Mining, livelihoods and forest conservation in the DR Congo

Gruvedrift, livsgrunnlag og skogbevaring i DR Kongo

Philosophiae Doctor (PhD) Thesis

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List of papers

Paper I
Ladewig, M., Angelsen, A., Masolele, R. N., & Chervier, C. (2024). Deforestation triggered by artisanal mining in eastern Democratic Republic of the Congo.
Postprint of a study published in Nature Sustainability, 7(11), 1452-1460.

Paper II
Ladewig, M., Angelsen, A., Imani, G., Baderha, G., Bulonvu, F., Kalume, J. & Cuni-Sanchez, A., (2025). Between a Rock and a Hard Place: Livelihood Diversification through Artisanal Mining in the Eastern DR Congo.
In review at 'Resources Policy'

Paper III
Ladewig, M. (2025). Increasing pressure on protected areas in the DR Congo over the last 20 years.
Manuscript

Abstract

The Democratic Republic of Congo (DRC) hosts large parts of the Congo Basin, the second biggest rainforest on the planet. The forest is a biodiversity hotspot, provides for the livelihoods of millions of people and serves important regulatory functions for the regional and global climate. Despite ambitious commitments to halt and reverse forest loss in the DRC by 2030, deforestation continues under the pressure of a rapidly growing population. Structured in three papers, this thesis broaches separate yet related topics connected to the Congo Basin rainforest of the DRC, particularly concerning the extraction of minerals in the eastern part of the country and the attempt to conserve the forest by putting it under protection. The analyses rely on econometric impact evaluation methods, geo-spatial data analysis of remotely sensed data, and household survey data analysis following fieldwork in the South Kivu province in the east of the country.

The first paper focuses on the role mineral extraction plays in the deforestation context of the eastern provinces of North and South Kivu, Maniema, Ituri and Haut-Uele. Mineral abundance and persisting armed conflict have given rise to a dominant artisanal mining sector in this region. Where new minerals are discovered, population pulls can induce sudden accelerations of human activities even in remote, sparsely populated areas. Using novel data on post-forest land use and a staggered difference-in-difference model, the analysis uncovers strong deforestation trigger effects within at least 5km distance from newly opened mining sites in the forest. Within this distance, an average additional 4 percentage points of forest cover is cleared 10 years after the beginning of mining operations. Particularly farming and settlement expansion around mines lead to forest loss that was 28 times as high as the area cleared directly for mineral extraction itself, highlighting the role of mining in attracting other drivers of deforestation. In this way, at least 6.6% of the total deforestation in the study area can be explained by direct and indirect impacts of mining - much more than previously assumed.

Artisanal mining is also central to the second paper of the thesis, although with a focus directed at its livelihood implications. The study is based on data collected during fieldwork in villages adjacent to Kahuzi-Biega National Park and Itombwe Nature Reserve in the South Kivu province of the eastern DRC. The role artisanal mining plays for local communities in these forested landscapes was investigated through the lens of a livelihood diversification framework. In the surveyed villages, artisanal mining was widespread and served as both complement and alternative to traditional farming livelihoods. Results from an analytical model as well as an empirical hurdle regression model suggested that particularly land-poor households are relying on mining as a source of income. The empirical estimates further showed a potential role of artisanal mining in increasing food security on the household level, thereby emphasising its function as a safety net for the rural poor.

The third paper shifts the focus to protected areas (PAs) as the predominant forest conservation strategy in the DRC. Although their remote location has provided a natural protection against deforestation in the past, progressing deforestation frontiers from agricultural expansion and resource extraction are increasingly exerting pressure on PAs. Using a geographic regression discontinuity design at PA boundaries in the tropical moist forest biome that spans horizontally from west to east across the country, the study investigates the status of protection and its change

as anthropogenic pressure rises. To this end, a typology was developed, using the remaining forest cover extent and the annual rate of loss as metrics to categorise conservation context and performance. Results indicated that the remoteness of PAs has been fading since 2000, with an increasing number giving in to anthropogenic pressure. Of all assessed PA boundaries, 18% were found to have deforestation sprawling inside, whereas 9% were able to actively contain it. Pressure may further exacerbate in the future, as industrial-scale logging and mining operations are expected to intensify in critical locations and create infrastructure that critically weakens forest protection.

Norsk sammendrag

Den Demokratiske Republikken Kongo (DR Kongo) er vertskap for store deler av regnskogen i Kongobassenget, den nest største på kloden. Skogen er et hotspot for biologisk mangfold, gir livsgrunnlag for millioner av mennesker og har viktige regulerende funksjoner for det regionale og globale klimaet. Til tross for ambisiøse forpliktelser om å stanse og reversere tapet av skog i DR Kongo innen 2030, fortsetter avskogingen. Denne avhandlingen er strukturert i tre artikler som tar for seg ulike, men beslektede temaer knyttet til regnskogen i Kongobassenget i DR Kongo, særlig utvinningen av mineraler i den østlige delen av landet og forsøket på å bevare skogen ved å etablere verneområder. Den baserer seg på økonometriske metoder for effektevaluering, romlige dataanalyser av fjernmålte data og data fra feltarbeid i Sør-Kivu provinsen.

Den første artikkelen fokuserer på hvilken rolle mineralutvinning spiller i avskogingen i de østlige provinsene Nord- og Sør-Kivu, Maniema, Ituri og Haut-Uele. Mineralrikdom og vedvarende væpnet konflikt har skapt grunnlaget for en stor småskala gruvesektor i regionen. Når nye mineraler oppdages, kan det føre til en økning i menneskelig aktivitet, selv i avsidesliggende, tynt befolkede områder. Ved hjelp av nye data om arealbruk etter skogrydding og en *difference-in-difference* modell viser analysen sterke utløsende effekter i form av økt avskoging innenfor en avstand på minst 5 km etter at gruvevirksomhet har startet. Innenfor denne avstanden ryddes i gjennomsnitt ytterligere 4 prosentpoeng av skogdekket etter 10 år. Resultatene viser at særlig jordbruk og ekspansjon av bosetninger rundt gruver fører til et tap av skog som er 28 ganger større enn arealet som ryddes direkte for mineralutvinning. På denne måten kan minst 6.6% av den totale avskogingen i studieområdet forklares med direkte og indirekte påvirkning fra gruvedrift - mye mer enn tidligere antatt.

Småskala gruvedrift står også sentralt i den andre artikkelen av avhandlingen, men her er fokuset rettet mot konsekvensene for livsgrunnlaget. Artikkelen er basert på data som ble samlet inn i løpet av feltarbeid i Kahuzi-Biega nasjonalpark og Itombwe naturreservat i Sør-Kivu-provinsen i den østlige delen av DR Kongo. Gjennom et teorirammeverk for diversifisering av inntektsgrunnlaget (*livelihoods diversificaton framework*) undersøker artikkelen hvilken rolle småskala gruvedrift spiller for lokalsamfunnene i disse skogkledde landskapene. Jobbing i gruvedrift er utbredt i de felt-landsbyene og fungerer både som et supplement og et alternativ til tradisjonelt jordbruk. Resultatene fra en analytisk modell og en empirisk regresjonsmodell tydet på at særlig landfattige husholdninger i stor grad var avhengige av gruvedrift som inntektskilde. De empiriske estimatene viste videre at småskala gruvedrift kan bidra til å øke matvaresikkerheten på husholdningsnivå, noe som understreker gruvedriftens funksjon som sikkerhetsnett for de fattige på landsbygda.

Den tredje artikkelen fokuserer på skogbevaring i form av vernedeområder som den dominerende strategien for skogbevaring i DR Kongo. Selv om den avsidesliggende beliggenheten tidligere har gitt en naturlig beskyttelse mot avskoging, blir verneområdene i økende grad utsatt for press som følge av landbruksekspansjon og ressursutvinning. Ved å bruke i en geografisk regresjonsdiskontinuitetsdesign i det regnskogbiomet som strekker seg over hele landet, undersøker studien statusen til vernet og hvordan den endrer seg etter hvert som det menneskeskapte presset øker. Det ble utviklet en typologi der gjenværende skogdekke og årlige avskoging ble brukt som kriterier for å kategorisere vernekontekst og verneeffektivitet. Resultatene ty-

der på at verneområdene har blitt mindre avsidesliggende siden år 2000, så gir de i økende grad etter for menneskeskapt press. Denne trenden kan bli ytterligere forsterket i fremtiden, ettersom industriell hogst og gruvedrift forventes å øke og medføre ny infrastruktur som har vist seg å svekke skogvernet betydelig. 18% av grensene, viste seg å ha avskoging på innsiden, mens bare 9% stod imot etter at avskogingsfronten. Dette presset kan bli ytterligere forsterket i fremtiden, ettersom industriell hogst og gruvedrift forventes å øke og medføre ny infrastruktur som har vist seg å svekke skogvernet betydelig.

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Introduction

1.1 Background of the thesis

Forests are of vital importance to life on the planet. They are crucial for biodiversity by providing habitats, fulfil important regulatory functions for the global and regional climate and water cycles (Duveiller et al. 2021; Abera et al. 2024), directly provide for the livelihoods of millions of people (Angelsen et al. 2014) and are essential to climate change mitigation efforts (IPCC 2023). This is especially true for tropical forests, which constitute about 45% of the worlds forest and yet host 60% of all vascular plants (FAO and UNEP 2020). Due to the high exposure to sunlight and rainfall around the equator, tropical forests are more productive than others, leading to denser vegetation and large amounts of biomass and hence higher carbon stocks (Ghazoul and Sheil 2010).

Despite their potential of being natural carbon sinks, continued deforestation and forest degradation have compromised the net carbon footprint of tropical forests and their climate regulatory properties (Harris et al. 2021; Boulton, Lenton, and Boers 2022). The Amazon, the largest rainforest on the planet, is already on the verge of turning from a carbon sink to a net carbon source (Harris et al. 2021). Ecological tipping points could further destabilise it and exacerbate these dynamics, as the resilience of the Amazon continues to fade (Boulton, Lenton, and Boers 2022; Steffen et al. 2018).

After the Amazon, the Congo Basin constitutes the second largest contiguous rainforest. It also hosts 36% of all tropical peatland area, which alone stores around two years of global carbon emissions (Crezee et al. 2022; Dargie et al. 2017). About 60 million people residing within or close to the Congo Basin rainforest rely directly on it for their livelihoods (Eba'a Atyi et al. 2022). Although less than 70% of the Congo Basin remains intact today and the stability of this unique ecosystem is at stake as loss continues (Garcin et al. 2022; Shapiro et al. 2021), the area remains under-researched compared to other major tropical forest areas (White et al. 2021).

This thesis focuses on the Democratic Republic of Congo (DRC), and in particularly on its tropical moist forest biome, which is characterised as closed evergreen or deciduous tropical forest with either seasonal or low rainfall variability (Vancutsem et al. 2021). About 106 million ha of undisturbed tropical moist forest and around 60% of the Congo Basin is located within the DRC (Eba'a Atyi et al. 2022). After Brazil, it is the country with the second largest extent of tropical moist forest, hosting 11% of what is remaining on the planet (Figure 1.1).

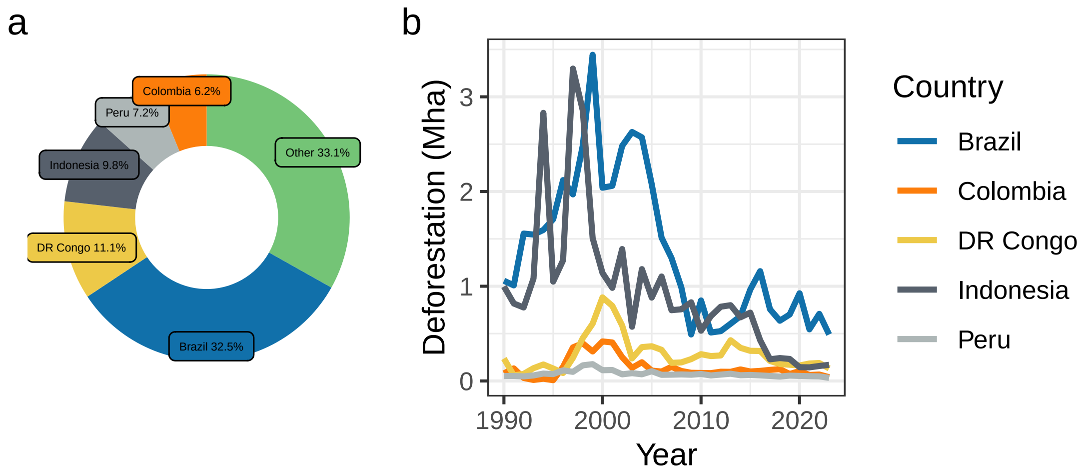

Figure 1.1: ***a*** *Share of the worlds undisturbed tropical moist forest in 2023 by country.* ***b*** *Trends in deforestation for major tropical moist forest countries. Both figures show Tropical Moist Forest (TMF) data (Vancutsem et al. 2021).*

Besides forests, the DRC is also among the most mineral abundant countries in the world. Despite its richness in gold, coltan, cobalt and copper, amongst others, the DRC is among the poorest countries in the world (United Nations Development Programme 2022). In 2020, 79% of the population lived on less than 2.15USD a day (World Bank 2025), and 41% faced severe food insecurity (FAO 2023). Government provisioning of public services does not reach all parts of the country, as the state authority remains fragmented and the infrastructure highly degraded (Schouten 2022).

While remote sensing studies have attempted to identify the main land uses that cause forest loss in the country (Tyukavina et al. 2018; Masolele et al. 2024; Shapiro et al. 2023), there is still much to be done to develop a better understanding of the context and the dynamics in which these emerge. The thesis aims to contribute to this end by exploring the context of deforestation drivers, livelihoods and conservation in the DRC.

The first two chapters are set in the eastern DRC, one of the most mineral rich regions on the planet (Figure 1.2). After the retreat of the mining industry with the ignition of the first Congo war in 1996, exploitation became increasingly dominated by artisanal extraction, with implications on both forests and traditional livelihoods (Kilosho Buraye et al. 2017). As a consequence, mining became integral part in the livelihoods of millions of households in the area. Where minerals deposits are discovered, mineral rushes can lead to sudden increases in human activity even in remotely located forest areas (Bryceson and Geenen 2016; Smith 2011). Using novel data on post forest land uses (Masolele et al. 2024), the first chapter uncovers the forest loss impacts of these mineral discoveries, whereas the second chapter highlights the role of artisanal mining in livelihood diversification strategies of people working in the sector. Finally, the third chapter zooms out to the entire tropical moist forest biome of the DRC and evaluates protected areas (PAs) as the most prevalent forest conservation tool, specifically focussing on frontier processes and the potential of PA boundaries to withstand deforestation pressure once their remoteness starts to fade.

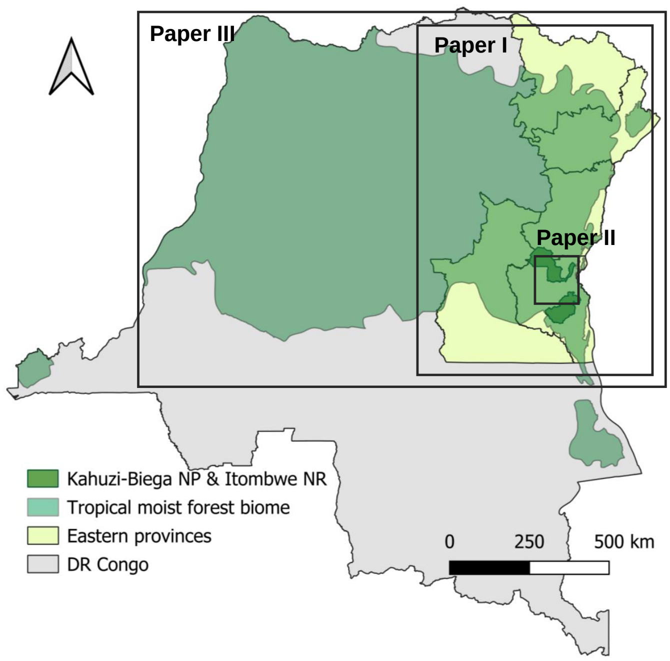

Figure 1.2: *Map showing the study areas of the three papers presented in this thesis.*

1.2 Preliminaries and definitions

Before diving into the thesis, it is useful to clarify essential underlying terminology and concepts. Starting with the definition of forest, what classifies as forest can vary substantially and also needs careful consideration when choosing the appropriate data set for an analysis (see Section 1.7.1).

A starting point is the distinction into forest and other tree covered land. For instance, the FAO defines forest as land of more than 0.5 hectares with more than 10% tree cover, and at least 5 meter canopy height (FAO 2020). The definition explicitly includes agroforestry systems and tree plantations for timber and other commodities. Such highly managed landscapes do not fall within the scope of this thesis, since they are in themselves irrelevant for the understanding of deforestation dynamics.

Within the forest category, further distinctions can be made along different gradients, such as the openness of the canopy, the age of the forest, the altitude, and the moisture level (i.e. dry, moist or flooded) (Shapiro et al. 2023). The resulting typology of forests is complex and fluent, and the remote sensing of deforestation is commonly simplified by applying a minimum threshold of forest cover that is suitable to reflect "natural" forest for the region and biome of interest. For the Congo Basin, this threshold is often set at 60% canopy cover to distinguish forest from other land with tree cover, such as fallow agricultural land (Molinario et al. 2017; Shapiro et al. 2023). A different approach was chosen by Vancutsem et al. (2021), who classified land with tree cover in absence of historical canopy cover disturbances as undisturbed forest, and thereby distinguished disturbed and re-grown forest from old-growth forest (see Section 1.7.1).

The understanding of deforestation throughout this thesis is in line with that of the FAO, thus defining it as a permanent conversion of forest to other land uses (FAO 2020). Forest degradation is understood as a change in forest conditions, induced for instance as a consequence of forest fragmentation, logging, droughts or fires, that compromises ecosystem functionings (Lapola et al. 2023; Ghazoul and Chazdon 2017). Given that the definition of degradation is rather broad, includes gradual small-scale but also macro processes, it is more challenging to quantify than deforestation. This thesis thus focuses mainly on deforestation events, although degradation is an increasing problem that requires more attention in its own right.

The terminology describing causes of forest cover change follows that of Meyfroidt (2016) who makes a useful distinction between causal effect and causal mechanism. Causal effects are defined as the changes in outcomes, such as deforestation or forest degradation, caused by the existence of some factor of interest. They can be described in a potential outcomes framework, as further specified in section 4 of this introduction. A causal mechanism is a process through which the causal effect impacts an outcome. In complex processes like land cover change, single mechanisms are seldomly sufficient to explain observed dynamics (Meyfroidt 2016), which emphasises the role of context in the analysis of deforestation drivers.

It is useful to further distinguish causes into direct (proximate) causes and indirect (underlying) causes of forest change (Angelsen and Kaimowitz 1999; Geist and Lambin 2001). Indirect causes are factors that lead to the occurrence of a direct cause. For instance, population growth does not directly lead to deforestation, but it can be causally linked to agricultural expansion which does. Indirect and direct causes can thus be thought of as linked in a causal chain, in which indirect causes lead to the direct cause located at the end of the chain, often the post forest land use (Meyfroidt 2016).

A concept particularly used in Paper I of the thesis is that of a trigger factor. A trigger of deforestation explains the time and the place of a deforestation event (Meyfroidt 2016). Especially in core forest areas that would otherwise remain shielded from frontier processes due to their inaccessibility, trigger factors can explain the emergence of disturbance events. Mineral discoveries are an example of deforestation triggers, as they can lead to rapid intensification of human activity in previously remote forests (see Paper I). Given the importance of forest integrity for ecosystem resilience and biodiversity, trigger dynamics can give crucial insights for forest conservation strategies (Haddad et al. 2015; Watson et al. 2018).

1.3 The context of deforestation and livelihoods in the DRC

The DRC is a large and heterogeneous country in central Africa. It contains an area of 235 Mha, of which 44% is covered by dense rainforest (Vancutsem et al. 2021). The resulting inaccessibility of many areas, but also protracted conflict have given rise to a fragile state that is not able to provide services in many parts of the country. A dysfunctional transport infrastructure and the territorial presence of a variety of armed groups, especially in the eastern DRC, pose obstacles for lasting improvements of the situation (Schouten et al. 2022). Beyond the activities of countless paramilitary groups with scattered agendas, access to land has been a recurring source of conflict (Van Acker 2005). Persistent tensions involve different sets of actors, for instance pastoralists and farmers, local and immigrant communities, and statutory and customary land right holders (Huggins 2010). Also conservation policies and the extractive industries have created instances of friction with customary land holders, often resulting in displacement of communities and resistance (Inogwabini 2014; Geenen 2014).

The conflicts and the eroded state have contributed to the deterioration of rural livelihoods in the country, lead to mass displacement and also conditioned the dissolving of agricultural markets (Cox 2012; Kelly 2014). Prior to the recent advance of the M23 rebels that found its preliminary climax in early 2025 in the seizure of North Kivu's regional capital Goma, 5.8 million people in the DRC were already internally displaced due to violence and conflict (McAuliffe and Oucho 2024). Even before the latest wave of violence, extreme poverty was widespread: the DRC is ranked 180th out of 193 countries on the Human Development Index (HDI) (United Nations Development Programme 2022), and food insecurity is a serious issue in many regions ("Food Assistance Outlook Brief" 2023, FAO 2023). In this challenging policy environment, addressing deforestation without adding more burden on already deprived communities is a complex challenge.

Given the insecurity in parts of the country and the eroded infrastructure, extractive industries and large-scale agribusinesses that tend to drive deforestation in many other tropical rainforest areas (Pendrill et al. 2019) have not fully settled in the DRC (Ordway et al. 2017; Radley 2020; Eba'a Atyi et al. 2022). Forest loss in most of the Congo Basin countries and particularly in the DRC is dominated by shifting agriculture on a small scale (Masolele et al. 2024; Shapiro et al. 2023; Tyukavina et al. 2018). More than 90% of all loss in the country is attributed to this farming system in which fields undergo cycles of cultivation and vegetation regrowth to restore soil fertility. Most deforestation occurs in proximity to roads and villages in mosaics that have been termed the *rural complex* (Potapov et al. 2012; Molinario et al. 2017; Shapiro et al. 2023). These mosaics consist of cultivated fields, fallow land with regrowing vegetation, secondary forest, and settlement structures.

Also other activities that compromise forest integrity are mostly conducted artisanally. Fuel wood collection and charcoal production, for instance, can lead to substantial forest degradation, especially in proximity to urban areas (Schure, Levang, and Wiersum 2014), but usually have limited impact on deforestation. At the same time, they satisfy the energy needs of a rapidly growing population and also provided important income opportunities.

Industrial logging in concessions is situated only in the western part of the country, but is less developed than in other Congo Basin countries and dwarfed by the amount of timber that is harvested artisanally and processed in local chain saw mills (Eba'a Atyi et al. 2022; Lescuyer et al. 2014). Artisanal logging occurs all over the country, often illegally within a few kilometers distance to roads. However, it affects only a few species and trees with a large diameter (Ferrari and Cerutti 2023; Lescuyer et al. 2014). A substantial share of the logs is exported to neighbouring countries without proper documentation (Ferrari and Cerutti 2023). Where industrial logging operations take place, forests roads can trigger deforestation by providing access to previously remote forest areas (Kleinschroth et al. 2019; Slagter et al. 2024). However, the only study that systematically evaluated deforestation impacts of logging concessions in the DRC has not found increasing forest loss within concession areas (Chervier et al. 2024).

Predominantly in the mineral-rich eastern and southern part of the country, artisanal mining has become an important part in people's livelihoods over the past decades. Whereas the south is covered by dry woodlands, mineral deposits in the east are often located in the tropical moist forest, and their exploitation has significant impacts on its deforestation (Ladewig et al. 2024). A crucial aspect about mineral-driven deforestation is its distinct location. Within the rural complex, forest conversion mostly affects secondary forest and adjacent primary forest along forest edges (Shapiro et al. 2023). For deforestation to move into core forests, however, stronger incentives are required (Molinario et al. 2020). In the eastern part, minerals provide such incentives due to the income opportunities they offer. Several studies have described the unparalleled potential of mines to attract people even into the most remote of places (Bryceson and Geenen 2016; Jønsson and Bryceson 2009; Smith 2011). The impact of mineral rushes on surrounding forests is central to Paper I of this thesis.

Also conflicts reportedly had their toll on core forests, as the extraction of forest resources is a common coping strategy in times of hardship. Further, forests have served as hiding places for displaced people and combatants alike (Draulans and Krunkelsven 2002; Nackoney et al. 2014; Plumptre et al. 2016).

1.4 Economic theories of land use change

As the main driver of land use change, both globally and in the DRC, agricultural expansion is at the core of economic theories that describe the process of forest clearing (Curtis et al. 2018; Pendrill et al. 2019; Shapiro et al. 2023). A distinctive feature that sets apart the different theories is the degree to which they assume actors to operate within market environments (Angelsen 1999; Babigumira et al. 2014; Meyfroidt et al. 2018). Benefits of land conversion, market prices and transport costs often explain forest conversion in scenarios embedded in functioning agricultural markets, such as the prominent von Thünen-type models (von Thünen 1826).

1.4.1 Land rent models

The essence of von Thünen's work is the idea that actors decide to put land to the use that provides the highest expected profit. In the case of agriculture, return is assumed to increase with proximity to urban centres where markets are located, as transportation costs make farming increasingly unprofitable with the remoteness of land. Where the costs of forest conversion are higher than the expected returns of conversion to farmland, forest cover remains. Functioning roads are therefore essential to explain forest clearing in this framework. Also other rent-determining factors may contribute to the rate of agricultural expansion, such as productivity per land area, market prices for agricultural outputs, and input costs (Angelsen 2010).

The von Thünen framework can give useful insights for forest conservation. First, it can help to prioritise target areas for conservation that face particularly high incentives of forest conversion. Much of the Congo Basin rainforest is protected by its inaccessibility that makes most market-oriented land uses unprofitable. In more accessible areas within road proximity, however, this passive protection is weakened, showing in higher deforestation rates (Kleinschroth et al. 2019).

Conservation strategies aiming to prevent forest conversion then have different levers they can use to reduce deforestation pressure. The first is to increase the profitability of keeping forest standing rather than removing it. This can be done either by reducing land rent from other uses, most notably agriculture, or by increasing forest rent. Policies that reduce land rent are typically undesirable, as they reinforce poverty and food insecurity, and - if a substantial share of agricultural production serves subsistence needs - may be inefficient (see the following section 1.4.2 on imperfect market models) (Angelsen 1999). Thus, increasing forest rent relative to other land rent may be the preferred policy option, for instance by paying land holders for conservation. Different mechanisms have been used in this attempt, which are further explained in section 1.5.4.

A second way to conserve forest when land rent is determining forest conversion are command-and-control policies. Where the land rent is higher than the forest rent, deforestation can be restricted by public authorities. Paper III in this thesis looks at protected areas as one such policy, although PAs have a bias to be placed in remote areas where deforestation pressure is low regardless (see section 1.5.1). In a context like the DRC, where state capacity to enforce policies is weak, command-and-control can be of limited impact.

A third way to spare forest can be through promotion of livelihoods that are not dependent on land expansion and deforestation. If other income generating activities that are not involving forest clearance are available and profitable enough, they provide incentives to substitute activities that cause deforestation. This was observed, for instance, in Paper II in the case of mining. However, Paper I also showed that mining itself causes deforestation, especially indirectly.

1.4.2 Models in imperfect markets

While land rent models may be able to explain some of the deforestation dynamics at the urban periphery and around larger towns, most agricultural produce in the DRC is to satisfy subsistence needs (Moonen et al. 2016). Markets are frequently imperfect or inaccessible, and even where transport infrastructure exists, road taxes levied by armed groups can make its use for trade costly (Schouten et al. 2022). Land rent models are thus often not accurate in explaining land cover change in the DRC. Risk minimisation and “full belly” considerations, i.e., minimal consumption requirements, also matter to explain households’ land use strategies (Angelsen 1999; Moonen et al. 2016). Land use change in incomplete markets and subsistence-oriented production settings have been discussed early in the works of Chayanov (1966) and Boserup (1965). The model of Paper II of this thesis in which the livelihood diversification process of households is modelled is within this tradition.

In Chayanovian models, agricultural expansion is driven by household characteristics such as the number of "bellies to fill" in relation to the available labor force, and the age of a household head (i.e. the life cycle stage of a household) (Babigumira et al. 2014). Farmers mainly engage into clearing of new land when they are young, and generally face a trade-off between farm labor and leisure (Angelsen 1999). As opposed to the von Thünen model, wage rate is therefore not determined by the market, but within the household. Population growth increases the overall required amount of food in this context. In absence of off-farm labor opportunities, the farmer is left with the choice to either intensify or expand agricultural production (Erb et al. 2016).

According to Boserup (1965), decreasing marginal labor productivity and lacking capital to intensify production by other means make expansion the preferred choice, at least to the point where scarcity of land sets in (Meyfroidt et al. 2018). Over the past six decades since Boserup, the relationship between intensification and expansion has been subject to much debate. Whereas some argued that intensification will enable more food production per area and thereby spare expansion of agriculture into forests, others highlighted increasing land rents under productivity gains as a driver of expansion (Angelsen and Kaimowitz 2001). Both hypotheses have found contextual empirical support (Lambin and Meyfroidt 2011), and have become known in the literature as the Borlaug hypothesis and the Jevon's paradox, respectively. Globally, the empirical trend has shown simultaneous increases in both yield per area and agricultural area over the last decades (Ramankutty et al. 2018; Rudel et al. 2009), and agriculture is considered by far the most important driver of forest loss (Pendrill et al. 2019). However, the world has also seen an exorbitant increase in population over the same period and thus requires more food.

Around urban centres and larger towns, the von Thünen model may provide insights into the processes of land cover change in the DRC. Where transport costs to local markets are low, forest clearing for market produce can be a major factor. However, in remote areas with poor market access, land rent alone cannot explain conversion dynamics. Here, forest loss is often driven by increasing need for land under a growing population. For instance, Moonen et al. (2016) found increasing deforestation around villages closer to the city of Kisangani and among households selling produce on the market as predicted in von Thünen models, but also evidence for Boserup's hypothesis of agricultural expansion under a growing population. Also Mayaux et al. (2013) and Ernst et al. (2013) found strong deforestation feedbacks once the population density exceeded about 8 people per km^2. As population density grows further, shorter fallow periods on already converted land also reduce soil fertility over time, requiring even more land for the same amount of agricultural output (Ernst et al. 2013).

1.5 Forest conservation in the DRC

In this context, where deforestation is largely a poverty- and population-driven phenomenon by small-holders under weak institutions, a crucial question is how conservation of the Congo Basin rainforest can be achieved without compromising livelihoods of the people who depend on the forest and the land.

1.5.1 Protected areas

Protected areas (PAs) have been at the core of forest conservation policies in the DRC (Inogwabini 2014). The World Database on Protected Areas (WDPA) lists 60 terrestrial PAs throughout the country, covering 15% of its terrestrial surface (WDPA 2024). Historically, the implementation of the first PAs goes back to early colonial times and was aiming to conserve forest by preventing people from accessing it (Inogwabini 2014). It followed the long-held idea of tropical rainforests as a pristine, unpopulated space without human influence - a view that is increasingly challenged by the understanding that humans have a long history of living in these landscapes and have contributed to shaping ecosystems (Roberts, Hamilton, and Piperno 2021). In the DRC, much of the conservation effort still relies on exclusionary protection of forest (Inogwabini 2014; Simpson and Geenen 2021). As a consequence, PAs often encounter low acceptance from communities living in and around affected areas, which also weakens their conservation performance (Inogwabini 2014; Kujirakwinja et al. 2019).

Limited capacity and funding to effectively enforce protection in the DRC has given its PAs the reputation as "paper parks" - areas where protection exists on paper, but where consequences on deforestation are negligible when they are put to the test. To strengthen the implementation and management of PAs, collaborations between government and large international NGOs have emerged, and have shown improved potential to withstand deforestation pressure (Debureaux et al. 2025). However, co-managed PAs also tend to be located in more remote areas where their potential of avoiding deforestation is not used.

Based on the discussion of economic theories above, pressure on PAs could arise when expected rents from forest conversion are sufficiently high, but also when the rural complex expansion reaches PA boundaries due to the increasing need for land to feed a growing population. In terms of conservation outcomes, this means that PAs maintain their forest cover if (i) expected profit from clearing forest remains negative, i.e. the deforestation front has not arrived at PA boundaries (ii) rural complex expansion comes to a halt, for instance through intensification of agriculture or slowing down of population growth, or (iii) forest protection provided by PAs effectively prevents deforestation. Paper III in this thesis establishes a typology to systematically contextualise the effectiveness of PAs under varying deforestation dynamics.

1.5.2 The forest code revision of 2002

Since the issue of a 1973 ministerial decree under the Mobutu regime, all land in the DRC officially belongs to the state, regardless of its customary land use (Van Acker 2005). This standpoint was reinforced under the forest code of 2002, which declared all forest as state property, and as such gave the state authority to establish PAs, productive areas for timber harvesting, or classified forest areas to be managed under state mandate.

At the same time, the 2002 forest code laid the foundation for improved governance of forests and its resources. Drafted by FAO experts, it aimed at making logging operations adhere to socially and environmentally sound practices while dissolving illegally signed contracts (Majambu et al. 2021). This involved the requirement to submit management plans in which companies expound how they intend to incorporate such practices, including the rotational harvesting cycle that should allow forest to recover from logging disturbances, and the social contributions granted to local communities residing in concession areas.

The forest code also, for the first time, recognised forests held under customary land rights, and provided legal ground for the creation of conservation concessions. Conservation concessions allow title holders to monetarise environmental services provided by the forest without extracting any of its resources, as specified in Decree n° 011/27 of 2011. Thus, they are particularly interesting for private companies to sell carbon credits. At least 24 of these conservation concessions have been granted since 2020 (Kengoum et al. 2024). Many conservation concessions are former logging concessions that have been transformed, which has been criticised for providing the perverse incentive of first extracting the highest value timber and then monetarising what is left through carbon schemes, thereby undermining the intention behind conservation concessions.

1.5.3 Community forest concessions

The first community forest concessions were established in 2017, 15 years and three decrees after the revised forest code provided the legal basis for their creation. Since then, 200 community forests were established, and 40 more are in process in the beginning of 2025 (Forest Management Directorate 2025).

Community forest concessions give communities who have customary forest rights the exclusive and irrevocable right to manage up to 50,000 ha of forest according to their own terms of forest use (Vermeulen and Karsenty, 2017). It thus gives them the chance to sustainably use forest resources according to an approved management plan while securing it against the appropriation and exploitation by other actors.

Whether or not community forests can become a model for more participatory landscape conservation approaches with involvement of communities in land use decisions has to be seen, as implementation is still in its infancy and impacts are yet to be evaluated. It has already been highlighted that the establishment process of community forests is costly and not viable for communities without external support, as it requires the mapping of the forest, the creation of a forest inventory and a management plan (Lescuyer et al. 2014).

1.5.4 Incentive-based mechanisms

Incentive-based conservation mechanisms are often targeting land rents and aim at making forest conversion less profitable than forest conservation. Mechanisms include Payments for Environmental Services (PES), carbon credits and conditional cash transfers, although the borders between them are blurry.

A large global forest conservation framework is the "Reducing emissions from deforestation and forest degradation" initiative as established under the Paris agreement, more commonly known by its acronym REDD+. The "+" signifies other forest-related activities that mitigate climate change. It works by offering countries results-based payments for reducing their deforestation compared to a historical reference level. Funding comes from bilateral and multilateral aid payments, corporate investments and the voluntary carbon market. Depending on the kind of effort that was undertaken, benefit-sharing mechanisms distribute the funds to the projects, jurisdictions, communities or households that engaged in avoiding deforestation, thereby increasing forest rent relative to the rent from other land uses.

A major controversy with REDD+ has been concerning the question of additionality, as the amount of avoided deforestation is frequently calculated from inadequate historical baselines that do not represent realistic counterfactuals for deforestation in absence of REDD+ (West et al. 2023). Consequently, the impact of REDD+ projects tends to be severely overstated, at times even to an extent that avoided deforestation becomes negligible.

The DRC has entered the so-called readiness phase of REDD+ in 2009 and signed a USD 500 million heavy agreement for the years 2021-2031 to halt and reverse forest loss and degradation by the end of that period (Kengoum et al. 2024). However, impeded by the state's low capacity to engage into long-term planning, the DRC's implementation process still suffers from various institutional short-comings, such as inadequate monitoring, reporting and versification (MRV) systems, low participation of civil society in the REDD+ process, insufficient integration into broader national politics and high levels of corruption (Pham et al. 2021; Karsenty and Ongolo 2012; Kengoum et al. 2020). As Kengoum et al. (2024) note, it is not even clear how many REDD+ projects currently exist in the DRC, given that an official registry is missing. They counted a minimum of 45, of which 25 are already discontinued. For the remaining active projects, benefit-sharing mechanisms are unclear. In 2024, the Mai-Ndombe project was the only one with an approved benefit-sharing plan in the form of a PES scheme (Kengoum et al. 2024).

1.6 Methods

1.6.1 Potential outcomes, counterfactuals and the "credibility revolution"

Quasi-experimental methods have seen rapidly increasing popularity since the beginning of the century and became essential equipment in the toolbox of empirical micro-economics (Goldsmith-Pinkham, n.d.). As research designs such as difference-in-differences, regression discontinuity, instrumental variable estimation, and lately also increasingly synthetic control methods already found wide applications in public, health, labor and development economics, the field of conservation sciences was lagging behind for a long time (Baylis et al. 2016; Ferraro and Pattanayak 2006). Yet, robust impact evaluation of conservation programs or quantification of negative externalities on biodiversity and deforestation from anthropogenic activities are essentially requiring counterfactual thinking: How much deforestation was *avoided* by policy X? What is the *additional* amount of deforestation that occurred because of event Y? The two adjectives highlighted in italics indicate the comparison to a baseline state in absence of an intervention that helps identifying its effect - a counterfactual that is not observable. The inability to observe the same object in two different states of the world at the same time has become known as the "foundational problem of causal inference" (Holland 1986).

In the notation of Rubin's potential outcomes framework, the problem can be formalised as

$$\tau = E[Y|D=1] - E[Y|D=0] \tag{1.1}$$

where D indicates whether an intervention (or treatment) has occurred or not, Y is some outcome of interest, and τ is the intervention effect. The problem that motivates quasi-experimental research methods is that the identification of the intervention effect τ in equation 1.1 requires insights on both $Y|D=1$ and $Y|D=0$. One of these two states of the world will inevitably remain unobserved and is called a counterfactual.

Randomised treatment assignment can help to estimate the counterfactual by creating statistically identical control and treatment groups, such that τ in equation 1.1 only captures the difference from a change in treatment status. Randomised experiments are usually costly to implement and not applicable in all research settings, especially in the field of conservation sciences. Quasi-experimental research methods represent attempts to nevertheless recover τ, given that certain identification assumptions are met. Different methods invoke different assumptions, and the choice of the design requires careful consideration (see Table 1.1).

Only recently have quasi-experimental methods gained in popularity in the application to the field of conservation (Jones and Shreedhar 2024; Ferraro and Hanauer 2014). Especially statistical matching has been on the rise for its ease and versatility in application (Schleicher et al. 2020; Joppa and Pfaff 2010; Andam et al. 2008). Although in principle better than linear regression analysis for allowing more flexible functional forms, matching still ultimately relies on the selection of observable characteristics for the identification of treatment effects (Smith and Todd 2005). The methods used in this thesis largely draw on the rapidly developing field of quasi-experimental inference methods. By choosing the appropriate research design, they allow to - at least partially- control for confounding variables that would otherwise bias treatment effect estimates by design, based on the assumptions one is willing to make given the research question at hand.

1.6.2 Difference-in-Differences

In Difference-in-Differences (DiD) estimation, the key assumptions for the identification of τ is that counterfactual outcomes would have developed in parallel had there not been a treatment intervention. The estimated effect then follows from the deviation from this counterfactual trend. In the potential outcomes framework from above and a simple setting with two time period, the Average Treatment Effect on the Treated (ATT) can be derived from DiD as:

$$\tau_{DiD} = (E[Y_{post}|D=1] - E[Y_{pre}|D=1]) - (E[Y_{post}|D=0] - E[Y_{pre}|D=0]) \tag{1.2}$$

τ_{DiD} can then be estimated in a Two-Way Fixed-Effects (TWFE) regression.

In case of a staggered treatment roll-out where different groups get treated at different points in time, the estimation becomes more complicated. Several studies have shown that the TWFE estimator under heterogeneous treatment timing and dynamic treatment effects runs into problems with arbitrary weighting and forbidden

Table 1.1: *Quasi-experimental research methods employed in the thesis papers and their key assumptions.*

Research method	Key assumptions	Reference	Thesis paper
Staggered Difference-in-Differences	• Parallel counterfactual time trends in the outcome variable between treatment and control units. • No anticipation of treatment.	Callaway and Sant'Anna (2021), Borusyak, Jaravel, and Spiess (2024), de Chaisemartin and D'Haultfœuille (2020)	Paper I
Geographic regression discontinuity design	• No sorting across treatment boundary • No compound treatment	Keele and Titiunik (2015), Dell (2010)	Paper III
Geographic Difference-in-Discontinuities design	• Constant discontinuities over time	Grembi, Nannicini, and Troiano (2019); Butts (2023)	Paper III

sub-group comparisons (Goodman-Bacon 2021; Chaisemartin and D'Haultfœuille 2020; Borusyak, Jaravel, and Spiess 2024). In response, a number of studies have also proposed alternatives to TWFE estimation to obtain consistent DiD estimates even when treatment adoption is heterogeneous (Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024; Gardner et al. 2024; de Chaisemartin and D'Haultfœuille 2020; Sun and Abraham 2021).

The approaches of Borusyak, Jaravel, and Spiess (2024) and Gardner et al. (2024), amongst others, are also referred to as imputation estimators. Both use all available pre-treatment periods to estimate the counterfactual trend in a simple OLS regression before imputing the DiD parameter from it. Although it makes them more efficient than other estimators, it also makes them susceptible to early violations in parallel trends. Callaway and Sant'Anna (2021) chose a different approach by computing and averaging individual group-time ATT parameters. Principally, the parallel trends assumption must only begin to hold starting one period prior to treatment, although a credible research design typically shows parallel pre-trends over a longer time period (Roth 2023).

The DiD model in Paper I used the estimator proposed in Callaway and Sant'Anna (2021) in the main specifications for its ease of implementation, its well-developed software environment and the flexible conditioning on covariates. The estimator of Gardner et al. (2024) was further used as a robustness test, to investigate treatment effect heterogeneities and to implement a spillover-robust estimator suggested in Butts (2023).

1.6.3 Geographic regression discontinuity

A different quasi-experimental research method is regression discontinuity (RD) design. RD designs can be employed when an externally determined threshold divides observations into treated and non-treated units based on some observable characteristic, referred to as running variable. The key assumption for the identification of a treatment effect is that, had treatment not occurred, all observable characteristics would be continuous across the treatment determining threshold. Given this assumption holds, the treatment effect can be estimated as the discontinuity in the outcome of interest along the running variable as treatment switches on:

$$\tau_{RD} = \lim_{\epsilon \to 0} E[Y|X \in N_{\epsilon}^{+}(c_0)] - \lim_{\epsilon \to 0} E[Y|X \in N_{\epsilon}^{-}(c_0)] \tag{1.3}$$

where X is called the running variable that indicates the distance to the treatment-defining cutoff c_0. In contrast to τ_{DiD}, τ_{RD} is a Local Average Treatment Effect (LATE) as it only reflects the estimate in a close environment around c_0.

Paper III in this thesis uses a special case of RD called geographic regression discontinuity (GRD) design, where the running variable is a function of an observation's location in relation to a spatial treatment-cutoff. As opposed to the conventional regression discontinuity design, GRD has to take into account that location (on a map) is determined two-dimensionally, e.g., by longitude and latitude (Keele and Titiunik 2015). Different methods have been proposed to use location in regression discontinuity designs. Dell (2010) adopted a semi-parametric approach by splitting the treatment boundary into different segments and calculating the distance of observational units to the boundary. Polynomials of latitude and longitude and their interactions were added as covariates. Keele and Titiunik (2015) proposed a non-parametric method in which they sampled individual points along the treatment boundary and estimated local polynomials for each point separately. This approach was adopted in Paper III, as it is very flexible in aggregating the individual boundary point estimates into treatment effect parameters of interest, and also less sensitive to the bandwidth selection (Wuepper and Finger 2022). Finally, Cattaneo, Frandsen, and Titiunik (2015) have proposed to treat observations in a close window on either side of the treatment cutoff as quasi-randomised, such that the difference of average outcomes can recover the LATE. However, this local randomisation approach requires a large number of observations to be reliable.

1.6.4 Spillovers and leakage

In conservation and land use systems, interventions in one location can have unintended land use implications on other nearby or distant locations (Meyfroidt et al. 2020). These effects are known as spillovers and can be positive or negative. In cases where spillovers counteract the intervention's effect, they are also referred to as leakage.

Pfaff and Robalino (2017) identified several channels through which forest conservation programs can lead to spillovers. For instance, deforestation actors may simply shift their activities to land that is not affected by the intervention. On a large scale, this was observed with soy production in the Brazilian Amazon, when the moratorium displaced soy expansion to other regions (Fehlenberg et al. 2017; Gasparri and le Poulain de Waroux 2015). Displacement of deforestation may also occur around PAs, either when land uses are pushed outside PA boundaries, or when positive feedbacks onto the surroundings exist. This can be the case when land use restrictions inside PAs also reduce human activities in the surroundings. Empirically, both positive and negative spillovers of PAs have been identified in different contexts, with most studies indicating negligible or positive spillovers onto the surroundings (Ferraro et al. 2013; Fuller et al. 2019).

Besides displacement of deforestation from avoidance, spillovers can also occur as a result of market dynamics. For instance, when interventions reduce the supply of agricultural and forest goods, this leads to increases in output prices and may stimulate production elsewhere (Pfaff and Robalino 2017). Further, reduced demand for agricultural inputs lowers the cost of agricultural production, with similar effects. Whereas higher agricultural production may lead to farmland expansion and thus leakage, lower demand for labor in intervention areas may also lead to out-migration and consequently positive spillovers on conservation outcomes, at least in the nearby surroundings (Pfaff and Robalino 2017).

Depending on the research question and the empirical design, spillovers can be a problem for the identification of treatment effects. Econometric impact evaluation models usually rely on the stable unit treatment value assumption (SUTVA) for identification of treatment effects. SUTVA requires that (i) there are no hidden treatment variants, and (ii) the treatment status of one unit does not have an impact on the outcome of another unit (Keele 2015). Given that land use change follows complex spatial processes, especially the second part of the SUTVA assumption can be problematic in the analysis of deforestation impacts. The GRD model in Paper III of the thesis, for example, can be sensitive to leakage, given that the estimated effect is local around the boundary of PAs. If the protection inside PAs leads to an increase outside, discontinuity estimates no longer reflect only the effect of protection. However, as the effect of interest is not the avoided deforestation at the boundaries, but the potential to keep deforestation outside of the PA, coefficients still give useful insights even in presence of spillovers.

Identification of potential spillovers from an intervention is not well established in the empirical literature so far (Pfaff and Robalino 2017; Roth et al. 2023). In the case of PAs, for instance, spillover analysis was usually conducted by drawing concentric rings around PAs in a predefined distance from the PA and comparing deforestation within these rings with matched areas further away (Ferraro et al. 2013; Fuller et al. 2019). Based on a similar logic, Butts (n.d.) has established a more sophisticated *spillover-robust* DiD estimator as an extension to the staggered DiD estimator of Gardner et al. (2024). In addition to treatment and control units, treatment effects in this approach are also estimated for a third group: the spillover-exposed units. In Paper I of this thesis, the spillover-robust estimator was used to investigate whether the deforestation impact of mines can be influenced by the exposure to other nearby mining sites.

Either way, estimation requires an assumption on the spatial extent within which spillovers can occur. If the area of spillover influence is not clearly defined, or if the impact is not limited to nearby locations, identifying coupled land use change dynamics is challenging. This also made it impossible to establish a statement on the amount of agricultural deforestation that occurred additional due to mining in Paper I, as a relocation of farming from other areas to the vicinity of mining sites is possible.

1.6.5 Hurdle regression model

In addition to quasi-experimental methods used in Papers I and III, Paper II analyses the mining involvement of households in a hurdle model. Given that the collected data used for the analysis allows to distinguish households not only into mining households and non-mining households, but also by their degree of reliance on mining, the data follows a zero-inflated distribution which can be modelled in two parts: one that seeks to explain the difference between mining and non-mining households, and one that compares mining households with different degree of involvement (Cameron & Trivedi, 2013).

In contrast to the previous methods, hurdle model coefficients should be treated much more carefully in terms of causal interpretation, as they do not control for confounding factors by design such as the methods shown in Table 1.1. Further, the direction of causality is not unambiguous, as the decision to mine or not is influenced by other livelihood activities and outcomes, but also affects them.

1.7 Data

1.7.1 Monitoring forests from space

For economists working in the field of land use and land cover change, the increasing availability of satellite images has opened a whole new universe of opportunities. Data is often a central limitation to quantitative research, as it is expensive and time-consuming to collect (Blackman 2013; Mitchell, Rosenqvist, and Mora 2017). In the analysis of deforestation in the early days, data had to be collected from ground observations. Although remote sensing has not replaced the necessity for field observations to assess forest conditions, satellite images enable researchers to extract a lot of different information, including tree canopy cover and loss thereof, for virtually any area in the world.

Satellite images store information on reflectance and absorption of light in different spectra of wavelengths. While the human eye can only perceive wavelengths between 400 and 750 nm, remote sensing analysis exploits a much larger range. Given that different types of land cover have unique spectral profiles of reflection across different wavelengths, this information can be used to determine changing land uses. A difference is made between optical remote sensing that utilises the reflectance of sunlight, and active remote sensing that is reliant on the reflectance of transmitted signals. Although the work presented in this thesis does not directly rely on the interpretation of satellite images, it uses secondary data derived from remote sensing. Since these datasets have different qualities and employ different methods to process images, resulting levels and even trends in forest disturbances can vary substantially (Figure 1.3) This section introduces some of the most frequently used data, their distinct characteristics and discusses potential pitfalls in their usage.

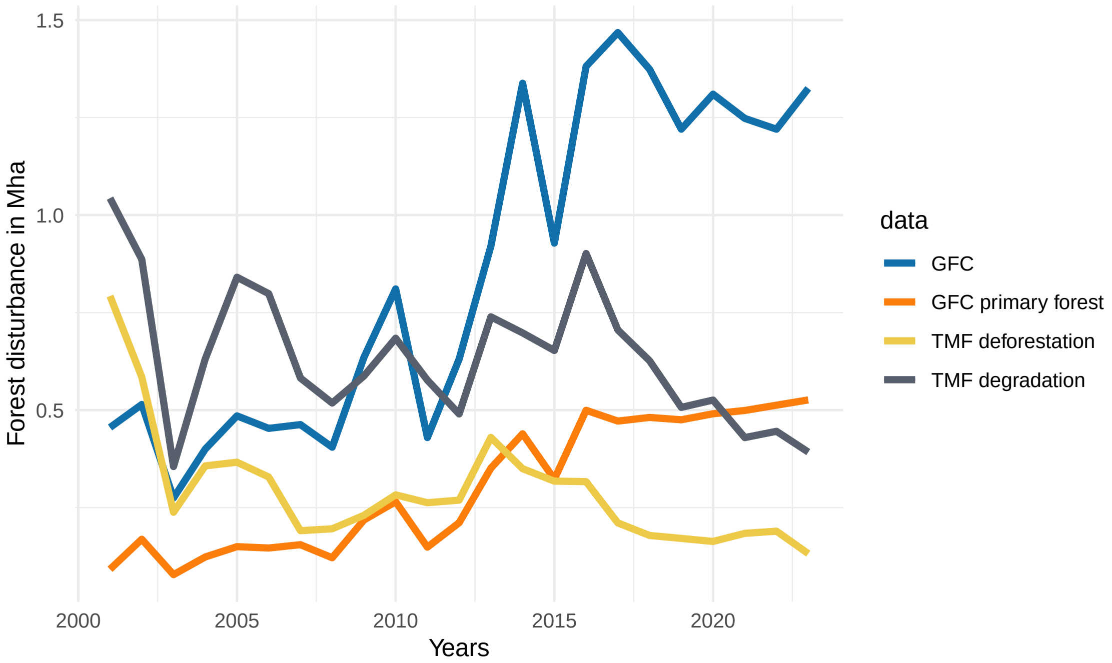

Figure 1.3: *Forest disturbances in the DRC by data set for the years 2001-2023.*

Temporal and spatial resolution of datasets are constrained by the satellite image catalogues that are used for their creation. Images from the often used and freely accessible Landsat collection, for instance, date back to 1982, and have a spatial resolution of ˜30m at the equator (Reiche et al. 2021; Vancutsem et al. 2021). For more small-scale forest disturbances, more recent data products, e.g. from Sentinel-1 (10m resolution) (Reiche et al. 2021) or planet (5m resolution) (NICFI 2021) can be used, but do not go as far back in time. Especially for higher resolution images, improved computer capacity and server infrastructures, such as Google Earth Engine, are immensely helpful to cope with the sometimes heavy computation demands.

Perhaps the most known dataset is the Global Forest Change (GFC) product (also called the *Hansen data*) (Hansen et al. 2013). The name is somewhat misleading, since the data in fact does not display forest but tree cover and loss thereof (see Section 1.2 for a discussion on the difference). The latter is described as a stand replacement or complete removal of tree cover. The data importantly also incorporates non-forested land with tree cover, such as plantations, and also captures disturbances in tree cover that did not necessarily lead to changing land use and hence deforestation (Pendrill et al. 2022). A separate layer in the GFC data product with tree cover extent for the year 2000 can be used to apply a minimum canopy cover thresholds to forest loss events, as done for instance in Paper I of this thesis. It should also be noted that the GFC has weaknesses in picking up small-scale disturbances. It misses up to 50% of disturbances smaller than 1-2 hectares, which is particularly problematic in the DRC were small-scale land use change is common (Milodowski, Mitchard, and Williams 2017; Reiche et al. 2021; Tyukavina et al. 2015).

More recently, the Tropical Moist Forest (TMF) data (Vancutsem et al. 2021) was published with a particular focus on tropical moist forest cover and its disturbances. It uses the entire time series of Landsat images (1982-2023) to distinguish undisturbed forest, degraded forest in case of short-term and low-intensity disturbances in tree cover, and deforestation if permanent land cover conversion was observed. A comparison between TMF and GFC data found that 59% of disturbances detected in the TMF data were not reported in GFC, especially when disturbance followed a gradual process (Vancutsem et al. 2021). However, the TMF also has its limitations. One, for instance, is that it also relies on Landsat's 30m resolution which makes it difficult to detect disturbances smaller than 0.09 ha, such as selective logging (Dupuis et al. 2023; Vancutsem et al. 2021). What is classified as undisturbed forest may consequently in fact be already degraded from small-scale human activities that were not picked up from the images.

Given that Landsat images were collected using optical remote sensing reliant on sunlight reflectance, both GFC and TMF were affected by atmospheric noise in the images when deriving the data. Especially in tropical rainforests where the evapotranspiration from plants is high and intertropical convergence of winds leads to cloud concentration, cloud-free observations can be more than a year apart, leading to potential temporal dis-allocation of forest loss events (Reiche et al. 2021; Tyukavina et al. 2018). As opposed to optical remote sensing, active radar remote sensing has the advantage that it can penetrate through clouds. Sentinel-1 satellite images, for instance, are available at 10m resolution with high revisiting rate, allowing for the near real-time detection of even small-scale changes in canopy cover (Reiche et al. 2021). This is especially important in the Congo Basin, where 80% of forest disturbances are smaller than 0.5 hectare and cloud cover often impedes optical remote sensing (Reiche et al. 2021). Another application has been the detection of forest road establishment in the Congo Basin, which requires high resolution data (Slagter et al. 2024). A downside is that Sentinel-1's C-band wavelengths of 5.6 cm can be complex to interpret, given that its backscatter can be influenced by other factors than tree canopy, e.g. angle, direction or surface moisture (Bae et al. 2019; Reiche et al. 2021). Additionally, it is important to note that observations are only going back to January 2019, which can be a problem for many analyses that require longer time series.

Table 1.2: *Commonly used datasets for the analysis of forest cover change and their distinct characteristics.*

Dataset	Forest/deforestation definitions	Time	Resolution
Global forest change (GFC) (Hansen et al. 2013)	• Quantifies tree cover instead of forest, and loss thereof as a stand replacement disturbance or removal of tree cover.	2001-2023	30m
Tropical moist forest (TMF) (Vancutsem et al. 2021)	• Defines undisturbed forest cover as closed evergreen or semi-evergreen forest without disturbances over the entire Landsat catalogue. • Disturbances are classified as either degradation events (low intensity and <2.5 years in duration) or deforestation events in case of a permanent forest conversion.	1990-2023	30m

Dataset	Forest/deforestation definitions	Time	Resolution
Forets d'Afrique Central Evaluee par Teledetection (FACET) (Potapov et al. 2012)	• Quantifies tree cover instead of forest, and loss thereof as a stand replacement disturbance or removal of tree cover. • Forest is land with >30% canopy cover, and forest cover loss as a stand replacement.	2000-2010	60m
GFC primary forest (Turubanova et al. 2018)	• Primary forest is defined as forest with no signs of human alteration. • Primary forest loss is defined as a stand replacement disturbance in the forest canopy.	2001-2023	30m
Forest Resource-Assessment (FRA) (FAO 2020)	• Land of more >0.5 hectares with >10% tree cover of >5m canopy height is categorised as forest. • Deforestation is defined as the conversion of forest for other land uses.	Every 5 years since 2000	Country level assessments
RADD deforestation alerts (Reiche et al. 2021)	• Forest extent is defined as land with more than 50% tree cover according to Hansen et al. (2013) • Disturbance is the partial or complete removal of tree cover in a pixel.	Every 6-12 days since January 2019	10m

As the discussion above shows, the choice of the dataset when analysing deforestation is non-trivial. All have their own strengths and weaknesses, and importantly also different in underlying assumptions of what defines a forest and what is entailed in deforestation (Zalles et al. 2024). The FAO has settled on a definition according to which land of at least 0.5 hectares with a minimum of 10% tree cover above 5m classifies as forest (FAO 2023). As such, it also classifies tree plantations as forest, and explicitly allows for clear cutting activities for timber harvesting in the forest definition. Deforestation according to the FAO is described as the conversion of forest for other uses (FAO 2023).

In the densely forested parts of the DRC, the FAO's definitions of forest and deforestation can be problematic, since it would allow for up to 90% of tree cover to be removed without a landscape being counted as deforested (Zalles et al. 2024). Especially forest fragmentation and small-scale clearing, as often practised in the rural complex of the DRC, would be overlooked then, severely understating the actual loss of forest. Therefore, countries tend to apply their own canopy cover thresholds, ranging between 10% and 60%, that may differ substantially from the 10% threshold proposed by the FAO (Melo et al. 2023).

Usually, datasets are published with accuracy statistic that help assessing the precision of the data. The accuracy also crucially impacts the precision and even the bias of the estimates of subsequent analysis, and is influenced by cloud cover, atmospheric corrections, training of models and other factors that may lead to non-classical measurement error (Jain 2020; Meyer and Pebesma 2021). Until now, there has not been a standardised way to correct standard errors or biased estimates from satellite-derived data products in econometric analysis (Alix-García and Millimet 2023; Jain 2020). This is even more complicated by the fact that the accuracy can vary substantially for different regions, depending on the degree of extrapolation from the sample data that has been used for training and validating the model (Meyer and Pebesma 2021). GFC data, for instance, has been found to systematically perform better for pine forests than for tropical forests (Alix-García and Millimet 2023). Also the procedure of drawing the validation sample can impact accuracy statistics, as randomly drawn samples may mask group-specific trends (Simpson's paradox) (Boser 2024).

A different problem in the use of deforestation data in statistical analysis is that it is usually coded as a binary, non-repetitive variable. As such, using it as an outcome variable in econometric models can lead to substantial bias in the estimates, as Garcia and Heilmayr (2024) have shown for the case of DiD estimation. A simple solution to avoid this issue can be to aggregate deforestation outcomes over spatial extents of interest (as done in Paper I), or to resample the raster to a coarser resolution in order to obtain continuous outcomes (Paper III).

1.7.2 Household surveys and socio-economic data

Also socio-economic information is increasingly derived from remote sensing. Nightlights, for instance, are commonly used as a proxy for economic activity and hence prosperity, but are not suited to assess living conditions in contexts of extreme poverty where the main part of the population does not have access to grid electricity (Gibson et al. 2021). Machine learning models, such as convolutional neural networks, are becoming better at combining different metrics to derive granular poverty estimates from satellite images (Sarmadi et al. 2024). Satellite images can also be supplemented with survey data to achieve better results. For instance, a recent study trained a machine learning model on geo-referenced livelihood survey data and then predicted poverty for nearly the entire world (Ton et al. 2024). Yet, predicting living conditions from space has its limits and cannot replace data collection in the field. An analysis of livelihoods, as in Paper II, demands data on the household level that is impossible to detect from satellite images. In the DRC, household survey data are hardly available. The Afrobarometer has run surveys in more than 30 African countries but does not cover the DRC, and the last wave of the Demographic and Health Survey (DHS) in the country was conducted in 2014. Political instability, low state capacity and insecurity have further impeded census data collection.

Given this void, fieldwork was conducted in South Kivu during June and July 2022 to analyse livelihoods of artisanal mining households in rural areas at the forest edge. The data was collected in villages in the territories of Mwenga, Walungu, Kalehe and Kabare located in the south and south-east of Kahuzi-Biega National Park, as well as the north-west of Itombwe Nature Reserve.

Kahuzi-Biega National Park is a protected area of IUCN category II. After having been declared a forest reserve under Belgian rule in 1951, it received the status as a national park in 1970 and was declared a World Heritage Site in 1981. During the establishment and management of the national park, repeated incidences of violent displacement of indigenous Batwa communities and atrocities against them have been reported (Barume 2000, Flummerfelt 2022). In 2018, some Batwa communities have begun to reoccupy parts of the park, causing a spike in deforestation inside affected park areas (Simpson et al. 2025).

The Itombwe Nature Reserve was first established by ministerial decree in 2006 following the sharp decline of gorillas and elephants in the area during prolonged conflict (Simpson and Pellegrini 2022). From the start, the nature reserve faced fierce resistance from local communities for the absence of dialogue in the establishment process, and ultimately resulted in a regazettement following a participatory mapping process in 2010-2014 (Kujirakwinja et al. 2016). However, also the redrawn nature reserve boundaries remain disputed among some of the affected communities (Simpson and Zirhumana 2021).

In total, 278 household interviews were conducted, and 150 focus group interviews with artisanal miners. Most villages were small, so that households were surveyed as they appeared at the village centres. Interviews were conducted in native languages by co-authors and field assistants, but I was personally present with a few exceptions where the security situation prohibited it. The questions mainly concerned livelihood strategies, household asset ownerships and livelihood outcomes, and the data was analysed in Paper II. Additionally, GPS coordinates of forest-located mining sites were collected inside Itombwe Nature Reserve with the help of local hunters, which were intended for usage as training data for the identification of mining sites for the analysis of Paper I. Overall, impressions greatly helped to develop a better understanding of the study area, which was essential for the conceptualisation and contextualisation of all analyses presented in this thesis.

1.8 Synthesis

The chapters that follow in this thesis cover separate, but related topics. The element connecting all three is the Congo Basin rainforest of the DRC (Figure 1.4). The first two papers are both concerned with artisanal mining in the eastern part of the country. Whereas Paper I addresses deforestation impacts of mining activities, the second uncovers their importance for livelihoods of communities living adjacent to the forest. Finally, the third chapter analyses the protected area system in the DRC, its role in preventing deforestation in the Congo Basin rainforest and the interactions with resource frontiers. This section briefly summarises the research motivation, methodology and findings of each chapter.

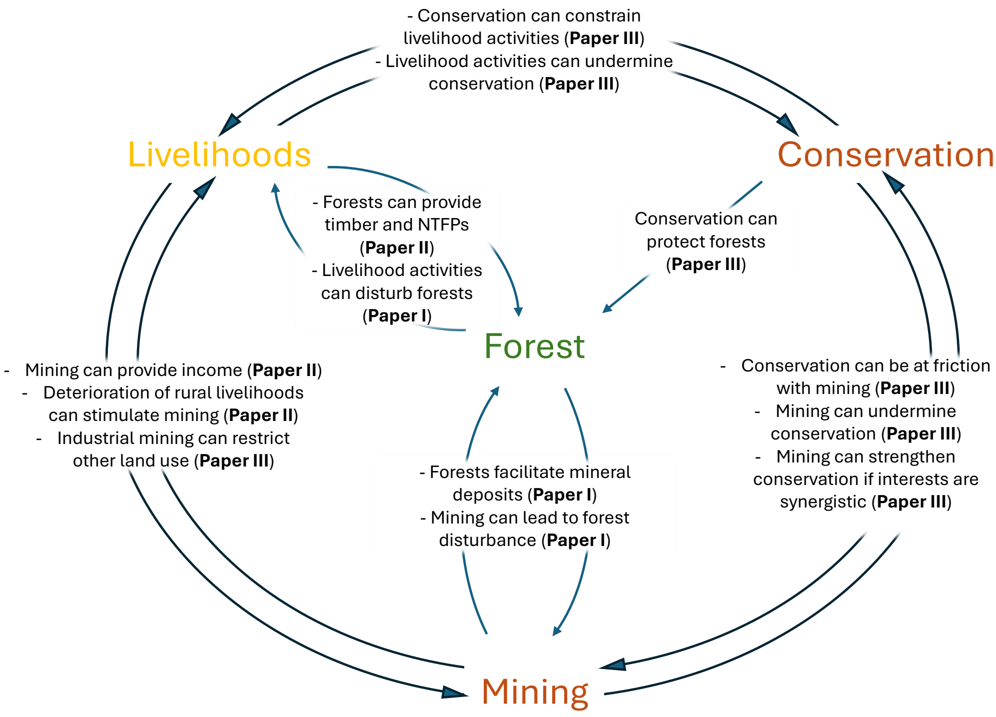

Figure 1.4: *Graphical display of the relationship between the different thesis papers.*

1.8.1 Chapter 1: Deforestation trigger effects of artisanal mining

Artisanal mining is a widespread livelihood activity in forest areas of the eastern DRC. Yet, studies on drivers of deforestation have not documented any meaningful impacts of mining on forests (Masolele et al. 2024; Shapiro et al. 2023). Looking beyond only the area directly cleared for extraction activities, we investigate the forest loss dynamics that unfold with the start of artisanal mining operations in the surrounding forests.

The analysis relies on novel data from Masolele et al. (2024) - the first for the region that does not only indicate when tree cover loss occurred, but also what land use followed on it. A density-based clustering algorithm was applied on the data to organise raster cells identified as mining into mining sites, which were then used as units of observation in a staggered DiD model. Outcomes were calibrated as the share of forest cover in 2000 that was cleared in the respective year within rings of increasing distance from the mining site.

Findings show that mineral discoveries triggered deforestation for farming and settlement expansion within at least 5km distance from the mine. Within this extent, the additional forest loss was found to be 28 times as high as the loss directly attributed to the mining surface itself, the most part of it being attributed to agricultural expansion around mining sites. The study is the first to use quasi-experimental research methods to document these extensive deforestation trigger effects of artisanal mining in tropical forests.

1.8.2 Chapter 2: Livelihoods of artisanal miners in South Kivu

While the first paper focuses on the forest impacts of artisanal mining in the eastern DRC, the second chapter shifts the focus on its livelihood implications in forest-adjacent communities. In the DRC's context of widespread poverty, environmental degradation and livelihoods can be closely linked. Paper 2 dives into the integration of artisanal mining into livelihood strategies as a coping mechanism and as means to reduce risks associated with agricultural practises.

The study adopts a simple analytical model to show the relationships between expected income, income risk, and livelihood diversification. Derivations suggest that diversification increases with higher levels of risk aversion, greater risk associated with farming, and greater expected income of mining relative to farming.

The hypotheses were then tested in a hurdle regression model with data collected during field work in villages surrounding Kahuzi-Biega National Park and Itombwe Nature Reserve in South Kivu, eastern DRC. Results indicated that households that diversified into mining experienced lower food insecurity than non-mining households. With a larger degree of reliance on mining, we further observed that households involved in mining cultivated less agricultural land.

1.8.3 Chapter 3: Protected areas as a conservation strategy in the DRC

The third paper is concerned with the protected areas (PAs) in the entire tropical moist forest biome of the DRC (see Figure 1.2). Historically, PAs have been the main strategy of forest conservation in the country. Although the first ones were established as early as the 19th century and land area under protection is continuously increasing since then, systematic evaluations of PA effectiveness in withstanding deforestation pressure of different kinds are lacking. The study situates PA boundaries in a context of progressing and emerging deforestation frontier processes to determine the state of forest cover and the dynamics of forest loss at PA boundaries.

A geographic regression discontinuity design is employed at the boundaries to test their exposure to - and resilience against - deforestation pressure from the outside. For more context sensitivity, forest cover and deforestation metrics on either side of the boundaries are used to construct a typology of protection. Heterogeneity analysis further investigates how these change under varying strictness of PA management and in the presence of emerging resource frontiers, specifically in the form of mining and logging title acquisitions.

The results of the study suggest that the remoteness that has long been keeping deforestation pressure away from PAs has been fading over the last twenty years, with 18% of boundaries in the sample having shown deforestation sprawling inside and another 9% withstanding pressure. Especially less strict PAs, as indicated by their IUCN classification, were experiencing increasing pressure on forest cover at their boundaries.

1.9 Implications and Outlook

Compared to the Amazon and the remaining Asian rainforest regions, research on the Congo Basin is lagging behind (White et al. 2021). This thesis aims to contribute to filling this void, addressing different issues and using distinct angles.

From Paper I, a main lesson is that deforestation drivers should not be understood as following isolated processes. In the case of mining, results have shown a strong link between the discovery of minerals and the occurrence of farmland and settlement expansion. Without such contextual understanding, the role of mining for deforestation processes in the eastern DRC has been greatly underestimated. Similar research on other drivers is needed to improve the understanding of complex land use change dynamics, and to move from an isolated understanding of the direct causes of land use change to their interdependence and to the causal mechanisms behind them. Such knowledge is crucially needed to address the complex challenge of halting forest loss.

Better knowledge on the causal mechanisms of forest change also require insights on how deforestation processes are embedded in the socio-economic environment, as Paper II showed. Especially in a context of widespread poverty, like the DRC, forest conservation should not come at the expense of local communities' livelihoods. In the case of mining, results presented in this thesis have highlighted its role in complementing, but also substituting farming in conditions where agriculture has become increasingly unviable and alternative sources of income are rare.

Given that much of the deforestation is result of poverty and population growth, the context for conservation policy in the DRC is complex. The government's weak capacity to pursue long-term strategies to halt deforestation poses further limitations on the available options (Karsenty and Ongolo 2012). A perspective that takes causal mechanisms leading to deforestation into account rather than one resorting to one-size-fits-all responds is essential for lasting and effective solutions. PAs, as they have been implemented in the past, could not live up to this standard as they struggled to reconcile the needs of local communities with that of conserving forest (Inogwabini 2014). A stronger focus on livelihoods in forest conservation is necessary to identify equitable anti-deforestation strategies, and can become a leverage point for change and part of the solution. Ferraro and Simorangkir (2020), for instance, found that a conditional cash transfer program aimed at reducing poverty in Indonesia simultaneously lead to a 30% reduction in deforestation, as it reduced households' reliance on clearing forest. A similar program in Ethiopia was found to increase tree cover by 3.8% (Hirvonen et al. 2022). These examples show that it is possible to improve living conditions while at the same time reducing deforestation, although different contexts have produced different outcomes (Alix-Garcia et al. 2013).

The recent emergence of community forests in the DRC may provide opportunities for win-win scenarios, as they give communities the right to exploit forest resources for subsistence and commercial purposes in sustainable ways (Lescuyer et al. 2019). With the first forests being established in 2017, the impact of community forests on livelihoods and conservation is yet to be seen. In other countries where community forests are already implemented longer, effects on deforestation are mixed, but overall positive (Porter-Bolland et al. 2012). Useful lessons can be learned from neighbouring Cameroon, where more than 20 years of community forestry have not yielded the desired results (Kenfack Essougong, Foundjem-Tita, and Minang 2019). Among others, issues were identified in ensuring equitable access to the forest for all community members, in preventing elite capture, and in providing the necessary support structures to establish and manage the concessions. This is also largely in line with generally identified conditions for successful community forestry across countries (Baynes et al. 2015).

In an early evaluation of local perceptions towards community forests in three locations of the DRC, Lucungu et al. (2022) found that only few respondents reported economic gains after the community forest establishment compared to before. However, most people thought it helped them to secure their forest against exploitation by other actors. Thus, if property rights are ensured, the governance within community forests well defined, and necessary support structures in place, community forests have the potential to improve the socio-economic situation of communities while preventing the over-exploitation of forest resources.

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Paper I

"Some forest mining towns grew up so fast that their existence seems impossible; for example, the large town of Bisie, some 45 kilometers into the Walikale rain forest, did not exist before 2002, when trappers found cassiterite there. As of my last visit in 2009, it had as many as 15,000 people. Bisie is connected to other towns only by a treacherous walking trail, but the town is more cosmopolitan than road-connected administrative towns; traders (who carry an average of 50 kilos on their heads on the two-day walk through the forest) have even managed to bring in satellite dishes."

(Smith, 2011)

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Deforestation triggered by Artisanal Mining in the eastern Democratic Republic of Congo

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Abstract The discovery of valuable minerals in the mineral-abundant eastern DR Congo can stimulate extensive migration into remote areas of the Congo Basin rainforest. Despite the widespread practice of artisanal mining, its role in the ongoing deforestation has not received adequate attention. Using Difference-in-Differences estimation, we show that artisanal mining triggers deforestation at least 5 km from mining sites. Within this distance, the onset of mining causes an additional 4 percentage points of forest loss after 10 years. In total, the indirect deforestation caused by mining through the expansion of other land uses is 28 times larger than the forest area directly cleared for mining. Most of this loss is caused by increased farming around mines, followed by forest cleared for settlements. These indirect effects reveal a much larger role played by artisanal mining in deforestation dynamics than previously assumed and explain at least 6.6% of the total deforestation in the eastern DR Congo.

2.1 Introduction

With 107 million hectares (ha) of rainforest, the Democratic Republic of Congo (DRC) is home to about 60 percent of the Congo Basin, the second-largest rainforest in the world (Mayaux et al. 2013). Despite widespread poverty in the country, it is among the richest in valuable minerals, particularly in the east and south of the country (Edwards et al. 2014). This study focuses on the eastern provinces Haut-Uele, Ituri, North-Kivu, South-Kivu and Maniema (Figure 2.1). Together, they span 18% of the country and comprise an area larger than Germany. The region is among the most biodiverse on the continent (Plumptre et al. 2007), while being known for its richness in gold and "3T" minerals: tantalum and tungsten, which are both classified as critical by the EU for their use in the production of electronic devices such as smartphones and laptops, as well as tin (IPIS 2023; European Commission 2023).

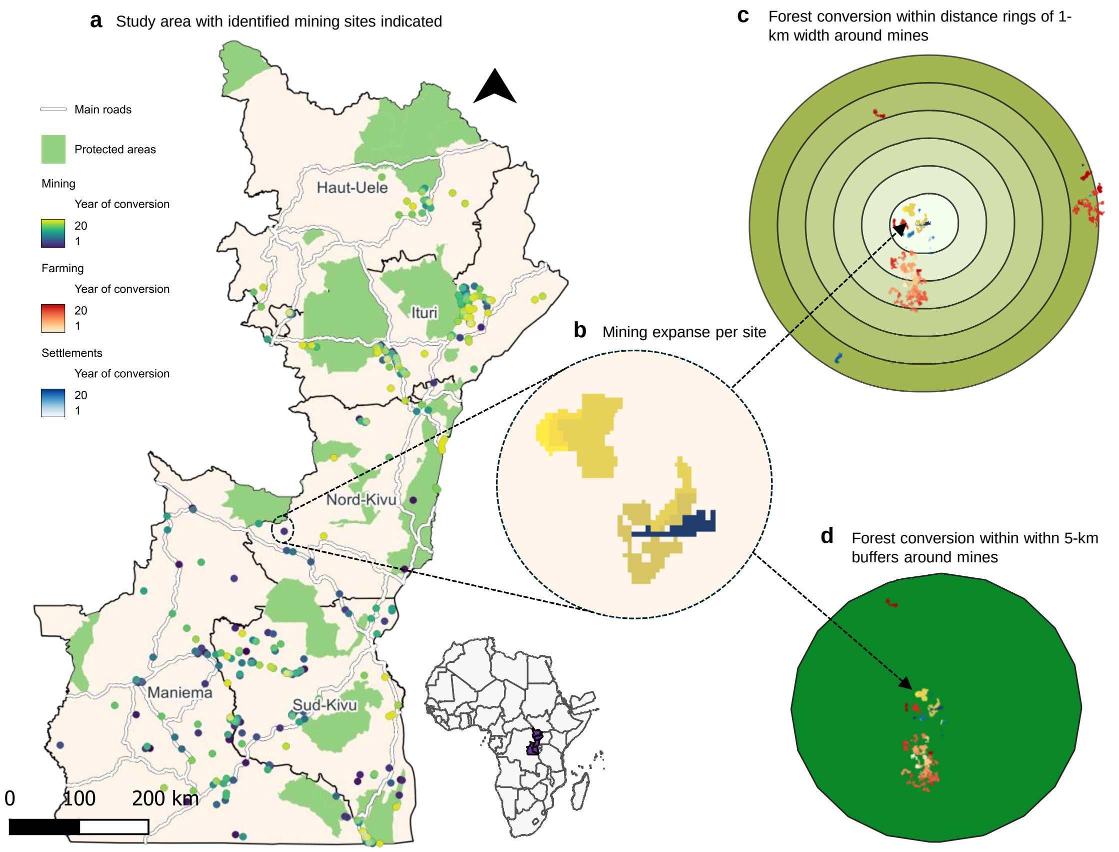

Figure 2.1: *Left: map of the study area and the location of identified mining sites by year of establishment. Right: data processing steps. First, mining pixels are organised into clusters. The first incidence of mining per cluster is then used to draw buffers around it, either (i) as concentric rings of 1 km width of increasing distance, or (ii) as 5-km buffers. Pixels displayed in red scales indicate forest loss from small-scale agriculture, those in blue scales show settlement expansion.*

The minerals are predominantly extracted on artisanal and small-scale mining (ASM) sites. The International Peace Information Service (IPIS) currently counts 2,700 of these mines across the five eastern provinces and 332,000 associated miners (IPIS 2023). While artisanal mining still largely relies on manual hand-held tools for extraction and remains a labour-intense activity, the sector also sees an increasing adoption of small efficiency-enhancing machinery (Kabunga and Geenen 2022; Matthysen, Muller, and Bulakali 2022). Operations can occur in different forms depending on the location and type of deposits, and include alluvial extraction along rivers, dredging of riverbeds, open pit mining following the removal of surface layers, and underground mining in tunnel systems (Geenen and Bikubanya 2024).

Social and political tensions in the eastern DRC have a long history (Büscher and Mathys 2019), and the rise of artisanal mining over the past decades has been entrenched with the ongoing armed conflict. Mining as a livelihood activity was spurred by the deterioration of rural livelihoods during decades of instability (Kelly 2014; Cox 2012), but resource revenues also contributed to the proliferation of warfare (Vogel 2018; Geenen 2012). Efforts to reduce interference of armed groups in the ASM sector and extend government control were mostly unsuccessful, as the state remains fragmented and incapable of providing even basic services in many regions (Vogel 2018; Büscher 2018; Kilosho Buraye, Stoop, and Verpoorten 2017; Geenen and Bikubanya 2024; Geenen 2012).

Mining operations often take place in forest areas and pose several problems to the surrounding forest ecosystems (Luckeneder et al. 2021; Sonter, Ali, and Watson 2018): extensive hunting around mining sites threatens biodiversity (Spira et al. 2019; Plumptre et al. 2016); the use of mercury and increasingly also cyanide impacts human health and the environment (Nkuba, Bervoets, and Geenen 2019; Kabunga and Geenen 2022); and sediment load in rivers affects water quality and aquatic life (Dethier et al. 2023). This study focuses on the impacts artisanal mining has on deforestation dynamics in the eastern part of the DRC, where deforestation is defined as the removal of forest for other land uses.

Deforestation in the DRC is dominated by small-scale rotational agriculture (Tyukavina et al. 2018; Shapiro et al. 2023). It mostly occurs along roads in a pattern that has been labelled the *rural complex*, consisting of mosaics of productive agricultural plots, fallows, regrowing secondary forest patches and to a minor extent settlements (Molinario et al. 2017). Under the pressure of a growing population that is expected to triple by the end of the century (Vollset et al. 2020) and related issues of land scarcity, declining soil fertility (Cox 2012) and food insecurity, the increasing need for land leads to the expansion of rural complexes into surrounding forests (Molinario et al. 2020).

Whereas this expansion drives deforestation at the forest edges, deforestation of core forest requires stronger incentives due to its inaccessibility (Shapiro et al. 2023; Molinario et al. 2020). Industrial logging, large-scale mining and agricultural plantations have the potential to slice open core forests and provide access through road construction but are largely absent in the eastern DRC (Kleinschroth et al. 2019; Ferrari and Cerutti 2023). Artisanal mining activities do not rely on transport infrastructure but can induce human activities in remote forests given the high income prospects and exogenously determined location of deposits (Bryceson and Geenen 2016; Shapiro et al. 2023; Smith 2011; Matthysen, Muller, and Bulakali 2022). In *mineral rushes*, newly discovered minerals can rapidly attract large numbers of people, initially living in improvised tarpaulin settlements that potentially develop into booming towns with a diversified portfolio of economic activities (Bryceson and Geenen 2016; Büscher 2018; Smith 2011). In this way, the discovery of valuable minerals in forests acts as a deforestation trigger (Meyfroidt 2016) in attracting not only mining activities, but also farmland and settlement expansion to provide food and shelter to miners and their families.

In contrast to industrial mining's impacts on deforestation (Giljum et al. 2022; Sonter et al. 2017), difficulties to identify ASM from satellite images (Tyukavina et al. 2018; Caballero Espejo et al. 2018) and to account for the dynamics unfolding around these mines have impeded their quantitative impact assessment. Studies from other countries have reported substantial regional impacts on direct forest loss, including the south-west of Ghana (Barenblitt et al. 2021), the Peruvian region of Madre de Dios (Asner and Tupayachi 2017) and the Brazilian Legal Amazon (Siqueira-Gay and Sánchez 2021). However, none of them have assessed indirect impacts. For the DRC, we only found three studies that have attempted to quantify forest loss from mining. The first, a pan-tropical study focused on large-scale mining operations, found only minor impacts for the DRC (Giljum et al. 2022). The second study investigated direct drivers of Congo Basin deforestation between 2000 and 2014 but found no loss to mining in the DRC, not explicitly distinguishing between artisanal and industrial mining (Tyukavina et al. 2018). The third, most recent study estimated deforestation and forest degradation in the Congo Basin between 2015 and 2020 for different land use archetypes, of which artisanal mining was found to be the least important (Shapiro et al. 2023). However, the archetype labelled *artisanal mining* was defined such that it would neither capture the interrelation with multiple other land uses, nor the spatio-temporal dynamics by which mining sites establish.

Using a Difference-in-Differences (DiD) model (Callaway and Sant'Anna 2021), we quantitatively assessed the deforestation dynamics that accompany artisanal mining operations. We identified 255 forest-located artisanal mines from temporally explicit data on post-forest land use between 2001 and 2020 (Masolele et al. 2024) and showed that forest clearing for the actual mining area is dwarfed by the cumulative impact of other, triggered land uses. Our findings contribute to a more differentiated understanding of deforestation drivers in the eastern DRC and highlight the importance of accounting for the indirect contribution of mining to deforestation to uncover its full forest loss impacts. Given the ongoing deforestation in the DRC (Vancutsem et al. 2021), such understanding is greatly needed in the effort to slow down and halt forest loss.

2.2 Results

The identification of the true causal effect of mining on the surrounding forests requires the comparison of the same area with and without mining activities, which is a counterfactual and not hence observable. We used heterogeneity-robust Difference-in-Differences (DiD) estimation (Callaway and Sant'Anna 2021) to estimate this counterfactual, where mines established at a later point in time served as control units for already established mines. The effect was estimated by comparing deforestation trends of mining sites and controls before and after the onset of mining. Additional specifications with randomly selected and covariate-conditioned control units were conducted as robustness checks and are reported in the Supplementary Information Figure 3.1

The validity of the DiD design relies on the assumption of similar average deforestation trends between control units and mines had mining not occurred. For each model specification, we provided evidence in support of this assumption by estimating pseudo-effects for the years before the first mining incidence was recorded (see Methods section). The outcome of interest was the share of forest present in 2000 that was deforested by a given year, calculated over (i) 1-km wide rings in increasing distance from mines, and (ii) a fixed 5 km buffer around mines (Figure 2.1). Since the surface area covered by the 1-km concentric rings increases with their distance to mines, the effects were calculated scale-neutral as percentage points (pp) of forest cover in 2000 that got converted to other land uses.

2.2.1 Forest loss around mines

The deforestation estimates showed continuous yet decreasing additional deforestation as time passed and distance from the mines increased (Figure 2.2). Overall, increased forest-clearing effects were statistically significant up to a distance of 5 km for most tested time periods after mining started. As expected, the effects were largest close to mining sites. Within a 1 km distance, an average additional 9.6 percentage points (pp) of forest was cleared within 10 years after mining started. Within the 4-5 km distance ring, an additional 2.7 pp was deforested after 10 years.

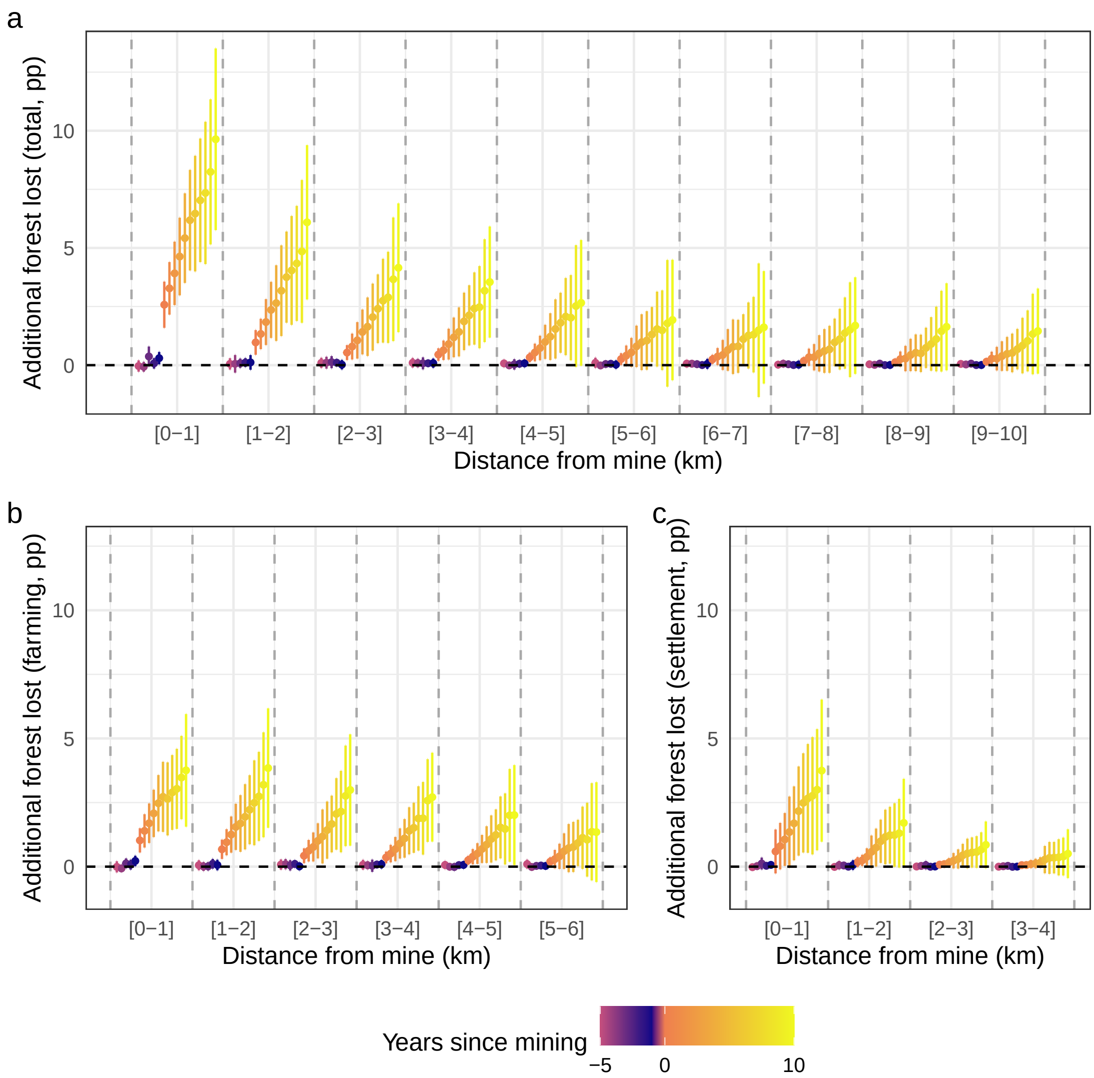

Figure 2.2: *Spatio-temporal estimates of impact on cumulative deforestation since 2001, as percentage points of additional forest cover lost, over time since mining detection. For every additional kilometre from the mine, a new ring is estimated. Panel **a** displays the coefficients of deforestation for all land uses, **b** for small-scale agriculture and **c** for settlement expansion only. Bootstrapped standard errors are clustered at the mine level. Points indicate ATT estimates following the DiD estimator proposed in Callaway & Sant'Anna (2021) and errorbars refer to 95% confidence bands. n = 255 mines.*

Additional forest loss around mines kept growing over the examined 10-year period, but also expanded over time. While deforestation close to mines showed an immediate increase with the start of mining (e.g., 2.6 pp within 1 km distance in the first year) and a continued growth afterwards, the effects further away set in more gradually, e.g., 0.5 pp in 4-5 km distance.

Given that the estimates for different distance rings from mines yielded mostly statistically significant results up to 5 km, we drew 5-km buffers around mines and estimated the overall forest loss inside (Figure 2.3). Within these buffers, we found that 4 pp additional forest was cleared within 10 years after a mine was first identified. Alternative estimation results with randomly selected control sites and under inclusion of covariates are reported in Figure 3.1 in the Supplementary Information as robustness tests, overall confirming the findings.

2.2.2 Post-forest land uses triggered by mining

We disaggregated the deforestation effects into different direct drivers of land cover change to untangle the trigger dynamics of mining. Small-scale farming kept on expanding over the years following the first mining incidence (Figure 2.2b). The farming-driven deforestation triggered by mining was most extensive immediately after mining started, but kept on growing over time and distance from the mine. Estimates were statistically significant up to a distance of 5 km, where an additional 2 pp of forest was cleared for farming after 10 years. Forest loss driven by settlement expansion showed similarly strong deforestation effects within 1 km of the mines, but estimates were less precise and faded sooner further from mines, with mostly statistically insignificant results beyond a 2-km distance (Figure 2.2c).

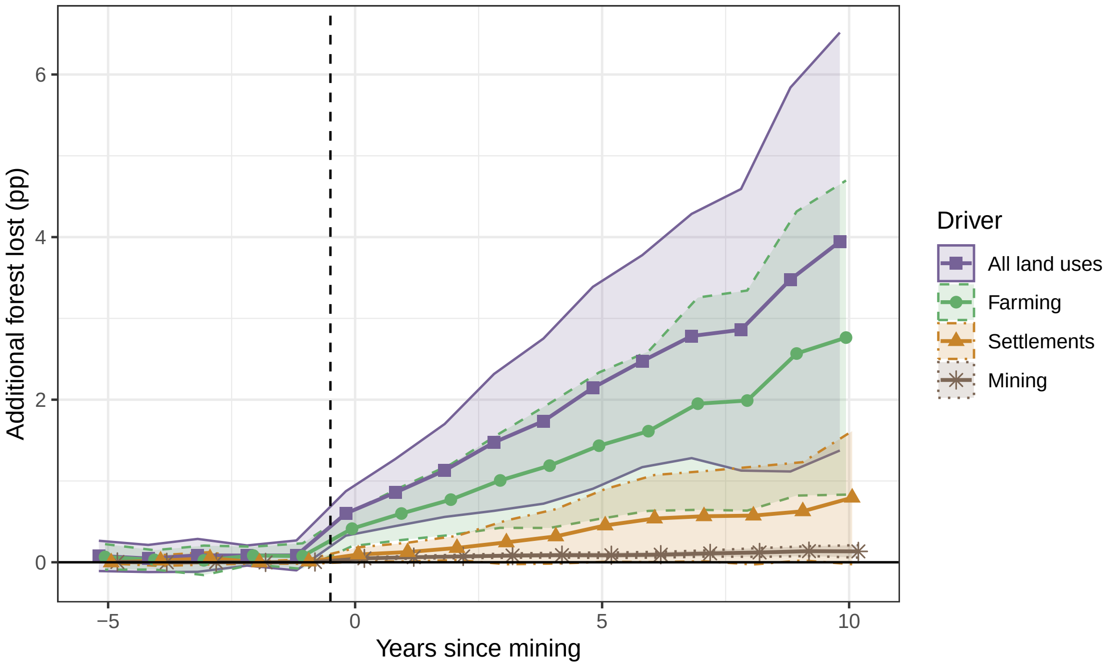

Figure 2.3: *Estimates of impact on cumulative deforestation since 2001 as percentage points of additional forest cover lost, within a 5-km radius around mines, over time since treatment for various land uses following deforestation. The category Other aggregates all 15 land use classes reported in Masolele et al. (2024), All refers to the sum of all post-forest land uses. Bootstrapped standard errors are clustered at the mine level. Points indicate ATT estimates following the DiD estimator proposed in Callaway & Sant'Anna (2021) and errorbars refer to 95% confidence bands. n=255 mines.*

With respect to the 5-km buffers around mines, disaggregated results for the different land use categories showed that small-scale agriculture and settlement expansion increased substantially when mining commenced: within 10 years, trigger effects led to the additional clearance of 2.8 pp of forest for farming and 1.2 pp for settlement expansion (Figure 2.3). When estimating this effect for the hectares of deforested area instead of the share of cleared forest, we found that every hectare of forest loss due to mining caused another 28.4 ha loss from other land uses within 10 years, of which 21.8 ha are associated with agriculture and 4.73 ha with settlement expansion.

2.2.3 Trigger intensity heterogeneity

The occurrence and magnitude of deforestation triggers are determined by predisposing factors that activate them (Meyfroidt 2016). We tested how deforestation trigger effects varied with a number of geographic factors of a mining location. To do so, we used the first estimation step of recently developed imputation-based DiD estimators (see Methods) to impute the benchmark deforestation from not-yet-established mines, and then compared the change in deviation from this benchmark along the gradient of values for different covariates (Figure 2.4; see Methods for details). The tested covariates included the travel time to cities (Weiss et al. 2018), the agricultural suitability of a location(Fischer et al. 2021), the proximity to rivers, the amount of forest in the surroundings proxied through the share of dense tree cover (>60%) in 2000 (Hansen et al. 2013), and the number of conflict events since the start mining (Raleigh et al. 2010).

The trigger effects were higher in conditions favourable to human settlement, such as accessibility (Figure 2.4a and 2.4b), agricultural suitability (Figure 2.4c) and river proximity (Figure 4d). Whereas trigger effects from settlement expansion were limited to more accessible locations with better agricultural growing conditions (suitability score >8,500) and within 2 km from rivers, additional forest loss from farming was relatively constant along different covariate gradients.

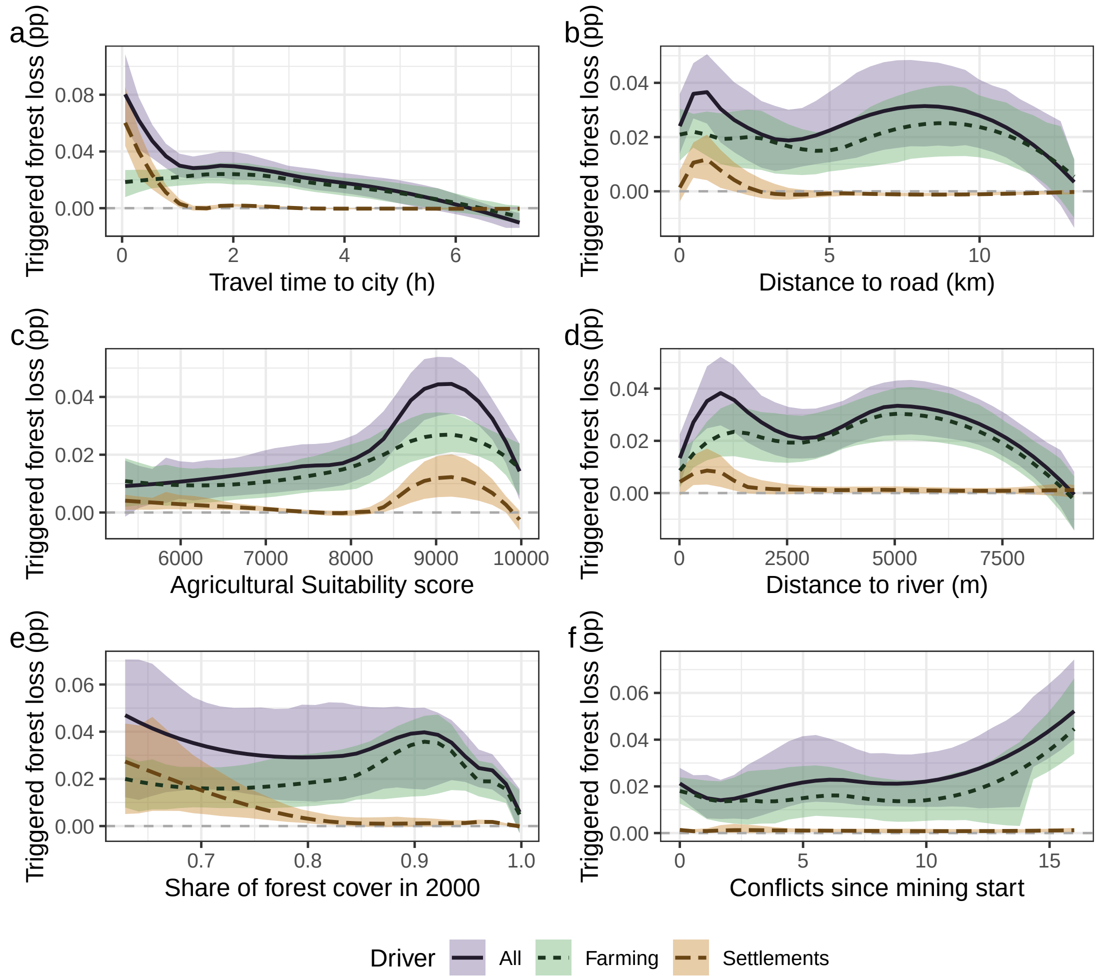

Figure 2.4: *Deforestation heterogeneity in response to the establishment of a mine, calculated as the deviation from the counterfactual baseline as estimated from the first stage regression of Gardner (2022) within 5km buffers (see Methods). The displayed variables are **a** travel time to cities (Weiss et al. 2018) (n=143 mines), **b** distance to main road (OpenStreetMap) (n=150 mines), **c** agricultural suitability, based on FAO global agro-ecological zones (Fischer et al. 2021; higher scores imply better suitability) (n=144 mines), **d** distance to rivers (OpenStreetMap) (n=138 mines), (e) share of pixels with ¿60% tree cover (Hansen et al. 2013) (n=129 mines), **f** conflict incidences since the beginning of minning, from Raleigh et al. (2010) (n=124 mines). Bootstrapped confidence levels displayed at the 95% level.*

Effects also varied with the amount of dense forest in the surroundings (Figure 2.4e). Mining sites with initially lower forest cover were experiencing relatively higher settlement expansion, potentially due to expansion of existing rural complex formations. Mines in more dense forest areas experienced farming-dominated trigger effects.

The relationship between conflict events and mining-related forest loss was increasing (Figure 2.4e), although we cannot say whether this can be explained by mining causing more militia activity or by mining becoming a survival strategy in response to conflict-related hardship (Büscher 2018; Kelly 2014). It is also likely that mines with larger revenue prospects are attracting both people and militia, thereby increasing not only deforestation but also conflict events.

2.3 Discussion

Artisanal mining is a widespread livelihood activity in forest landscapes of eastern DRC. However, the full extent of its impacts on the deforestation of the Congo Basin rainforest in the area remains understudied at this point. Using post-forest land use data (Masolele et al. 2024) and quasi-experimental research methods, our analysis shows how mineral discovery can act as a deforestation trigger. In line with previous studies, we found that the forest area directly converted to mining use is small when compared to other land uses (Shapiro et al. 2023; Tyukavina et al. 2018). However, the quantification of the indirect effect from other land uses reveals 28.4 times as much loss as from the direct effect, predominantly through increasing agricultural activity and to a lesser degree settlement expansion in the proximity of mines.

Of the total 924,502 ha of dense forest converted to other land uses in the five eastern provinces of the DRC between 2002 and 2018, 6.6% were directly or indirectly caused by new mines in the same period, not counting impacts beyond 5 km from mining sites. Of the total 752,077 ha cleared for farming in the study area, 6.8% was additionally triggered within this 5-km distance. For the 23,299 ha of settlement expansion into forest, it was even 23.9% that was triggered by mining. These figures are conservative, given that dynamics likely reach further than 5 km, and would be even larger if older mines were also included, as mining settlements can turn into booming towns and enter urbanisation processes over time (Bryceson and Geenen 2016; Büscher and Mathys 2019).

Some limitations of the study are worth noting. First, our analysis cannot account for spatial leakage of deforestation. Negative leakage could occur if more forest conversion to farmland around mines reduces agricultural expansion elsewhere. We assume leakage to be small, given that mining is more likely than other land uses to occur in remote forest areas (Shapiro et al. 2023). Another leakage effect in the opposite direction could be caused by out-migration once environmental pollution from mining adversely affects livelihoods and ecosystem services (Nkuba, Bervoets, and Geenen 2019). However, controlling for any such leakage effects is beyond the scope of this analysis and does not rebut our findings that artisanal mining acts as an underlying driver of deforestation.

Second, the data of Masolele et al. (2024) captures mining incidents that have caused tree cover loss between the years 2001 and 2020 as indicated in Hansen et al. (2013) (see Data section). We therefore cannot rule out that some of the identified "new" mining sites are only expansions of old ones from before 2000, or that mining has started on non-forested pixels and therefore does not appear as tree cover loss in the dataset. Further, the forest loss data can be temporarily misallocated and underestimate disturbances of less than 2 ha (Milodowski, Mitchard, and Williams 2017). However, the reliance on Hansen et al. (2013) data improves the tractability in the identification of deforestation cause and the impressive accuracy statistics stated in Masolele et al. (2024) particularly for mining make the data a suitable choice for our analysis.

Further research is needed to better understand the predisposing factors that facilitate the deforestation triggering of mining. Our analysis suggests that the location of minerals could play an important role. Whereas the literature on deforestation drivers typically assumes that accessibility and farming conditions are associated with higher land rents and thus deforestation pressure (Angelsen 2010; Busch and Ferretti-Gallon 2017), our results imply that farming expansion around mines also occurs in less accessible areas. This is not surprising given that insecurity in east DRC has led to a dissolution of local markets for selling agricultural produce and to predominantly subsistence-oriented farming (Cox 2012; Kelly 2014). Further, food around mining sites is initially often externally supplied from nearby villages, which is challenging to uphold in more remote areas and creates the need to grow food close to the mines (Bryceson and Geenen 2016; Smith 2011).

The proximity to roads and rivers, both associated with higher settlement expansion, also characteristise rural complex mosaics of shifting cultivation and settlements (Molinario et al. 2017). Mining activities increase population pressures in these land use systems and lead to their expansion into the forest. However, the results also showed that agriculture-related trigger effects may set in in dense forest areas away from pre-existing rural complexes, underpinning the potential of mines to open previously undisturbed core forests. In this way, artisanal mining can contribute to forest fragmentation with lasting impacts on the integrity of ecosystems and biodiversity in an area known for its richness in endemic and endangered species, such as the *Grauer's Gorilla* (Plumptre et al. 2007; Plumptre et al. 2016; Watson et al. 2018; Lhoest et al. 2020).

The relationship between mining, conflict and deforestation is complex. Decades of conflict have led to a retreat of timber, mining and agricultural industry, but have also pushed people into the forest in search of shelter and resources and conditioned the rise of artisanal mining (Nackoney et al. 2014; Draulans and Krunkelsven 2002; Kilosho Buraye, Stoop, and Verpoorten 2017). Conflict-related displacement has been a significant force behind internal migration in eastern DRC, where especially less remote mining sites have been identified as safe havens for the large number of landless displaced people who seek the livelihood opportunities provided in and around mines (Büscher and Mathys 2019; Kelly 2014).

Simultaneously addressing the problems of hazardous working conditions, armed actors' involvement and adverse environmental impacts inherent to the artisanal mining sector presents itself as a complex challenge that defies an easy solution. Previous attempts to regulate the sector did not have the desired effects. National laws to organise miners into cooperatives that operate in designated artisanal extraction zones have only been implemented partially, and the cooperatives that exist have turned into vehicles of elite capture rather than protection of workers' rights (Iguma Wakenge et al. 2021; Haan and Geenen 2016; Matthysen, Muller, and Bulakali 2022). Transnationally, the mineral traceability scheme iTSCi was initiated in 2012 in an attempt to ensure conflict-free tin supply chains and includes an increasing number of mines (Iguma Wakenge et al. 2021). However, especially in less accessible areas, interference and control by armed groups are still common, and reports of a fraudulent system with a disproportional burden on the miners prevail (Matthysen, Muller, and Bulakali 2022; Vogel 2018).

Mining emerged as a poverty-driven consequence of deteriorating rural livelihoods of millions of people, not only in DRC but throughout the entire Sub-Saharan Africa (Kelly 2014; Hilson and Garforth 2012). As long as viable income alternatives remain absent and the global demand for critical minerals persists, it will continue to play this crucial role in supporting rural livelihoods. Solutions must therefore focus on both, short-term relief to prevent the forms most problematic to people and forest, and long-term strategies to improve rural living conditions in order to conserve the planet's second-largest rainforest without failing the people who live inside and around it.

2.4 Methods

2.4.1 Data

We used data on post-forest land use in 30x30 metre resolution (Masolele et al. 2024). The data was constructed by first locating tree cover loss between the years 2001 and 2020 as indicated in Global Forest Change (GFC) data (Hansen et al. 2013). Afterwards, high-resolution Planet-NICFI images (NICFI 2021) with a 4.77m spatial resolution were utilised in an attention U-Net deep learning network architecture to classify different forms of post-forest land uses, including mining, farming and settlement expansion. Land use classification relied on images from 2022, which implies that potential intermediate land uses between a deforestation event and the year 2022 are not captured in the data, but also that the identified forest conversion is permanent.

The data is particularly useful for our analysis of artisanal mining in the eastern DRC for several reasons. The temporal allocation of the initial disturbance event prior to identified land uses enabled us to track changes over the years, which is crucial to analyse the dynamics around mining sites. Further, the application of high resolution Planet-NICFI images enabled the identification of even small-scale land uses that are common in the region, and the model was specifically trained with geolocated mining sites from eastern DRC (IPIS 2023). The product has 98% users' accuracy and 82% producers' accuracy for mining pixels (85% and 84%, respectively, across all land use categories; see Masolele et al. (2024) for full accuracy statistics), which gives us high confidence that the mining pixels in the data indeed correspond to mines.

GFC data detects stand-replacement or disturbance of tree cover, which is not necessarily deforestation as it also counts loss on non-forested land with tree cover (Pendrill et al. 2022). Consistent with previous studies for the region (Molinario et al. 2017; Shapiro et al. 2023; Potapov et al. 2012), we therefore only considered forest conversion on pixels that had a minimum tree canopy cover of 60% in the year 2000. To test the sensitivity of the findings to the definition of forest and deforestation, we compared the results for different datasets, reported in Figure 3.2 in the Supplementary Information.

As the unit of analysis is different mining sites, it was necessary to group the mining pixels from the post-forest land use data into clusters (Figure 2.1). When minerals are discovered and a mine established, the expansion of excavations into the immediate surroundings can occur over time. In order not to conflate such expansion effects with new mining incidences, we performed density-based clustering. Compared to other clustering algorithms, density-based clustering does not require a predetermined number of clusters and it allows clusters to grow into arbitrary shapes (Sander 2010), which is important given that mining sites often expand along riverbanks. A mining pixel was classified as a member of a cluster if it was within a 1km distance of at least one other member pixel (alternative distance threshold specifications in Table 3.2 in the Supplementary Information). Each of the pixel clusters represents a mining site, with the earliest identified pixel determining the starting year.

The analysis focused on the impacts of mining on forests. We therefore used GFC data to filter for mines with at least 30% densely forested pixels characterised by a minimum of 60% tree cover in 2000 inside a 5-km buffer. Furthermore, we excluded any industrial mines in our sample by overlaying and visually inspecting the identified mines with mining polygons from other data (Maus et al. 2022). After dropping 64 mines located outside the forest, as defined above, and two industrial mines, a sample of 255 artisanal mines remained.

The outcome variables were defined as forest loss events over varying geographic extents between the years 2001 and 2020 (Figure 2.1). Aggregating deforestation over polygons has the advantage of preventing biases that can occur in pixel-level analysis (Garcia and Heilmayr 2024). First, the spatio-temporal dynamics of forest loss in proximity to mines were examined by drawing a set of concentric rings of 1 km width in increasing distance to the first mining incidence within each cluster. For each ring, we calculated the share of forest pixels in 2000 that is lost by a given year.

Second, a buffer of 5 km width around mines was used to analyse the extent of forest loss in the surrounding area, where 5 km presented itself as a suitable buffer width in the results for the different distance rings from the first part of the analysis. Within these 5 km buffers, the calculated outcomes encompassed the cumulative *hectares* of forest loss in addition to the share of forest cleared, to get an estimate of the gross area that was deforested.

2.4.2 Difference-in-Difference model

The impact of the establishment of a mining site on the surrounding forest cover was estimated in a difference-in-differences (DiD) framework. To exploit the temporal dimension in the data, the model adopted a staggered design, where the treatment was defined as the start of mining activities, i.e., the earliest year for which mining pixels were identified in a mining location. In the main specifications, we use not-yet-treated instead of never-treated mining sites. Not-yet-treated controls have the advantage of providing a more comparable counterfactual if the never-treated controls are likely to differ from the treated units in non-random ways (de Chaisemartin and D'Haultfœuille 2022). We elaborate on this choice in the Supplementary Information, where we also report DiD results conditional on covariates for both not-yet-treated and never-treated controls.

The recent literature shows that the conventional two-way fixed effects (TWFE) estimator may produce biased results in settings with varying treatment timing and treatment effect heterogeneity due to the way that it places weights on the different sub-group comparisons (Chaisemartin and D'Haultfœuille 2020; Sun and Abraham 2021). Therefore, for our main specifications, we used the estimator proposed by Callaway & Sant'Anna (2022) (henceforth CSA).

The estimator developed by CSA relies on the calculation of group-time specific average treatment effects on the treated (ATTs), such that

$$ATT(g,t) = \frac{1}{N_g} \sum_{i:G_i=g} [Y_{it} - Y_{i,g-1}] - \frac{1}{N_{\tilde{G}}} \sum_{i:G_i \epsilon \tilde{G}} [Y_{it} - Y_{i,g-1}]. \tag{2.1}$$

The estimated ATT for mines starting in year g as observed in year t is the difference in the respective outcome Y between year $g-1$ and year t, averaged across all mines established in year g, and then substracted by the same averaged difference between year $g-1$ and year t for all mines $\tilde{G}$ that are not-yet-established. We then aggregated the ATTs across groups relative to the time of treatment exposure to obtain dynamic ATT estimates.

Similar to the TWFE estimator, identification of a treatment effect using the estimators proposed above relies on the assumptions of parallel counterfactual trends. If, on average, forest loss in both treated and control units would have developed in parallel had mining not occurred, the ATT estimates can be interpreted as the causal effects of mining on deforestation (de Chaisemartin and D'Haultfœuille 2022). To test parallel pre-trends, we calculated pseudo ATTs for pre-treatment periods. Pseudo ATTs, also referred to as placebos, estimate an ATT parameter as specified in Equation 1, but artificially shift the treatment timing to period $g-p$ for a pseudo effect estimate p periods before the actual treatment. If the pseudo ATTs are statistically insignificant and close to 0, they can be interpreted as evidence that the pre-trends are indeed evolving in parallel (Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2022).

We estimated pseudo-effects for 10 pre-treatment periods for all distance rings between 1 km and 25 km from the mines, as well as for the 5km buffers. Of all pseudo-coefficients, only the estimate in 1 km distance one year before mining was statistically different from zero (Figure 2.2a, Figure 2.3). Therefore, we interpret the pseudo-effects as evidence supporting the parallel counterfactual trends assumption.

For additional robustness, we rerun the estimates with a recently developed, heterogeneity-robust two-stage estimator (Gardner 2022). Further, we employ a spillover-robust extension of it (Butts 2023) to ensure that no contamination of estimates from other mines in the surrounding areas would systematically bias the estimates through spillover deforestation (Figure 3.5).

2.4.3 Heterogeneity of impacts

The heterogeneity analysis shown in Figure 4 was conducted by estimating conditional ATTs using non-parametric partial linear estimation (Cleveland, Grosse, and Shyu 1992; Ferraro, Hanauer, and Sims 2011). The residualised outcome from the first stage regression of recently developed imputation based DiD estimators (Gardner 2022; Borusyak, Jaravel, and Spiess 2024) was used as dependent variable (i.e. the difference between the expected deforestation in the absence of mining based on the estimated counterfactual trend from the first stage regression and the observed deforestation; see Supplementary Information section C).

The residualised outcome was then regressed on different covariates identified in the literature as potentially influential for the extent of triggered deforestation around mines. Given that multivariate non-parametric regressions were not possible with the limited number of observations, we ensured that the covariates did not capture the same predisposing characteristic by calculating correlation coefficients between them (see Supplementary Information Table 2.3).

We used forest loss observations one year before and five years after the start of mining to see how the heterogeneity in forest loss changes with the onset of mining activities. We chose 5 years as a suitable comparison time span in a trade-off between giving trigger dynamics enough time to set in and maintaining a large enough sample of mines with sufficiently long time series. Observations that showed as outliers in the distribution of the respective covariate were removed to avoid extrapolation in the tails.

Data availability The data for the replication of the statistical analyses are available under `https://github.com/maladewig/ASM-deforestation-DRC`.

Code availability The code for the replication of the statistical analyses is available for download under https://github.com/maladewig/ASM-deforestation-DRC.

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Competing Interests Statement The authors declare no competing interests.

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Appendix A

Alternative control regimes

The DiD estimates reported in the article use not-yet-established mines as control units for calculating the group-time average treatment effects for already established mines. This strategy allows us to not rely on randomly chosen control units that may differ from mining locations in non-random ways, but also imposes a slightly stronger parallel trends assumption than estimation with never-treated control units (Marcus and Sant'anna 2021). Following Callaway & Sant'Anna (2021) (Callaway and Sant'Anna 2021), the parallel trends assumption for group g in time period $t > g$ under a never-treated control regime without treatment anticipation is formalised as

$$E[Y_t(0) - Y_{t-1}(0)|G_g = 1] = E[Y_t(0) - Y_{t-1}(0)|X, C = 1] \tag{3.1}$$

where $Y_t(0)$ is the outcome in year t, G_g indicates whether a unit received first treatment in period g, X is a vector that allows to include covariates if parallel trends only hold conditional on covariates and C indicates whether a unit is never-treated. It is important to note that the left side of the equation in assumption 1 involves a counterfactual that is not observable and typically inferred from the analysis of pre-trends.

In comparison, the parallel trends assumption with not-yet-treated control units is formalised as

$$E[Y_t(0) - Y_{t-1}(0)|G_g = 1] = E[Y_t(0) - Y_{t-1}(0)|X, D_s = 0] \tag{3.2}$$

with D_s being a treatment indicator and $s \geq t$. Comparing the two assumptions, it can be seen that the former restricts parallel trends for each group g to a comparison between g and the group of never-treated control units that remains constant over time, while the latter assumption imposes parallel trends between group g and the group of not-yet-treated units that changes over time.

The question which control regime to use then ultimately depends on whether one believes parallel trends are more reasonable to hold between mining sites and randomly chosen control units, conditional on covariates (assumption 1), or whether the assumption is more reasonable to hold for mining sites established in different years, as they serve as control units for each other (assumption 2). Given that assumption 1 in our case relies crucially on the inclusion of all relevant covariates that could lead to a violation of parallel trends to account for the heterogeneity between randomly chosen and mining locations, we opted for not-yet-established mines as the more comparable control units in the main specification (de Chaisemartin and D'Haultfœuille 2022).

The DiD design can be enhanced with the inclusion of covariates with the rational to correct for violations of the parallel trends assumption (Callaway and Sant'Anna 2021). Although we interpreted the pseudo-effect estimates for the unconditional specifications with not-yet-treated control units in the article as evidence in favor of parallel trends, testing how results change after conditioning on covariates can provide a useful robustness test (Roth 2022). Therefore, we conditioned the pre-trends on a number of covariates (Table 3.1) and reran the analysis. As reported in Figure 2.1, results were smaller than without covariates, now amounting to 2.7 pp additional forest lost compared to the 4 pp from before. However, the effect remained significant and clearly visible.

Table 3.1: *List of covariates used as control variables under conditional parallel trends.*

Variable	Description	Source
Tree cover in 2000	Share of pixels with >60% tree cover in spatial extent	Hansen et al. (2013)
Accessibility	Travel duration via surface transport to nearest town of at least 50,000 inhabitants or contiguous area with 1,500 or more inhabitants per square kilometre	Weiss et al. (2018)
Distance to roads	Distance to the closest road, classified as either *primary* or *secondary*	OpenStreetMap
Distance to rivers	Distance to the closest river	OpenStreetMap
Altitude	Altitude of the location	FAO's GAEZ (Fischer et al. 2021)
Slope	Slope of the location	FAO's GAEZ (Fischer et al. 2021)
Temperature	Average temperature	FAO's GAEZ (Fischer et al. 2021)
Precipitation	Annual precipitation	FAO's GAEZ (Fischer et al. 2021)
Distance to logging roads	Distance to logging roads established before 2003	Kleinschroth et al. (2019)
Distance to border	Distance to the nearest national border	DRC Forest Atlas (WRI)
Distance to Protected Areas	Distance to the nearest protected area border, with negative values for locations inside.	DRC Forest Atlas (WRI)

In a second variation from our basline specification, we picked random locations with more than 30% pixels of > 60% tree cover within 5km buffers (Figure 3.4b). We then estimated the DiD for the "never-established" mines while conditioning on the covariates in Table 3.1. For this specification, we found an additional loss of 3 pp after 10 years, again slightly lower than the estimate from the main specification but larger than the covariate-matched approach with not-yet-established mines as control units. However, we note that the two of the pseudo coefficients are statistically different from 0 in this case.

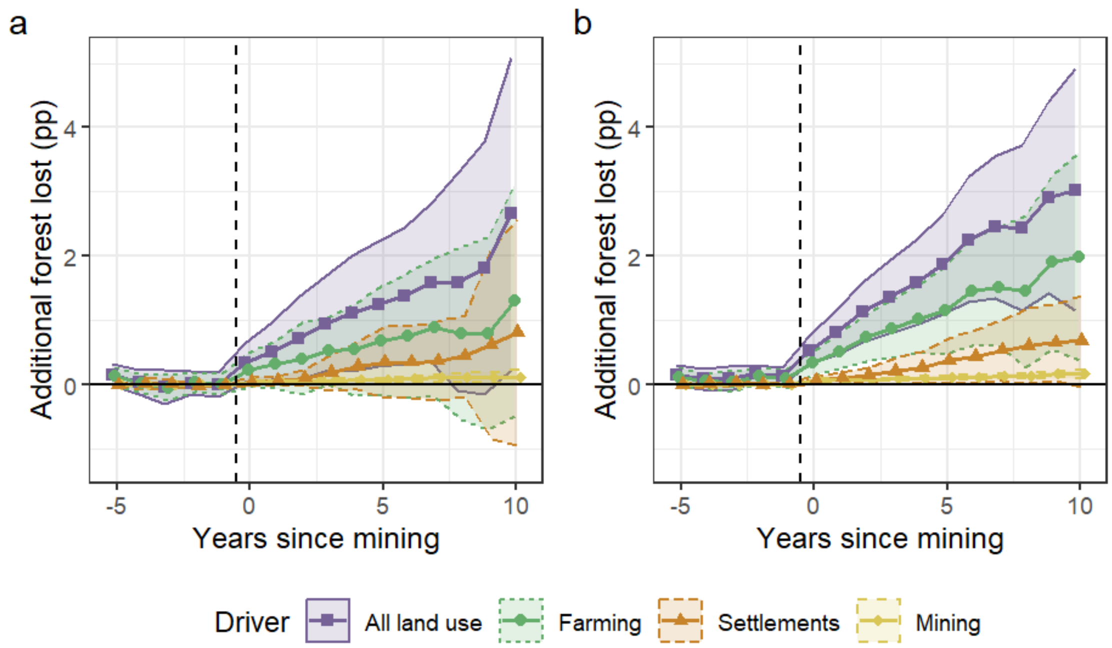

Figure 3.1: *Estimates of impact on cumulative deforestation since 2000 as percentage points of additional forest cover lost, within a 5-km radius around mines, over time since treatment for various land uses following deforestation. All estimates conditional on the covariates tree cover in 2000, accessibility, distance to roads, distance to rivers, altitude, location, growing period length, distance to logging roads and distance to national borders.* ***a*** *Not-yet-established mines as controls (n=255) and* ***b*** *Never-treated randomly chosen control units (n=1255). Bootstrapped standard errors are clustered at the mine level. Points indicate ATT estimates following the DiD estimator proposed in Callaway & Sant'Anna (2021) and errorbars refer to 95% confidence bands.*

Alternative data

The data used in our main analysis is based on Masolele et al (2024) Masolele et al. (2024) . Although it relies on Global Forest Change (GFC) data (Hansen et al. 2013) for the detection of deforestation events, it markedly differs from GFC. GFC identifies tree cover loss since 2001, which can be a consequence of deforestation or degradation, but also canopy cover loss on non-forest land (Pendrill et al. 2022). In contrast, the data from our main analysis focuses on post-forest land use and therefore on persistent land-cover change, which excludes many forest loss events in GFC.

To illustrate this difference, we reran the analysis with GFC data and compared it with results estimated with the Tropical Moist Forest (TMF) data set developed by (Vancutsem et al. 2021). TMF has the same resolution as GFC but does not work with a canopy threshold to define forest loss. Instead, TMF tracks forest changes since 1986 and classifies them as undisturbed, degraded or deforested forest pixels, depending on the severity and duration of canopy cover disturbance. To be classified as deforested, disturbance within a forest pixel must exceed 2.5 years.

As the results in Figure 3.1 show, the deforestation estimates using TMF are similar to those from our main analysis, while TMF degradation and GFC forest loss are substantially higher.

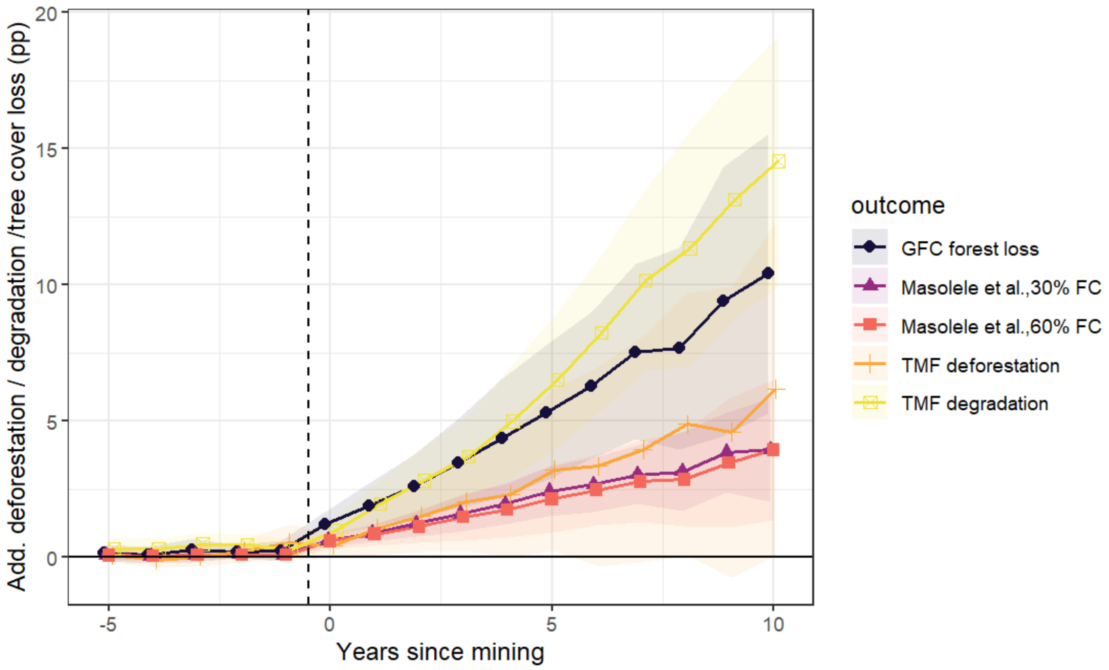

Figure 3.2: *Additional disturbance effects by datasets. Points indicate ATT estimates following the DiD estimator proposed in Callaway & Sant'Anna (2021) and errorbars refer to 95% confidence bands. n=255 mining sites.*

Alternative estimator

In addition to Callaway and Sant'Anna's (2021) (Callaway and Sant'Anna 2021) (CSA) group-time specific estimator, we also used the two-stage procedure proposed by Gardner (2022) (Gardner 2022) (GAR) (see also Borusyak et al. (2024)(Borusyak, Jaravel, and Spiess 2024)for a similar approach). In contrast to CSA, it follows a two-stage procedure. First, counterfactual trends that would occur in the absence of treatment are imputed by using the not-yet-treated units only:

$$Y_{it} = \mu_i + \lambda_t + u_{it} \tag{3.3}$$

Once Y is imputed, the ATTs can be estimated using a second stage regression of treatment dummies on the imputed outcome.

Lead coefficients for the years before treatment can be included into the second-stage regression to test the plausibility of the parallel trends assumption. As Roth et al. (2023) (Roth et al. 2023) note, the GAR estimator relies on a more stringent parallel pre-trends assumption than that of CAS to obtain unbiased estimates, since it requires parallel pre-trends to hold for all included pre-treatment periods to impute the counterfactual. In contrast, CSA's group-time weighted average estimator only relies on parallel trends in the period before treatment begins for a valid counterfactual, although it seems unlikely that parallel trends would have been observed in the absence of treatment in such a case. It can therefore be useful to limit the number of lead coefficients that are used to impute the first stage. In the absence of an established procedure by which to determine the number of leads, five pre-treatment periods were used throughout the analysis.

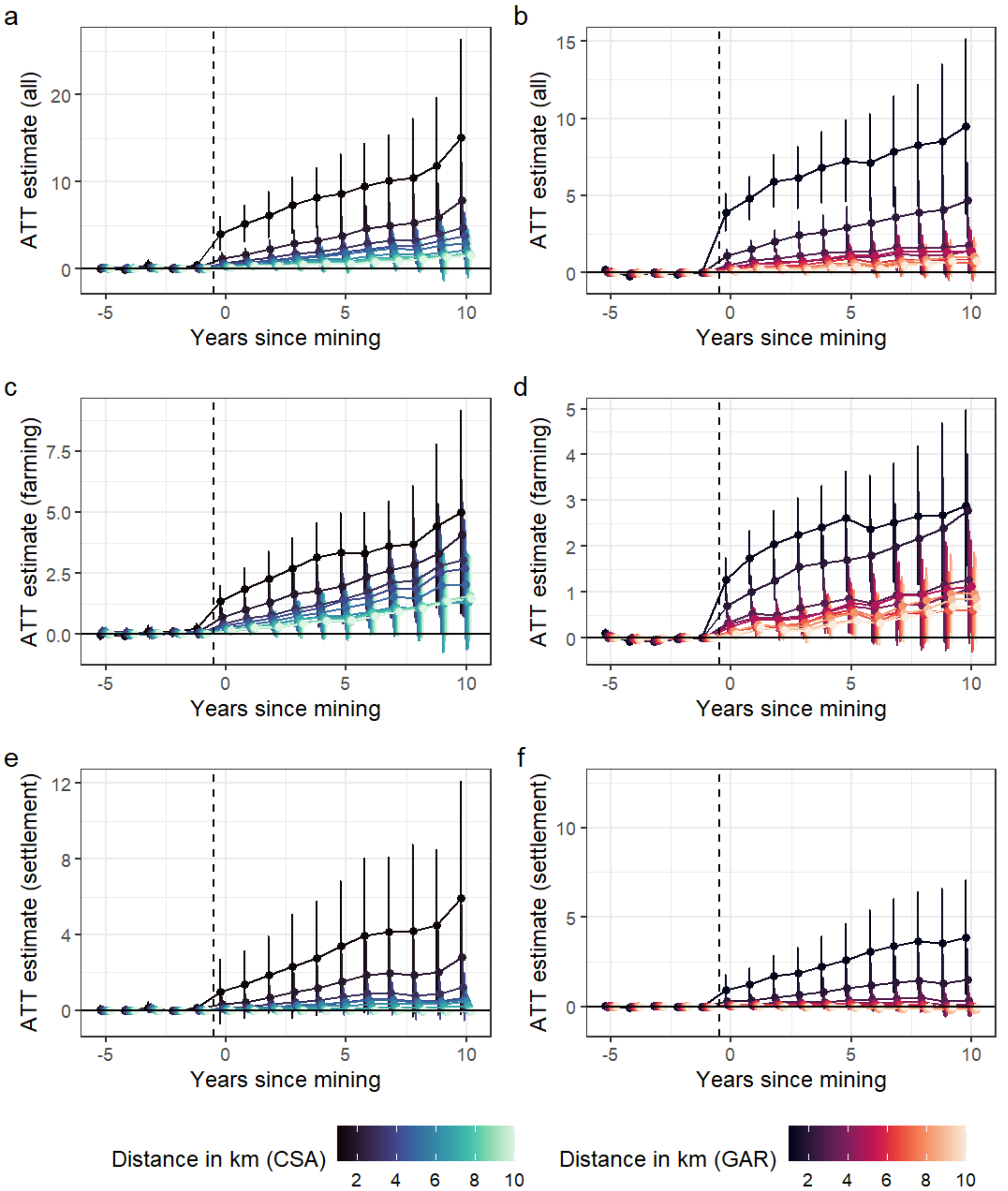

Figure 3.3: *Event-study plots showing the ATT estimated as additional percentage points of forest lost within rings of increasing distance from the mining sites, over time. Plots **a**, **b** and **e** are estimated following Callaway & Sant'Anna (2021), while **b**, **d** and **e** employed the Gardner (2022) two stage procedure. The colours refer to the increasing distance from the mines. Confidence intervals are displayed at 95% level. n = 255 mining sites.*

Figure 3.2 compares the CSA and GAR estimates in relation to time since the first mining incidence and distance from the mine. It shows that estimates run using GAR are more conservative across all specifications, although they still clearly reveal the effects of mining on surrounding forests.

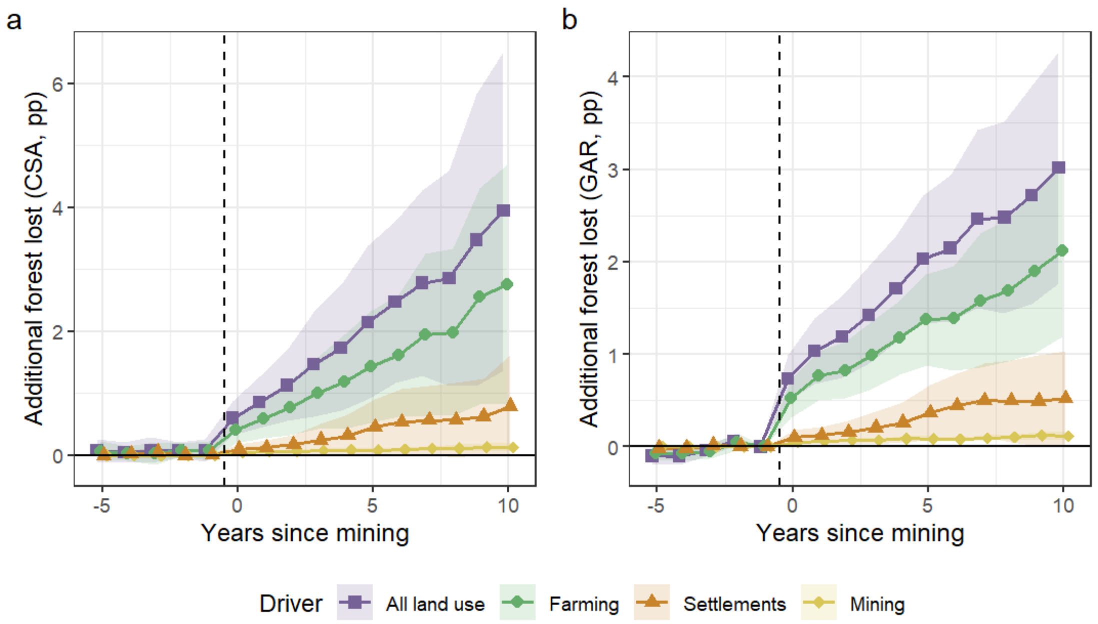

Figure 3.4: *Estimates of impact on cumulative deforestation since 2000 as a share of forest cover in 2000 within a 5-km radius around mines for different periods following treatment, showing various land use following deforestation. For every additional kilometre from the mine, a new ring is estimated using **a** the estimator used by Callaway & Sant'Anna (2021), and **b** the estimator proposed in Gardner (2022). Displayed confidence intervals at 95%.n = 255 mining sites.*

Figure 3.3 compares the estimates for the CSA estimator, shown in panel A, and the GAR estimator, panel B. As with the spatio-temporal estimation, results from GAR are more conservative than from CSA, but still convey a similar message: mining leads to substantial forest loss within a 5-km buffer around sites, and farming activities play an important role in explaining the forest loss.

Cluster threshold variations

	500m		1000m		1500m		3000m	
period	ATT	SE	ATT	SE	ATT	SE	ATT	SE
-5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
-4	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.1
-3	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
-2	0.1	0.0	0.1	0.0	0.1	0.0	0.1	0.0
-1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0	0.6*	0.1	0.6*	0.1	0.6*	0.1	0.6*	0.1
1	0.9*	0.1	0.9*	0.1	0.9*	0.2	0.9*	0.1
2	1.1*	0.2	1.1*	0.2	1.1*	0.2	1.1*	0.2
3	1.5*	0.3	1.5*	0.3	1.5*	0.3	1.5*	0.3
4	1.7*	0.4	1.7*	0.4	1.7*	0.4	1.7*	0.4
5	2.1*	0.4	2.1*	0.4	2.1*	0.4	2.1*	0.4
6	2.5*	0.5	2.5*	0.5	2.5*	0.5	2.5*	0.5
7	2.8*	0.6	2.8*	0.6	2.8*	0.5	2.8*	0.5
8	2.8*	0.6	2.9*	0.6	2.9*	0.7	2.8*	0.6
9	3.5*	0.9	3.5*	0.9	3.5*	0.9	3.5*	0.9
10	3.9*	0.9	3.9*	0.9	3.9*	0.9	3.9*	0.9

Notes. Impact estimates within 5-km buffers around mines using Callaway & Sant'Anna (2021) estimator for different cluster thresholds. ATT estimates without 95% confidence intervals spanning zero are indicated with *. n = 255 mining sites.

Table 3.2: *Cluster threshold variations*

Spillover-robust estimation

A challenge in the empirical strategy is the isolation of one mine's forest loss effect from another proximate mine's spillover effects. Such contamination could bias pre-trend estimates or lead to problems of "double counting", where the forest loss effect of one mine inflates the estimated effect of another. Although important to consider in many settings, DiD designs with spatial spillovers are still poorly understood (Roth et al. 2023). We account for potential spillovers in a ring-estimator framework as outlined in Butts (2023), where control units can be exposed to treatment effects from nearby treated units. The spillover estimation is similar to the two-stage estimator of Gardner (2022), the difference being that the first stage is imputed from observations that are not-yet-treated and, additionally, not-yet-spillover-exposed, i.e. they do not have any active mines located nearby. By including spillover-exposure dummies into the second-stage regression, the treatment effect can be spllit into the spillover deforestation from other mines and the actual deforestation from the mine itself, given that the parallel-trends assumption extends to the spillover area.

Figure 3.5 shows that the spillover-robust ATT estimates do not differ systematically from the ATTs estimated using the two-stage procedure outlined in Gardner (2022). The spillover effects appear insignificant and relatively constant over time. Therefore, we conclude that spillovers do not impact the validity of our findings.

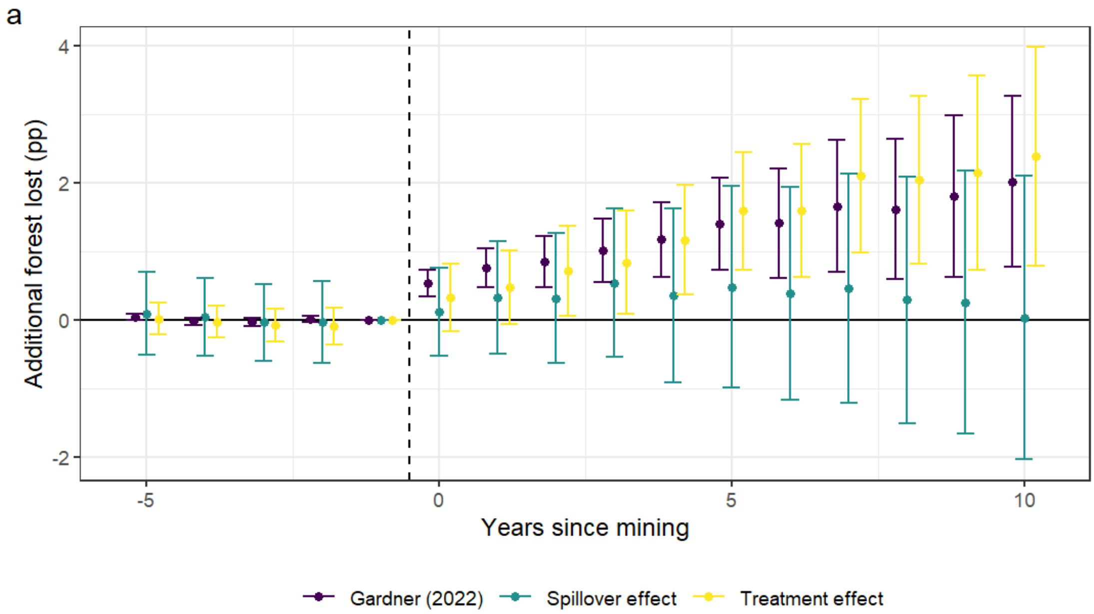

Figure 3.5: *Spillover-robust estimation. Points represent effect estimates with ' Gardner (2022)' referring to ATTs estimated with the two-stage estimator proposed in Gardner (2022), while 'Spillover effect' and 'Treatment effect' refer to estimated parameters as suggested in Butts (2023). Bootstraped 95% confidence intervals are displayed.*

	Accessibility	Agr. Suitability	River distance	Primary road dist.	Main road dist.	Forest cover in 2000	Conflict events
Accessibility	1	.	.	.	.	.	.
Agr. Suitability	-.08	1	.	.	.	.	.
River distance	-.05	.02	1	.	.	.	.
Primary road dist.	.39	-.15	-.21	1	.	.	.
Main road dist.	.57	-.18	-.17	.36	1	.	.
Forest cover in 2000	.32	-.15	.11	.10	.14	1	.
Conflict events	-.02	-.05	-.01	-.09	-.02	-.16	1

Table 3.3: *Pearson correlation coefficients for the different variables tested in the heterogeneity analysis.*

Descriptive statistics

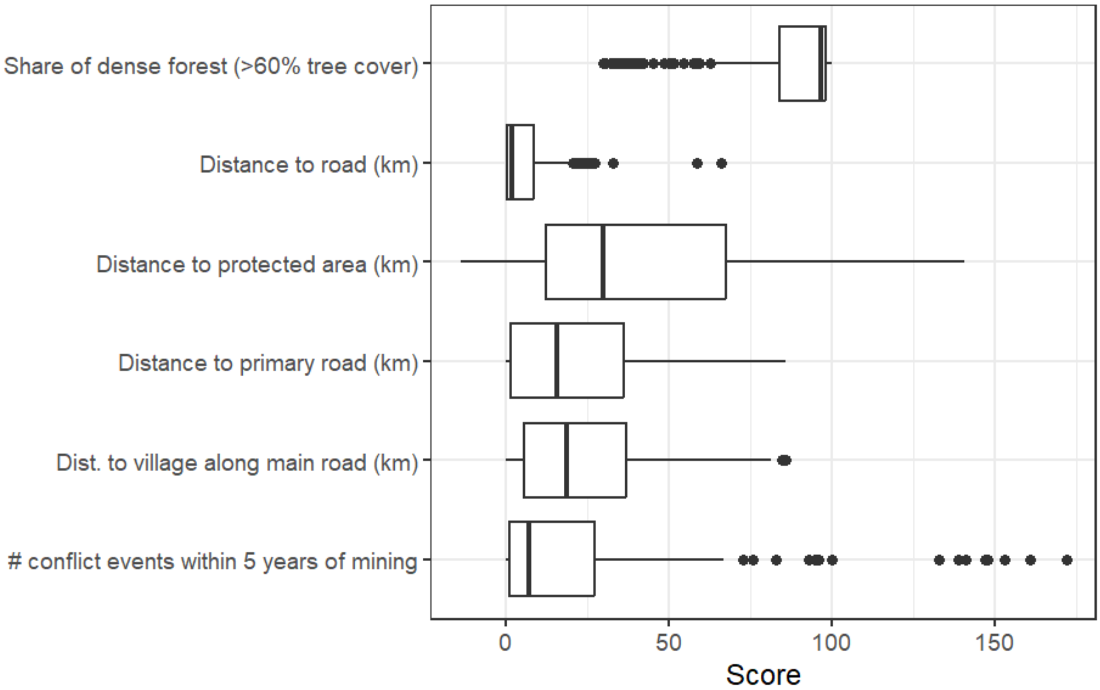

Figure 3.6: *Boxplot diagrams for identified mining sites (n=255) drawn for different covariates. The unit of the score on the x-axis changes with covariates as in indicated in the variable discription on the y-axis.*

Software

The analysis was conducted in R version 4.3.2. For the data processing, we used the packages *terra* (Hijmans et al. 2023) and *sf* (Pebesma et al. 2023). The statistical analysis relied on the packages *did* (Callaway and Sant'Anna 2022)and *did2s* (Butts [aut et al. 2023).

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Paper II

"The 'tired' soil is both an agronomic reality and a second symbol of change, encoded with all of the frustrations and diminishing returns of agrarian life. To the misfortune of farmers, continuity and rupture are not exclusive. Households are trapped between the legacy of the past in the allocation of land, and a present without the synergies or social structuring of mixed farming. Dismaying of this, many are turning to the future instead. The new realm of modern activities completes the break with the poisoned past, leaving behind the risks and constraints of the farm, albeit for new games with long odds."

(Cox, 2012)

Between a Rock and a Hard Place: Livelihood Diversification through Artisanal Mining in the Eastern DR Congo

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Abstract Living conditions of the rural population in the eastern Democratic Republic of Congo (DRC) have suffered from prolonged violent conflicts, poor governance, declining soil fertility, and lack of infrastructure to support economic development. In parallel, artisanal mining has become a widespread livelihood activity in the area. This study investigates the ways mining integrates into households' livelihood strategies and its implications on livelihood outcomes. It draws on household surveys conducted around Kahuzi-Biega National Park and Itombwe Nature Reserve in the South-Kivu province to show that mining households tend to experience higher food security compared to non-mining households. They also tend to rely less on agriculture for their livelihood, suggesting substitution of farming activities in favour of mining.

4.1 Introduction

The Democratic Republic of Congo (DRC) is one of the richest countries in mineral resources, having large deposits of cobalt, tin, gold and copper, among others (Edwards et al., 2014). Despite this abundance, poverty is widespread and large-scale extractive industries have not settled in many parts of the country after decades of political instability (Kilosho Buraye et al., 2017; Radley, 2020). Especially in the eastern part of the country where extensive gold and 3Ts (tin, tungsten and tantalum) deposits are located, extraction tends to occur artisanally at a small scale with handheld tools, involving more than 200,000 miners in the North- and South-Kivu provinces alone (IPIS, 2023).

The largely informal artisanal mining sector faces environmental, social and political challenges. It is commonly associated with environmental pollution (Nkuba et al., 2019), loss of forest and biodiversity (Ladewig et al., 2024; Sonter et al., 2018; Spira et al., 2019), spurring of conflict and violence (Stoop et al., 2019; Vogel, 2018), and human exploitation from the precarious working conditions under which minerals are extracted (Sovacool, 2019). While having these negative associations, artisanal mining has become a cornerstone in the livelihood strategies of many rural households in eastern DRC as a comparably profitable and accessible income opportunity (Spira et al., 2019). It has been described as a safety net in times of hardship (Kelly, 2014; Smith, 2011), and provides an income opportunity even in remote locations where other alternatives are scarce (Bryceson & Geenen, 2016; Smith, 2011).

Motivations of households to engage in mining are commonly distinguished into push and pull factors (Banchirigah & Hilson, 2010; Hilson, 2010; Maclin et al., 2017). Push factors describe those that make people abandon their traditional farming livelihoods in response to hardship and poverty and look for alternatives. For rural households, such hardship can have various origins, including the deterioration of farming conditions (Hilson & Garforth, 2012). Pull factors, on the other hand, relate to characteristics of mining that draw people towards it, such as the expectation that mining will provide an opportunity to earn a lot of money in a short time.

Although such a distinction might be a useful simplification, push and pull factors often act simultaneously and their boundaries can be fluent (Hilson & Hu, 2022). The context of the eastern DRC showcases this well, as rural livelihood conditions have suffered greatly under decades of political instability, while the density of artisanal mines in the region is among the highest in the world.

In this study, we use the livelihoods framework of Ellis (2000) to investigate the motivations and implications of households' decisions to diversify their livelihoods through artisanal mining around protected areas in South-Kivu, eastern DRC. Moving beyond the push and pull factor dichotomy, we distinguished miners by their reliance on mining to investigate how permanent, occasional and non-mining households differ in their livelihood strategies and outcomes. We first construct a simple analytic model to describe households' decisional processes to allocate labour resources away from farming towards mining. We then introduce an empirical model based on data collected during fieldwork around Kahuzi-Biega National Park and Itombwe Nature Reserve in South-Kivu, eastern DRC. The results suggest that non-mining households experienced a higher degree of food insecurity. De-agrarianisation was observed, but only among households with a high reliance on mining for their livelihoods.

4.2 Background

4.2.1 Study area

The data collection for the paper took place in villages surrounding Kahuzi-Biega National Park ("Parc National de Kahuzi-Biega", PNKB) and Itombwe Nature Reserve (INR) in the Albertine Rift, known for its outstanding biodiversity, including large numbers of endemic and endangered species (Plumptre et al., 2007) (Figure 4.1).

The montane forest around Mt Kahuzi in South-Kivu, eastern DRC, was first declared a forest reserve in 1937 under Belgian colonial rule and enlarged in 1951 to also encompass Mt Biega (Flummerfelt, 2022). It gained National Park status in 1970, when communities living inside the park were violently displaced without compensation for the purpose of conservation (Domínguez & Luoma, 2020). Many

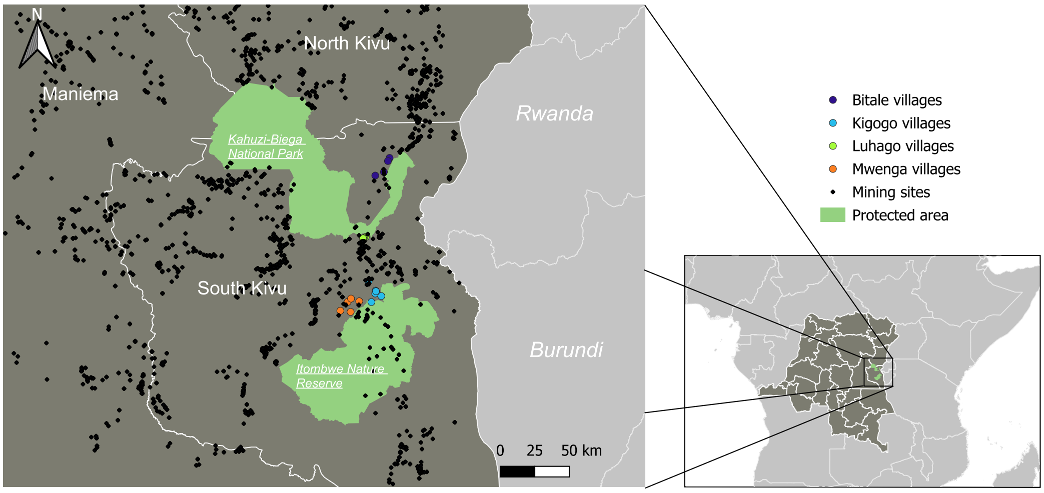

Figure 4.1: *Map of study area with surveyed villages and mining sites from IPIS (2023) and GPS coordinates collected during field work.*

of the evicted people belonged to the indigenous Batwa people who relied on the forest for their hunter-gatherer livelihoods, and who consequently were stripped off their spiritual, cultural and intellectual identity (Cuni-Sanchez et al., 2019; Simpson & Geenen, 2021). PNKB was further extended in 1975, leading to more evictions, and eventually became listed a World Heritage Site in 1981, even if the title is at risk as of 2022 due to threats from illegal human activities, such as mining and hunting (Kirkby et al., 2015).

In 2018, Batwa communities who became landless after the evictions attempted to resettle in their ancestral lands inside the protected area (Barume, 2000; Flummerfelt, 2022; Simpson & Geenen, 2021). At the same time, deforestation inside the park surged. Some related the forest loss to changing Batwa livelihoods from their traditional forest reliance to more extractive activities after decades of living outside of the forests, such as the extraction of charcoal, timber and minerals (Simpson & Geenen, 2021). Others interpreted the change to be the result of outside actors instrumentalising the Batwa and using their resettlement to cover up for illegal activities inside the park (Flummerfelt, 2022). Ultimately, in 2019, a new wave of atrocities occurred when armed park rangers joined forces with the Congolese army and expelled communities once more, leaving behind destroyed villages and injured or in some cases even dead Batwas (Flummerfelt, 2022). Thus, the history of PNKB displays itself as a case of fortress conservation, where green militarization has been used to isolate the forest from human interference, posing important constraints on the livelihoods of communities who have traditionally lived inside them (Domínguez & Luoma, 2020).

In contrast to PNKB, the discussion to protect the forest of the Itombwe massif only took off in the late 1990s, after observations were made that gorilla and elephant species declined dramatically during the First Congo War (1996-1997) (Simpson & Pellegrini, 2022). The Rwandan genocide in 1994 had initiated a stream of refugees across the border, followed by several armed groups who chose the sparsely inhabited forests as hide-aways and to the day destabilize the region. The area was eventually declared a nature reserve per decree by the minister of the environment in 2006. The absence of dialogue during the gazettement process led to resistance from local communities and conservation NGOs alike, and ultimately to a redrawing of the park boundaries following a participatory mapping process in 2016 (Gauthier & Pravettoni, 2016; Kujirakwinja et al., 2019). The new nature reserve foresees different zones that allow for sustainable hunting and agriculture outside of the core zones (Kujirakwinja et al., 2019). However, the conservation area remains contested in some communities even after its re-establishment (Simpson & Zirhumana, 2021). The ethnic groups surveyed for this study were mostly of the Warega and Nyindu, of which the latter are farmers who are sometimes considered related to the Twa (Cuni-Sanchez et al., 2019).

Both protected areas impose restrictions on land use and forest resources, thereby reducing the options of coping with deteriorating living conditions during the decades of prolonged armed conflict. In addition, violence-driven displacement limits access to agricultural land and makes long-term planning difficult, as several interviewees reported. The looting of fields by armed groups and raiding of large livestock, once considered the highest valued asset but now largely vanished, have further exacerbated rural poverty and also impacted manure-reliant farming practices in some parts of South-Kivu (Cox, 2012; Kelly, 2014; Verweijen & Brabant, 2017). In combination with declining soil productivity, the dissolution of local agricultural markets and limited capacity to adapt to a changing climate, it has become increasingly challenging to rely solely on farming (Amani et al., 2022; Cox, 2012).

Whereas farming became less viable, mining remained a widespread income opportunity both outside and inside of PNKB and INR (Simpson & Zirhumana, 2021; Spira et al., 2019). It provides a livelihood alternative with higher income than farming and neither requires training nor assets to engage (Bryceson & Geenen, 2016). While providing income to people, "conflict minerals" also act a source of revenue to rebel groups who operate mines, thereby fueling the conflict and adding another layer to the complex livelihood context (Matthysen et al., 2019; Radley & Vogel, 2015; Stoop et al., 2019).

4.2.2 Artisanal mining in eastern DR Congo

Although mineral extraction has a long history in the DRC, the actors involved have changed over time. During Belgian colonial rule, mining occurred predominantly in industrial form. However, with increasing insecurity during the Congo wars, extractive industry abandoned the country and artisanal mining emerged as a major alternative to the unstable farming conditions (Huggins, 2023; Kelly, 2014).

Towards the end of the Second Congo War in 2002, former president Joseph Kabila attempted to regain government control over the mining sector, among others through unsuccessful attempts to re-establish industrial operations through tax reductions and other incentives (Geenen, 2014; Kilosho Buraye et al., 2017). In parallel, new laws were passed to formalise the dominant and largely informal artisanal mining sector. The revised mining code of 2002 and subsequent decrees in 2003, 2010 and 2012 resulted in a number of stipulations by the Ministry of Mining (Haan & Geenen, 2016). According to the 2002 code, workers are obliged to operate inside designated Artisanal Extraction Zones (AEZs). In practice, the number of AEZs is limited, and their status can be revoked at any time, e.g., if large-scale industries claim an interest in an area (Kilosho Buraye et al., 2017). Geenen (2012) also notes that AEZs are created by authorities without knowledge of local circumstances and in absence of consultation with miners, leaving many unsatisfied with the areas assigned as AEZs. In practice, artisanal mining continues to occur also outside of AEZs (Kilosho Buraye et al., 2017).

The second stipulation of the mining code aimed at formalizing artisanal mining by organizing miners into cooperatives (Haan & Geenen, 2016). By law, artisanal miners are required to acquire a 'carte de creuseur', a mining card, paid in cash or an equivalent value in minerals (PACT, 2010). In a context of undemocratic hierarchical structures and lacking alternatives, the cooperatives create strong dependencies instead of increasing workers' agency (Haan & Geenen, 2016). Cooperatives also serve as a middle-actor through which miners sell minerals to the market. Since the *de facto* implementation was limited in the years after the law was passed, a six-month-lasting artisanal mining ban for the regions North-Kivu, South-Kivu and Maniema was announced (Geenen, 2012). However, the ban only had minor effects, as the implementation remains low and the sector is still largely informal (Kilosho Buraye et al., 2017).

Finally, in 2012, the *International Tin Supply Chain Initiative* (ITSCI) introduced a color code to label artisanal mines according to risk factors as *green* ("safe"), *yellow* or *red* ("unsafe") based on a mine's human rights standard and the absence of armed groups (Haan & Geenen, 2016; Iguma Wakenge et al., 2021). Minerals from *green* sites are granted certification and are allowed to be traded on the international market, while minerals from unsafe sites are theoretically prevented from entering supply chains. In reality, the coverage of ITSCI remains partial and loopholes exist, having the miners incur the additional costs (Vogel, 2018). Among the 3T-mines listed on the web-map of the International Peace Information Service (IPIS) covering eastern DRC, 41% are currently assessed under the iTSCi scheme, and only 21% earned green classification status (IPIS, 2023). The sector thus remains informal, with an array of competing actors involved.

4.3 Conceptual framework

4.3.1 Livelihoods framework

We adopt a livelihoods framework as developed in Ellis (2000) and Scoones (1998), among others. Assets play a central role in the framework and are distinguished into natural, physical, social, human and financial assets. Conditional on these assets, a household chooses a livelihood strategy consisting of one or more accessible activities, which ultimately determines its welfare and vulnerability status. The asset stock of a household may change over time, depending on the outcomes it realises from the chosen livelihood strategy. The larger institutional, environmental and socio-economic context a household is situated in further influences a household's assets, livelihood strategy and outcomes.

Livelihood diversification is a common phenomenon among the rural poor and describes a process by which households develop a diverse portfolio of activities to rely on in their livelihood strategies. The motivations to diversify can be manifold, including a reduction of income failure risk, seasonal gap filling during agricultural off-season, and responding to negative shocks (Ellis, 2000). The pluriverse of motives commonly gets reduced to factors of necessity and choice (sometimes also referred to as push and pull) in the literature on livelihood diversification (Barrett et al., 2001). This dichotomy has also established itself in the literature for explaining livelihood diversification through artisanal mining (Banchirigah & Hilson, 2010; Hilson, 2016). Diversification by necessity describes a response to distress and shocks, of which the rural poor tend to experience numerous and which force housholds to seek alternatives from their traditional livelihoods. Diversification by choice, on the other hand, is rather motivated as a forward-looking strategy, adopted to reduce risk of income failure and to increase expected income (Banchirigah & Hilson, 2010; Ellis, 2000).

The livelihood space of communities in the study region of South-Kivu has been shaped by regular disturbances in the form of immediate shocks, but also as gradual shifts that have initiated a reorientation of livelihood strategies. Ongoing conflicts for the past decades have exposed households to sudden shocks of various forms. Violence-driven displacement stripped farmers of their land or made them lose livestock, harvest and other productive assets, as they became target of raiding armed groups (Kelly, 2014; Verweijen & Brabant, 2017). Branching out into other activities, especially those with low entry barriers, often provided a safety net against shocks in the absence of savings or assets to liquidise (Angelsen & Dokken, 2018). The constant state of insecurity has also lead to a more gradual reshuffle of livelihood strategies. Pastoral activities have disappeared in large parts of Eastern DRC due to raiding of livestock, also affecting manure-dependent agricultural practices (Cox, 2012; Verweijen & Brabant, 2017). Farming has been entirely replaced by mining in some locations (Kelly, 2014; Smith, 2011).

Conservation interventions, present throughout the study area in the form of protected areas, can further disturb traditional livelihoods, given that they limit access to land and forest resources (Baird & Leslie, 2013; Kujirakwinja et al., 2019). Several forms of forest income such as timber extraction, charcoal production and hunting are restricted. These are income sources which usually offer readily available responses to shocks for forest communities due to their low entry barriers and quick returns (Angelsen et al., 2014; Wunder et al., 2014). Conservation can also create new opportunities, e.g., through eco-tourism, Payments for Ecosystem Services (PES) or Integrated Conservation and Development Projects (ICDPs) (Baird & Leslie, 2013), but such opportunities have not emerged in eastern DRC where basic structures are lacking to make these work and insecurity remains high.

Further distress on traditional rural livelihoods is exerted by the overall deterioration of agricultural conditions. Most farming activities are rain-fed with low inputs, and the adaptation capacity to shifting weather patterns from climate change remains low (Amani et al., 2022; Balasha et al., 2023). Also, crop diseases have decreased yield in recent years and made farming less attractive (Amani et al., 2022).

Long-term strategic investment and the build-up of assets are challenging in such an unstable context. Cash crops like coffee or oil palm, for instance, take several years to mature, whereas mining and other forms of resource extraction represent an accessible way to quick returns, making them an efficient response to shocks (Wunder et al., 2014). When alternative coping strategies such as the selling of assets or the spending of savings (Angelsen & Dokken, 2018) are no options, choices necessarily fall on alternative activities with low entry barriers and quick returns. Given the high spatial density of artisanal mines in eastern DRC, mining is an accessible option for diversification, as it does not require initial investment into assets, promises instant cash income and can flexibly complement other livelihood activities. However, it does require the strategic reshuffling of labor resources. As labor is limited by household size and composition, committing more into one livelihood activity implies a trade-off in terms less time spent on another activity.

4.3.2 A simple analytical model

We illustrate a household's decision to branch out into alternative income opportunities in an analytic model. In the tradition of Singh et al. (1986) and Sadoulet & De Janvry (1995), we assume a household to maximise its expected utility by allocating its available labor L between different livelihood alternatives, which for the sake of the analysis are limited to farming, mining and other income-generating activities (indicated with subscripts f, m and o, respectively). Assets also influence the choice of livelihood activities, but are here assumed fixed and, unlike labor, not subject to an allocation across activities.

We assume households to be risk averse with strictly increasing and strictly concave utility functions, such that:

$$u(E[y]) \geq E[u(y)] \quad \text{with} \quad u'(y) > 0, u''(y) < 0. \tag{4.1}$$

The optimal allocation of labor can be specified as a constrained optimisation problem of a household's certainty equivalent (CE):

$$\begin{aligned} \max_{L_f, L_m, L_o} \quad & CE = E[w + y] - \pi - \delta(L_m, L_o) \\ \text{s.t.} \quad & y = \sum_{i \in \{m,f,o\}} y_i(L_i, X), \\ & \bar{L} = \sum_{i \in \{m,f,o\}} L_i \end{aligned} \tag{4.2}$$

Here, the utility depends on the initial wealth w, the risk premium π, the reluctance from reducing labor in traditional farming livelihoods, and the realised cash and subsistence income y, i.e., the sum of income from the different livelihood activities. The income y_i from activity i depends positively on the assigned amount of labor L_i and the endowment of other assets X of a household. Especially farming relies on assets such as access to arable land, livestock units (lsu) and other agricultural inputs, whereas mining income does not directly depend less on such asset endowments. The amount of labor to be allocated is constraint by a household' s overall available labor force, $\bar{L}$.

If all activities were equally exposed to risk, the risk-reducing effect of diversification could be derived from the risk premium, as defined by Arrow (1971) and Pratt (1978) (see e.g., Bezabih & Sarr (2012) or Baumgärtner & Quaas (2010) for relevant applications). Since differences in risks between activities drive diversification decisions, we consider the case of multivariate risk exposure. Without further information on the covariance structure of the different risks, we make the simplifying assumption that risks are mutually independent and additive (Duncan, 1977).

Assumption 1
(i) $\frac{\partial y_i}{\partial L_i} > 0$*: The income from activity* i *increases with the amount of allocated labor* L_i*.*
(ii) The risks associated with different livelihood activities $i, j \in \{m, f, o\}$ *are mutually independent, such that* $\sigma_{ij} = 0$ *for all* $i \neq j$*.*

Although point *(ii)* assumption 1 is a strict one and unlikely to hold, we prefer it over assuming an arbitrary covariance structure. It is not *a priori* clear whether covariances between risks would be negative or positive, as some shocks have negative impacts on all activities (e.g., sickness of household members) while others can be positive (e.g., the complementary seasonality of mining and farming). Then, similar to Bezabih & Sarr (2012), the risk premium π is specified as the income-weighted sum of risk premiums on the different activities in the livelihood portfolio of a household given the chosen labor allocation:

$$\pi = \frac{\rho}{2} \sum_{i \in \{m,f,o\}} y_i^2 \sigma_i^2 \tag{4.3}$$

ρ represents the Arrow-Pratt coefficient of risk aversion (Sadoulet & De Janvry, 1995), and σ_i^2 is the variance of output y_i.

As a simplifying assumption to derive the relationship between labor allocation towards farming and mining, we focus only on these two activities in solving equation 4.2. We make the following assumptions about the income and the risk relationships between farming and mining:

Assumption 2
$\frac{\partial \pi}{\partial L_f} > \frac{\partial \pi}{\partial L_m}$ *for* $L_f = L_m$*: A marginal increase in farming labor leads to a higher increase in risk premium than a marginal increase in mining labor for a given amount of allocated labor.*

Assumption 2 states that farming is associated with higher risk than mining. Both statements find well-documented support in the literature (Cox, 2012; Maclin et al., 2017; Spira et al., 2019).

From the first order conditions from equation 4.2, it can be shown that the optimal allocation of labor is given by (see appendix):

$$[\frac{\partial y}{\partial L_m}(L_m^*) - \frac{\partial \pi}{\partial L_m}(y_m, \sigma_m^2)] - [\frac{\partial y}{\partial L_f}(L_f^*, X)) - \frac{\partial \pi}{\partial L_f}(y_f, \sigma_f^2)] = \frac{\partial \delta}{\partial L_m}(L_m^*) \tag{4.4}$$

Given that assumption 2 holds, we know that the left-hand side of equation 4.4 is positive. Under optimal labor allocation, a household thus diversifies its livelihoods towards mining until the additional risk-adjusted marginal income from mining, compared to risk-adjusted income from farming, equals the marginal disutility from having to move from farming to mining.

Assumption 3
(i) $\frac{\partial y_f}{\partial X} > 0, \quad \frac{\partial y_f}{\partial X} = 0$*: Asset endowment X increases farming income, but has no effect on mining income.*
(ii) $\frac{\partial y_f^2}{\partial L_f \partial X} \geq 0, \quad \frac{\partial y_m^2}{\partial L_m \partial X} = 0$*: An increase in assets X increases the marginal productivity of labor in farming, but has no effect on marginal productivity of labor in mining.*

Assumption 3 reflects the characteristic of mining being an accessible livelihood activity with low entry barriers that does not require mentionable investments into assets (Bryceson & Geenen, 2016).

Given assumption 3, the following relationships can be derived from the model (see appendix):

$$\frac{\partial L_m}{\partial \sigma_f^2} > 0 \tag{4.5}$$

$$\frac{\partial L_m}{\partial \rho} > 0 \quad \text{if} \quad \sigma_f^2 y_f \frac{\partial y_f}{\partial L_f} > \sigma_m^2 y_m \frac{\partial y_m}{\partial L_m} \tag{4.6}$$

$$\frac{\partial L_m}{\partial X} < 0 \quad \text{if} \quad \frac{\partial \pi}{\partial y_f} < 1 \tag{4.7}$$

Equation 4.5 states that households will allocate more labor to mining as farming gets more risky. This results explains the emergence of artisanal mining as a consequence of deteriorating conditions of farming, as it has been described in the literature (Cox, 2012; Kelly, 2014). Equation 4.6 states that more risk-averse households will allocate more labor to mining if the resulting variance-weighted increase in income for mining is lower than the one for farming. Thus, a trade-off between risk and income gain ultimately determines the degree of diversification into mining of risk averse households. Finally, given the higher asset intensity of farming compared to mining, equation 4.7 establishes that a higher asset endowment is associated with less labor allocation to mining in the respective household. As farming productivity increases with asset ownership, it is intuitive that more assets reduce the attractiveness of mining.

4.4 Empirical analysis

Given the unstable political context in the region, quantitative empirical research has been scarce. In the absence of longitudinal data, the causal dynamics underlying livelihood diversification cannot be tested in robust ways. Nevertheless, to empirically assess the relationships derived in the analytical model and identify correlations, we employed regression analysis on cross-sectional data collected during fieldwork in June and July 2022 in four different areas, two adjacent to PNKB and two in proximity of INR.

4.4.1 Data

Surveys were conducted in the form of 150 focus group interviews with miners in the village groups (*groupements*) around Kigogo and Mwenga (INR), and 278 randomly selected household interviews in the villages surrounding Mwenga (INR), Bitale (PNKB) and Luhago (PNKB) (Figure 4.1). All interviews were held in either Swahili or one of Rega, Mashi or Tembo.

The 150 focus group interviews targeting miners were conducted to understand better the structural aspects behind mining integration into livelihood portfolios. For this purpose, we used a snowball sampling strategy (Shively, 2011). Since we were also interested in understanding the share of the population that engages in mining and want to compare mining to non-mining households, we further collected a more representative sample of 278 households. No registry of all households in the village exists, preventing us from drawing a truly random sample, and household visits were constrained by cultural norms. All interviews were held in a neutral place in the village centers and targeted passing people. Although not fully randomised, we believe that this sampling strategy was sufficient to draw tentative conclusions about the overall populations given the generally small village sizes. Yet, we cannot rule out that the sampled sub-population varies from the overall village population in non-random ways. Structural relationships between variables are, however, less sensitive to any biases in the sample.

Given the difficulty to quantify income (or income-equivalent subsistence produce), involvement in different livelihood activities was coded as dummy variables (0-1) and subsequently ranked according to their importance for the household's overall livelihood. Only mining was measured in annual working weeks. Livestock was aggregated into livestock units (FAO, 2011) and recorded assets of a household summarised in a principal component analysis, of which the first component was used as a wealth score.

4.4.2 Methods

Given that mining is frequently only one among several livelihood activities, the degree to which households rely on it varies. To capture this variation in the outcome variable, we used the number of working weeks spent in a mine as a proxy for the importance of mining in a household's livelihood strategy. The outcome variable is right-skewed but has a high density of zero observations (many households do not mine at all). In the presence of zero-inflated count data, researchers commonly use either zero-inflated models or hurdle models with different underlying distributional assumptions (Hu et al., 2011). The essential difference between the two is that the latter assumes zero-observations to come exclusively from a structural process, while the former also allows for zeros "by chance" from the sampling process (Hu et al., 2011). Since mining as a livelihood strategy is a choice and annual weeks spent in mines are not stochastically zero by chance, we adopted a hurdle model that estimated the model in two steps, defined in Cameron & Trivedi (2013) as:

$$Pr[y = j] = \begin{cases} f_1(0) & if\ j = 0 \\ \frac{1-f_1(0)}{1-f_2(0)} & if\ j > 0 \end{cases}. \tag{4.8}$$

The first part follows a binomial model which only differentiates between households that have at least one member actively involved in mining activities and those that do not, with a binary mining indicator as the outcome variable, thereby accounting for the zero mass point. The second part of the model seeks to explain the degree of involvement among households involved using a truncated-at-zero count data model (Cameron & Trivedi, 2013).

The two-part model is especially useful for our purpose, as it can give potential insights into characteristic differences between mining as an occasional risk-dispersing activity (first part) and mining as a major income-generating occupation (second part).

It is important to make the right assumptions about the underlying distribution, since misspecification leads to inconsistent estimates (Cameron & Trivedi, 2013). Given that the distribution is over-dispersed, i.e., the mean is larger than the variance of the count distribution, a negative-binomial distribution was assumed for the model estimation (Cameron & Trivedi, 2013; Hu et al., 2011), and the choice was confirmed when comparing it to a model with a Poisson distribution in a Vuong test (p value <0.001) (Vuong et al., 1989).

We used information on alternative livelihood activities to understand how they relate to artisanal mining (see Table 1). The distinction into forest income (categorised into charcoal, timber and non-timber forest products (NTFP) income) and other income is made as these are structurally different. Like mining, forest income represents an easy-access and flexibly substitutable income source to farming, and may therefore be competing with the choice of working in the mines. The area cultivated by a household was included among the covariates to investigate the relationship between farming and mining engagement.

As argued above, it is reasonable to assume that households who live closer to the subsistence minimum are less willing to take risks, and therefore more likely to diversify. To test this, we included the number of months without sufficient food a household experienced over the last year as a covariate in the estimation.

Finally, in an additional analysis, we used survey information on the names of mining sites and matched that to their location from our own data collection and from the IPIS database (IPIS, 2023) to understand the role of geographic location for livelihood diversification through mining. By drawing connections between village locations and the mines that people target, we got insights on the geographic mobility that miners display (see Figure 5.1 in the appendix).

4.4.3 Results

Descriptive statistics

Looking at the livelihood activities pursued by households, we found that 73% relied on more than one livelihood activity and 35% were engaged in more than two. With 32% of all interviewed households involved, artisanal mining was the second most practiced occupation after farming (Table 4.1), although the village-to-village variation was large, with 8% in the lowest and 47% in the village with the highest share of miners. Comparing figures between the two protected areas, we found a higher share of mining households in PNKB (36%) than in INR (24%), where fish farming also played a major role.

Overall, only 19% of mining households stated mining as their most important livelihood activity, as opposed to 72% who ranked farming first, again with notable regional differences between the two study sites (22% in PNKB and 12% in INR). To further understand the extent to which households engage in mining, we collected information on the time each miner spent in the mines over the last year.

Table 4.1: *Share of households reliant on different livelihood activities, by village group.*

Village group	Obs.	Farming	Livestock	Mining	Commerce	Wage labor	Forest income	Other
Bitale	100	0.88	0.47	0.37	0.21	0.16	0.39	0.01
Luhago	75	0.96	0.00	0.35	0.09	0.13	0.07	0.00
Mwenga	103	0.99	0.18	0.27	0.13	0.13	0.05	0.37
all	278	0.94	0.22	0.33	0.14	0.14	0.17	0.13

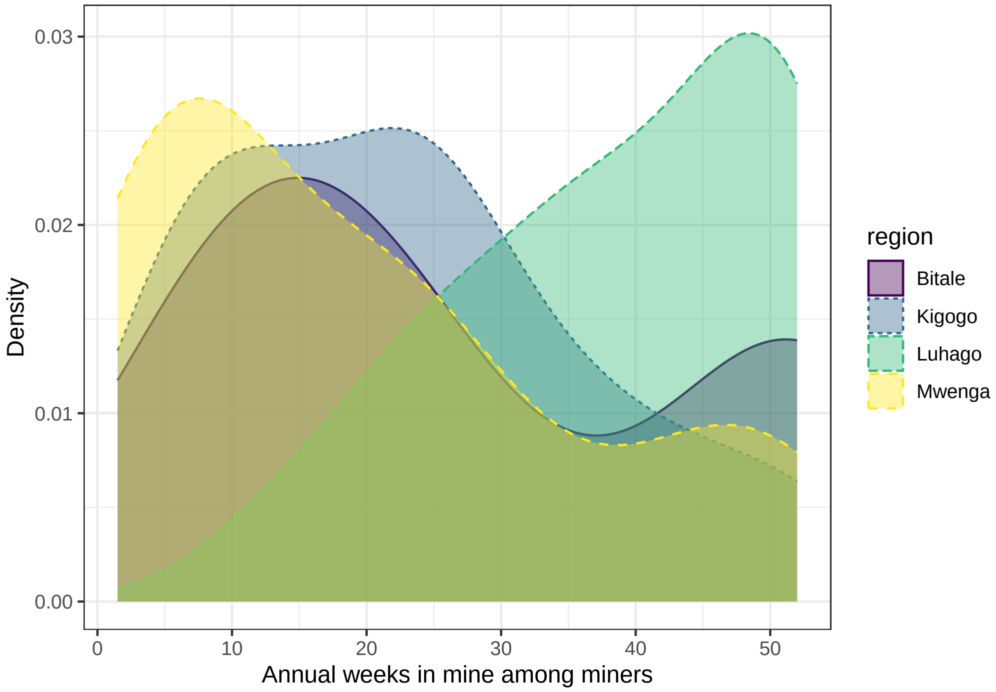

Figure 4.2: *Distribution of time spent in mines by miners*

Plotting the distribution of mining weeks per miner for the sample regions, Figure 4.2 shows some regional differences. The proportion of miners who worked in the mines on a daily basis was lowest in the INR sites Mwenga (5%) and Kigogo (6%) and highest in PNKB sites Luhago (26%) and Bitale (29%). Especially in Luhago, the density distribution was strongly left-skewed, implying that mining was more a regular livelihood choice than an occasional activity.

These differences could not be explained by geographic location alone, since they even occurred between neighboring villages and geographic distance to mines did not appear to pose an obstacle. This becomes clear from spatially reconstructing the connections between the villages and the mines where people worked (Figure 4.1 in the appendix). Especially in the villages around Luhago south of PNKB, distances between villages and mines were small and miners were most likely to work in mines on a daily basis. Other miners covered remarkable distances from their home villages to mining sites, often through difficult terrain without roads.

In the villages around INR, miners predominantly targeted mining sites located deep inside the forests of INR. Given that these are often controlled by rebel groups (IPIS, 2023) and therefore less subjected to governmental regulation and taxation, they may be better suited to provide a quick extra income in times of need compared to mines that are organized in cooperative structures. This fits with the observation that miners in villages around INR spent fewer weeks per year in the mines as compared to those in PNKB.

A comparison in means between mining and non-mining households showed that mining households on average had more household members, experienced less food insecurity and were less likely to engage in commerce and wage labor as other income-generating activities (Table 5.1 in the appendix).

Regression results

Table 4.2 shows regression results from the two-part hurdle model. The outcome for all specifications is the annual mining weeks of a household (see Methods). The zero model in the first part in the first four columns was estimated in a binomial logit, while the second part in the last four columns was specified as a truncated count model with a negative binomial distribution.

Model (1) in columns 1 and 4 shows results for the villages around INR. Coefficients were mostly insignificant, which largely owes to the small number of observations and hence noisy estimates.

Model (2) shows results for a sub-sample of villages around PNKB. The sample size was larger and hence the coefficients more precise. The zero model part in column 2 showed a significant and negative relationship between the number of mining weeks per year and alternative income strategies. More specifically, forest income generation decreased the odds that household members spent at least some time in the mines to 0.25 ($p < 0.05$), while other forms of income even indicate odds of 0.16 ($p < 0.001$). In the count model part, we found a baseline count of 3.79 mining weeks among mining households. This decreased by a factor of 0.84 with every additional hectare of cultivated farmland ($p < 0.05$).

Finally, models (3) and (4) used the entire sample and therefore the most precise estimates. The latter, which included fixed effects for each site, indicated in the zero model (column 4) that every month without sufficient food experienced by a household significantly decreased its odds of being a mining household by 0.47 times ($p < 0.05$). Further, and in line with the labor allocation model derived in the previous section, generating forest income reduced these odds by a factor of 0.27 ($p < 0.05$), and other income by 0.29 ($p < 0.01$). Among the count model coefficients, we only found the cultivated hectares of farmland to be significant, decreasing the number of mining weeks per household by a factor of 0.86 for every hectare of farming.

Overall, mining households were less likely to go short on food and to engage in other alternative livelihood strategies compared to non-mining households. Among households that mine, we further observed that the number of mining weeks decreased with the cultivated area. Coefficients on the wealth score coherently showed a positive relationship in the zero model and a negative relationship in the count model, although all coefficients were statistically insignificant.

4.5 Discussion

Artisanal mining has become an essential element in the livelihood strategies of rural households in the eastern DRC. With the high availability of mines over the region and the willingness of miners to travel tens of kilometers to reach mines, it is

Table 4.2: *Hurdle model regression results for the total number of working weeks per year and household*

	Zero model (first part)				Count model (second part)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
(Intercept)	-2.80^{*}	-0.46	-0.90^{*}	-1.00^{*}	4.74^{***}	3.79^{***}	3.64^{***}	3.46^{***}
	(1.09)	(0.54)	(0.44)	(0.50)	(0.85)	(0.28)	(0.27)	(0.35)
Men in HH (#)	0.15	0.07	0.03	0.04	0.12	-0.19	-0.18	-0.15
	(0.39)	(0.23)	(0.19)	(0.19)	(0.29)	(0.15)	(0.13)	(0.14)
Women in HH (#)	-0.01	0.28	0.09	0.09	-0.42	0.14	0.14	0.13
	(0.42)	(0.23)	(0.19)	(0.19)	(0.47)	(0.12)	(0.12)	(0.12)
Children in HH (#)	0.23^{*}	0.07	0.10^{**}	0.10^{*}	-0.13	0.02	0.02	0.02
	(0.09)	(0.05)	(0.04)	(0.04)	(0.07)	(0.02)	(0.02)	(0.02)
Months w. insufficient food (#)	-0.07	-0.13	-0.11^{*}	-0.11^{*}	0.06	-0.06	-0.02	-0.01
	(0.06)	(0.08)	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)
Cultivated area (ha)	-0.04	-0.23	-0.03	-0.02	0.09	-0.18^{*}	-0.17^{*}	-0.15^{*}
	(0.19)	(0.15)	(0.10)	(0.10)	(0.15)	(0.09)	(0.06)	(0.07)
Wealth score	0.56	0.25	0.48	0.47	-0.31	-0.06	-0.10	-0.12
	(0.51)	(0.41)	(0.31)	(0.31)	(0.45)	(0.24)	(0.21)	(0.21)
Livestock units	2.02	0.38	0.24	0.22	0.59	0.02	0.00	-0.01
	(2.16)	(0.31)	(0.23)	(0.23)	(1.71)	(0.07)	(0.07)	(0.07)
Forest income (0-1)	-0.33	-1.09^{*}	-0.91^{*}	-0.93^{*}	-2.03	-0.41	-0.46	-0.49
	(1.25)	(0.45)	(0.41)	(0.41)	(1.24)	(0.26)	(0.27)	(0.27)
Other income (0-1)	0.07	-1.63^{***}	-0.91^{**}	-0.88^{**}	-0.70	0.28	-0.05	0.01
	(0.56)	(0.45)	(0.31)	(0.32)	(0.44)	(0.26)	(0.20)	(0.21)
Study site	INR	PNKB	All	All	INR	PNKB	All	All
PA fixed effects	no	no	no	yes	no	no	no	yes
AIC	332.35	810.60	1134.25	1137.47	332.35	810.60	1134.25	1137.47
Log Likelihood	-145.18	-384.30	-546.12	-545.73	-145.18	-384.30	-546.12	-545.73
Num. obs.	102	175	277	277	102	175	277	277

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

accessible to a large part of the rural population and has already shaped livelihoods significantly (Cox, 2012; Kelly, 2014; Smith, 2011). Using data from South-Kivu in Eastern DRC, we analytically and empirically investigated the relationship between traditional farming livelihoods and the widespread adoption of mining in a context where it is increasingly economically viable and often necessary to branch out.

In Eastern DRC, the deterioration of the livelihoods of smallholder farmers has been severe during decades of violent conflicts and poor governance. The depletion of productive assets due to looting and displacement challenges long-term planning that is essential to agricultural development (Cox, 2012; Kelly, 2014; Verweijen & Brabant, 2017). Furthermore, the collapse of transport infrastructure and dissolution of markets and have impeded the sale of produce with detrimental impacts on farmers (Kelly, 2014; Schouten et al., 2022). Under the pressure of a rapidly growing population and declining soil fertility, livelihood diversification has become an important survival strategy (Cox, 2012; Vollset et al., 2020).

The relationships between mining and non-mining and less and more reliant households revealed interesting characteristic differences. In accordance with the idea of mining as a way to cope with economic distress ("pushing" people away from farming) (Banchirigah & Hilson, 2010; Hilson & Garforth, 2012), we found that households engaged in mining experienced less food deprivation, but that this relationship faded for households that were more reliant on mining. These results empirically underpin findings presented in previous studies that identified the spread of artisanal mining as a symptom of the reduced viability of farming (Banchirigah & Hilson, 2010; Hilson & Garforth, 2012; Kelly, 2014). The tendency also reflected in the household interviews, where it was reported that more pests have lead to crop failures, and that the availability of agricultural land has decreased in recent years. Shifting rainfall patterns have also begun to adversely impact planning in the predominantly rain-fed agricultural production (Amani et al., 2022; Balasha et al., 2023). Climate change is expected to continue deteriorating growing conditions, as DRC is among the most vulnerable countries due to low adaptation capacities (Batumike et al., 2022; Edmonds et al., 2020).

Although certainly extreme in the context of the eastern DRC, the inability of smallholders to live off their land has been connected to the rise of artisanal mining in several Sub-Saharan African countries, too, including Tanzania, Zimbabwe and Guinea (Banchirigah & Hilson, 2010; Hilson & Garforth, 2012). De-agrarianisation dynamics in which farmers abandon their land to work in mines have been observed in several countries, including Tanzania, Zimbabwe and Guinea (Huntington & Marple-Cantrell, 2022). In other regions, artisanal mining was portrayed as complementary to farming (Hilson, 2016). In Sierra Leone, for example, mining is often practiced during the dry season when agricultural labor demand is low (Carter & Barrett, 2006), and in Mozambique and Ghana, miners have reported to reinvest their revenues to enhance their agricultural productivity (Dondeyne & Ndunguru, 2014; Pijpers, 2014).

We did not identify a higher wealth in assets for more engaged miners, which would be expected if higher income prospects drew people towards the mines. Given that assets build up over a longer period of time, whereas mining engagement was reported for the previous year only, increased income from mining may not immediately reflect in the measured wealth score of a household (Angelsen & Dokken, 2018; Carter & Barrett, 2006). Further, the direction of the relationship is not obvious, as it could also mean that asset-poor households were more likely to engage more into mining, as implied in the analytical model presented earlier.

A few caveats should be kept in mind in the interpretation of the empirical results. First, the geographic area covered by the study is relatively small and the limits of their external validity should be recognized, especially beyond the unique context of the eastern DRC. Second, as indicated earlier, the number of observations and the structure of the data do not allow us to address causality. For instance, it is not possible to disentangle whether more mining-reliant households give up agricultural land or if land-poor households are more likely to develop a higher dependence on mining. The analytical model helps to provide intuition and it generally matches with the regression results, but does not ultimately resolve these issues.

4.6 Conclusion

Artisanal mining has established itself as a widespread livelihood strategy in eastern DRC, but has seen increasing attention in international policy debates for its adverse social and environmental effects. Our analysis adds to the understanding of motivations behind livelihood diversification through mining, acknowledging that diversification comes in many forms and degrees. We point to important differences between miners who only mine occasionally and those who seek it as a more regular income opportunity. We found that livelihood diversification through mining can work as an efficient gap-filler in reducing food insecurity and in reducing agricultural dependency. Potential crowding-out of agriculture, however, only occurred among those who engage in mining on a regular basis throughout the year.

The artisanal mining sector in the DRC has been targeted with sectoral reforms and supply chain policies to improve the conditions under which mining occurs, especially the often precarious working conditions. Also, the environmental consequences of artisanal mining start gaining attention among policymakers (Sonter et al., 2018; World Bank, 2021). Policies aiming to improve livelihoods in rural Eastern DRC need to address these sides of artisanal mining, while at the same time keeping in mind that many people rely on it for their survival. The availability of income alternatives can reduce the reliance on mining in the medium- to long-run, but crucially requires the stabilization of the region that would give rural households the needed securities to invest in long-term livelihood activities. With rebel groups financing their warfare through minerals, mining is not only a consequence of conflict due to the unavailability of other income opportunities but also fuels it (Stoop et al., 2019). The increasing destabilization of weather patterns as climate change proceeds further deteriorates rural livelihoods, creating a complex set of challenges that has no easy solutions.

4.7 References

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Appendix B

Descriptive statistics

Table 5.1: *Differences in covariate means between mining and non-mining households*

	non-mining		mining			
	Mean	SD	Mean	SD	Diff. in means	SE
HH size	9.8	3.9	11.6	5.3	1.9**	0.6
Insufficient food	4.0	3.6	3.1	3.0	-0.9*	0.4
Cultivated area	1.0	1.5	1.1	1.4	0.2	0.2
LSU	0.2	0.5	0.4	1.4	0.3+	0.2
Wealth score	2.0	1.1	2.2	1.2	0.2	0.2
Fallow years	1.5	1.5	1.6	1.3	0.1	0.2
Commerce income	0.2	0.4	0.1	0.3	-0.1*	0.0
Wage income	0.2	0.4	0.1	0.3	-0.1*	0.0
Timber income	0.2	0.4	0.1	0.3	0.0	0.0
Charcoal income	0.0	0.1	0.0	0.1	0.0	0.0
NTFP income	0.0	0.1	0.0	0.0	0.0+	0.0

$^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Proofs

Equation 4.4 is obtained by solving the maximisation problem

$$V = \sum_{i \in \{m,f,o\}} y_i(L_i, X) - \frac{\rho}{2} \sum_{i \in \{m,f,o\}} y_i^2 \sigma_i^2 - \delta(L_m, L_o) + \lambda[\bar{L} - L_m - L_o - L_f] \quad (5.1)$$

where λ is the Lagrange multiplier.

From equation 5.1, and assuming interior solutions, the following first order conditions can be obtained:

$$\frac{\partial V}{\partial L_f} = \frac{\partial y}{\partial L_f} - \frac{\partial \pi}{\partial L_f} - \lambda = 0 \quad (5.2)$$

$$\frac{\partial V}{\partial L_m} = \frac{\partial y}{\partial L_m} - \frac{\partial \pi}{\partial L_m} - \frac{\partial \delta}{\partial L_m} - \lambda = 0 \quad (5.3)$$

$$\frac{\partial V}{\partial L_o} = \frac{\partial y}{\partial L_o} - \frac{\partial \pi}{\partial L_o} - \frac{\partial \delta}{\partial L_o} - \lambda = 0 \tag{5.4}$$

$$\frac{\partial V}{\partial \lambda} = \bar{L} - L_m - L_0 - L_f = 0 \tag{5.5}$$

We are mainly interested in the relationship between farming and mining. To simplify the comparative statics, we ignore for the moment off-farm work. Solving equation 5.2 for λ and inserting into 5.3 yields equation 4.4.

To obtain the relationship between mining diversification and farming risk, the implicit function theorem (IFT) can be used as done in, for example, Bezabih & Sarr (2012) :

$$\begin{aligned}\frac{\partial L_m}{\partial \sigma_f^2} &= \frac{-\frac{\partial V^2}{\partial L_m \partial \sigma_f^2}}{\frac{\partial V^2}{\partial L_m^2}} \\ &= \frac{-\frac{\partial \pi^2}{\partial L_f \partial \sigma_f^2}}{\frac{\partial y^2}{\partial L_m^2} - \frac{\partial \pi^2}{\partial L_m^2} - \frac{\partial \delta^2}{\partial L_m^2}} > 0\end{aligned} \tag{5.6}$$

From equation 4.3, it is easy to see that the numerator in equation 5.6 is negative, while the denominator is negative under the assumption that the second order condition holds, i.e., that the solution is a maximum.

The relationship $\frac{\partial L_m}{\partial X}$ is derived similarly. Using the IFT and equation 4.3, we obtain:

$$\begin{aligned}\frac{\partial L_m}{\partial X} &= \frac{-(\frac{\partial^2 y}{\partial L_m \partial X} - \frac{\partial^2 y}{\partial L_f \partial X} + \frac{\partial^2 \pi}{\partial L_f \partial X} - \frac{\partial^2 \pi}{\partial L_m \partial X})}{\frac{\partial V^2}{\partial L_m^2}} \\ &= \frac{-((1-\rho\sigma_m^2 y_m)\frac{\partial^2 y_m}{\partial L_m \partial X} + (\rho\sigma_f^2 y_f - 1)\frac{\partial^2 y_f}{\partial L_f \partial X} - \rho\sigma_m^2 \frac{\partial y_m}{\partial X}\frac{\partial y_m}{\partial L_m} + \rho\sigma_f^2 \frac{\partial y_f}{\partial X}\frac{\partial y_f}{\partial L_f})}{\frac{\partial y^2}{\partial L_m^2} - \frac{\partial \pi^2}{\partial L_m^2} - \frac{\partial \delta^2}{\partial L_m^2}} \\ &= \frac{-((\frac{\partial \pi}{\partial y_f} - 1)\frac{\partial^2 y_f}{\partial L_f \partial X} + \rho\sigma_f^2 \frac{\partial y_f}{\partial X}\frac{\partial y_f}{L_f})}{\frac{\partial y^2}{\partial L_m^2} - \frac{\partial \pi^2}{\partial L_m^2} - \frac{\partial \delta^2}{\partial L_m^2}}\end{aligned} \tag{5.7}$$

The last step uses assumption 3.

The denominator is the same as in equation 5.6 and hence negative, while the numerator is negative as long as $\frac{\partial \pi}{y_f} < 1$.

To obtain relation 4.6, the numerator in equation 5.6 would be:

$$\begin{aligned}-\frac{V^2}{\partial L_m \partial \rho} &= -(\frac{\partial \pi^2}{\partial L_f \partial \rho} - \frac{\partial \pi^2}{\partial L_m \partial \rho}) \\ &= -\rho(\sigma_f^2 y_f \frac{\partial y_f}{\partial L_f} - \sigma_m^2 y_m \frac{\partial y_m}{\partial L_m})\end{aligned} \tag{5.8}$$

where the second equality is established from equation 4.3. By assumption 1, it then follows that $\frac{\partial L_m}{\partial \rho} > 0$.

Spatial mobility

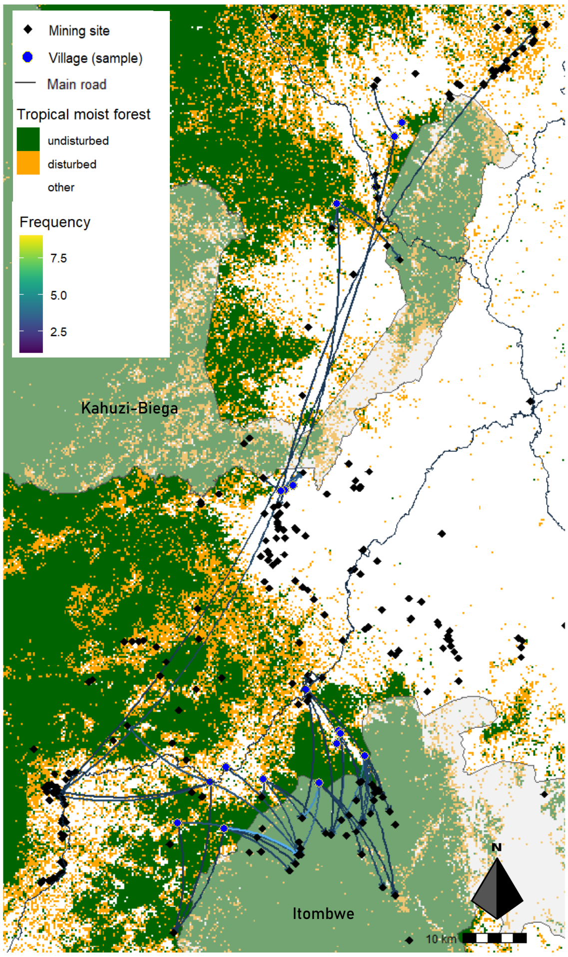

Figure 5.1: *Spatial connection between villages and the mining sites miners go to work. Mining locations collected during field work and from IPIS. Forest extent as indicated in data of Vancutsem et al. (2021).*

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Paper III

"The idea of the preservation of scenery, flora, and fauna, in their natural state, which in itself is not at all new, is based in varying degrees on two main objectives. As a secondary consideration, care is devoted to the preservation of natural beauties from modern constructions, mostly far from attractive in appearance, such as factories and advertisement boardings. The main object, however is to prevent man, whose means of transport and weapons of destruction increase in proportion to scientific progress, from breaking up for his own temporary benefit the equilibrium of the three kingdoms of nature."

(Institut des Parcs Nationaux du Congo Belge, 1939)

"I will never leave this forest. This is not a park, this is our forest. The Batwa were the first to live in this forest. My great grandfather died in this forest. My father's father died in this forest. And now my father has been killed in this forest. I will die in this forest."

(Indigenous Batwa quoted in Flummerfelt, 2022)

Increasing pressure on protected areas in the DR Congo over the last 20 years

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Abstract Protected Areas (PAs) are an essential element in strategies to conserve the Congo Basin rainforest. In the past, PAs in the Democratic Republic of Congo (DRC) have been able to maintain most of their forest cover, primarily due to their remote locations. As this passive protection is starting to fade with the progression of the deforestation frontier, the future role of PAs in conserving the Congo Basin rainforest is uncertain. Using a geographic regression discontinuity design and a novel discontinuity-based typology to categorise protection by its spatio-temporal context, the study investigates dynamics of forest loss at PA boundaries and assesses their potential to withstand deforestation as anthropogenic pressures rise. On average, PAs have deforestation sprawling in at 18% of their boundaries in 2022, and only 9% have been able to actively contain it. In expectation of a rapidly growing population and a renewed interest in the region's resources from industrial actors, more evidence on what works in conserving the rainforest of the DRC without compromising local livelihoods is needed.

6.1 Introduction

The Congo Basin rainforest is a biodiversity hotspot, has important regulatory functions for the regional and global climate and directly provides for the livelihoods of millions of people (Eba'a Atyi et al. 2022b). Yet its extent continues to decrease, mostly driven by the expansion of small-scale agriculture under a growing population (Tyukavina et al. 2018; Masolele et al. 2024; Vancutsem et al. 2021). Conservation hopes have largely relied on the extension of Protected Areas (PAs) coupled to the ambition to designate 30% of land to conservation by 2030 (Hughes and Grumbine 2023). Today, already 15% of the global terrestrial area, and 14% of the Democratic Republic of Congo (DRC), are under some form of protection (UNEP-WCMC 2022). Assessing whether PAs are effective in protecting forests can be challenging, given their non-random locations (Joppa and Pfaff 2009; Joppa and Pfaff 2010). PAs tend to have higher forest cover not necessarily as a result of effective protection, but rather their remoteness. This has been particularly the case for the DRC. Forest conservation areas were often established in locations with low deforestation pressure due to their inaccessibility (Joppa, Loarie, and Pimm 2008; Pfaff et al. 2014), and thus have little additionality in avoiding deforestation.

Since conservation efforts in the DRC rely extensively on PAs, a crucial question concerns their mitigation potential once remoteness fades and deforestation pressure increases. For the last 20 years, scientists have been calling for better conservation impact evaluation to understand what works in halting forest loss and what does not (Baylis et al. 2016; Börner et al. 2020; Ferraro and Hanauer 2014; Sutherland et al. 2004). The call is emphasized by the apparent gap between available and required conservation funding and a closing time window to act, making efficient allocation of the resources available even more important (Ferraro and Pattanayak 2006). However, a systematic understanding of what works when remains thin, especially in the Congo Basin (White et al. 2021).

In experimental settings, treatment can be assigned randomly to make treated and controlled units comparable and thereby allow to infer causal effects. Given the non-random location of PAs, it is necessary to control for confounding factors that influence both, deforestation outcomes and protection status. Quasi-experimental methods can implicitly control for confounders through the choice of the appropriate empirical design (Jones and Shreedhar 2024). Which design is appropriate depends on the research question, the context and the available data. For PAs, the mainstream strategy to evaluate conservation effectiveness has become propensity score matching, where protected areas are matched to non-protected areas based on a set of *ex ante* and *a priori* defined observable characteristics to control for non-random locations (Andam et al. 2008; Geldmann et al. 2019; Joppa and Pfaff 2010; McNicol et al. 2023).

The findings of matching-type studies of PA effectiveness in the DRC are ambiguous. Sze et al. (2021), Shah et al. (2021) and Abman (2018) found only marginally lower deforestation within PAs compared to matched areas outside, while Bowker et al. (2017) found substantially less forest loss under protection. However, matching does not overcome bias from non-random location if variables that explain both deforestation and protection status are omitted, a condition which essentially cannot be tested (Smith and Todd 2005). It can further run into problems when the common support, i.e. the overlap between propensity scores of treatment and control groups, is poor (Börner et al. 2020).

This study takes a different approach to evaluating PA effectiveness by focussing on frontier processes at their boundaries. Previous research has shown that deforestation outside of PAs is a strong predictor of forest loss inside (Burivalová et al. 2021). Most of the deforestation, in the DRC and beyond, occurs in the form of expanding land use frontiers as a result of growing populations and resource extraction (Meyfroidt et al. 2024; Molinario et al. 2020; Shapiro et al. 2023). Frontiers can be defined as "places or regions with specific land-use dynamics, leading to the rapid development of the exploitation of some land or resource, and that experience marked social-ecological transformation accompanying and resulting from resource exploitation." (Meyfroidt et al. 2024). Agricultural expansion, mining and logging are examples that can bring about such dynamics, but also the territorialisation of conservation has been framed as a frontier process connected to fundamental social and ecological transformation (Buchadas et al. 2022a; Meyfroidt et al. 2024). As unexploited natural resources often coincide with critical ecosystems, PA boundaries can be locations of friction between conservation and other frontier dynamics (Buchadas et al. 2022a; Luckeneder 2021; Simpson and Zirhumana 2021; Vuola 2022). On the one hand, the establishment of PAs can be a response to the expansion of deforestation frontiers - or at least a precaution against their future emergence (Buchadas et al. 2022a). On the other hand, conflicting land uses may also lead to degazettement and downgrading of existing conservation areas under the pressure of other actors and interests, seen for instance in the cases of Virunga

National Park and Salonga National Park for oil and gas explorations, and Itombwe Nature Reserve following conflicts with local communities (Kujirakwinja et al. 2019; Qin et al. 2019; Tesfaw et al. 2018).

Where land use rents and population densities are low, PAs maintain high forest cover by virtue of their remote location (Pfaff et al. 2014). Protection in such contexts has been described as *passive* protection (Joppa, Loarie, and Pimm 2008). As the opportunity costs of forest cover or the need for more land under a growing population increase, *passive* protection may turn into *active* protection in case a PA is successfully holding back deforestation. While the distinction between *passive* and *active* protection is a useful simplification, frontier processes often follow much more complex spatio-temporal patterns that can give useful insights into the state of forest conservation.

This study proposes a novel metric-based typology to assess the status of protection at PA boundaries of the DRC. In a geographic regression discontinuity (GRD) framework, forest cover and deforestation on either side of PA boundaries are taken into consideration to assess their potential of withstanding deforestation. It is further analysed how this potential changes with the presence of other land use frontiers in the form of industrial mining and logging concessions. Given that the remoteness of PAs will keep on fading and that signs of emerging commodity frontiers are already revealing, it is concluded that conservation in the DRC is at a crucial point in time with important implications for the future of the Congo Basin rainforest.

6.2 Conservation and other land use frontiers in the DR Congo

The political turmoil the DRC has been going through over the last decades, including two wars and persisting instability especially in the eastern part of the country, has given rise to a fragile state with limited capacity of planning (Karsenty and Ongolo 2012). This has also impeded conservation efforts in the country.

Market mechanisms aim at making it more profitable for land users to keep forest rather than converting it. However, especially in settings where deforestation follows to a large share subsistence needs and not profit maximisation, the effectiveness of such instruments can be low (Angelsen et al. 1999). Pantropically implemented conservation initiatives that work with incentives, such as REDD+ (Reducing Emissions from Deforestation and Degradation + other forest-based activities), have not fully unfolded in the DRC, despite the formal joining of the program in 2009, as institutional shortcomings hinder the implementation and the capability to engage into long-term anti-deforestation commitments (Karsenty and Ongolo 2012; Kengoum, Pham, and Mihigo 2024; Pham et al. 2021).

Most forest conservation efforts in the DRC have concentrated on the establishment of PAs. In line with the Kunming-Montreal Global Biodiversity Framework, the ambition has been formulated to designate 30% of terrestrial land as protected by 2030 (Convention on Biological Diversity 2022). The long history of PAs in the DRC reflects the notion that the removal of people is essential to conserve forest. Under colonial rule, authorities declared all unoccupied land as vacant and henceforth property of the state, on which they began to establish the first national parks (Van Acker 2005; Inogwabini 2014). In 1973, the law was augmented under the

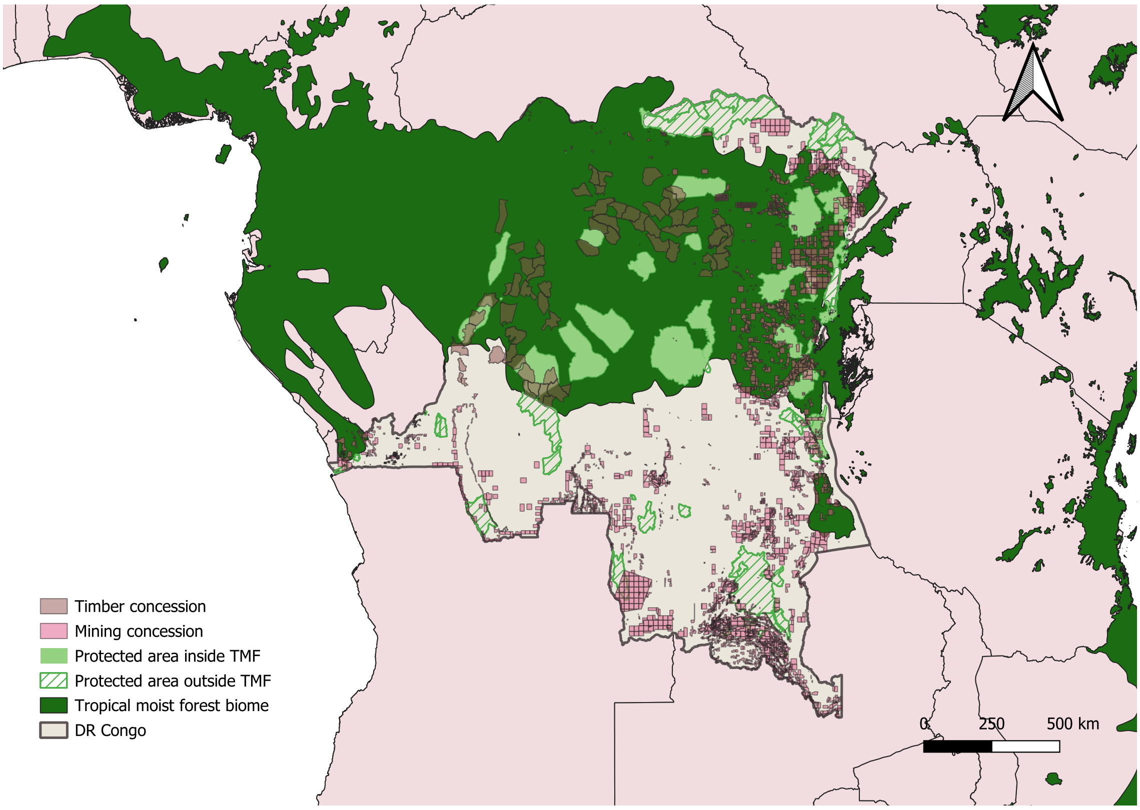

Figure 6.1: *Tropical moist forest biome coverage of the DRC and locations of PAs and mining and timber concessions. Note that most of the concessions are inactive (see Section 3)*

presidency of Mobutu who rendered all land, regardless of its tenure status, as state property (Van Acker 2005). These laws provided the basis for the establishment of numerous PAs, now counting a total of 60 and covering 15% of the country (World Database on Protected Areas 2024).

In the process, communities were often displaced and prohibited from accessing the forest, where necessary under the use of military force and without compensation (Flummerfelt 2022; Marijnen and Verweijen 2016; Domínguez and Luoma 2020; Inogwabini 2014; Simpson and Geenen 2021). Local communities and indigenous people who had lived inside the forests for centuries were removed from their ancestral lands under the legitimisation of forest protection, as happened in the case of the Batwa in Kahuzi-Biega National Park. (Barume 2000; Simpson and Geenen 2021).

Whereas protection exists on paper, conservation impacts on the ground are not obvious. Insufficient government funding and low legitimacy of PAs among communities impede the implementation (Inogwabini 2014). Programs to support communities and provide alternative livelihoods are also missing (Barume 2000; Spira et al. 2019). One way to compensate for the lack of funding and management capacities of the state has been the installation of co-management schemes, in which international NGOs partnered with government agencies. Co-managed parks have been found to increase avoided deforestation in the face of deforestation pressure (Desbureaux et al. 2025). However, only six PAs are currently managed collaboratively in the country.

Additionally, political priorisation appears to be a challenge, since conservation status has not prevented the allocation of protected land to industrial mining and logging concessions (Cirimwami, Baguma, and Mushagalusa 2021; Simpson and Pellegrini 2022). The implications of industrial mining operations on conservation areas are unreported this far (Cirimwami, Baguma, and Mushagalusa 2021). The eastern part of the country, where many of the mineral deposits are located (Figure 6.1), has been suffering from insecurity for a long time, largely preventing mining industry from setting foot and leaving most of the exploitation to artisanal and small-scale producers (Draulans and Krunkelsven 2002; Kilosho Buraye, Stoop, and Verpoorten 2017; Simpson and Pellegrini 2022). However, the industry's interest in the region re-surges (Geenen 2014; Kilosho Buraye, Stoop, and Verpoorten 2017; Radley 2020), and concessions for exploration and exploitation activities have been granted inside and outside of PAs alike.

Industrial logging concessions are only located in the western part of the country, where the Congo river is used to transport logs to the port (Ferrari and Cerutti 2023) (Figure 6.1). Compared to the neighbouring Congo Basin countries, timber production in the DRC has been low (Eba'a Atyi et al. 2022b). A moratorium issued in 2002 prohibited the signing of new logging titles while aligning the sector to principles of good governance, although concessions were assigned illegally while the moratorium was in force (Majambu, Demaze, and Ongolo 2021). The moratorium was accompanied by the adoption of a new forest code which obliged logging companies to adhere to social and environmental principles in their operations, as laid down in obligatory management plans (Majambu, Demaze, and Ongolo 2021). While the government has signaled intentions of lifting the moratorium in the near future, the implementation of management plans is still lagging behind (Chervier et al. 2024; Global Witness 2018a; Karsenty et al. 2017).

Given the anticipated expansion of conservation, mining and logging frontiers in the DRC, and the large overlap they have, the question of how these interact is crucial, but not evident. On the one hand, extractive industry and conservation actors may have synergistic interests of restricting territorial access for other actors, especially small-holder farmers and artisanal producers (Buchadas et al. 2022a; Geenen 2014; Tritsch et al. 2020; Vuola 2022). On the other hand, extraction itself requires the removal of vegetation and the construction of infrastructure, thereby triggering even more deforestation by providing access to other actors and undermining conservation agendas (Giljum et al. 2022; Kleinschroth et al. 2019).

6.3 Data

Forest disturbance data and data on remaining undisturbed forest was extracted from the Tropical Moist Forest (TMF) dataset of Vancutsem et al. (2021). The uniqueness of the TMF data is that it stores information on both deforestation and degradation for the years 1990-2023. In the data, forest cover is determined with the help of a procedural sequential decision tree. In comparison with other commonly used data sets, such as Hansen et al. (2013), TMF data does not rely on tree cover quantification and loss thereof, but instead distinguishes undisturbed and disturbed tropical moist forest, and other (non-forested) land cover. Undisturbed forest is classified as that which has neither been degraded nor deforested over the entire Landsat time series (i.e., since 1982), and forest disturbance marks the loss of canopy cover. Disturbances of high intensity or of a duration of more than 2.5 years are classified as deforestation events, whereas low intensity and short duration disturbances are classified as degradation. The focus of the TMF data on undisturbed forest is especially useful in the DRC context, where fallow land during cycles of shifting cultivation can quickly restore forest cover and easily be mistaken for forest (Potapov et al. 2012). Further, TMF data reportedly performs better in detecting disturbances than other frequently used datasets, such as that of Hansen et al. (2013) (Vancutsem et al. 2021).

As an irreversible, binary outcome variable, pixel-level analysis of deforestation can lead to bias in the estimation. The data was therefore aggregated from 30m to 500m resolution to obtain variation in the outcome variables (Garcia and Heilmayr 2024).

Shapefiles with the location of protected areas, mining and timber concessions were accessed through the DRC Forest Atlas (Bélanger and Mertens, n.d.). All data were clipped to the tropical moist forest biome, thereby excluding the Miombo dry forest in the southern part of the DRC (see Figure 6.1). 36 of the 54 PAs were covered at least partially by this area of which 6 did not have an IUCN classification reported in the data. After consulting with experts from the DRC, one PA was dropped for not having been established yet (*Kibali-Ituri*) and 3 missing IUCN categories were assigned as category VI, leaving only two small-sized PAs unclassified (*Kwada* and *Mont Homas*). For all PA boundaries within the tropical moist forest biome, boundary points were placed every 15km, which were then used to estimate local deforestation and forest cover discontinuities (see Methods section).

PAs with overlapping land use allocations were identified by overlaying mining and timber concessions with PA boundaries. For mining concessions, 144 overlapping boundary segements of more than 5km length were identified, of which 41 were exploitation permits covering a total length of 639 km[1]. However, only one of these mining concessions was hosting an operational mine: the *Twangiza* mine, operative between 2012 and 2020 (Maus et al. 2022; Radley 2020). This mine was used as a case study to see how forest cover discontinuities changed with the start of mining operations.

Also logging concessions shown in the Forest Atlas were not all operative. A moratorium on new logging titles in 2002 demanded concessions to have management plans approved to get concession rights validated (Chervier et al. 2024; Majambu, Demaze, and Ongolo 2021). Among all validated and active concession signed since then, four titles overlapping with the Oshwe Hunting Reserve and the Tumba-Lediima Reserve were used as a case study for mining-logging frontier dynamics.

[1]The data on mining concessions from the DRC Forest Atlas (Bélanger and Mertens, n.d.) was substantially more conservative than other data provided via Global Forest Watch. A comparison with official maps displayed on the DRC Mining Cadastre portal suggested that the former was more accurate and is therefore depicted in Figure 6.1.

6.4 Methods

6.4.1 A protection typology

Theories on deforestation processes highlight the importance of the spatio-temporal context in which a landscape is located to understand its land use trajectory (Meyfroidt et al. 2024; Barbier, Burgess, and Grainger 2010; Angelsen 2007; Lambin and Meyfroidt 2010). Once an area is deforested, forest has to regrow over a long time period before it is fully recovered, which makes deforestation a quasi-irreversible event (Garcia and Heilmayr 2024). Due to this absorbing property, the stage of land use transformation a PA is situated in has decisive implications on conservation.

Boundary discontinuities alone cannot fully disclose frontier dynamics. The absence of discontinuities in deforestation across PA boundaries, for instance, can lead to three different conclusions on protection effectiveness, depending on remaining forest cover and previous dynamics. In the first case, discontinuities can be absent in case the deforestation frontier has not yet reached PA boundaries. Forest cover would be high and deforestation low on either side of the boundary, and protection can be described as passive. In the second case, when deforestation has already reached the PA, discontinuities would be absent if deforestation spreads across boundaries and does not stop at PAs. Protection is then not able to stop deforestation at the boundary and hence inefficient. A third case could arise when forest is already scarce around PA boundaries and the deforestation frontier has moved inside the PA. Again, no discontinuity in deforestation or forest cover would be visible, but the context would be very different from the previous two cases.

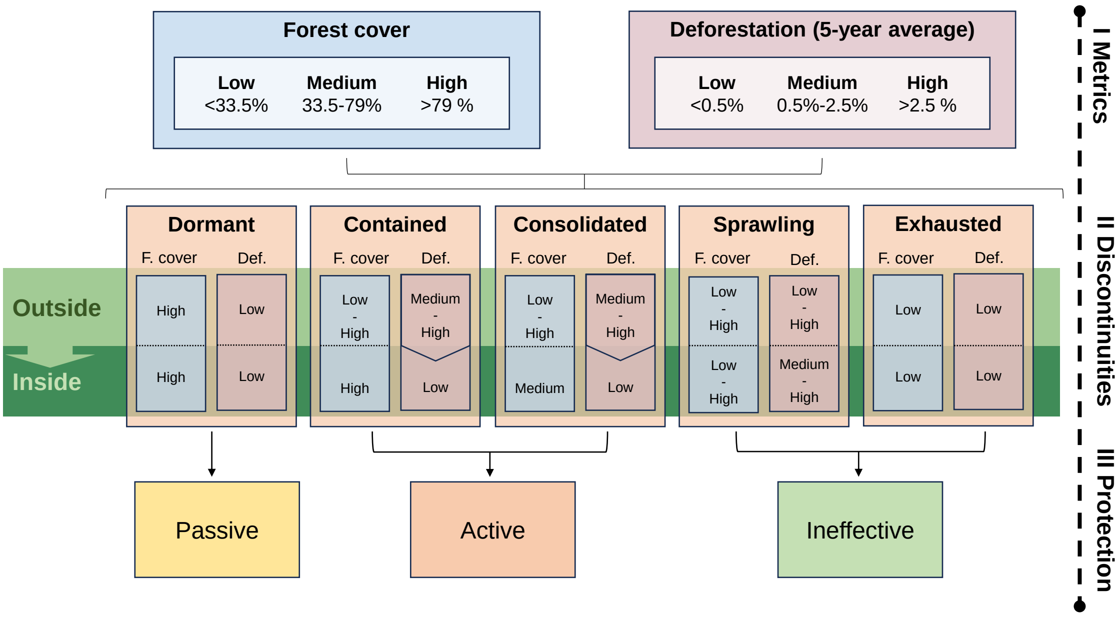

Figure 6.2: *Metric-based typology of forest protection used to classify PA boundary segments.*

To account for the variety of contexts in which discontinuities may or may not appear, this analysis develops a novel typology of forest protection is conceptually related to the forest transition theory (Barbier, Delacote, and Wolfersberger 2017; Mather 1992), and to landscape-level typologies of land use change developed in Buchadas et al. (2022b) and De Sy et al. (n.d.) (Figure 6.2). Data on remaining undisturbed forest cover and the annual rate of forest disturbance on either side of PA boundaries were used to identify the deforestation setting in which a PA is situated in. Forest cover and deforestation metrics were determined in a data-driven approach following interval classification methods adopted in Jamaludin et al. (2022), categorising each side of PA boundaries according to low, medium and high forest cover (<33.5%, 33.5-79%, >79%) as well as low, medium and high annual deforestation (<0.5%, 0.5-2.5% and >2.5%), where deforestation is estimated as the share of pixels that were cleared in a given year. Boundaries that already had low forest cover in 1990 were discarded from the analysis, as forest cover might be naturally low at these points. This also implies that points are excluded that experienced extensive deforestation dynamics before 1982, i.e. the year of the first available Landsat images. The metrics were then combined to analyse the type of conservation frontier that was present at different PA boundaries. Alternative threshold specifications were tested and are reported in the appendix, but did not lead to notable differences in the results.

Based on the estimated discontinuities, PA boundaries were distinguished into five different stages of protection. As PAs tend to be placed in remote locations, protection in the first stage can be described as *dormant*. Similar to the first stage in the forest transition theory (Mather 1992), forest cover is high and deforestation low on either side of the boundary. When the deforestation frontier progresses and reaches PA boundaries, the passive protection in the dormant stage fades, and deforestation is either *contained* by PA boundaries with high deforestation outside but low inside, or *sprawling* in case forest loss enters PAs, shown by high loss on either side of the boundary. If deforestation enters PAs, it may be stopped before the forest cover has fully disappeared, in which case deforestation has been *consolidated*. Ultimately, if forest cover has already vanished both inside and outside the park, protection is *exhausted* and has become locally redundant.

In the classification, forest loss is averaged over five years to smooth out annual fluctuations. The categorisation ultimately allowed to distinguish the mechanisms through which protected areas are associated with deforestation as either passive due to remote location, active by enforcement of protection, or ineffective in cases where protection does not contain deforestation.

Temporal information was used to determine how PA protection changed over time. Under a functioning PA system, it would be expected that *passive* protection from remoteness turns into *active* protection as the PA boundaries stop the forest edge from moving inwards and resist anthropogenic pressures. However, if protection was flawed, this would result in deforestation *sprawling* across boundaries and make protection exist on paper, but without any conservation effects.

6.4.2 Geographic regression discontinuity design

To account for the non-randomness of PA locations (Joppa and Pfaff 2009), this study used a geographic regression discontinuity (GRD) design for estimating discontinuities of forest cover and forest disturbance along PA boundaries. The identification of causal effects in this GRD relies on the assumption that under the same treatment status, potential outcomes on either side of the treatment cutoff are continuous, i.e. that deforestation would not show a discontinuous jump across PA boundaries in absence of protection (Keele and Titiunik 2015). Hence, all discontinuities in relevant covariates across PA boundaries should be a result of treatment itself for the design to be valid. Since the units of analysis are grid cells, and given that geophysical features are often continuous across space (Figure 7.1 in the appendix), the main concern for the validity of the empirical strategy is that other policy parameters change with protection status, so that the effect of protection and that of other policies can no longer be separated. This is known as the problem of compound treatment (Keele and Titiunik 2015). To avoid compound treatment, PA boundaries overlapping with country borders were removed from the analysis, as these have been shown to create discontinuities in forest cover due to differences in policy environments (Wuepper et al. 2024).

The empirical strategy followed Keele and Titiunik (2015) by sampling points along PA boundaries in the tropical moist forest biome of the DRC and non-parametrically estimating local discontinuities for each point separately. Instead of estimating only one treatment effect coefficient, as in the parametric case, a treatment effect curve along PA boundaries is estimated. The individual boundary point effects can then be aggregated into parameters of interest, such as effects by IUCN category or average effects over all boundary points. In addition to its flexibility, non-parametric regression has the advantage over linear regression that it is less sensitive to the choice of bandwidth around treatment cutoffs (Wuepper and Finger 2022) and that it explicitly shows location-specific treatment responses (Keele and Titiunik 2015). For this analysis, sampled points were placed every 15km along PA boundaries, resulting in a total sample of 810 points. For each of these points and all years between 2000-2022, local effects on forest cover, deforestation and forest degradation were estimated.

Formally, the effect on a forest outcome Y at boundary point p in time t can be written as:

$$\tau_t(p) = \lim_{x \to 0^+} E[Y_t|X = x] - \lim_{x \to 0^-} E[Y_t|X = x] \tag{6.1}$$

with x indicating the distance to boundary point p and Y_t being the observed forest outcome at time t. The limits from above and below the treatment cutoff at point p are then estimates in a local linear regression following Keele and Titiunik (2015) as follows:

$$\begin{aligned} \mu_t^+(p) =& arg\ min \sum_{i \in N^+} (Y_{it} - \alpha_p^+ - \beta_p^+ f(i,p))^2 w_{ip} \\ \mu_t^-(p) =& arg\ min \sum_{i \in N^-} (Y_{it} - \alpha_{pt}^- - \beta_{pt}^- f(i,p))^2 w_{ip} \end{aligned} \tag{6.2}$$

N^+ and N^- refer to the neighbourhoods within the chosen bandwidth around boundary point p, $f(i,p)$ is a function to indicate the euclidean distance between observation i and p, and $w_{i,p}$ are spatial weights determined by a triangular Kernel weighting function, with higher weights on observations in closer proximity to p.

The optimal bandwidth around p was calculated following the mean-square-error optimal bandwidth selection of Calonico, Cattaneo, and Titiunik (2014) for each point, and robust bias-corrected standard errors were reported as proposed in

Calonico, Cattaneo, and Farrell (2021).

6.4.3 Difference-in-Discontinuities

In addition to PA boundary effects on forest loss, it was tested how mining and logging concessions interact with the protection provided by PAs, in cases where new titles overlapped with boundaries. This was done in a geographic difference-in-discontinuities design in which the timing of a new land allocation was used to compare discontinuities before and after the placement. Under the assumption that the protection-impact remains constant over time, it can be estimated how mining and logging concessions affected protection (Butts 2021; Grembi, Nannicini, and Troiano 2019). Butts (2021) showed that, in absence of compound treatment and sorting, the treatment effect can be recovered from the regression discontinuity of the differenced outcomes as

$$\tau_D = (Y_{t+s} - Y_{t-1})^{+} - (Y_{t+s} - Y_{t-1})^{-} \tag{6.3}$$

where t is the time in which a concession was placed on PA boundaries and $s > 0$.

Instead of the non-parametric approach from equation 6.2, a semi-parametric estimation for the different PA boundary segments with overlapping concessions was implemented, similar to that proposed in Dell (2010). The diff-in-disc resembles Wuepper et al. (2024) and Baragwanath and Bayi (2020) in its functional form in estimating the following regression separately for each year:

$$\tilde{Y_i} = \alpha + \beta \mathrm{d}_i + \tau \mathrm{D}_i + \gamma_b + \delta_i + \epsilon_i \tag{6.4}$$

where $\tilde{Y_i}$ is the differenced outcome of cell i as specified in equation 6.3, d_i is a cells distance to the PA boundary, D_i is a treatment dummy indicating whether or not cell i is inside a PA, γ_b are boundary segment fixed effects and δ_i controls for longitude and latitude of a cell.

6.5 Results

The non-parametric GRD estimates for different boundary points were aggregated in different ways to compute treatment effect parameters of protection. This section first reports the aggregate results on the country level, before documenting heterogeneities by IUCN categories and by individual PAs. Finally, results at overlapping mining and logging frontiers are reported.

6.5.1 Conservation performance of PAs in the DRC

Country-level discontinuities

Aggregated over all PAs in the DRC, estimates showed positive, statistically significant and increasing discontinuities in forest cover across boundaries over time (Figure 6.3a). Hence, forest cover outside of PAs generally declined at a faster rate. While there was 3 percentage points higher undisturbed forest cover on the inside of PA boundaries in 2000, this difference stabilised at around 4.2 percentage points between 2015 and 2022, suggesting that on the aggregate level protection has some effect, but also that pressure on forests inside PAs has risen noticeably over the past two decades.

In comparison, discontinuities in the annual rate of deforestation was negative in 16 out of the 23 years, but only statistically significant in the year 2016 (Figure 6.3b). Meanwhile, discontinuities in annual forest degradation was significantly lower in 6 years and showed an overall larger discontinuity compared to deforestation results.

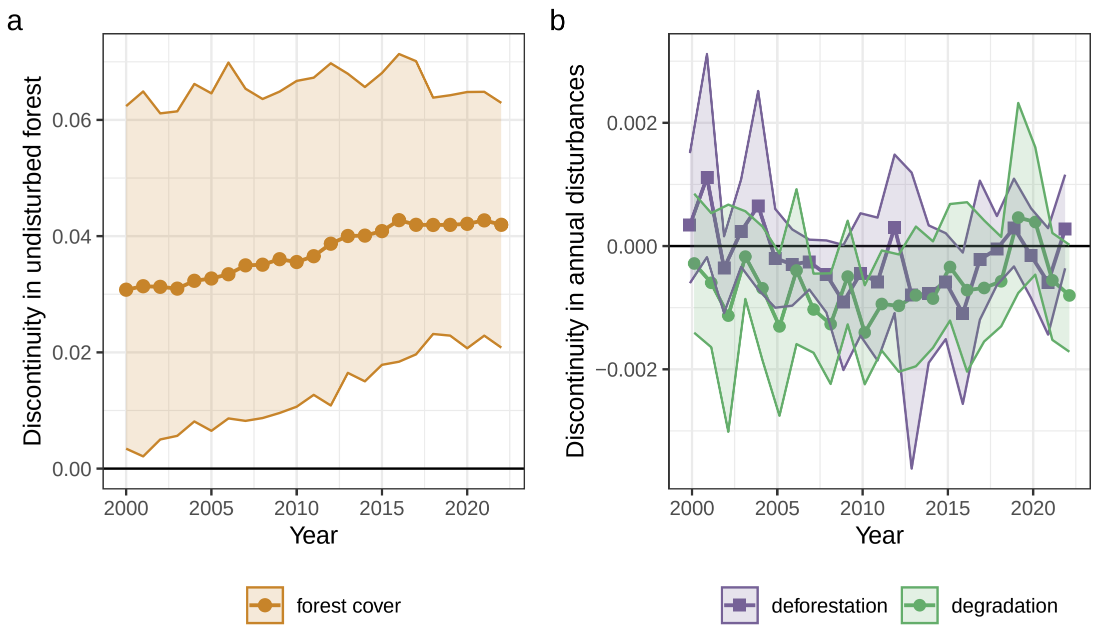

Figure 6.3: *Average regression discontinuities across PA borders aggregated from 811 non-parametric border point estimates within the tropical moist foret biome for* ***a*** *undisturbed forest cover and* ***b*** *deforestation and forest degradation. Positive estimates indicate higher incidence within PAs. 95% confidence intervals from blocked bootstraps displayed.*

Although the presence or absence of discontinuities can inform about the anthropogenic pressure that rests on PA boundaries, interpreting the effectiveness of PAs in resisting these pressures requires additional context. A classification of PAs according to the typology shown in Figure 6.2 gives more insights into the past and present dynamics of forest loss in the immediate surroundings of PA boundaries. It shows that the share of *dormant* protection, i.e. boundaries protected by remoteness, has decreased from 66% in 2002 to 55% in 2022 (Figure 6.4). Over the same time period, the share of boundaries with *contained* deforestation increased from 3% to 9%, and boundaries that have already exhausted their forest cover have increased only slightly from 8% to 9%. The highest increase was seen for share of boundaries with *sprawling* deforestation, i.e. where protection did not stop at the PA boundary, as it increased from 7% to 18%.

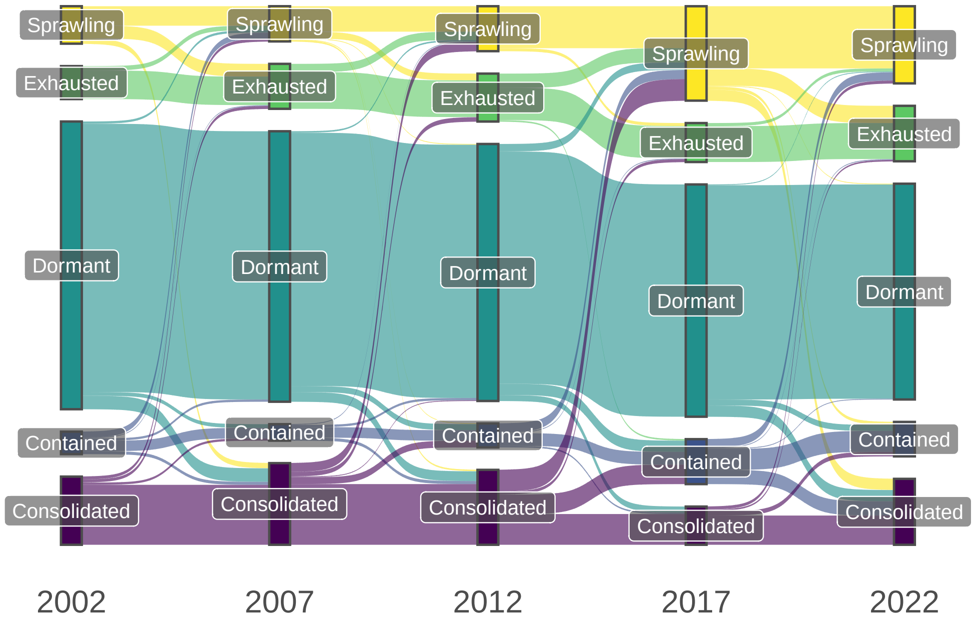

Figure 6.4: *Classification of forest protection according to the typology presented in Figure 2.*

Conclusively, aggregated country-level effects suggest that the remoteness of PAs in the DRC is gradually fading. As the deforestation frontier moves closer and pressure on PA boundaries rises, only a minor share is able to contain pressure in keeping deforestation out of the PAs. Most of the analysed boundaries were found to give in to deforestation as it arrived at the boundary.

Heterogeneities across PAs

When aggregating forest cover discontinuities by PA, heterogeneities become apparent (Fig 6.5). Focusing only on PAs that are not adjacent to country borders, 5 of the 19 investigated PAs had statistically significant discontinuities in undisturbed forest cover in 2022. The highest discontinuity in 2022 was observed for the Tumba-Lediima Reserve, with 10.8 percentage points higher forest cover inside, followed by Kahuzi-Biega National Park with 8% and Tanya Nature Reserve with 6.9 percentage points. The largest increases in forest cover discontinuity between 2012 and 2022 were found in Mangai, whereas the largest decrease was observed in Kahuzi-Biega National Park.

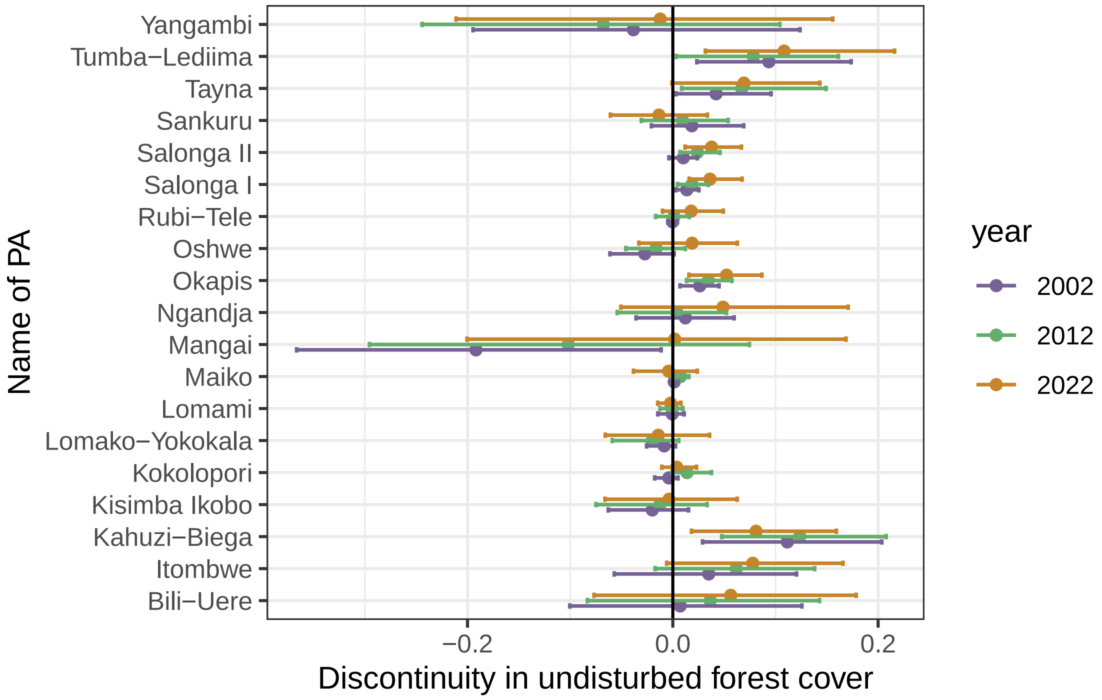

Figure 6.5: *Discontinuities in forest cover across PA boundaries, by PA. Positive numbers mean higher forest cover inside the PA. Confidence interval displayed at 95%. Inflated confidence intervals may be result of a low number of boundary points, and PAs with less than 10 border point observations were entirely dropped. See Table 7.1 for details.*

Applying the protection typology to the individual border points of each PA shows more of these heterogeneities (Table 7.1 in the appendix). While some PAs are not experiencing much deforestation pressure and have predominantly dormant boundaries due to their remote location, others have already been deforested substantially around PA boundaries or are currently seeing extensive deforestation sprawling inside. Of the 21 assessed PAs, 15 had at least some border point estimates with deforestation sprawling across boundaries, and 8 of them had at least a quarter of all border points classified as sprawling.

On average, PAs with more than 10 boundary points had 17.5% of their boundaries classified as sprawling, with the highest share found in the Sankuru Nature Reserve, followed by Yangambi and Virunga National Park [2]. The larger National Parks Maiko, Salonga and Lomami were almost exclusively characterised by dormant protection. The highest share of contained deforestation was observed for the Mangai Hunting Domain (27%), and the average across PAs was at 8.7% of border points categorised as contained.

Heterogeneity by strictness of protection and other characteristics

PAs differ in the human activities they allow within their boundaries, reaching from strictly scientific use to permitted resource extraction and land uses under certain conditions. The strictness is indicated by the IUCN categorisation of a PA

[2]Since Virunga National is partially located outside of the tropcial moist forest biome and is located adjacent to the Ugandan and Rwandan border in the east (Figure 6.1), only a fraction of its boundary is assessed in this analysis to avoid compound treatment effects.

(Stolton, Shadie, and Dudley 2013), although enforcement on the ground may differ. The tropical moist forest biome of the DRC overlaps with 4 strict nature reserves (IUCN category Ia), 1 wilderness area (Ib), 6 national parks (II), 12 habitat/species management areas (IV) and 10 protected areas with sustainable use of natural resources (VI).

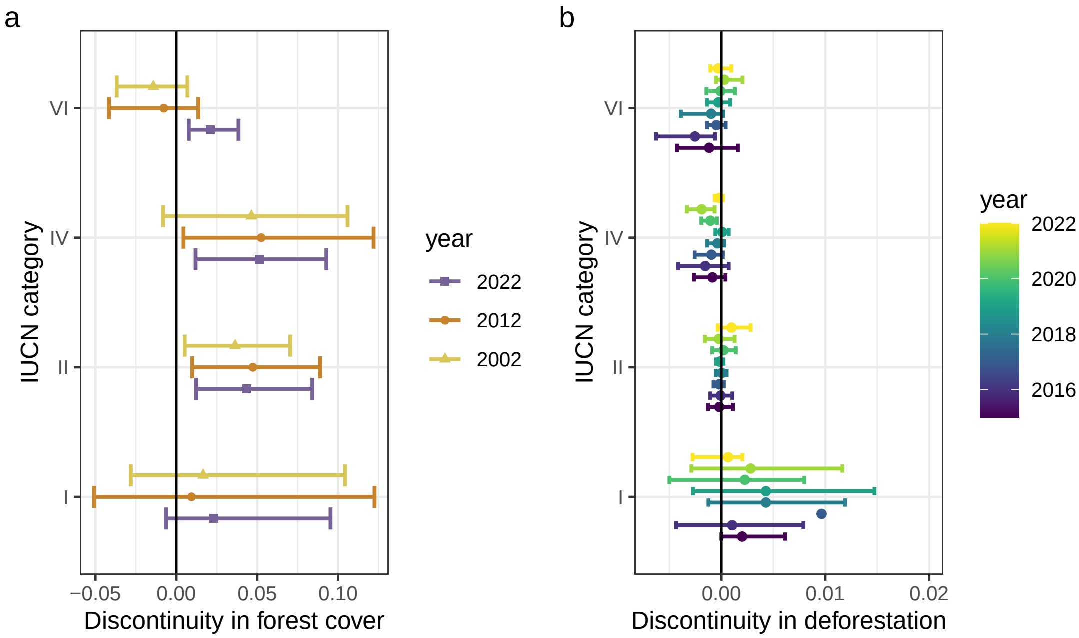

Figure 6.6: *Discontinuities in **a** undisturbed forest cover and **b** deforestation, by IUCN classification. All effects were aggregated from 809 individual boundary point estimates as specified in Keele and Titiunik (2015), and standard errors derived from blocked bootstrap procedure. Confidence interval displayed at 95%. Note that category Ia and Ib were merged into one category to obtain more points, but still remained the smallest of the categories, which might explain the large confidence intervals.*

Comparing the discontinuities for PAs with different IUCN categories between 2012 and 2022, the largest forest cover discontinuities are found for PAs in categories II and IV (Figure 6.6a). National parks in category II are large areas that are assigned to conserve large-scale ecosystem functionings and have frequently lead to displacement among local communities during the establishment, as they foresee strict prohibition of land-use and resource extraction from within park boundaries (Stolton, Shadie, and Dudley 2013; Inogwabini 2014). Category IV PAs are particulary targetting the preservation of critically endangered or threatened species and their habitats through interventions that are considered necessary to this end (Stolton, Shadie, and Dudley 2013).

The largest change in discontinuity over the last 10 years was visible for category VI PAs. These are explicitly allowing for traditional and cultural resource use practises and aim to promote sustainable ways of forest use. Consequently, they are also more likely to be established in areas where human-nature interactions are more prevalent, which may explain increasing deforestation pressure in the form of rising forest cover discontinuities. Discontinuities in deforestation over the last years were less evident. On average, discontinuities in stricter PAs of category I were larger than in others, but estimates were statistically insignificant for the most part throughout the different categories (Figure 6.5b).

In addition to forest cover and deforestation discontinuities for different IUCN categories, it was tested how the typology categorisation varied by the strictness of a PA (Table 7.3 in the appendix). With 77% of *dormant* border points, i.e. low forest disturbance on either side, national parks of category II had the largest share of this type in 2022. The lowest share was found for boundaries of nature reserves in IUCN category IV, with 53%. Effectiveness of protection under deforestation pressure was identified most frequently for strict nature reserves of category Ia and category IV nature reserves, with 7.4% and 6.3% of *contained* boundaries, respectively. The highest shares of boundaries with *sprawling* deforestation were found in strict nature reserves (Ia, 19%) and category IV and VI PAs (both 14%).

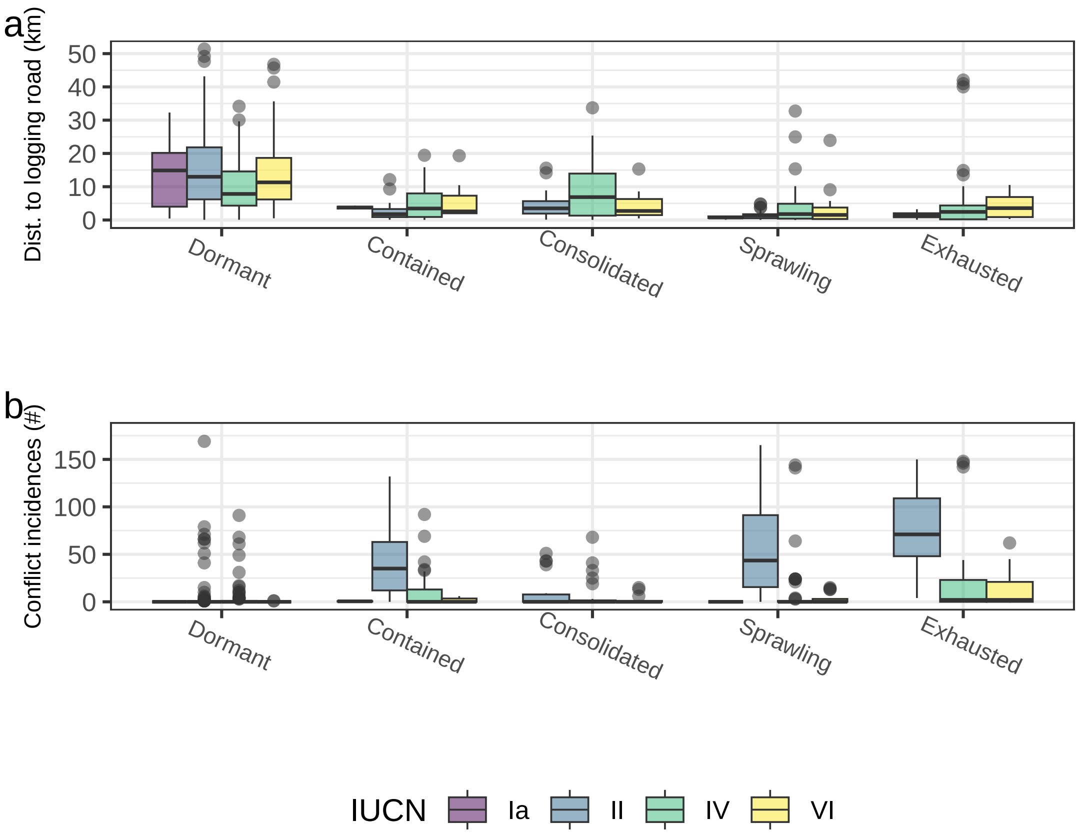

Figure 6.7: *Covariate distribution by protection type and IUCN category for* ***a*** *distance to nearest forest roads (Kleinschroth et al. 2019) and* ***b*** *number of conflict events within 10km of PA boundary since 2010 (Raleigh et al. 2010). Other covariate distributions are reported in Figure 7.3 in the appendix.*

To understand better how the protection performances of the different categories related to geographic characteristics of their location, Figure 6.6 and Figure 7.3 in the appendix depict covariate distributions by type of protection and IUCN category. Unsurprisingly, *dormant* PA boundary segments tend to be located away from forest roads (Kleinschroth et al. 2019) for all IUCN categories (Figure 6.6a). The weakest link with remoteness was observed for PAs of category VI, where deforestation outside of PA boundaries also occurred a few kilometres away from roads.

Across all IUCN categories, PA boundaries categorised as *sprawling* and *exhausted* were in closest proximity to forest roads. These findings were mostly confirmed by using data on accessibility (Weiss et al. 2018) and on roads (Meijer et al. 2018) (Figure 7.3 in appendix).

Further, remotely sensed data from Slagter et al. (2024) on newly developed forest roads since 2019 was used to show that 244km of new roads have been constructed within 5km of PA boundaries (Table 7.3 in the appendix). Of all PA boundaries in proximity of new forest roads, 59% were classified as *dormant* in 2022 and 22% already as *sprawling*. This shows that the establishment of new roads in the proximity of PAs continues to undermine protection efforts.

Another important factor in the assessment of PAs is the role of conflict. Conflict can be caused by land use restrictions imposed through conservation and result from the resistance against them (Inogwabini 2014; Pfaff et al. 2014). At the same time, conflict leads to displacement and hardship, and has people turn towards the forest in seek of shelter and resources (Merode et al. 2007; Nackoney et al. 2014). ACLED data (Raleigh et al. 2010) shows that armed conflicts were predominantly occurring close to the boundaries of category II PAs. Only dormant boundaries, where anthropogenic pressure was low, did not have any noteworthy occurrence of conflict events (Figure 6.7b).

The relationship between protection and collaborative governance of PAs was evaluated using data from Desbureaux et al. (2025), who mostly distinguished PAs governed in a co-managed or delegated way (Table 7.3 in the appendix). Among the sample of PAs, only three were co-managed in collaboration of public authorities and NGOs: Kahuzi-Biega National Park, Salonga National Park and Lomami National Park. Results confirm Desbureaux et al. (2025)'s findings that co-managed parks are predominantly located in remote areas with dormant protection. Only 4% of boundary points in co-managed PAs were categorised as sprawling, and none were found in PAs with delegated governance. While it is difficult to isolate the impact of co-management from other confounders in this setting, such as the IUCN category II that they all have in common or remoteness of their location, financial and technical support can have positive effects on PA outcomes in cases where the weak state capacity in the DRC hinders efficient PA management. Also other PAs not listed in the database of Desbureaux et al. (2025) received funding and support from both international and local NGOs to varying degrees, but the intransparency of the allocation makes a more detailed analysis on the role of support challenging.

6.5.2 Overlapping land allocations

A large part of PA boundaries in the DRC are overlapping with logging and mining titles. Although many of them are not yet productive, they have the potential of becoming extractive frontiers with both current and future implications for conservation, for instance by adding more stress on existing pressures or creating new pressures where none have existed previously. Contrarily, titles might as well ease pressure by helping to enforce land use restrictions imposed through PAs, especially under weak institutions. Insights on where titles have been allocated can help to contextualise the interactions of conservation-extraction frontiers and where they are most likely to occur.

The protection type varies with the category of overlapping concession title (Ta-

Table 6.1: *Overlapping land allocations by concession title and type of forest protection. Protection mechanisms are classified as displayed in Figure 6.2.*

Frontier	Dormant	Contained	Sprawling	Consolidated	Exhausted	N
Mining concessions						
Exploitation permit	46.67%	6.67%	20%	6.67%	13.33%	15
Research permit	59.62%	11.54%	11.54%	9.62%	7.69%	52
Logging concessions						
Active	42.86%	-	57.14%	-	-	7
Valid	66.67%	3.7%	14.81%	11.11%	-	27
In process	78.57%	7.14%	14.29%	-	-	14

ble 6.1). The share of PA boundaries with sprawling deforestation is highest for mining concessions under exploitation permit (27%) and active logging concessions (57%), while dormant PA boundaries are most commonly located within valid - but non-active - logging concessions (81%) and logging concessions that are still in process of validation (79%). Consolidated frontiers were most prevalent in overlaps with mining exploitation permits (20%), potentially a result of the exclusionary practises of extractive industry that drives out other actors. This has for instance been documented in the case of the Twangiza mine in the South Kivu province, the only operative industrial-scale mine in the DRC whose concession was overlapping with a PA in recent years.

Case study I: Twangiza mine

Despite the large area of mining concessions, only three industrial-scale mines in the eastern DRC were operative in recent years, of which only the Twangiza mine in South Kivu is located in a concession that overlaps with a PA, the Itombwe Nature Reserve (Radley 2020; Maus et al. 2022). To analyse the potential impact of industrial mining operations in proximity of PAs, a Diff-in-Disc model is estimated close to the Twangiza mine. The mine itself is located 6 km outside of the Itombwe Nature Reserve and was operative between 2012 and 2020, while the concession granted to the company also spans inside the reserve (Radley 2020; Maus et al. 2022) (see Figure 7.4 in the appendix).

Before applying for exploitation permits, mining actors are given exploration rights to scout the territory. For the Twangiza mine, the company Banro started exploration in 2005 that lasted five years. After receiving an exploitation title, Banro identified 2,000-2,500 people living inside the concession for relocation, and prohibited communities from building new constructions and from cultivating fields (Geenen and Claessens 2013). An agreement for replacement and compensation was signed in 2010, although concerns about the legitimacy of the agreement and its compliance were raised. The production of the mine started in 2012 (Geenen and Claessens 2013; Radley 2020).

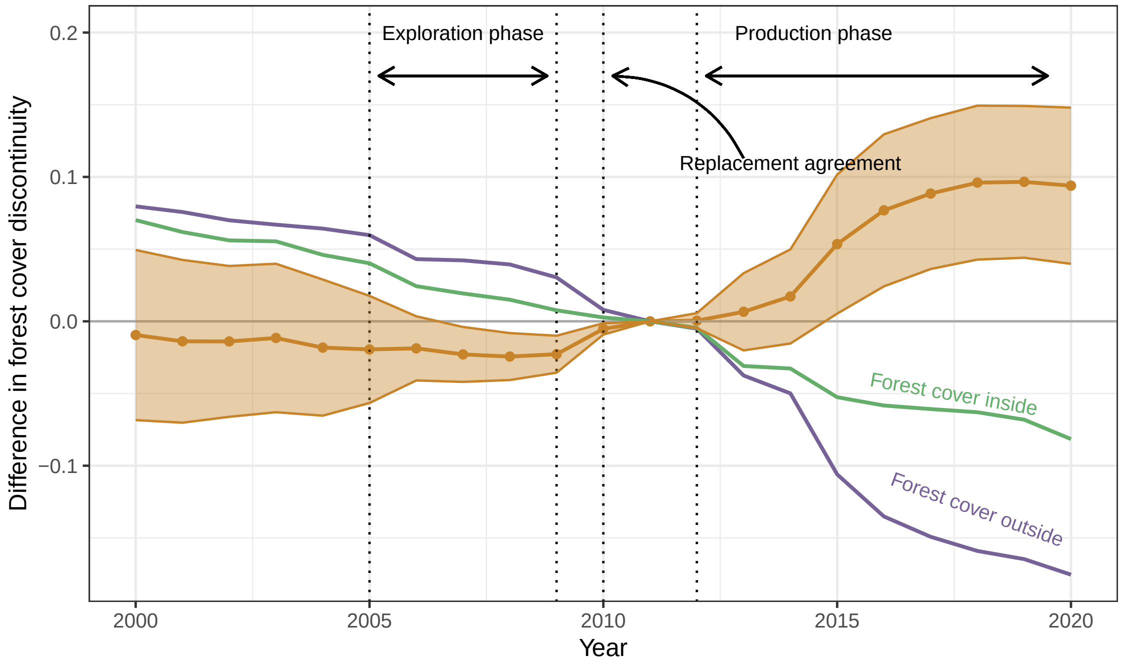

Figure 6.8: *Difference-in-Discontinuity estimates over time, normalised around the year before mining began. Discontinuities were estimated in a semi-parametric model around the affected PA boundary segment, with covariates controlling for longitude and latitude. 4634 observations to the left and to the right of the cutoff. Confidence interval displayed at 95%.*

Diff-in-Disc estimates for the PA boundary segment that lies within the mining concession have been relatively constant during the exploration phase for the Twangiza mine (Figure 6.8). However, after the replacement of communities and with the beginning of the production phase, forest cover outside - where the mine is located - started to diminish at a faster rate. The trend in forest loss inside the nature reserve has not changed in a meaningful way at any stage of the establishment of the mine.

Given that the Itombwe Nature Reserve entered a participatory process of regazetting its boundaries in 2010-2014 (Kujirakwinja et al. 2019), an additional analysis was conducted for the initial boundaries. When first established, the boundaries of the nature reserve were never fully recognised by local communities, and results accordingly do not show significant changes in the discontinuities over time (Figure 7.4 in the appendix). However, it cannot be excluded that the change in discontinuities at the redrawn boundaries during the production phase is influenced by the regazetting process.

Case study II: Logging concessions inside Tumba-Lediima Reserve and Oshwe Hunting Reserve

Despite the lasting 2002 moratorium on new logging concessions in the DRC, the government has been granting new logging titles starting in 2011. Under the forest code of 2002, all logging companies were obliged to submit management plans for their concessions the latest five years after issue. The plans involved commitments of sustainable harvesting and social benefits for residential communities, although their implementation is often flawed (Karsenty et al. 2017; Global Witness 2018a).

Overlap of concessions with PAs was observed particularly in three PAs: Tumba-Lediima (IUCN category IV), Oshwe (category VI) and Rubi-Tele (category VI). Given that, according to the data, Rubi-Tele only had concessions assigned in 2020, the analysis of overlapping logging-conservation frontier dynamics focuses on the former two.

As the earlier analysis in Figure 6.7 showed, the Oshwe Hunting Reserve and the Tumba-Lediima Reserve both indicated positive discontinuities in forest cover at their boundaries in 2022, although Oshwe Hunting Reserve only insignificantly. Each had two overlapping concession titles assigned in 2011 and one in 2014. However, one concession in each PA did not show signs of actual logging activities by 2018 (Global Witness 2018b), leaving a sample of four overlapping boundary segments (see Figure 7.5 in the appendix).

Among these overlapping concessions, an investigatory report by Global Witness showed that only one had their management plan approved by 2019 and did not harvest timber outside of the designated annual harvest area (concession 035/11 in Figure 6.9a). One concession had an approved management plan, but did not restrict itself to operating within the designated perimeter (concession 039/11, Figure 6.9b). Finally, two of the logging concessions had no approved management plan by 2019 but showed signs of logging activities regardless (concessions 020/11 and 015/11, Figure 6.9c and d).

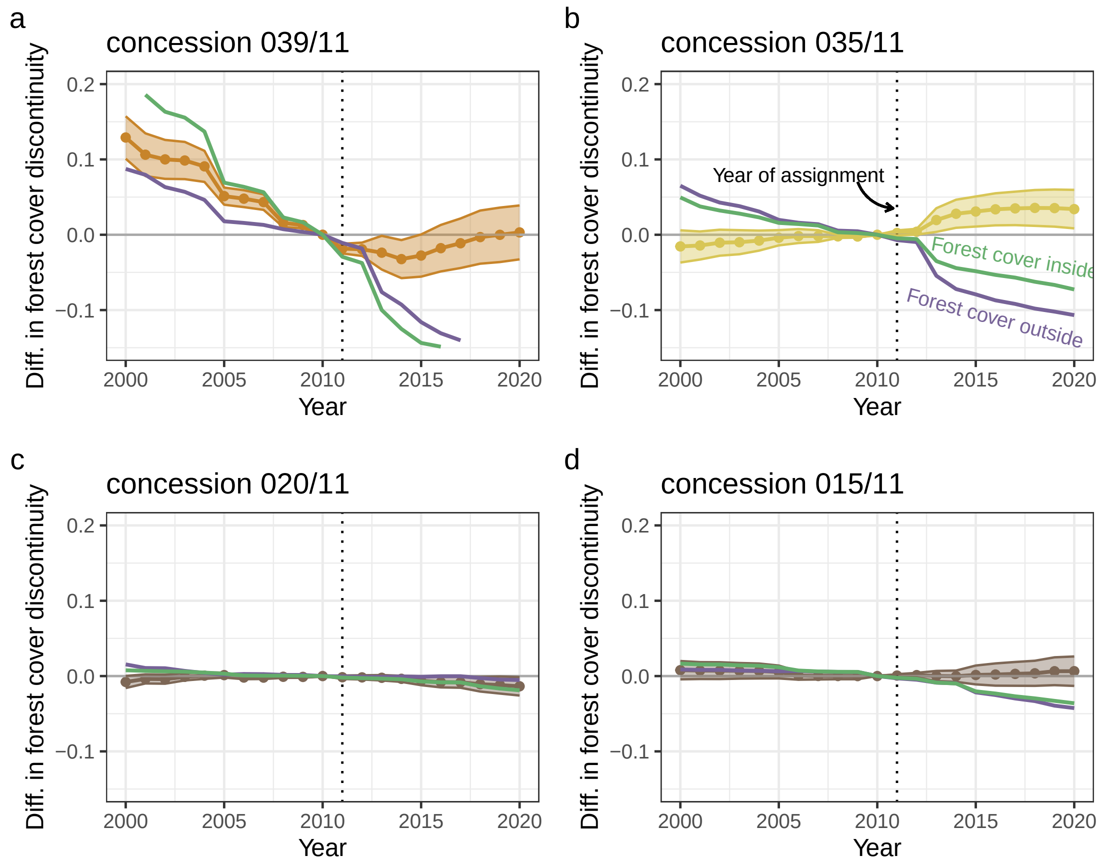

Figure 6.9: *Difference-in-Discontinuity estimates over time, normalised around the year prior to forest concession assignment. Confidence intervals displayed at the 95% level. Concessions displayed in* ***a*** *and* ***c*** *are located in Oshwe Hunting Reserve,* ***b*** *and* ***d*** *in Tumba-Lediima Reserve.*

The discontinuities in forest cover followed different trajectories for the four concessions (Figure 6.9). Concessions 020/11 and 015/11 did not reveal any noteworthy changes in forest cover discontinuity over time, regardless of the concession title assignment in 2011 (Fig 6.9c,d). The two concession with positive change in forest cover discontinuity after the title had been granted were concession 035/11 and 039/11, both of which had an approved management plan (Global Witness 2018b) and could thus indicate a positive interaction effect between well-managed logging concessions following the sustainable practises outlined in the management plans and conservation areas. However, when also considering the trajectory of forest cover extent inside and outside of PA boundaries, both concessions in fact show a drop in forest cover on either side as concessions were assigned, with a larger drop outside compared to inside. Hence, the increase in discontinuities was not associated with a decrease in deforestation inside the PAs due to better enforced protection, but rather a relatively stronger increase in forest loss outside.

6.6 Discussion

6.6.1 Remoteness protects, but is fading

Protected areas in the DRC stand at a crossroads. So far, protection has relied largely on remoteness (Joppa and Pfaff 2009). Although remoteness still plays an important part, the results presented in this study show that it has started to fade, and anthropogenic pressures on the PA system of the DRC are rising. Discontinuities in forest cover have been increasing to now 4% percent more undisturbed forest cover across boundaries on average, implying higher forest disturbance outside of PAs compared to inside over the last two decades.

A positive finding is that, even in a country with such fundamental institutional shortcomings as the DRC, not all PAs are conclusively inefficient. In 2022, 8% of investigated boundary points actively contained deforestation outside of the PA. However, twice as many have not succeeded in stopping deforestation at PA boundaries once the frontier arrived, casting doubt on this currently dominant conservation strategy. These results are coherent with findings by Burivalová et al. (2021) that, once the deforestation has arrived at PA boundaries, it is likely to spread inside.

In line with previous studies, results highlighted the role that forest roads play in attracting deforestation (Kleinschroth et al. 2019) and in weakening protection attempts. Most PA boundaries exposed to deforestation were located in close proximity to forest roads, and this exposure has further increased in the recent past as new forest roads are established (Slagter et al. 2024). With the anticipated growth in logging operations once the current moratorium on logging concessions ceases, pressure on PAs in the DRC will further increase.

Differences between IUCN categories

Previous studies have indicated that stricter protection does not necessarily lead to better conservation outcomes in terms of avoided deforestation (Ferraro et al. 2013; Pfaff et al. 2014; Elleason et al. 2021). One explanation for this observation is that stricter PAs tend to be located in more remote places where land use frictions and anthropogenic pressures are low (Ferraro et al. 2013; Pfaff et al. 2014). This is also in line with the finding that stricter category II PAs had the highest share of dormant protection among all IUCN categories.

Additionally, strict PAs are more likely to induce conflict over the use of land under protection and its resources (Ferraro et al. 2013). Acknowledgment by local communities is important for PAs to function, as for instance seen in the case of the indigenous Batwa in Kahuzi-Biega National Park. After initially having been forcefully removed from the park, the Batwa reoccupied a part of the park, with devastating impacts on its forest cover (Simpson et al. 2025). The findings in this study show that category II PAs were indeed associated with significantly more conflict incidences at their boundaries than other PAs that allow for certain forms of land use, underpinning this connection between strictness and conflict. Even among multiple use PAs, the degree to which communities were consulted in the implementation process can vary substantially, with implications on the social acceptance of installed land use rules (Pfaff et al. 2014).

Given the differences in location and the fact that GRD estimates are local to specific PA boundary segments, it is difficult to draw conclusions on comparative conservation performances of different IUCN categories when deforestation pressure rises. However, results presented in this study did show some interesting differences between the categories. One notable observation was that road access was particularly closely associated with sprawling boundaries of strictly protected category II national parks, although they also increased the likelihood of deforestation entering PAs with less stringent protection to a lower degree.

Co-management and delegated management of PAs have previously been found to increase the effectiveness in avoiding deforestation, but are found mostly in remotely located national parks under strict protection (Desbureaux et al. 2025). Given the dire need of funding and other kind of support for the PA system of the DRC, extending funding and collaborative management to less strict PAs with sustainable use could help to navigate land use frictions and offer support to the places facing the highest pressure (Buřivalová and Rakotonarivo 2025).

Looming mining and logging frontiers

Early signs of emerging land use frontiers in the form of concession title acquisitions represent another looming threat to protected forests in the DRC, with largely unknown implications at this point (Chervier et al. 2024; Meyfroidt et al. 2024; Radley 2020; Weng et al. 2013). So far, most of the granted mining titles are not operative, and only 55% of the timber concessions are productive with low harvest numbers compared to sectors in the neighbouring Congo Basin countries (Eba'a Atyi et al. 2022a). However, a substantial overlap between concession titles and PAs exists, frequently located at PA boundaries where deforestation has not reached yet. This coincidence of resource extraction and conservation frontiers will grow even stronger under the adopted Kunming-Montreal Global Biodiversity Framework aimed at declaring 30% of terrestrial area as protected by 2030 (Convention on Biological Diversity 2022). Given that the establishment of resource frontiers commonly requires infrastructural development (Meyfroidt et al. 2024; Slagter 2024), their emergence is likely to draw in other deforestation actors with potentially devastating impacts on intact forest landscapes and their biodiversity (Kleinschroth et al. 2019; Ladewig et al. 2024; Laurance, Sayer, and Cassman 2014; Weng et al. 2013).

Although first evidence on interaction effects between resource frontiers and land-based conservation in the DRC were provided in this study, more research is needed to generalise findings and account for the complex land use interactions in these processes (Meyfroidt et al. 2024). In principle, concessions can be understood as land titles, which have shown ambiguous effects on deforestation (Börner et al. 2020). Titles define access rights and can thereby exclude outside actors from engaging in deforestation, especially in the context of the DRC where institutional capacity to enforce conservation is low (Abman 2018). This has for instance been observed during the establishment of the Twangiza mine in eastern DRC, when artisanal miners and communities were removed from the mining concession area (Geenen 2014), although associated with counterproductive conservation outcomes at PA boundaries.

A similar logic was adopted to analyse logging concessions in other Congo Basin countries and in the Peruvian Amazon (Rico-Straffon et al. 2023; Tritsch et al. 2020). Findings from this study do not provide evidence for positive interaction effects of logging concessions and PAs on forest cover, with increased loss after concessions were established in two of the four analysed cases. Although the sample is too small to interpret findings as conclusive evidence, and a precise timeline of events in the establishment process of concessions is missing, they hint at the importance to insist on sustainable and lawful practises in the timber sector of the DRC. In neighbouring Congo Basin countries, certified concessions and those operating under management plans were found to have a much lower toll on forest cover (Tritsch et al. 2020). Further, the closing of abandoned logging roads is important, as the remaining infrastructure can leave scars in the forests that remain long after logging operations have ceased and is subsequently used by other actors to clear forest (Chervier et al. 2024; Kleinschroth et al. 2019; Potapov et al. 2017).

6.6.2 Limitations

A limitation in assessing PAs in a close environment around boundaries is the potential of leakage (Andam et al. 2008; Pfaff and Robalino 2017). Leakage may lead to to increased forest conversion outside of PAs as a consequence of restrictions posed on land use inside. Given that the GRD estimates are local to a close neighbourhood around PAs, they are more sensitive to be impacted by such spillovers than other methods. Although a relocation of deforestation from inside to the outside of PAs would inflate discontinuity estimates, it can also be interpreted as a consequence of effective protection. The typology developed in this study explicitly takes into account dynamics on either side of the boundaries and thereby helps to assess the effects of protection even if a part of the deforestation has been relocated to the outside of PAs. Quantifying leakage effects themselves is challenging, as it requires precise knowledge of their spatial extents to separate them from other dynamics (Pfaff and Robalino 2017), and is thus beyond the scope of this study.

A different problem concerns the use of PA boundaries as the treatment-defining cutoff in the regression discontinuity design. Although boundaries appear on maps, they may not always be visible on the ground, especially in remote locations. In such cases, no discontinuity in deforestation would be expected, and PAs would thus be assessed as inefficient in resisting deforestation pressure. A larger conceptual problem are shifting boundaries. Especially when frictions exist with other land uses, PA boundaries can get regazetted, as it happened for instance in the case of the Itombwe Nature Reserve after its initial establishment in 2006 (see Figure 7.4) (Kujirakwinja et al. 2019). In such cases, estimates for the wrong boundaries can make PAs appear inefficient although they were in fact only evaluated in the wrong locations. Besides the Itombwe Nature Reserve, no such instance since 2000 are known to the author, but information can be scarce and not readily available.

Finally, it should be noted that effectiveness of PAs is only evaluated based on forest cover loss in this study. It therefore does not account for other anthropogenic activities that cannot be as readily detected from satellite images but still compromise forest integrity. Defaunation, for instance, can be a disconnected and severe issue (Sagar et al. 2023). Also socio-economic implications of conservation were not considered in this analysis, but are important to take into account when assessing the eligibility of PAs to prevent deforestation given restrictions they pose on adjacent communities (Burivalová and Rakotonarivo 2025).

6.7 Concluding remarks

Previously, forest protection in the DRC has been known to rely largely on the remoteness of its PAs. In this study, a new typology of protection was developed to classify the activeness of the deforestation frontier at PA boundaries and their potential to resist it. The findings revealed that, in fact, the pressure on PAs along their boundaries has been increasing substantially over the past 20 years. While some PAs were able to withstand the pressure so far, twice as many did not succeed in keeping deforestation from entering inside. Especially in the later decade, these dynamics have further been accompanied by a renewed interest in the natural resources of the DRC by extractive industries, as seen through the acquisition of numerous concessions for timber and mineral extraction that coincide with PAs in many places. In the light of these developments, the conservation of the Congo Basin rainforest in the DRC is located at a crossroads: continuing on the path of protection-by-exclusion hoping to keep the deforestation front away from core forest areas, or adopting a new conservation paradigm in which communities are included in conservation planning and practise.

In the DRC, the large part of deforestation is not commodity-driven, but caused by small-scale rotational agriculture for subsistence consumption (Shapiro et al. 2023; Tyukavina et al. 2018). The increasing need for land is a result of a rapidly growing population that needs to support itself (Ernst et al. 2013; Molinario, Hansen, and Potapov 2015). Forest conservation strategies aimed at excluding communities from using the land may thus not be a lasting solution to halt deforestation. Instead, incorporating them in conservation strategies can provide more stable and inclusive ways to strengthen the resilience of both communities and conservation initiatives, especially in a context where the state does not have the capacity to provide alternatives (Berkes 2007; Hajjar et al. 2021). Attempts in recent years to give stronger agency to communities, for instance by legally enabling the creation of community forests since 2016 or allowing stronger community participation in PA establishments, are steps in the right direction, but also depend on the institutional setting (Lucungu et al. 2022; Kujirakwinja et al. 2019; Campos-Silva et al. 2021). Today, community forests in the DRC still face implementation challenges to become a viable alternative (Lescuyer et al. 2019), and further research on impacts and obstacles are urgently needed to understand the potential of creating win-win situations.

Data availability The data for the replication of the statistical analyses are available under `https://github.com/maladewig/PAs_DRC`.

Code availability The code for the replication of the statistical analyses is available for download under `https://github.com/maladewig/PAs_DRC`.

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Appendix C

Continuity of covariates

A common test for the validity of the GRD is to assess whether geographic covariates are continuous across treatment thresholds, such that treatment was not assigned based on certain geographical features. As the figure beneath shows, there are no discontinuous changes for terrain slope, altitude, precipitation or temperature across PA boundaries.

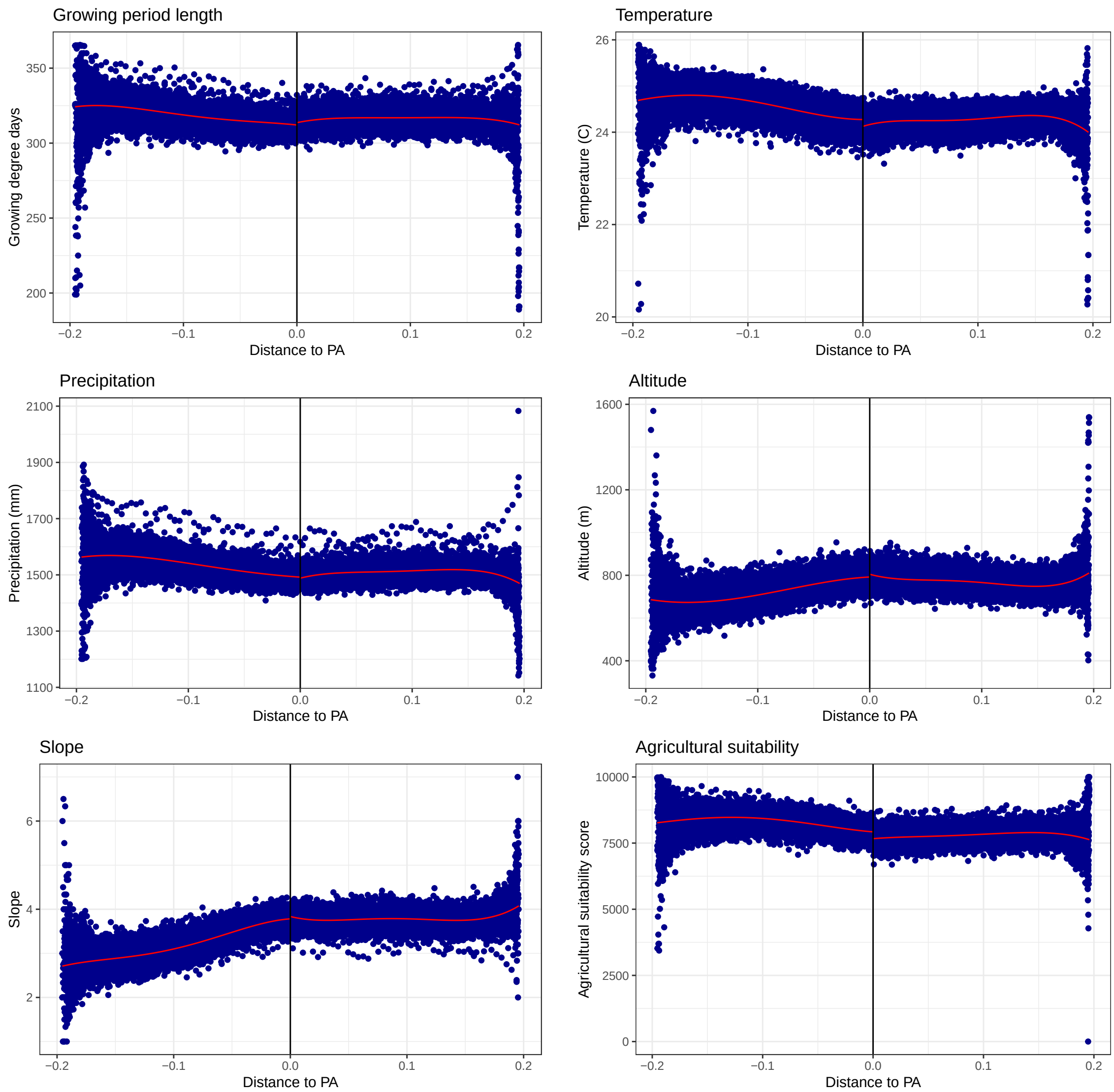

Figure 7.1: *Discontinuity plots around PA boundaries for different geophysical characteristics. All variables are taken from the Global Agro Ecological Zones (GAEZ) model (Fischer et al. 2021). Temperature, Precipitation and Growing Degree Days represent annual means.*

Pre-establishment discontinuity estimates

By testing for discontinuities existed prior to the establishment of PAs, it is possible to assess whether the observed differences in forest cover across thresholds have already existed before protection (Keele et al. 2017). Tanya Nature Reserve and Yangambi Biosphere Reservewere indicated in the data as established after 2000, but in fact had existed already before with different IUCN status and were therefore excluded. Of nine remaining PAs established after the year 2000, only Tumba-Lediima had a statistically significant discontinuity in forest cover already before PA establishment.

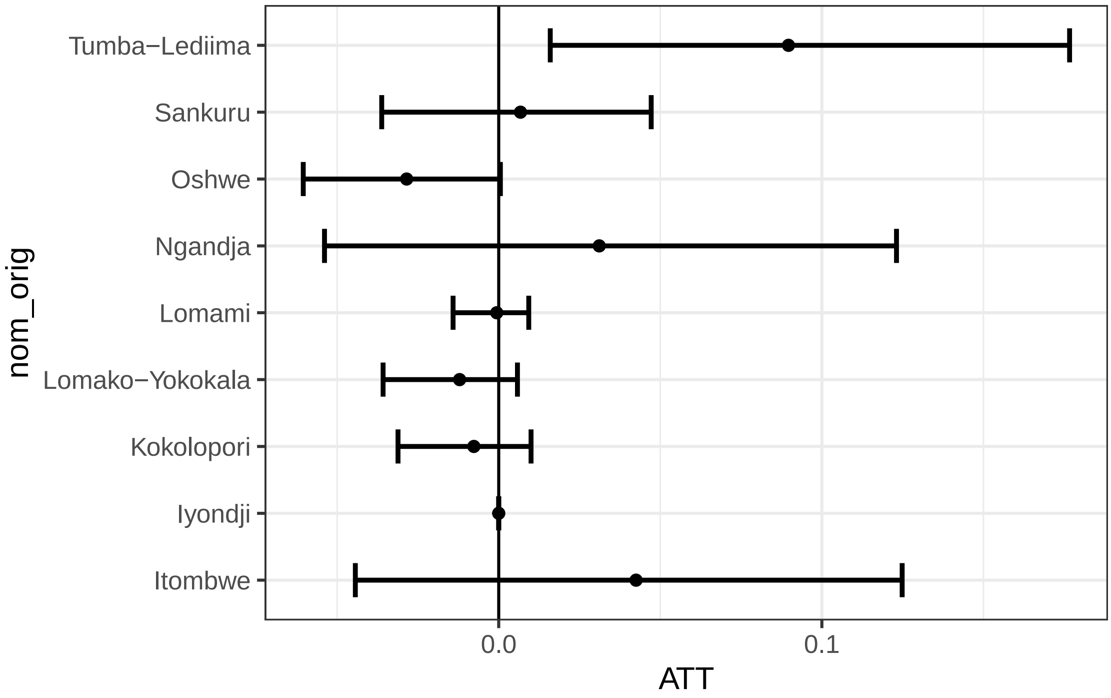

Figure 7.2: *Forest cover discontinuities across PA boundaries one year prior to PA establishment for PAs established after 2000. Confidence interval displayed at 95%.*

Protection type by PAs

Table 7.1: *Share of boundary points with different conservation frontier types by PAs in 2022 for PAs with more than 10 observations*

Name	IUCN	Area (km2)	Contained	Dormant	Exhausted	Sprawling	Consolidated	N
Domaine de chasse d'Oshwe	VI	1692.482	0.08	0.62	0.00	0.28	0.03	39
Domaine de chasse de Bili-Uéré	VI	3273.280	0.07	0.29	0.07	0.14	0.43	14
Domaine de chasse de Mangai	IV	1194.843	0.27	0.09	0.27	0.36	0.00	11
Parc national de Lomami	II	887.522	0.00	1.00	0.00	0.00	0.00	39
Parc national de la Maiko	II	1052.867	0.00	0.96	0.00	0.00	0.04	52
Parc national de la Salonga	II	1714.055	0.03	0.90	0.00	0.00	0.06	63
Parc national de la Salonga	II	1622.774	0.02	0.89	0.00	0.02	0.07	56
Parc national des Virunga	II	782.642	0.16	0.19	0.19	0.40	0.07	43
Parc national du Kahuzi-Biega	II	673.086	0.16	0.47	0.04	0.20	0.13	45
Réserve des primates de Kisimba-Ikobo	IV	97.041	0.19	0.56	0.00	0.00	0.25	16
Réserve naturelle d'Itombwe	IV	571.789	0.19	0.28	0.19	0.28	0.06	32
Réserve naturelle de Tayna	IV	89.967	0.07	0.86	0.00	0.00	0.07	14
Réserve Tumba-Lediima	IV	746.268	0.16	0.48	0.00	0.19	0.16	31
Réserve de biosphère de Yangambi	Ia	223.108	0.08	0.46	0.00	0.46	0.00	13
Réserve de chasse de Rubi-Télé	VI	1127.300	0.03	0.86	0.00	0.05	0.05	37
Réserve de faune à okapis	IV	1393.957	0.13	0.74	0.04	0.02	0.06	47
Réserve forestière de Lomako-Yokokala	IV	362.822	0.00	0.88	0.00	0.12	0.00	17
Réserve naturelle de Ngandja	IV	387.060	0.06	0.11	0.50	0.33	0.00	18
Réserve naturelle de bonobo de Kokolopori	IV	374.085	0.00	1.00	0.00	0.00	0.00	13
Réserve naturelle du Sankuru	IV	2664.194	0.05	0.33	0.05	0.53	0.05	43
Réserve naturelle du triangle de la Ngiri	IV	523.505	0.08	0.04	0.29	0.29	0.29	24

IUCN heterogeneity

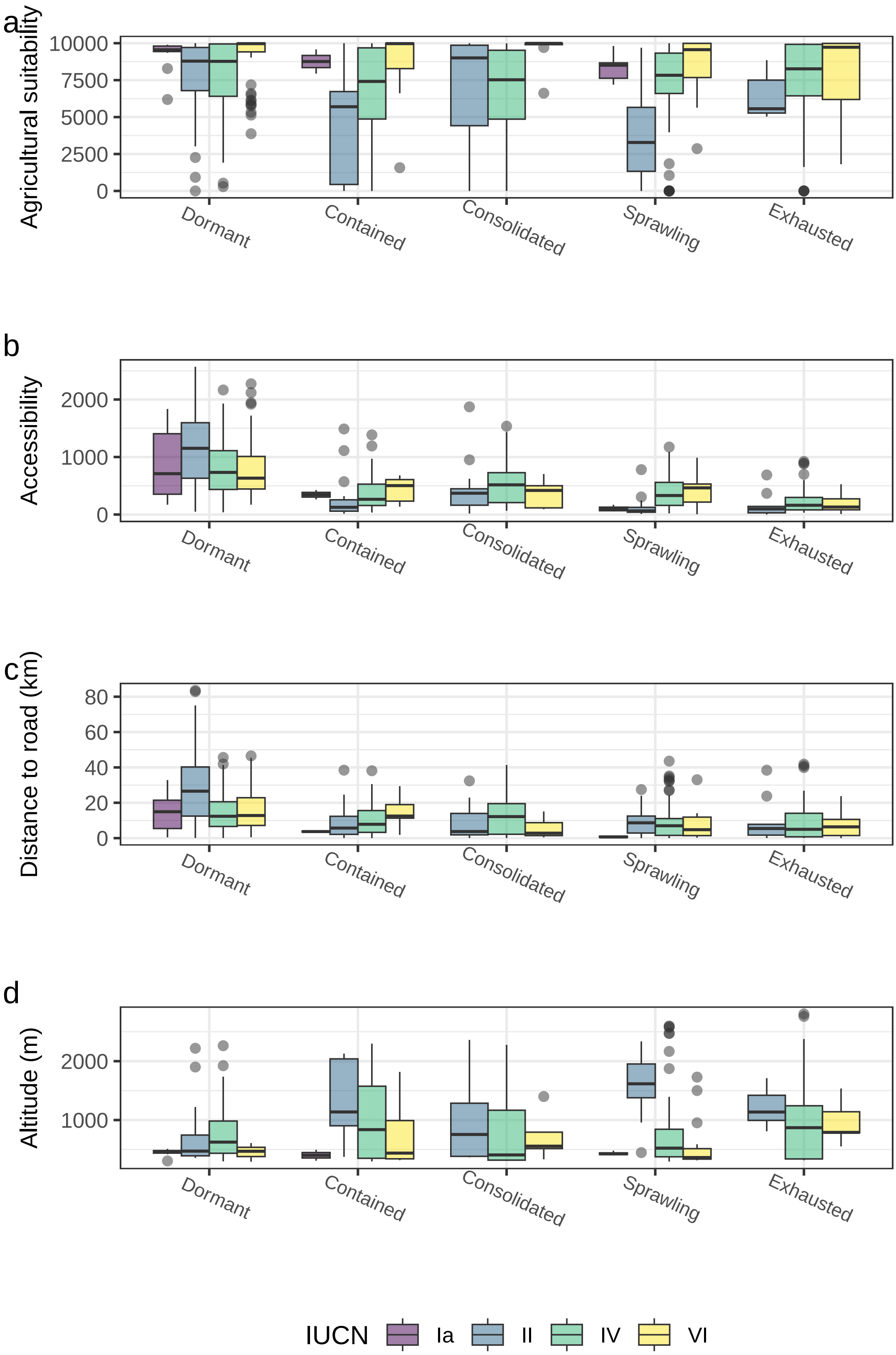

Figure 7.3: *Covariate distribution by IUCN category for **a** Agricultural suitability (Fischer et al. 2021), **b** travel time to nearest city (Weiss et al. 2018), **c** distance to roads (Meijer et al. 2018) and **d** altitude (Fischer et al. 2021).*

Metrics for protection typology

The classification into protection typology followed metrics derived from a jenks classification algorithm. The resulting threshold metrics were similar to a those obtained in Jamaludin et al. (2022). To test the sensitivity of the classification results to the specified metrics, thresholds used in Buchadas et al. (2022) and De Sy et al. (n.d.) were used. Buchadas et al. use 10% and 55% thresholds to distinguish low and high forest cover, but apply them to tropical dry woodlands which generally have lower forest cover density. De Sy et al. (n.d.) apply 15% and 50% thresholds in their application to tropical moist forests, but these thresholds are originating from a country-level study by Pendrill et al. (2019) and need to be treated with caution when applied to a finer landscape-scale.

For distinguishing high and low deforestation, Buchadas et al. (2022) used 0.6% of annual converted land cover as a threshold, and De Sy et al. used 0.37%.

Comparing classification of border points for the year 2022 for the different metrics, only minor differences are visible for consolidated and sprawling categories. Whereas Buchadas et al. (2022) metrics resulted in 8% consolidated boundary points and 12% with sprawling deforestation, a classification following De Sy et al. found 4% and 15%, respectively (Table 7.2).

Table 7.2: *Conservation frontier typology classification with threshold metrics of Buchadas et al. (2022) and De Sy et al. (in preparation) in comparison.*

Category shares in 2022	Buchadas et al. (2022)	De Sy et al. (in preparation)	Jenks clustering intervals
Dormant	0.66	0.65	0.61
Contained	0.06	0.07	0.08
Consolidated	0.08	0.04	0.08
Sprawling	0.12	0.15	0.16
Exhausted	0.08	0.08	0.07

Characteristics of protection types

Table 7.3: *Characteristics of different types of conservation frontiers in 2022 classified according to Figure 2 in the main document. Exposure to new logging roads established after 2019 was calculated based on data from Slager et al. (2024), and governance type was determined from Desbureaux et al. (2025). Row sums with shares do not add up to 1 due to unclassified boundary points.*

	Consolidated	Contained	Dormant	Exhausted	Sprawling	Points (#)
IUCN categories						
Ia	0.04	0.07	0.70	–	0.19	27
II	0.04	0.04	0.77	0.02	0.08	325
IV	0.11	0.06	0.53	0.10	0.14	288
VI	0.13	0.03	0.61	0.09	0.14	115
Accessibility (h to city)	7.11	4.75	15.85	4.6	4.21	–
Altitude (m)	757.62	1110.22	632.95	930.43	1053.5	–
Logging road distance (km)	6.02	3.91	12.96	6.73	2.24	–
New forest road w/in 5km						
No	0.09	0.05	0.65	0.06	0.11	714
Yes	0.06	0.04	0.59	0.02	0.22	51
Road distance (km)	8.06	9.32	15.1	9.3	6.36	–
PA governance type						
co-managed	0.04	0.03	0.85	0.01	0.04	221
delegated	0.15	0.02	0.81	–	–	48
other	0.10	0.06	0.53	0.09	0.16	496

Overlapping extractive frontiers

Given that the Itombwe Nature Reserve was first established in 2006 by ministerial decree, but entered a participatory mapping process for redrawing the boundaries in 2010-2014 in response to resistance by local communities and international NGOs (Kujirakwinja et al. 2019). Therefore, the analysis in Figure 6.8 was rerun for the former boundaries of the reserve, although they were never accepted by local communities.

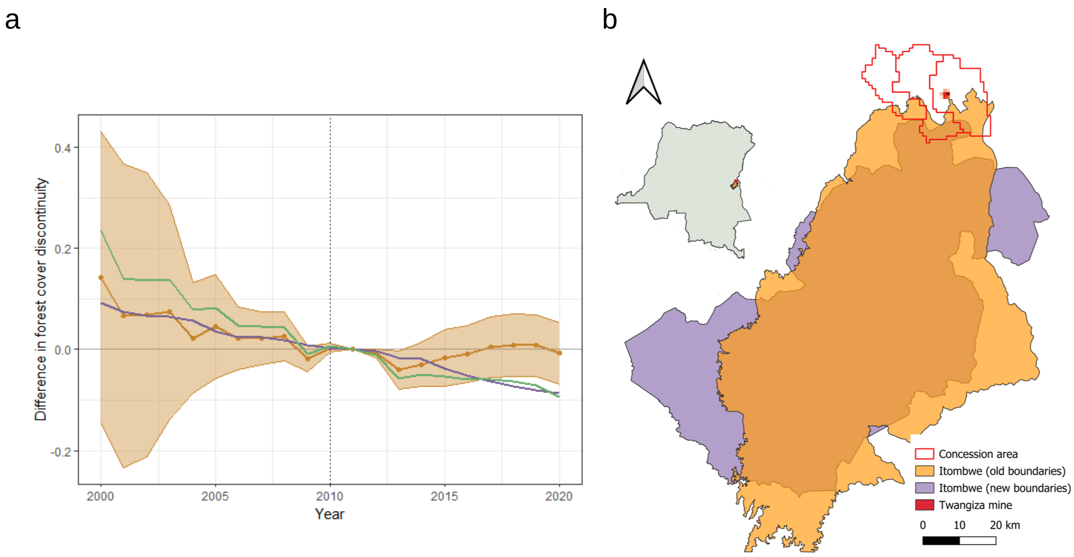

Figure 7.4: ***a*** *Dif-in-Disc estimates for previous Itombwe Nature Reserve boundaries. Purple line indicates forest cover outside, green inside.* ***b*** *Map with the location of the Twangiza mine and concession, as well as old and new boundaries of the Itombwe Nature Reserve.*

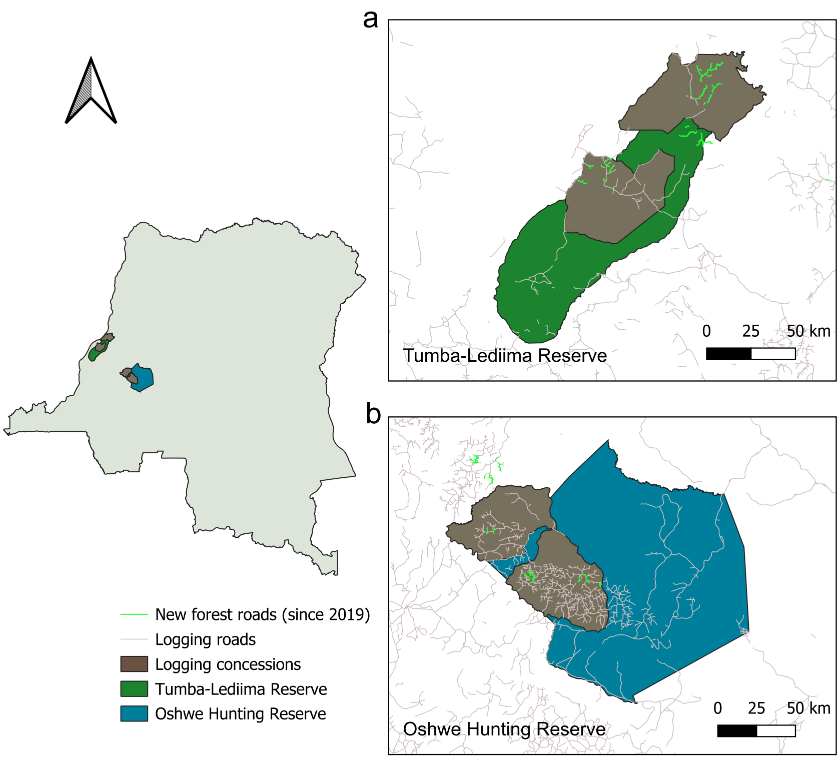

Figure 7.5: *Map with the location of selected logging concessions around* ***a*** *Tumba-Lediima Reserve and* ***b*** *Oshwe Hunting Reserve. Displayed logging roads from Kleinschroth et al. (2019) and newly constructed forest roads from Slagter et al. (2024).*

Software

The analysis was conducted in R version 4.4.2, using mainly the packages "tidyverse", "terra" and "rdrobust". Some adapted code chunks were used from the package "SpatialRDD", and jenks interval classification for deriving forest cover and deforestation thresholds was done with the package "classInt". The R script was partially executed on the ORION high performance cluster of the Norwegian University of Life Sciences.

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