increase in conflicts has a further reaching effect in neighboring areas. The Hausman test was significant at the 0.005 level, therefore we reject the null hypothesis and use the fixed effects model including spatial lags with higher goodness of fit measures for our major assessments and conclusions.

4.4.1. Temporal Trends of Fire and Conflict

Having addressed the importance of spatially and temporally variant determinants versus static ones, we use the high temporal resolution of two dynamic variables to determine where they are changing over time to demonstrate the importance of time variant variables and the resulting policy implications. Conflicts and fires are the variables with the highest temporal resolution, and we determine where the greatest increases in fires and conflicts are occurring. The trends of these variables appear to be clearly spatially divergent (**Figure 36**).

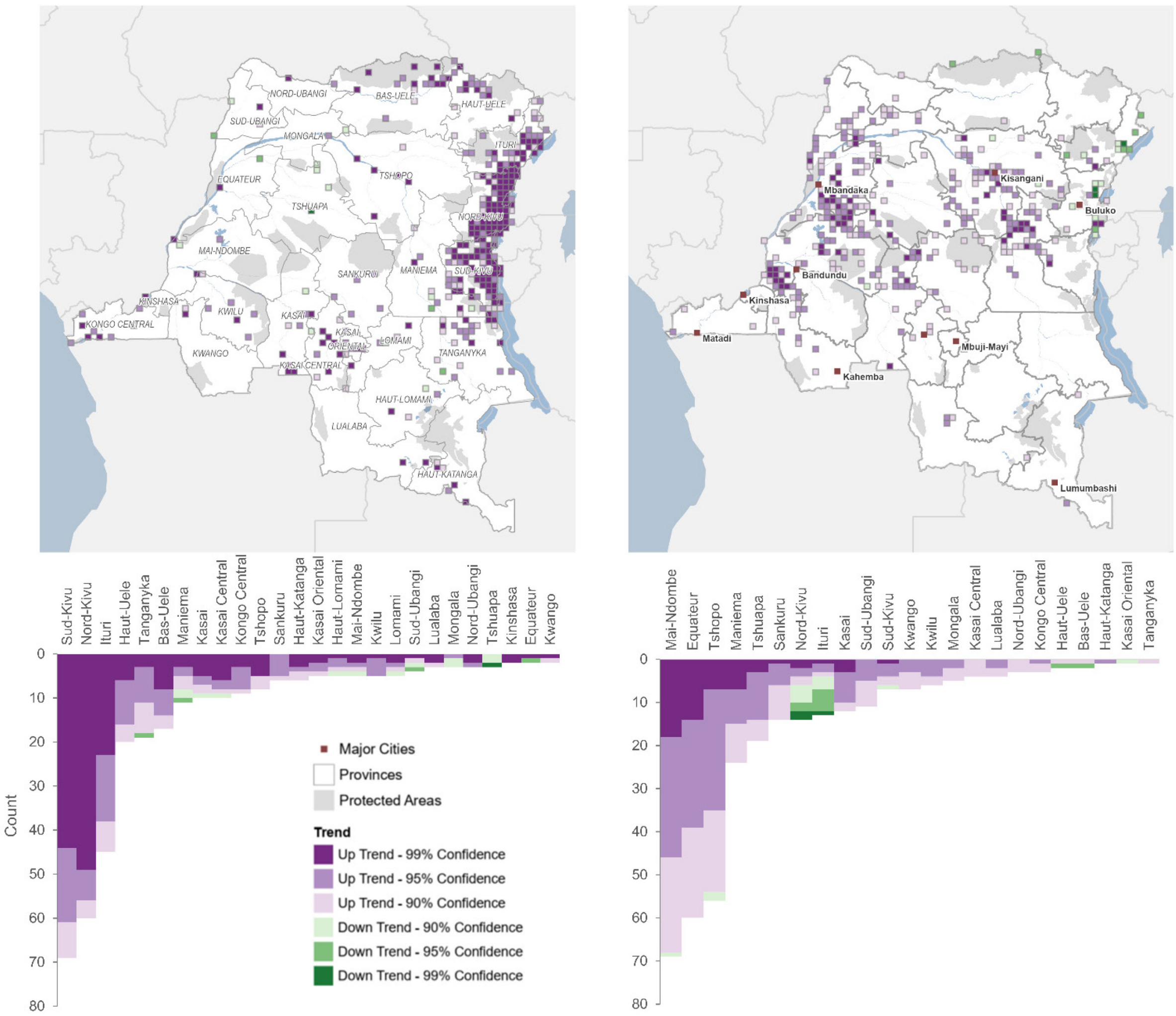

Figure 36. Trends in conflicts (left) and fires (right) assessed by Mann-Kendall trend analysis

Whereas conflicts and fires were both shown to be negatively correlated with FC, we note that these variables are increasing in opposite regions of the country. Conflicts are notably present in the eastern DRC and have been increasing in the last two decades, most importantly in North and South Kivu and Ituri province overlapping with protected areas in the eastern region. We note a different pattern of changes in fire frequency, which is decreasing in these three eastern provinces, but increasing in Tshopo in the central cuvette, and Mai-Ndombe and Equateur in the western regions. Future research could explore a potential interaction between these variables, where a greater number of conflicts could be causing a reduction in fires.

4.5. Discussion

The proximate causes and spatial determinants of forest disturbance and degradation have been often identified in the literature but are rarely quantitatively assessed. We provide a spatial panel analysis of drivers of FC, an index of forest degradation in the DRC using both time variant and time invariant variables to assess their relative impacts in time and space. We also assess the synergistic effects of variables and in concert with the spatial neighborhood to determine the potential impacts of neighbors. This provides important insight into the patterns and direct causes of forest disturbance, including the further reaching impacts of some drivers, the potential leakage or displacement of impacts by direct threats or land uses, and informs interventions or policies related to proximal drivers.

A greater area of swamp ecosystem could effectively be serving as a natural barrier to anthropogenic disturbance locally. However, an increased swamp area in neighboring areas may be displacing these threats. The Congo Basin peatland system is the most extensive swamp system in the world and largely forested and by nature difficult to penetrate due to peat depth (Dargie et al., 2017). There are few inhabitants directly in swamp forests. Forest clearing activities are more cost effective in *terra firme* forests, meaning most impacts in swamp ecosystems are currently limited to small scale sustainable uses (Dargie et al., 2019). Therefore, human activities are expected to be more present in areas neighboring swamp ecosystems. The addition of the spatially lagged swamp area variable to our models indicate that the natural protection of swamps is local, displaying pressure on forests in areas neighboring to swamp ecosystems. This concept of protection might not be permanent, as the effects of climate change are expected to increase accessibility and pave the way for more logging to feed increasing demand for resources. The presence of large oil and gas concessions and some forest concessions in these peatlands are raising alarms within the conservation community as these are directly threatening vast carbon reserves and extraordinary biodiversity (Miles et al., 2017). A portion of these swamp forests were placed under formal protection in 2011 (Pélissier et al., 2019), which could prevent them from being exploited.

While swamp forests might afford natural protection, the assessment of formally established protected areas as a spatial determinant of FC is not as clear. Without considering the effect of the spatial neighborhood, the presence of protected areas is unexpectedly negatively correlated with FC. This could be explained by the context of protected areas in DRC. First, the establishment of protected areas in DRC were implemented to represent different ecotypes and protect major faunal population (Inogwabini et al., 2005), which means they often are located in intact, inaccessible locations, as demonstrated by the positive correlation (Pearson correlation coefficient: -0.33) of protected areas with travel time (Table 15). Although we have temporal data for protected areas, and several new protected areas were established in the middle of the study period (Figure 34) the positive effects of protection could take many more years to materialize into increased FC. Protected areas in DRC also face a difficult history, where in some locations, implementation with support of local and indigenous communities and increased militarization has limited their acceptance and effectiveness (Duffy et al., 2019). Additionally, protected areas can be targets for rebel and armed groups who seek to profit from natural resources or poaching activities and illegal trade of ivory (Draulans & Van Krunkelsven, 2002). The Virungas National Park for example is one of the oldest parks in Africa, and remains at the center of one of the longest armed conflicts on the continent and throughout recent years has served as a base and hub for a variety of rebel groups. All of these issues are exacerbated by critical underfunding, which can significantly reduce effectiveness (Inogwabini et al., 2005). With the inclusion of the spatial neighborhood, we find a weak positive impact of protected area, with a greater negative effect from surrounding protected area. This could show that in the context of a larger area, protected areas might displace disturbances to 25-50km beyond their borders, where they can attract development and similar activities when local communities benefit from protected areas, or use its resources, indicating a potential leakage effect (Bernhard et al., 2020; Sabuhoro et al., 2017).

Many forests remain unexploited inside forest concessions (for example swamp as described above), therefore the positive impact of timber concessions on FC is not entirely illogical. While industrial timber extraction remains a major threat to forests around the world, this pressure is actually lower in Africa (Kissinger et al., 2012; Megevand, 2013). The DRC has the lowest timber production of all Congo Basin nations, despite having the largest forest area (de Wasseige et al., 2012) which is a result of conflicts, political instability, and lack of access and transport (Tchatchou et al., 2015). There are few large clear-cutting activities, logging is primarily selective, and damage is limited to areas around logging roads which can often quickly regenerate (Zhuravleva et al., 2013). It is suggested that most logging activities in DRC are illegal (Lawson, 2014), and could therefore be outside of identified concessions, several of which are in defiance of a 2002 moratorium on new forest concessions to re-assess their legality, a factor compounded by major weaknesses in governance.

We find mining concessions to negatively correlate with FC, but when considered along with its spatial lags, the reverse correlation exists where the area of local mining concessions is positively correlated with a decrease in FC, while the spatial neighborhood is positively correlated. In the context of all forest changes observed in the region, mining is considered a rare forest disturbance driver (Tyukavina et al., 2018). Large-scale mining operations tend to be older and resulted in deforestation before the time period addressed in this study. This suggests that current mining activities are less actively causing deforestation or degradation (Putzel et al., 2011). Larger established mining concessions also tend to be associated with higher security (Hönke, 2009), which can displace artisanal or illegal extractive activities into the spatial neighborhood of our analysis. It should also be noted that this variable does not include artisanal mining, or activities which might be pushed outside concession boundaries. Unfortunately, the only available datasets for artisanal mining are not based on consistent remote sensing and are biased in terms of location and time of detection.

Most of the forest disturbance in DRC is due to small scale agricultural activities dominated by shifting cultivation, which can be difficult to discern in satellite imagery (Tyukavina et al., 2018). The travel time, built-up, and fire variables support the assessment of human activities related to agriculture as these are associated with repeated fire and ease of access (Morton et al., 2008). Our data supports the results of Molinario et al. (2020) which determine that shifting cultivation is the major cause of primary forest loss in the DRC via slash and burn activities, with strong effects of proximity to industrial activities. We identify this via the presence of larger built-up areas (roads, paths, settlements) which are associated with expansion of the rural complex, and is quantified here by reduced FC in the 25 km x 25 km area. Built-up areas are indicative of greater population presence, which incurs greater demand on local resources – and per square kilometer of developed area has the largest impact on FC. However, population density plays a role, and potentially at a greater scale than the local neighborhood assessed here, although few reliable recent census data exist for DRC. For large cities, the relative influence of the large capital city is difficult to quantify, but Kinshasa, with its large population is still reliant on charcoal for energy, coupled with a large appetite for bushmeat that can impact forests well beyond the area of our estimated spatial neighborhood, especially as more roads facilitate wider access (Behrendt et al., 2013). Larger cities might be located closer to forests that are already degraded, and easier to further disturb, while smaller urban centers could be feeding both local demand and larger urban centers (Molinario et al., 2015). The lack of detailed population data make the evaluation of human density difficult to untangle. The model results suggest that the impact of developing one square kilometer of area for human use on FC (-0.12) is ten times larger than protecting the same area (0.01).

The presence of conflicts can affect forests in several ways, notably through higher pressure on forests for energy resources such as charcoal, increased illegal logging, mining and hunting (de Merode et al., 2007). Similar to Butsic et al. (2015), we find conflicts to be associated with forest disturbances resulting in lower FC, and the spatial neighborhood has an effect as well. This result is expected and can be explained by internal displacement of citizens fleeing unrest and threats, as is often the case in the Kivu provinces. The number of IDPs in the DRC is estimated to be over 5 million (UNHCR, 2020b), and many more are known to seek refuge from armed groups in forests, resulting in increased wildlife poaching and deforestation as a result of this insecurity (Draulans & Van Krunkelsven, 2002; Nackoney et al., 2014). Peaks in violent events with increased violence against civilians occurred between 2009 and 2014 (**Figure 33**). Refugee influxes to neighboring Uganda and Rwanda also spiked in 2016/17, which correlates with the significant upward trend in conflicts in Nord Kivu (UNHCR, 2020a). Unfortunately, the effects of conflicts can be long lasting on forests, whether via disturbance or the long-term effects of reduced faunal populations from overhunting of bushmeat which affect natural regeneration (Harrison, 2011; Nackoney et al., 2014; Nasi et al., 2011). The presence of armed conflicts in and around protected areas can affect their effectiveness, which is a result of the complex impact of institutions, and lack of resources (de Merode et al., 2007) indicating another potential interaction explored by Butsic et al. (2015).

Including spatially lagged elements to our models provides additional perspective on the far-reaching effects of some determinants. Higher travel time or lower accessibility of neighboring areas indicates a potential functional protection - whereby forests are protected simply by their inaccessibility by road, waterway, and land cover type. For example, an increase of one hour of accessibility increases mean forest condition by more than 1.5%. This could speak to engaging the responsibility of forest concessionaires to limit access to newly opened logging roads, which can be more effective in limiting access than protected areas (Sheil et al., 2010), but at the same time could increase conflicts with local populations and therefore should be addressed with caution. Limited accessibility in the neighborhood might also imply that the target cell is less connected to larger cities or markets. The spatial lags of mining concessions and protected areas were shown to have the opposite impacts of the target cell. In the case of protected areas, the negative correlation, which is explained above, with a low positive coefficient of neighboring areas could bring some good news for the wider reaching impacts of protected areas.

Applying both the random and fixed models demonstrates the importance of integrating time variant variables in our assessment. The proximate causes and spatial determinants of forest disturbance are not stable in time but change along with other exogenous influences including climate, politics, or pandemics. Kengoum et al. (2020) lament the fact that an up-to-date drivers analysis, potentially including relative impacts and spatial pattern was missing from the development of the national forest reference emissions level (FREL) in 2018. This spatial panel approach and in particular the comparison of both random and fixed effects model provides a useful mechanism to assess the relative impacts of drivers, combining both time variant and invariant datasets to assess the risk of forest degradation, which can be updated over time as new data become available. This is important to determine where specific interventions should be put in place, and prioritize the best use of limited funds.

To properly inform land use policies or interventions and to target resources we need to evaluate the covariates individually over time and space, which is particularly important in a vast country such as the DRC. We assess the trends of fires and conflicts over a time period extending beyond the statistical modeling and note that these two variables diverge spatially - there is an increased risk of forest degradation related to armed conflicts in the east, where fires are decreasing. Meanwhile fire frequency is increasing in the central cuvette and western portion of the country, potentially threatening emissions reductions programs and swamp forest ecosystems. This speaks directly to the importance of contextual information to guide use policies to drive change and spatially targeted approaches and interventions (Tegegne et al., 2016). In the example of REDD+ interventions, reduction of fires in the context of agricultural practices are a critical factor to be addressed to secure and manage forest carbon (Barlow et al., 2012). The information provided here can be used to design emissions reduction interventions related to fire that focus on high-risk areas (Holdsworth & Uhl, 1997) by promoting fire reduction or sustainable, managed or improved charcoal or biofuels for local energy needs (Megevand, 2013; Schure et al., 2014).

A number of uncertainties limit our analysis. The FC metric is dependent on accurate forest and biomass maps, which surely have a level of inherent error. The global tree cover change product used to identify loss at edges focuses on identifying tree cover loss but does not consider natural and anthropogenic regeneration, which could be occurring. New available datasets such as the Tropical Moist Forests (TMF) product from Vancutsem et al. (2021) which include both deforestation and degradation could provide opportunities for additional evaluation. Due to the nature of the tree cover loss product, the forest condition metric also includes naturally caused forest changes, although from a remote sensing perspective the causes of forest disturbance are practically impossible to separate. The increase in observed conflicts over time could also be influenced by the increase in social media and connectivity, which increases the potential information shared and reported on conflicts in recent years, more than in earlier years. We have demonstrated the importance of spatial neighborhood, but our models effectively end at the international border. Clearly, activities and varying threats in neighboring countries are going to influence Congolese forests, and these are only touched upon here. We did not include climate factors due to the coarseness of available datasets, although differences in rainfall and temperature could drive different types and trends of agricultural expansion. Next, the size of the grid unit might influence the outputs of the model. The size we selected, resulting in nearly 3000 units, is well below the scale of the smallest administrative unit. Finally, additional variables could improve the model, including an evaluation of the threat of bushmeat hunting. The presence of certain crop types, or socio-economic variables are unfortunately difficult to spatially quantify at this scale of analysis. Spatially explicit information on poverty indices, reliance on natural energy sources, information related to diets or the structure of local economies would be very valuable to assess the impacts on forests, but is only mostly available at national scale (Bawa & Dayanandan, 1997). This could be assessed in more depth via future studies using recently implemented national household survey approaches.

4.6. Conclusions

The proximate causes and spatial determinants of forest disturbance vary greatly in time and space, particularly in a diverse and vast country like the DRC. Therefore, to successfully safeguard forests and the people who depend on them, we need spatially targeted interventions that are informed by sub-national context. Especially considering limited financial resources for conservation, land management activities and interventions need to be implemented where they can be most successful. The increase in fire frequency in the central and western parts of the country, which are also heavily forested, should indicate the need to change where fire suppression activities are targeted. This can support the implementation of renewable energy for households or programs that reduce dependence on charcoal.

The importance of spatial neighborhoods for many spatial determinants are not only important at the local level, but also inform transboundary considerations. Multi-lateral agreements between neighboring countries to improve coordination and diplomacy, particularly in the face of moving threats is essential. Though once again, context varies. While some regions in Africa are successfully addressed by "Peace Parks", which employ protected areas as a form of peacebuilding, their location and historical context remains important. While peace tourism might be fruitful in some areas, the realities in the eastern DRC are more complicated and currently muddled by increased militarization to protect tourists (Trogisch & Fletcher, 2020). Before we achieve both forest conservation and socioeconomic development goals for forest adjacent communities, a drastic reduction in conflicts and better security is needed. While complicated, conservation peacebuilding should not be rules out. This spatio-temporal approach can be replicated at various scales or extents for transboundary decision support systems to the support the implementation of these kinds of interventions.

Finally, it is clear that forest disturbances change in dynamic fashion. The COVID-19 pandemic has demonstrated that all populations, especially those on the margins of poverty, are vulnerable to global events. The trends observed in DRC show little sign of relenting, exacerbated by increases in violent events. It is increasingly clear that humans rely on nature for survival and basic needs, it is important to provide intact and resilient ecosystems to allow communities, including the impoverished to overcome more future climate and economic perturbations.

4.7. References

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4.8. Further Consideration

For successful strategies to reduce human pressures on forests, countries need to address their national drivers in a context-specific approach – no intervention is applicable everywhere. No matter how successful these efforts are, there remain significant challenges to addressing the underlying or international drivers, whether market forces, climate change, or even unexpected events such as natural disasters or pandemics. Therefore, adapted international strategies are also needed, such as trade agreements, certification schemes, demand reduction or market approaches. Understanding the dynamics of forest change patterns and causes are also needed to define appropriate reference emissions levels (REL) and constructing reasonable future scenarios, or to justify an adjustment to RELs (Kissinger et al., 2012). Lastly, up to date drivers analyses are essential for informed land use planning that addresses and mitigates these threats and ensures functional forests that support biodiversity and local livelihoods in the long term.

A new project by the Central African Forest Initiative and the Food and Agricultural Organization of the United Nations (FAO) will build on this research and aim to determine the relative impact of direct drivers in six central African countries. The initiative uses cloud computing and open-source tools (OpenForis[6]) to map deforestation and degradation and use a sampling approach and validation from high resolution Planet satellite imagery provided by the Norwegian government to detect the presence of different drivers: from the expansion of the rural complex, to industrial and artisanal forest exploitation, mining and infrastructure. The results will be used to develop a land use planning tool that specifically responds to particular drivers as small scales. This will ensure that efforts at the national or sub-national scale are able to mitigate climate impacts while responding to the needs of local populations, ensuring adequate forest conservation for sustainable use while ensuring connectivity and natural barriers against human access into intact forests, which are playing a more important role in preventing spillovers of disease and potential sources of pandemics (Brancalion et al., 2020).

[6] http://www.openforis.org/newwebsite/home.html

Chapter 5: Summary of Findings

The answers to the three major research questions are addressed, via a remote-sensing based assessment of forest degradation and spatial analysis. The questions are recalled and summarized followed by a general discussion and recommendations and my own perspectives and potential of future efforts.

5.1. Addressing the research questions

This thesis has evaluated three central research questions related to the assessment of forest degradation through remote sensing and spatial statistics. The development of robust, repeatable methodologies to quantify degradation is essential for mitigating climate, conserving biodiversity, and ensuring sustainable development for local communities. This methodology is applied to determine the direct causes of degradation to apply appropriate solutions.

Three research questions were addressed using newly derived approaches that are described here with major findings and recommendations:

How can forest degradation be defined and mapped using remote sensing or proxy techniques?

Spatial pattern analysis was used to detect different levels of degradation at forest edges using above ground biomass (AGB) to define a degraded forest. I use this approach to report the areas of major primary and secondary degradation which are mainly in North Kivu province and in areas of the new Mai Ndombe province where significant REDD+ investments have been focused. Using this stratification based on spatial pattern I find that AGB is not only significantly different between all classes, but that AGB is progressively lower in more fragmented forests. This is important in that direct biomass monitoring can prove difficult in large, remote and dangerous forest areas such as the DRC, and this approach helps determine the biomass trajectory and carbon emissions implications of what is a high forest, low deforestation (HFLD) country. More importantly, I address the previously unreported and unknown estimates of forest degradation in the period of 2005-2015, which was estimated at more than three times the area affected by forest loss. The carbon emissions per hectare from degradation are lower, these changes nevertheless contributed to between 25% and 34% of total forest associated CO_2 emissions – disturbances, which when simply considering forest vs. non forest would be indetectable – because degradation is occurring in areas that by definition remain forest. I find that about one third of all deforestation in the DRC was initially degraded; while Vancutsem et al., 2021 estimate this value to be nearly one half in the 2000-2019 time period. The method has been successfully integrated into a global assessment of forest intactness as well as national emissions reduction programs for the assessment of reference levels (Forest Carbon Partnership Facility, 2018; Grantham, Shapiro, et al., 2020) and provides a simple and repeatable approach for discerning four types of changes from binary forest maps.

How can forest degradation be quantified and monitored on a continuous scale? How can these data be used for conservation planning?

In Chapter 3 I build on the categorical approach introduced in Chapter 2 to define a theoretical framework and a concept of forest condition (FC), a continuous measurement of degradation, constructed from the temporal history of forest cover and above ground biomass to assess forest condition from 0 (deforested) to 100% (intact). I validate the framework by discovering that the metric is negatively correlated with the presence of canopy gaps and fractional cover, and positively correlated with loss of biomass over time and the magnitude of the cumulative anomaly of direct remote sensing measures. The approach was scaled up to the larger extent of the entire Congo Basin, where I estimate that about 70% of forest ecosystems in the Congo Basin are intact with large areas of open forest determined to have low FC based on their increased vulnerability to human modification and observed degradation and fragmentation over time. This assessment is important for conservation planning -- particularly for efforts to conserve large, intact and connected forest ecosystems. I apply the metric to measure the potential of ecosystem collapse for ecosystem risk assessment via the IUCN Red List for Ecosystems methodology. I identify four critically endangered ecosystems in the Congo Basin region, which are restricted to only 0.15% of the total area. A further 15% of forests are considered endangered and these ecosystems are located primarily in the eastern edge of the DRC forest ecosystem between Lake Edward and Lake Kivu. Without the FC metric, ecosystem risk would have been underestimated for 11% of the regional Congo Basin forest area. Processing the metric for 64 forest types in annual intervals also provided the opportunity for finer monitoring, indicating that several of the most vulnerable ecosystems faced significant reduction in FC from 2012 onwards. The FC metric was also integrated into a prioritization algorithm for a regional HCV assessment. This assessment combined FC with habitat quality of apes and elephants, overlaid with human threats to help guide sustainable forestry efforts targeted towards the most intact, connected forests with high biodiversity.

What are the major proximate causes of forest degradation and how do they interact?

It is not enough to simply know where forest degradation is occurring in order to develop national forest emissions reference levels or inform polices and guide interventions. Understanding the temporal and spatial dynamics of proximal causes or direct drivers of degradation is crucial to implementing context-specific responses and mitigation efforts and enabling early warning and comprehensive risk assessments. Using the metric developed in Chapter 3, I use spatial panel models to determine the impacts of eight driver variables which represent the major causes of forest degradation in the DRC on forest condition (FC). These assessed variables include the presence of swamp ecosystems, which act as natural barriers to human activities; the extent of protected areas which are implemented to reduce disturbance and conserve forest areas; accessibility determined by infrastructure and land cover; built-up area and the presence of industrial mining and forest concessions, and finally the total number of fires observed by satellite, as well as the documentation of human conflicts determined from news sources and outlets. A panel dataset was constructed from the independent variables and mean FC, calculated for 25km x 25km units in three-year time intervals between 2002 and 2016. I assess the driver variables alone, as well as in combination with their spatial neighborhood to determine the relative impact of each variable on FC along with the potential effects from neighboring units.

I determine that fixed-effects models are more appropriate to the drivers and change dataset, and evaluate the impact of temporally variant drivers on FC while holding all other differences between units constant. Built-up area was found to have the largest relative impact on FC per km^2 than protected areas, mining or forest concessions or the functional protection afforded by swamp ecosystems. Unexpectedly, the presence of protected areas was found to be negatively associated with FC in the local context. But when considering the spatial neighborhood this changed, indicating that protected areas might effectively displace human activities. Most of the variables assessed were found to have greater impacts in the wider spatial neighborhood than locally, indicating the importance of understanding the potential far reaching impact of local decisions and land uses. Finally, I assessed temporal trends of conflicts and fires, the variables with the highest temporal resolution and found that they have spatially divergent patterns: fires are in fact decreasing in the eastern regions of DRC where conflicts are increasing, and the opposite pattern is observed in western provinces. Therefore, drivers do not spatially co-occur in all areas of high forest disturbance, and more importantly, these proximal causes change over time, which should be considered in successful context-specific management policies and the assessment of suitable reference levels.

5.2. General Discussion

Forest degradation remains a significant global problem which greatly affects the ability of forests to deliver essential ecosystem services – which includes providing habitats for wildlife, timber and other resources for local communities and an increasingly important climate mitigation service (Mitchell et al., 2017). Because forest degradation is not deforestation, the spatial and temporal impacts, associated emissions, policy responses and solutions are vastly different, requiring adapted approaches and methodologies to identify and quantify it differently from forest loss (Herold et al., 2011). Unlike deforestation, the accurate and timely detection of degradation still presents unique challenges due to its impacts on structure and function, and effects that vary in time and space, both temporary or permanent and confounded by wide ranging definitions. Robust and repeatable methods are needed to implement robust policies and payments schemes to reduce emissions (FAO, 2011).

Despite the massive increase in earth observation missions and satellite constellations and constant, complex data streams, it is nevertheless astounding that in the twenty-first century we can map the surface of the moon, fly a helicopter on Mars or detect changes occurring at unimaginable distances in our solar system but the world's scientists cannot agree on where forests are present, when and where they are cleared on our own planet. As part of the effort to map the world's "deforestation fronts" (Pacheco et al., 2021) to determine where deforestation is happening and increasing, a solid baseline dataset of forest cover is an essential requirement. Nevertheless, a compilation of five widely accepted, published and peer-reviewed global datasets from space agencies and research centers with focused efforts on forest and land cover hardly agree. These discrepancies are surprising, even as some of these approaches use the same data sources or classification methods. The data and estimates of forest cover change are even more inconsistent, with some sources citing an increase in global forest loss while other report a decreasing trend (FAO, 2020; Weisse & Goldman, 2021). How can robust regional and international monitoring systems be successful if countries can choose to align their data to most enhance the rewards or payments they can receive for positive results? How can we expect politicians and the public to truly engage in the fight to reduce deforestation we can't agree on the extent of the problem? These inconsistencies make it difficult for decision makers to believe what is being published and reported or promotes bias.

What is most important for transparency and clarity is a consensus on definitions and concepts and from this author's perspective, there is a crucial difference between forest loss and degradation in terms of timing and size. The most widely used global forest change monitoring product is the data published by Global Forest Watch (GFW) from Hansen et al., 2013 and represents a groundbreaking approach to mapping forest change at a global scale and unprecedented resolution. However, these assessments are muddled by the caveat that GFW data quantifies "tree cover loss" as opposed to actual deforestation or land use conversion, although many use these terms interchangeably (Tropek et al., 2014). Certainly, one should consider an adequate forest definition for monitoring, which is not only determined by cover, but resolution and extent. A few trees within a 30m pixel can hardly be identified as a functional forest, nor can one or two felled trees within that pixel be labeled as "deforestation" which is why I disagree with Bovolo and Donoghue (2017). The recurring claim that higher resolution is necessarily better for forest mapping and monitoring does not consider repeatable accuracy, consistency, or the functional forest definition. A forest is more than a single pixel on a map, and thus connectivity, intactness and patch size are important elements to consider for function, structure and resilience. Lower resolution products on the other hand --such as the Terra-I tropical deforestation product-- could actually be more accurate in detecting deforestation (particularly with low errors or commission) through their approach that makes a concerted effort to map human-caused deforestation as opposed to tree cover change. Unfortunately, as with many "global" data products it is only available for tropical region. The forest/non-forest map from the Japanese Space Agency (JAXA) should provide an optimal approach for the tropics as it is based on activate cloud-independent radar data, however, it is very much influenced by topography and soil moisture and produces erroneous results in swamp forests. A new product based on Sentinel-1 (Reiche et al., 2021), known as RADD (RAdar for Detecting Deforestation) is another alert product, meant to detect disturbance in real-time from active radar at 10m resolution and also cloud independent, with alerts confirmed after several observations. However, the definition of disturbance vs deforestation is not very clear in this approach – a clearing large enough to be a forest removal should technically be defined as deforestation rather than disturbance, and likewise a temporary disturbance (unconfirmed alert) could very well be degradation. The latest product from the Joint Research Commission of the European Union (JRC; (Vancutsem et al., 2021) is also limited to tropical moist forests, but is unique in that it applies both a spatial minimum mapping unit and a temporal filter to the forest mask and loss in order to apply appropriate definitions of deforestation and degradation, the latter is clearly defined as a disturbance of any size that does not alter the land cover.

All of these existing approaches have clear advantages and disadvantages and ultimately show that while there are globally applicable definitions, there is and probably will never be a globally applicable and accurate dataset – for countries to monitor forests, disturbance and degradation most accurately and robustly, they need to choose the appropriate datasets and methods that apply to their geography, forest type, climate, extent and forest definition while also considering the causes of forest disturbance (Achard et al., 2014; Milodowski et al., 2017; Romijn et al., 2013; Sandker et al., 2021). For the purposes of this research national and regionally specific datasets for the DRC and Congo Basin were used first and foremost, and all forest cover information downscaled to a one hectare forest definition regardless of the native resolution which also has implications for accurate biomass mapping (Mascaro et al., 2011).

In order to adequately assess degradation, one needs an applicable, consistent, clear and appropriate definition that separates it from forest loss (Schoene et al., 2007). The lack of a unified definition is preventing large scale applications and development of methods (Sasaki & Putz, 2009; Vásquez-Grandón et al., 2018). Most importantly degradation is a temporal process which is why certain definitions are ever more problematic as they consider only a static state: naturally sparse, dry forests such as woodlands are then defined as degraded (Gao et al., 2020). For this research, I apply a definition related to human-induced loss of carbon stocks, as suggested by IPCC (Karjalainen et al., 2003), although this is not ideal as there could be additional elements affecting intact functioning forest, unmeasurable from satellite, such as biodiversity or climate regulation. Nevertheless, a biomass-oriented definition enables a clearly framed approach that may account for changes in canopy cover, gaps, structure and height – which can be accurately measured from satellite, airplane or drone. Moreover, while the minimum mapping unit and appropriate resolution to map forest and deforestation has been discussed above, there is no clear argument that a minimum mapping unit for degradation should be defined. Because degradation should not change the forest definition of a specific pixel and can function on different scales or could be the result of impacts on a few trees (selective logging for example), it should be logical that degradation, by definition, can occur on a smaller area than deforestation, and therefore may not require any minimum area threshold.

There are two major kinds of approaches to estimating forest degradation: direct measurements that involve estimating specific parameters relative to forest structure, canopy gaps or intactness, and indirect methods that address proxies or associated variables, such a fragmentation, edges, or the presence of roads or fires. Direct measurements can require more effort and cost in terms of data and processing and validation data to ensure that the selected indicators are accurate. This may require more image processing and data volumes. Direct approaches can be further complicated by inherent dynamics of natural ecosystems and the difficulty in assessing the magnitude or extent of degradation on the ground – there are still no standard approaches or assessments that enable an independent observer to discern a degraded forest from a regenerating or secondary forest. This is complicated by the fact that degradation may be temporary. As degradation varies in time and space it can be difficult to validate a degradation event which could have happened months or years before a recently detected satellite observation. Nevertheless, with the increase in data streams and availability via new satellite constellations and sources, coupled with affordable and powerful cloud computing, direct approaches are becoming more commonplace than just a few years ago. For example, the approach by Vancutsem et al. (2021) takes direct measurements over time and decouples permanent disturbances attributed to deforestation or land cover change from temporary disturbances that don't incur a change below the forest definition. The temporal definition is also applied by repeated observations. In Chapter 3, I use a direct approach to estimating degradation using the magnitude of cumulative anomalies in the context of validating forest condition, representing a continuous estimation of magnitudes of variation from a historical mean. I find this method particularly appropriate to identifying the impacts of repeated, accumulated degradation events, which can be useful for monitoring on a continuous scale. This approach was also used in to successfully detect long-term changes in stable mangrove ecosystems and to assess associated emissions (Lagomasino et al., 2018).

On the other hand, indirect approaches are conceptually simpler, easier to replicate and scale, faster to implement and can still be robust enough for the assessment of emissions reference levels, conservation prioritization and planning scenarios. These approaches can suffer from oversimplification or lack of sensitivity to small scale changes and may rely heavily on auxiliary data. Nevertheless, they should be included in the requisite toolbox for monitoring approaches and may be applied in tandem with direct approaches and can have value for the identification of drivers if one is measuring a proxy such as the presence of roads or fires for example. Indirect approaches are indeed relevant as their consistency enables them to be more easily scaled to larger extents as shown in Chapter 3, and even applicable for global assessment (for example Grantham et al., 2020).

As less effort and investments are needed to restore a degraded forest than a converted or deforested area, timely responses to forest disturbance events have significant financial benefits. Forest degradation has often been shown to be a precursor to deforestation – in Chapter 2 I estimate around 30% of deforestation from 2000 to 2015 in the DRC started as degradation; the recent Tropical Moist Forest (TMF) product estimates around 50% of deforestation observed between 2000 and 2019 ends up being deforested. Therefore, the accurate and timely detection and quantification of degradation could present a valuable opportunity to be able to respond to disturbances and prevent deforestation before it happens. But we also cannot wait to observe degradation after it happens, understanding the complex processes of drivers is critical to identifying risk of human degradation, while observing changes in direct drivers can signal potential increases in forest disturbing activities or presence of additional threats. Regeneration in degraded areas can be successful through the cessation of direct causes and mitigation of drivers, or with interventions that can have many associated benefits in terms of biodiversity, local participation and climate change mitigation (Sasaki et al., 2011). A combination of direct and indirect approaches can provide a comprehensive and accurate monitoring and decision support system, while providing results-based payments can encourage better practices while implementing safeguards for local populations (Rey Christen et al., 2020).

In every chapter of this research, the eastern DRC, notably North and South Kivu and the vicinity of the Greater Virungas Landscape have repeatedly come up as hotspots of fragmentation, biomass loss and degradation. Furthermore, these are areas where plentiful mineral resources meet critically endangered ecosystems and biodiversity, entangled in a deeply devastating conflict. This results in tragic consequences for the natural environment and the local human populations, further affected trans-boundary issues and leakages which signal future dire consequences. But the increased international investments and efforts driven by climate change and global sustainability could potentially bring DRC out of the so-called resource curse. This includes new land tenure efforts and implication of local people in the protection and management of their own resources. Standing forests and functional ecosystems can potentially generate long-term payments and benefits through alternative livelihoods, sustainable and responsible exploitation which will hopefully outweigh the short-term payouts for forest destruction. These mechanisms need to remain appealing and engaging for Central African nations, which translated into the development of their capacity to assess and understand the critical importance of forest ecosystems in the sustainable development trajectory.

5.3. Future Perspectives

With new technologies, new constellations, bigger data streams with high spatial and temporal resolution, the way in which we observe and monitor forests from space is changing dramatically every year. The recent offering of free, high resolution (5m) monthly processing-ready mosaics from Planet, supported by the Norwegian government[7] is proving to have significant impact as it provides unprecedented access to high resolution for mapping, monitoring and validation (**Figure 37**). Tropical countries have barrier-free access to data that can image forest ecosystems at new scales and detail. In the figure below, newly cleared roads penetrate intact forest in the Democratic Republic of Congo, which is not entirely visible in a Sentinel image. These images are available monthly, and are not just images to visualize, but can be analyzed with image processing techniques.

Figure 37. New forest road detected in imagery from Planet monthly base map (March, 2021)

This, coupled with advanced cloud computing platforms such as Google Earth Engine, FAO's SEPAL, is making a great leap towards large-scale real-time monitoring with the ability not only to see, but rapidly interpret what changes we are seeing and attributing causes or drivers. This new high-resolution data is analysis ready, providing the opportunity, for example to create % forest cover outputs which previously required extensive training data and processing time. I selected training samples from distributed planet quads over the Congo Basin, identified forest and non-forest and then scaled up to percent tree cover at the Landsat pixel using both Landsat and ALOS-Palsar data, which can be a more accurate and consistent approach than downscaling MODIS (Sexton et al., 2013). The planet data were used as training for a continuous classification on a multi-sensor mosaic of Landsat, Sentinel-2 and ALOS Palsar using SEPAL, FAO's cloud computing satellite platform to instantaneously map percent tree cover for the entire Congo Basin (**Figure 38**). This could present a more flexible and customized approach to assess tree canopy cover at more regular intervals and with locally applicable models as opposed to

[7] https://www.planet.com/nicfi/

relying on external global data from other sources. This also enables the application of specific forest definitions for individual biomes based on tree cover percentage and could be used for degradation monitoring.

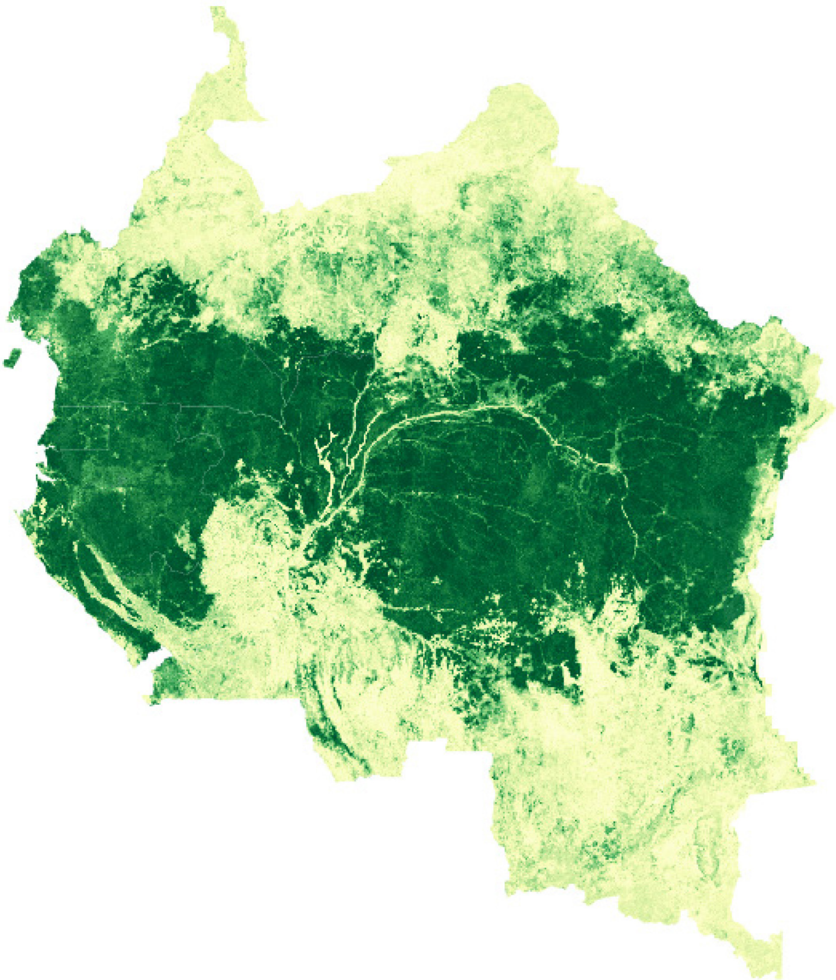

Figure 38. % tree cover (2015) for the entire Congo basin created by classifying Planet imagery into forest non-forest and up scaling to % forest at the 30m pixel. With freely available Planet, Landsat and Sentinel data this map can be updated monthly.

The availability of free data from active sensors such as Sentinel-1 is rapidly increasing the use of radar data, which was previously limited. Additionally, ALOS Palsar mosaics from the Japanese Space Agency are providing annual coverage of the tropics. Very high-resolution X-band data from commercial vendors such as Capella Space[8] present new opportunities to directly measure forest structure, above-ground biomass or detect canopy gaps or disturbances at increased spatial and temporal scales. The technology landscape is rapidly evolving – there are likely to be many new leaps in data and processing techniques in the next few years.

The massive increase in satellite data and technologies are putting more possibilities in to the hands of those who need it. Planet data, combined with long term Landsat and Sentinel sensors are being applied for Congo basin wide forest monitoring with a particular focus on degradation as part of a new FAO/CAFI initiative to study forest change and the associated direct drivers[9]. By the end of 2021, wall-

[8] https://www.capellaspace.com/

[9] http://www.fao.org/redd/news/deforestation-et-degradation-en-afrique-centrale

to-wall maps of deforestation, degradation and associated drivers will be developed, and more importantly these data will be analyzed and created by local stakeholders trained to use open-source data and software all in the cloud. The promises of this new technology are creating so many new options to closely monitor forests from space —information is power, and sharing data, open and transparent methods developed in this research will arm more people in the fight for our planet.

> ***"…it is less expensive to protect the planet now than to repair it later."***
>
> José Manuel Barroso, former President of the European Commission[9]

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