Evaluating Forest Degradation, Deforestation, and Reforestation in Boeny and DIANA: Current Efforts and Future Opportunities

Ferdinand Peters, Andreas Kempe, Daniel Kübler, Sven Günter

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Ferdinand Peters*
Dr. Andreas Kempe*
Dr. Daniel Kübler
PD Dr. Sven Günter
(* shared first authors)

Thünen-Institute of Forestry
Leuschnerstraße 91
21031 Hamburg
Tel.: +49 40 739 62 301
E-Mail: daniel.kuebler@thuenen.de

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Zusammenfassung

Die Wälder Madagaskars sind für ihre hohe biologische Vielfalt bekannt und beherbergen zahlreiche endemische Pflanzen- und Tierarten. Diese Ökosysteme sind jedoch stark durch menschliche Aktivitäten bedroht, die zu Abholzung und Walddegradierung führen. Wirksame Naturschutzmaßnahmen müssen sich sowohl auf den Erhalt der verbleibenden natürlichen Wälder als auch auf die Wiederherstellung bereits zerstörter Wälder konzentrieren. Zur Bewältigung dieser Herausforderungen führte das Thünen-Institut für Waldwirtschaft in Zusammenarbeit mit der Deutschen Gesellschaft für Internationale Zusammenarbeit (GIZ) das Projekt „Analyse des Waldbewirtschaftungs- und Wiederaufforstungspotenzials in den Regionen Boeny und DIANA in Madagaskar (AFOB)“ durch. Das Projekt analysierte die Entwaldung und Walddegradierung sowie deren Ursachen und den Erfolg von Wiederaufforstungsprogrammen, die in den letzten Jahrzehnten durchgeführt wurden. Diese Programme zielten darauf ab, nachhaltige Praktiken für die Holzkohlegewinnung zu fördern und so die Abhängigkeit von natürlichen Wäldern zu reduzieren. Um die Projektziele zu erreichen, verwendeten wir einen räumlichen Analyseansatz, der auf frei zugänglichen Fernerkundungsprodukten basierte.

Für Naturwälder haben wir ermittelt, wann und wo potenzielle Walddegradierung und Entwaldung erfolgten und die Dynamik der Waldfragmentierung aufgezeigt. Dabei haben wir zwischen geschützten und nicht geschützten Waldgebieten unterschieden. Unsere Ergebnisse zeigen, dass Entwaldung und Walddegradierung zwischen 2000 und 2023 erheblich zugenommen haben, und dass die Degradierung in der Vergangenheit ein größeres Ausmaß hatte als bisher angenommen. Zu den Hauptursachen gehören die Umwandlung von Wäldern in landwirtschaftliche Flächen, Waldbrände, illegale Holzkohleproduktion und der illegale Einschlag wertvoller Bäume. Wir konnten zeigen, dass sich die Ackerflächen in den letzten zwei Jahrzehnten deutlich ausweiteten, wobei die Zuwachsrate in den letzten Jahren nochmals anstieg. Unsere Ergebnisse deuten darauf hin, dass Entwaldung und Walddegradierung als unterschiedliche, aber miteinander verknüpfte Bedrohungen betrachtet werden sollten, denen jeweils spezifische Prozesse zugrunde liegen, die angepasste Strategien erfordern.

In den Wiederaufforstungsflächen war die Überschirmung während der ersten Umtriebszeit zunächst gering, zeigte aber über den Untersuchungszeitraum hinweg eine steigende Tendenz. Auf mehr als der Hälfte der Flächen blieb der Überschirmungsgrad jedoch unter 20 %, was darauf hinweist, dass das volle ökologische Potenzial nicht ausgeschöpft wurde. Eine weitergehende Analyse zeigte, dass Umweltfaktoren wie Topografie und Bodentypen die Entwicklung des Überschirmungsgrads in allen Regionen und Programmen ähnlich beeinflussten, während der Einfluss sozioökonomischer Faktoren je nach Programm und Region variierte. Diese Faktoren hatten jedoch insgesamt nur einen geringen Einfluss auf die Überschirmung. Im Gegensatz dazu deuten unsere Ergebnisse darauf hin, dass flächenspezifische kleinräumige Faktoren, die wir aufgrund eingeschränkter Datenverfügbarkeit nicht in die Analyse einbezogen werden konnten, signifikant zur Variation der Überschirmung beitrugen. Zu diesen Faktoren, deren genaue Natur spekulativ bleibt, könnten z.B. anfängliche Bepflanzungsdichten, Überlebensraten, Vorhandensein von Restvegetation, Feuermanagement und Bewirtschaftungsziele des Landbesitzers gehören. Dies deutet darauf hin, dass ein einheitlicher Wiederaufforstungsansatz ineffektiv ist; für den Erfolg ist vielmehr ein standortspezifisches, adaptives Management entscheidend. In einer zusätzlichen Analyse haben wir geeignete Gebiete mit potenziell hohen Wachstumsraten für die Wiederaufforstung identifiziert, die als Orientierungshilfe für künftige Wiederherstellungsinitiativen dienen können, in denen standortspezifische Planung eine größere Rolle spielt.

Die im Rahmen des AFOB-Projekts gewonnenen Erkenntnisse werden der GIZ bei der Planung und Umsetzung gezielter Wiederaufforstungs- und Schutzinitiativen helfen, um den Erhalt der einzigartigen Ökosysteme Madagaskars und ihrer ökologischen Integrität zu unterstützen.

Schlüsselwörter: Entwaldung, Walddegradierung, Fernerkundung, Wiederaufforstung, Waldlandschaften

Summary

Madagascar's forests are known for their rich biodiversity, and they are home to numerous endemic plant and animal species. However, these ecosystems face significant threats from human activities, leading to deforestation and forest degradation. Effective conservation efforts must focus on both protecting the remaining natural forests and restoring those already destroyed. To address these challenges, the Thünen Institute of Forestry, in collaboration with the German Society for International Cooperation (GIZ), conducted the project “Analysis of forest management and reforestation potential in the regions of Boeny and DIANA in Madagascar” (AFOB). The project analysed deforestation and forest degradation along with their drivers, and evaluated the success of reforestation programs implemented over the past decades. These past programs sought to foster sustainable charcoal production practices, thereby reducing reliance on natural forests. To achieve these objectives, we used a spatial analysis approach that relied on open-access remote sensing data products.

For natural forests, we identified when and where potential forest degradation and deforestation occurred and demonstrated forest fragmentation dynamics, differentiating between protected and non-protected areas. Our findings revealed that between 2000–2023, deforestation and forest degradation have increased substantially, with degradation having been a more significant issue in the past than previously understood. Key drivers include the conversion of forests into agricultural land, fire, illegal charcoal production, and the illegal extraction of valuable timber. We showed that over the last two decades, cropland has expanded significantly, with an even faster rate of increase in recent years. Our findings suggest that deforestation and forest degradation should be viewed as distinct but interrelated threats, each driven by different underlying processes that require tailored strategies, respectively.

In the reforestation areas, crown cover was initially low during the first rotation but showed an upward trend over the analysed period. However, more than half of the plots did not develop crown cover exceeding 20%, suggesting that they did not reach their full ecological potential. In a subsequent analysis, we found that environmental factors, such as topography and soil, consistently influenced crown cover development across regions and programs, while the influence of socio-economic factors varied by program and region. However, these factors had only a weak overall influence on crown cover. In contrast, our analysis suggested that unaccounted plot-level factors, which we could not include due to data limitations, had a significant impact on crown cover variation. These factors could potentially include initial planting densities, survival rates, presence of remnant vegetation, fire management, and management objectives of the landowner, though their exact nature remains speculative. This indicates that a uniform reforestation approach is ineffective; instead, site-specific adaptive management is crucial for success. In an additional analysis, we identified suitable areas with potentially high growth rates for reforestation, which can guide future restoration initiatives with a stronger focus on site-specific planning.

The insights gained from the AFOB project will assist GIZ in planning and implementing targeted reforestation and conservation initiatives, ultimately supporting the preservation of Madagascar's unique ecosystems and maintaining ecological integrity.

Keywords: deforestation, forest degradation, remote sensing, reforestation, forest landscapes

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1 Introduction

Forests in Madagascar hold high value for biodiversity as they are home to unique and often endangered flora and fauna, many of which are endemic (Myers et al. 2000). They also provide important ecosystem services, which are essential for the large rural population that depends on natural resources for their livelihoods (Fritz-Vietta et al. 2011). However, these forests face significant anthropogenic pressures. Madagascar is one of the world's poorest countries and it experiences high population growth, which is coupled with weak governance and enforcement (Waeber et al. 2016). Additionally, adverse climatic conditions over recent decades have driven migration from the southern to the northern provinces of the country (Lacroix et al. 2016). This growing population has increased the demand for agricultural land. Moreover, 85% of Malagasy households rely on wood fuel (Gade and Perkins-Belgram 1986; Holloway 2004). Slash-and-burn agriculture (tavy), the establishment of permanent cropland, and the production of fuelwood and charcoal are widespread in the country's native forest areas to meet these demands (Velo and Zafitsara 2020; Casse et al. 2004). As a consequence, Madagascar has lost nearly half its natural forest cover since 1953, leading to significant increases in forest fragmentation (Vieilledent et al. 2018). Additionally, the remaining natural forests have been increasingly degraded (Eckert et al. 2011).

Over the last decades, the German development cooperation has been implementing programs in Madagascar aimed at integrating poverty alleviation with forest conservation and restoration as well as sustainable wood production, particularly in the regions of Boeny and DIANA (Lacroix et al. 2016). Despite these concerted efforts, ongoing deforestation and forest degradation indicate that these interventions have not completely countered the substantial anthropogenic pressures on the forests (Waeber et al. 2016). Designing targeted, more effective interventions is often limited by knowledge gaps about the current state of natural forests, the various drivers of deforestation and forest degradation, and the success factors of previous efforts. The AFOB project, which started in May 2023 and ended in June 2024, aimed to support GIZ's future activities in Boeny and DIANA by filling some of the knowledge gaps. The project's two work packages each addressed a specific aspect of these challenges.

The first work package of the AFOB project analysed the deforestation and degradation of natural forests and forest landscapes. Deforestation is defined as a permanent change in land use, where forest areas are converted for other purposes (FAO 2020). In contrast, forest degradation refers to a gradual reduction in the quality and health of a forest ecosystem, which diminishes its capacity to provide goods and services (FAO 2015). Although more subtle than deforestation, the impacts of forest degradation are nevertheless profound (Pearson et al. 2017). It can result in biodiversity loss, reduced carbon storage, soil erosion, and impaired water regulation. Recent advancements in remote sensing made detailed information about deforestation available with high temporal and spatial resolution for Boeny and DIANA (e.g., Hansen et al. 2013). However, due to methodological challenges, similar detailed data is lacking for forest degradation (Gao et al. 2020).

Understanding the causes of forest degradation and deforestation is crucial for designing targeted interventions. On the national level, subsistence agriculture, often using slash-and-burn techniques, has been identified as the primary direct driver of deforestation in Madagascar (Curtis et al. 2018; Masolele et al. 2024). Forest degradation is often caused by fuel wood collection and charcoal production in large parts of Africa (Kissinger et al. 2012), which was also identified as a major threat to forests in Madagascar (PREB 2015a, 2015b). However, despite these broader understandings, there remains a significant knowledge gap regarding the relative importance of the direct drivers, with a lack of quantitative assessments of how the drivers compare to each other in influencing deforestation and degradation in Boeny and DIANA.

To address these knowledge gaps, the first work package aimed to:

1. Analyse temporal and spatial patterns of forest degradation, fragmentation, and deforestation over recent decades.
2. Quantify the most important direct drivers of forest degradation and deforestation.

The second work package focused on reforestation efforts in response to the high woodfuel demand, which has been largely sourced from natural forests in Boeny and DIANA. Over the last decades, various German development cooperation programs have supported communities and smallholders in reforestation efforts with Acacia and Eucalyptus species. For this, the approach “Reboisement Villageois Individuel” (RVI; Individual Village Reforestation) was primarily used, which aims to reduce the pressure on natural forests by establishing sustainable wood supply chains capable of meeting the growing woodfuel demand (Lacroix et al. 2016). Understanding the successes and challenges of previous reforestation efforts is important for the design of future interventions, particularly given the mixed success of reforestation and forest restoration efforts in the tropics, where the underlying mechanisms are often complex and poorly understood (Höhl et al. 2020). This is particularly relevant for Forest Landscape Restoration (FLR) initiatives in Madagascar, as the country has committed to restoring 4 million ha under the Bonn Challenge by 2030 (IUCN 2016), with a significant emphasis on the provision of energy and construction wood (MEEF 2017).

Previously, the success of reforestation in Boeny and DIANA has been analysed using forest inventories of individual plots or watersheds (BIODEV 2020; Rasoanaivo 2014; Richter and Andriampiolazana 2023). This approach is labour-intensive and provides only a limited view of the temporal and spatial dynamics at landscape or regional levels. In this work package, we leveraged recent advances in remote sensing which allow for monitoring the development of forest cover and tree cover in Boeny and DIANA over the last decades based on vegetation indices (Mulligan et al. 2020; Potapov et al. 2022a). The specific objectives of the second work package were to:

1. Assess the development of the reforestation plots supported by German development cooperation programs.
2. Identify which environmental and socio-economic factors influenced the success of these reforestation efforts.
3. Identify promising growth zones for future reforestation activities.

2 Data and methods

2.1 Research areas

The areas of interest were the two regions Boeny and DIANA in the north and north-west of Madagascar. Both regions have a predominant tropical savanna climate with a distinct wet and dry season. The wet season typically lasts from November to April, while the dry season, characterized by significantly reduced rainfall and lower humidity, spans from May to October. Parts of DIANA have a tropical rainforest climate, with higher humidity and more consistent rainfall throughout the year, especially on the windward sides of mountains. Although DIANA is only two-third the size of Boeny (Boeny: 31 254 km², DIANA: 20 013 km²), their populations are similar (Boeny: 978 350, DIANA: 939 280; INSTAT 2018). The population growth rates per year between 1993 and 2020 are similarly high in both regions, with Boeny at 3.48% and DIANA at 3.65%.

We assessed both protected and non-protected areas within the regions by conducting analyses on several national parks and areas outside their boundaries. National parks often serve as reference areas with minimal human impact, providing a baseline for comparison with non-protected areas that may experience more significant anthropogenic pressures. Additionally, this comparison can help to evaluate the success of conservation strategies in national parks. We included the national parks Ankarafantsika in Boeny and Montagne d'Ambre, Analamerana, and Ankarana in DIANA. The three national parks in DIANA have approximately the same size as Ankarafantsika, but show higher topographic diversity, ranging from sea level in Analamerana to an altitude of 1 400 m in Montagne d'Ambre. These parks are home to mangroves, tropical dry forests, savannah, grassland, and mountain rainforest. Ankarafantsika is characterized by tropical dry forest and grassland. Compared to the remaining province, they still harbour significant forest areas (see Annex A). Hence, they are part of Madagascar's biodiversity hotspots and provide important ecosystem services. The forest cover is different in the individual parks (Table 1).

Table 1: Area and forest cover of research areas.

Superficie et couvert forestier des zones de recherche.

	Montagne d'Ambre	Analamerana	Ankarana	DIANA	Ankarafantsika	Boeny
Area [km²]	587	712	485	20 013	1 694	31 254
Forest cover 2000*	81%	47%	59%	59%	66%	21%

* Derived from Hansen et al. (2013)

There are other national parks in both regions that were not included in our analyses, such as Baie da Baly and Namoroka in Boeny and Manongarivo and Tsaratanana in DIANA. To prevent these national parks from distorting the comparison between non-protected and protected areas, we excluded them from all regions-wide analyses. In our results, "outside national parks" thus only refers to areas without the excluded national parks. We did not exclude smaller protected areas to keep the work manageable.

To investigate the effects of different influencing factors on the national parks, we spatially divided the parks into a centre area and a 4 km wide edge area for the analysis of forest degradation indicators (Section 3.1.1) and fire frequency (Section 3.1.4.5). For the recommendation of growth zones for reforestation (Section 2.5.5), we took into account that areas directly surrounding national parks are subject to specific rules and regulations concerning resource use and land-use change. Therefore, we focused on a direct peripheral zone, defined by a 2.5 km buffer from the park edge, and an extended peripheral zone with a 2.5–7.5 km buffer, where reforestation regulations are less stringent.

2.2 Field trip for verification of results

We visited Boeny and DIANA for the verification of our results between 21.5.2024 and 2.6.2024. We travelled to Andranofasika at the southern side of Ankarafantsika National Park and to Sakaramy and Joffreville at the north-east side of Montagne d'Ambre. During the visit, we recorded and assessed various states of forest degradation and deforestation, as well as the success of the plantations. Using a GIS application on the smartphone allowed us to geolocate our position and to compare the ground truth in the forests and neighbouring plantations with our remote sensing-based findings. The length of inspections by foot totalled 27 km.

2.3 Compilation of joint project GIS database

To answer our research questions, we relied on pre-processed and freely available Analysis Ready Data products. As there were multiple overlaps between the two work packages, we created a project-wide project GIS database to prevent redundant data processing. We acquired relevant data for Boeny and DIANA, generated time series, and compiled the data in our database (Table 2). Maps of the data products are provided in Annex A.

The joint GIS database also includes Normalized Difference Fraction Index data (NDFI, see Section 2.4.2.1 for a detailed description). This dataset was utilized for the forest degradation analysis (Section 2.4.2), identification of factors influencing plantation success (Section 2.5.2), and estimation of future growth zones (Section 2.5.5).

Table 2: Analysis Ready Data products and data download links. The column WP describes if the product was used by WP1 (Natural forests and forest landscapes) and/or WP2 (Assessment of the productivity of reforestation).

Produits « Analysis Ready Data » et liens de téléchargement des données. La colonne WP indique si le produit a été utilisé par le WP1 (Forêts naturelles et paysages forestiers) et/ou le WP2 (Évaluation de la productivité du reboisement).

Data	WP	Download
Tree cover and tree cover loss	1, 2	https://storage.googleapis.com/earthenginepartners-hansen/GFC-2023-v1.11/download.html
Forest loss due to fire	1	https://glad.umd.edu/dataset/Fire_GFL
Cropland	1, 2	https://glad.umd.edu/dataset/croplands
Burned area	1, 2	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/3CTMKP
Global land cover and land use change	1, 2	https://glad.umd.edu/dataset/GLCLUC2020 or https://esa-worldcover.org/en
Digital elevation model	2	https://asterweb.jpl.nasa.gov/gdem.asp or https://dwtkns.com/srtm30m/
Cities and settlements	2	https://datacatalog.worldbank.org/search/dataset/0039931
Roads	2	https://datacatalog.worldbank.org/search/dataset/0041447/Roads-Madagascar
Population density	2	http://sedac.ciesin.columbia.edu/data/collection/gpw-v4/sets/browse
Climate	2	http://madaclim.cirad.fr/current-climate/
Soil	2	https://www.isric.org/projects/soil-property-maps-africa-250-m-resolution
Clay content	2	https://data.isric.org/geonetwork/srv/eng/catalog.search#/search?any=Africa%20SoilGrids%20-%20Clay%20content
Sand content	2	https://data.isric.org/geonetwork/srv/eng/catalog.search#/metadata/4727602b-d0f2-4a6d-bb2f-d50c0ee24298
Soil depth	2	https://data.isric.org/geonetwork/srv/eng/catalog.search#/metadata/c77d1209-56e9-4cac-b76e-bbf6c7e3a617

2.4 Natural forests and forest landscapes

2.4.1 Methodological approach to quantify forest change dynamics

We applied a remote sensing-based approach to analyse forest degradation, fragmentation, and deforestation over recent decades. For the quantification of forest loss, we used an Analysis-Ready Data product mapping tree cover and tree cover loss, which has been widely used over the last decades in deforestation analyses (Section 2.4.3). Forest degradation, in contrast, is much more challenging to quantify than deforestation (Gao et al. 2020). Whereas deforestation is characterised by a loss of tree cover and conversion to another land use, forest degradation is a gradual variation in forest cover. By the time degradation becomes visible on satellite images, it is often already in an advanced stage. To tackle these challenges, we used a method which was developed to detect forest degradation based on NDFI time series (Section 2.4.2; Figure 1). The quantification of forest fragmentation is described in Section 2.4.4.

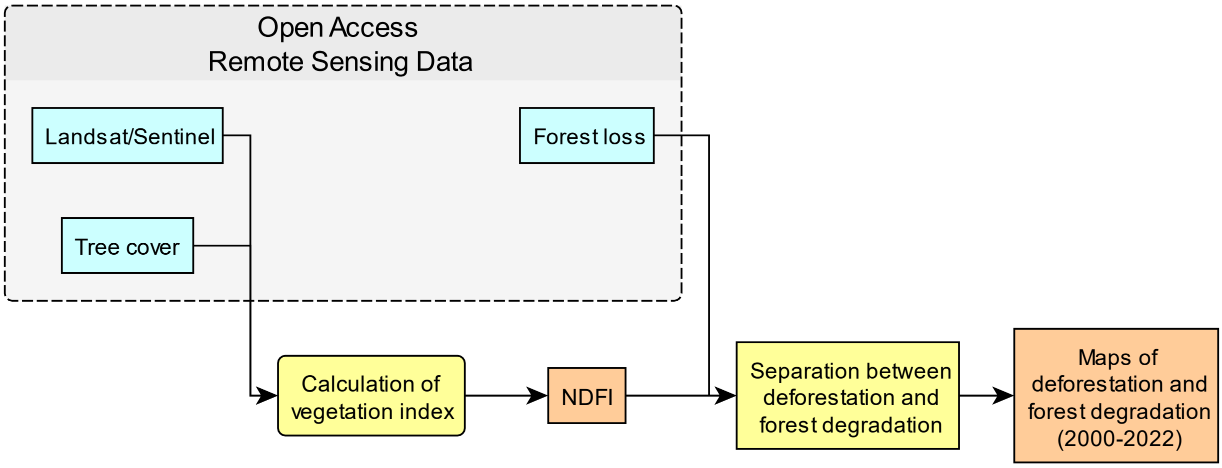


Figure 1: Workflow for separation of forest degradation and forest loss (French version in Annex E).

Flux de travail pour la séparation de la dégradation des forêts et de la perte de forêts (version française à l'Annex E).

2.4.2 Quantification of forest degradation indicators

2.4.2.1 Calculation of NDFI time series

The NDFI was developed to identify forest degradation using spectral decomposition of Landsat pixel information (Souza et al. 2005). This makes it possible to distinguish between fresh vegetation, dry vegetation, soil, and shade-covered materials. NDFI shows high values for intact forests, caused by a combination of high green vegetation and canopy shade fractions and low dry vegetation and soil fractions. The NDFI decreases with increasing dry vegetation and soil fractions. Deforested areas exhibit very low or no green vegetation and shade and high dry vegetation and soil fractions, resulting in low NDFI values.

We calculated NDFI data via the Google Earth Engine following Souza et al. (2024) and then compiled the downloaded data into our joint project database. Since the sensors of Landsat 5, 7, 8, and Sentinel 2 have the same wavelength ranges, NDFI can be calculated from all those satellite images. Landsat 5 was active from 1984 until 2012. Landsat 7 started in 1999 and failed in 2003. Landsat 8 started in 2013 and has been active until now, but pre-processed data were only available until the end of 2021. Sentinel 2 data have been available since 2016 until now. The advantage of these satellites is the frequent revisit time of approx. 16 days. NDFI was calculated from Landsat 5 and 7 (2000–2012), Landsat 8 (2013–2021) and Sentinel 2 (2016–2023).

In Madagascar, the months of April to November have the lowest cloud cover due to the dry season. In our analyses, we used two periods with a high likelihood of cloud free images: early dry season (April–July) and late dry season (August–November). NDFI values are lower in the late dry season compared to the early dry season due to lower water availability for the vegetation.

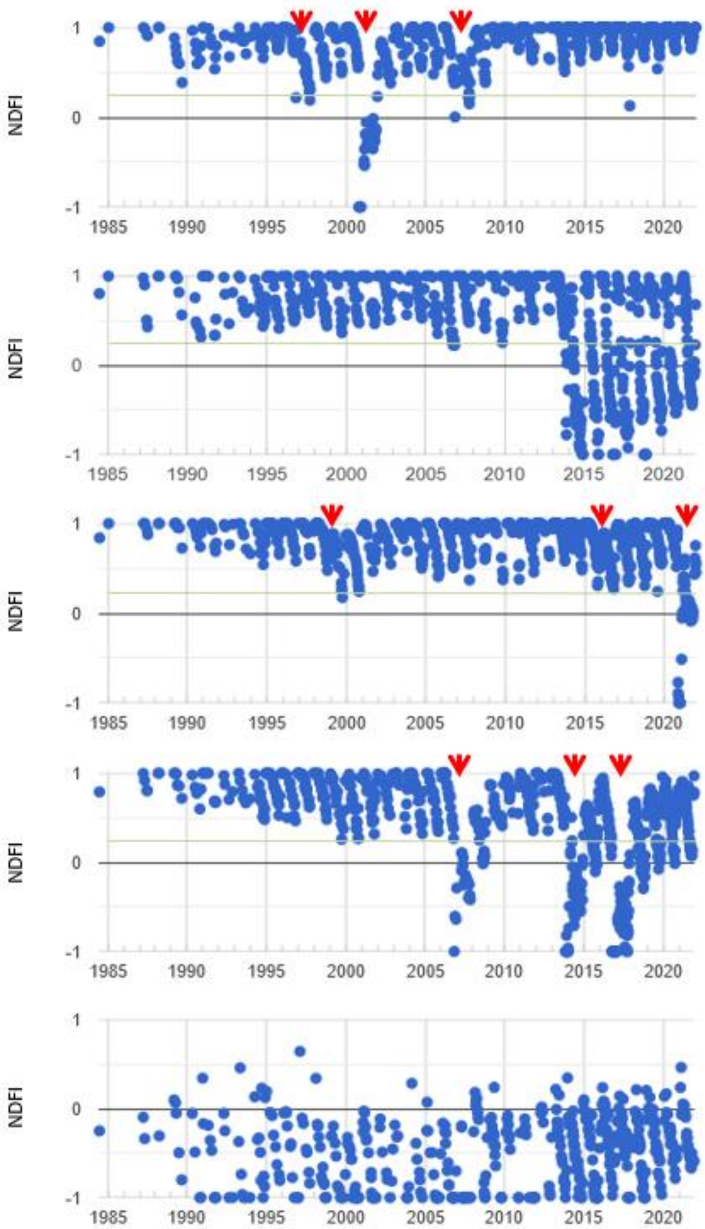
2.4.2.2 Detection of forest degradation indicators

We used the CODED tool in Google Earth Engine, a methodology developed for detecting forest degradation based on NDFI time series (Bullock et al. 2020). A detailed and comprehensive workflow is described in Bullock (2021). The tool displays the NDFI for individual pixels for every available observation of Landsat 4, 5, 7, and 8 from 1985 up to 2022. Visually analysing a large number of pixels in the study regions allowed us to get a thorough understanding of NDFI dynamics, and subsequently derive threshold values to differentiate between disturbed and undisturbed forest. Our threshold approach is a simplified adaptation of the method used by Bullock et al. (2020).

It is important to emphasize that by using this approach, we quantify temporary disturbances, expressed by structural changes of the forest canopy, as indicators of forest degradation. The approach does not allow to quantify to what extend the capacity to provide essential ecosystem services is reduced. Furthermore, we categorize forest pixels without temporary disturbance as undisturbed forests. However, we do not include data before 2000 in our analysis; we also do not consider the fact that intactness of forests is linked to a minimum forest size. Therefore, undisturbed forests should not be equated to intact forests, which are largely undisturbed by human activity, maintaining natural biodiversity and ecological processes.

Figure 2 shows examples for typical NDFI time series of forest pixels with forest degradation and deforestation events as well as grassland and cropland pixels. Undisturbed forests show NDFI values close to 1 in the wet season and decrease towards the end of the dry season. When NDFI values of undisturbed forest pixels fall below 0.25, we consider this as an indicator for forest degradation. These pixels can subsequently either return to pre-degradation levels, or continue to decline, resulting in deforestation, with NDFI values typical of grassland or agriculture. NDFI values of grassland pixels fluctuate between -1 and 0.25, or up to 0.75 in some cases, whereas cropland pixels fluctuate between -1 and 1. The examples illustrate that the analysis of NDFI time series allows to differentiate between forest and other land uses, such as agriculture or grassland, and to identify forest disturbance events. To link these examples to our field observations, we provide representative pictures of forest degradation, forest loss and deforestation in Ankarafantsika's tropical dry forest in Figure 3.

For the quantification of forest degradation, we used the NDFI threshold of 0.25 to differentiate between undisturbed and disturbed forest. For each year, we calculated the area of all forest pixels below this threshold and described it as potentially degraded forest area.



Minor degradation events 1997, 2007
Major degradation event 2001
Undisturbed for the last 14 years

Undisturbed forest until 2013 (possibly minor degradation events in 2007, 2010)
Conversion to agriculture in 2014

Minor degradation events 1999, 2016
Major degradation event 2021

Undisturbed forest until 2006
Repeated degradation events 2006, 2014, 2016

Persistent grassland

Figure 2: NDFI time series from 1984–2023. Each blue dot represent an observation in time. Red arrows mark degradation events. The green line marks a NDFI threshold of 0.25. There are less observations for the period before 1999 because only images captured by Landsat 4 and 5 were available.

Série chronologique du NDFI de 1984 à 2023. Chaque point bleu représente une observation dans le temps. Les flèches rouges marquent les événements de dégradation. La ligne verte indique un seuil NDFI de 0,25. Il y a moins d'observations pour la période antérieure à 1999 car seules les images capturées par Landsat 4 et 5 étaient disponibles.

Figure 3: Examples for forest degradation, forest loss and deforestation from Ankarafantsika's tropical dry forest. A: Undisturbed forest since 2000, trees up to 15-20 m tall. B: Forest loss in 2001, recovery of vegetation, tree heights 4–5 m, driver: fire. C: Forest degradation in 2021, recovery of vegetation, shrubs and small trees up to 2 m, driver: fire. D: Deforestation in 2001, new land use: permanent cropland.

Exemples de dégradation, de perte et de déforestation de la forêt tropicale sèche d'Ankarafantsika. A: Forêt non perturbée depuis 2000, arbres de 15 à 20 m de haut. B: Perte de forêt en 2001, rétablissement de la végétation, hauteur des arbres de 4 à 5 m, cause: incendie. C: Dégradation de la forêt en 2021, rétablissement de la végétation, arbustes et petits arbres jusqu'à 2 m, moteur: incendie. D: Déforestation en 2001, nouvelle utilisation des terres: cultures permanentes.

Additionally, we calculated recurring forest disturbances by counting the number of degradation events each pixel has experienced, as defined above. We categorized this frequency over the analysed period of 23 years into three classes: never degraded, once or twice degraded, and degraded three or more times.

To gain a better understanding of forest degradation dynamics, we further analysed NDFI trajectories after forest disturbances. For this, we first selected all pixels that met two criteria: 1) undisturbed forest over three subsequent years, and 2) a degradation event in the fourth year, as defined above. For these pixels, we then calculated the change of the NDFI value between the fourth and sixth year. We classified positive changes as regrowth, negative changes as ongoing degradation, and constant values as stagnation (Figure 4). We calculated the areas of these classes for all national parks and for two periods: 2003–2011 and 2012–2020 (in relation to the year of the degradation event). Each national park was divided into a central and an edge zone by applying a 4 km border zone inward from the park boundaries.

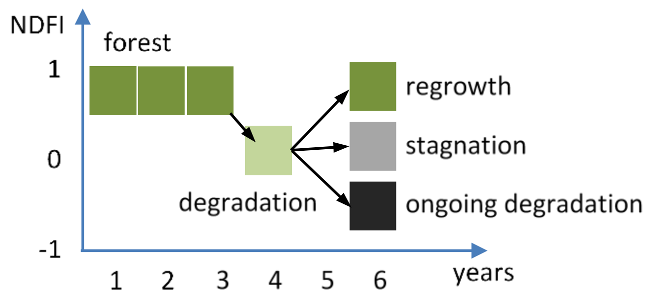


Figure 4: Scheme of post disturbance analysis.

Schéma de l'analyse après perturbation.

2.4.3 Quantification of forest loss

For the quantification of forest loss, we relied on the Global Forest Change dataset (version 1.10, Hansen et al. 2013). It has global coverage, with a spatial resolution of 30 m, and has been widely used in deforestation analyses. The dataset contains tree cover in the year 2000, encoded as a percentage, and annual tree cover loss for 2001–2022. Tree cover loss refers to the removal or mortality of tree cover and may result from various factors, such as mechanical harvesting, fire, disease, or storm damage. It is presented as binary data, i.e. either tree cover is lost or not. It should be noted that the data does not indicate if tree cover loss is temporary or permanent. Therefore, it should not be equated with FAO's definition of deforestation, which requires permanent land use change to occur (FAO 2020). Nevertheless, tree cover loss and derived forest loss data is an adequate proxy for deforestation due to its extensive documentation, error reporting, high overall accuracy, and consistency since 2001 (Burivalova et al. 2015).

In our forest loss analysis, we assumed that all areas with more than 25% tree cover were forest cover in 2000. This threshold is consistent with global land use and land change maps by Potapov et al. (2022a). We then removed all areas which had not been forest in 2000 from the annual tree cover loss data, thus ensuring that our forest loss estimates are conservative.

2.4.4 Quantification of forest fragmentation

Forest fragmentation refers to the process by which large, contiguous forested areas are broken up into smaller, isolated patches, often due to human activities such as urbanization, agriculture, or infrastructure development. This fragmentation results in the creation of smaller forest fragments surrounded by non-forest land or different types of land use. As a consequence, the connectivity and continuity of forest ecosystems are disrupted, leading to changes in habitat quality, species distribution, and ecological dynamics (Vieilledent et al. 2018).

To quantify forest fragmentation, we first calculated the size of individual forest fragments in 2000 and 2020. The forest extent for this was based on global land cover and land use data by Potapov et al. (2022a). We classified the forest fragments into six size classes: large core (>10 km²), medium core (1–10 km²), small core (<1 km²), islets (tiny forest patches of maximum 100 m width), perforations (forest gaps of at least 30 x 30 m), and edges (one pixel-wide, i.e. 30 m, border of forest to non-forest). We then calculated the total area of these classes for national parks and for the regions of Boeny and DIANA in 2000 and 2020.

2.4.5 Driver analyses for deforestation and forest degradation

While the remote sensing data utilized in the previous section enabled us to quantify forest degradation and loss, it did not identify the direct drivers of these changes. To address this challenge, we developed a systematic approach by intersecting various Analysis Ready Data products (Section 2.3) with our forest degradation and deforestation maps generated earlier. In our approach, we applied the decision tree depicted in Figure 5 to each pixel which, based on Hansen et al. (2013), was forested in the year 2000. The decision tree classified these pixels as either undisturbed forest or degraded/deforested by specific drivers (detailed below). We then aggregated and summarized the frequencies of the deforestation and degradation drivers for the different research areas.

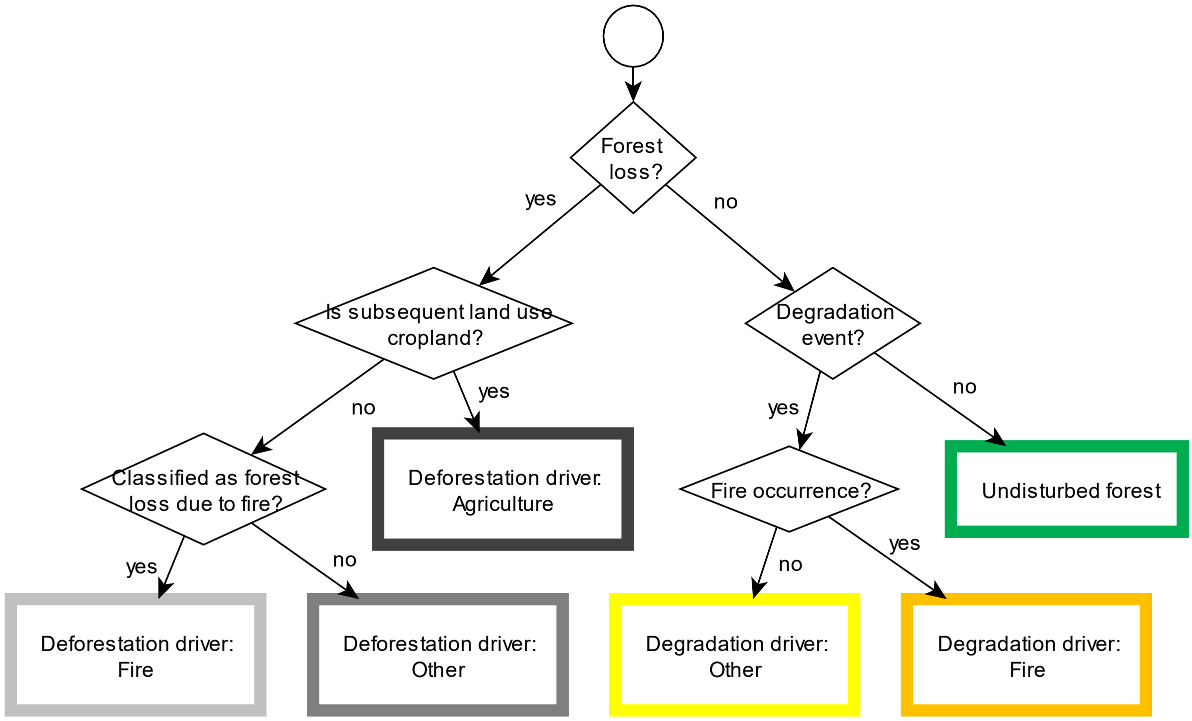


Figure 5: Decision tree for the driver analysis of deforestation and forest degradation. It was applied to each pixel which was forest in the year 2000.

Arbre de décision pour l'analyse des facteurs de la déforestation et de la dégradation des forêts. Il a été appliqué à chaque pixel qui était une forêt en l'an 2000.

In the following section, we describe the Analysis Ready Data products we used in detail and outline additional analyses we performed for specific drivers. It should be noted that we report results for the period of 2000 up to 2022, which did not match entirely the temporal availability of all datasets we used. While the forest loss and forest loss due to fire datasets were available until 2022, the NDFI and our additional cropland analysis ended in 2021. The global cropland dataset was analysed until 2019 and forest degradation due to fire until 2020.

2.4.5.1 Cropland expansion and forest conversion into cropland

We used a global cropland dataset (Potapov et al. 2022b) to identify deforestation attributed to agricultural expansion. In this dataset, cropland is defined as land used for annual and perennial herbaceous crops for human consumption, forage, and biofuel. It excludes perennial woody crops, permanent pastures, and shifting cultivation. The latter is achieved by applying a fallow limit of four years; areas with longer fallows are excluded from the cropland dataset. The data has a spatial resolution of 30 m and provide a global coverage. Cropland data were aggregated for the years 2000–2003, 2004–2007, 2008–2011, 2012–2015, and 2016–2019. The overall accuracy of the dataset was reported as high (Potapov et al. 2022b).

In addition to the main driver analysis described above, we distinguished between new cropland areas that originated from previously forested versus non-forested lands. This distinction was made by overlaying the annual cropland dataset on the forest area from the year 2000 from Hansen et al. (2013).

2.4.5.2 Identification of additional cropland converted from forest

The global cropland dataset we used has two limitations which are relevant for our study: shifting cultivation is excluded and cropland for Africa is generally underestimated due to spatial resolution limitations in mapping heterogeneous landscapes (Potapov et al. 2022b). A visual comparison of the cropland dataset and historical Google Earth Pro images confirmed that cropland area was indeed underestimated in our study regions.

To make our deforestation driver analysis more reliable, we carried out a land use analysis to identify additional cropland areas converted from forest. For this, we applied Random Forest, a machine learning algorithm based on decision trees (Breiman and Cutler 2022). We used the NDFI times series from 2000–2021 as predictor variables because different vegetation types and land uses have characteristic minimum and maximum NDFI values during an intra-annual change (Figure 2). For model training, we created a reference dataset which shows areas where forest has been converted to agriculture using high-resolution historical images from Google Earth Pro (Figure 6). We used 75% of the reference data to train the model and 25% for validation.

In line with the focus of our study, we trained a different Random Forest model for the area of each national park (including a 5 km wide buffer zone). It was not feasible to carry out a land use classification for the full extent of Boeny and DIANA, because creating a reference dataset would have been too time-consuming due to the large-scale absence of forests outside the national parks.

Figure 6: Exemplary reference data for the Random Forest model for additional cropland. White pentagon: transition from forest to cropland (Google earth historical imagery 2010, 2014, and 2023, location at 16°20’11’’ S, 46°52’24’’ E).

Données de référence exemplaires pour le modèle Random Forest pour les terres cultivées supplémentaires. Pentagone blanc: transition de la forêt aux terres cultivées (images historiques de Google Earth 2010, 2014 et 2023, localisation à 16°20'11'' S, 46°52'24'' E).

2.4.5.3 Forest loss due to fire

To identify deforestation attributed to fire, we use a dataset showing forest loss due to fire for the years 2000–2022 (Tyukavina et al. 2022). The authors used the tree cover loss dataset of Hansen et al. (2013) as a base to analyse where forest was lost to natural or accidental wildfires, such as escaped fires from slash-and-burn. Forest areas intentionally burned for shifting cultivation were not included in their analysis. The dataset has a spatial resolution of 30 m, provides a global coverage, and an annual temporal resolution. It should be noted that this dataset only has a moderate accuracy for Africa (Tyukavina et al. 2022), which should be taken into account when interpreting the results.

2.4.5.4 Forest degradation due to fire and fire frequency

To estimate areas of forest degradation due to fire, we could not rely on the dataset from Tyukavina et al. (2022) because it only records fires in areas where forest was lost. Instead, we utilized the more comprehensive burned area dataset from Long et al. (2021), which includes records of fires across all areas. This dataset combined different spectral indices to calculate the burned probability of each pixel using a machine learning approach. The resulting annual burned area maps have a spatial resolution of 30 m and provide a global coverage. Long et al. (2019) reported high overall accuracies for burned areas in different land cover types.

In addition to the main driver analysis described above, we calculated the fire frequency of all pixels which were classified as forests in 2000 (Hansen et al. 2013). For each pixel, we assessed if it has burned between 2001 and 2019, and if so, how frequently, based on the burned area dataset.

2.4.6 Estimation of the forest condition in 2023

To provide information about the current forest condition, we analysed forest degradation and loss for 2023 using specific NDFI thresholds, which we determined during our field observations (Section 2.2). The thresholds used were:

- Forest degradation in dry forests: NDFI < 0.25 (same value as detailed in Section 2.4.2.2),
- Forest degradation in mountain rain forests: NDFI < 0.5,
- Forest loss in dry forests: NDFI < -0.4,
- Forest loss in mountain rain forests: NDFI < 0.0.

Furthermore, we evaluated the regrowth in areas previously identified as degraded or deforested by intersecting these locations with the NDFI map of 2023. We assumed regrowth for all pixels with NDFI values above the set thresholds.

Following a recent update in June 2024, the tree cover loss dataset of Hansen et al. (2013) now also includes data for the year 2023 (version 1.11, GLAD 2024). This allowed us to additionally compare our NDFI-based estimates of forest loss with the tree cover loss dataset.

2.5 Reforestation and plantation development

We addressed reforestation supported by GIZ (Deutsche Gesellschaft für Internationale Zusammenarbeit) and GTZ (Deutsche Gesellschaft für Technische Zusammenarbeit) established between 1996 and 2014, and reforestation supported by KfW (Kreditanstalt für Wiederaufbau) under PLAE (Programme de Lutte Anti-Erosive) established afterwards. The following section gives an overview of the methods used in this work package and the underlying rationale. We addressed the underlying research questions in three separate steps (Figure 7):

1. We evaluated the development of the reforestation plots based on the development of crown cover.
2. We identified which environmental, socio-economic, and plot-related factors supported reforestation success, indicated by crown cover estimates. Using mixed effect models, we conducted these analyses for the whole dataset and for the GIZ- and PLAE-supported plantations in both Boeny and DIANA regions.
3. We identified promising future growth zones where both high crown cover values and high growth rates are likely. We then assessed whether these zones were available for future reforestation efforts.

In our analysis, we relied on the NDFI dataset described in Section 2.4.2.1. The advantage of this dataset is that it allows monitoring the development of vegetation cover through time with an almost annual resolution for all 13 901 reforestation plots established under GIZ- and KfW-supported PLAE programs between 2000 and 2021. However, linking NDFI values to existing forest inventory-based estimates of standing volume proved challenging due to the inconsistent quality of reference datasets. To tackle this issue, we estimated crown cover for all plots using existing data from selected plots elaborated in the ForestFlux study (Sirro et al. 2021).

Figure 7: Workflow for the analysis of reforestation development. A) describes the basis of the dataset, B) describes how factors contributing to reforestation success were identified, and C) describes the output for identifying future growth zones.

Flux de travail pour l'analyse du développement du reboisement. A) décrit la base du jeu de données, B) décrit comment les facteurs contribuant au succès du reboisement ont été identifiés, et C) décrit le résultat de l'identification des futures zones de croissance.

2.5.1 Data preparation

We received ten different shapefiles, which we integrated into a single database, standardizing and merging them based on common attributes. We recorded for each plot polygon whether the reforestation was executed under a GIZ or PLAE program and the year of planting. When two plots overlapped, we assumed that these plots were reforested multiple times. In case of full overlaps, we included the year of the second reforestation. In case of partial overlaps, a third plot polygon consisting of the overlapping area was created with the first and second reforestation years. Since the AFAFI program in Ambilobé was executed by GIZ only recently, we categorized it separately and excluded it from the analysis.

Table 3: Number of polygons in different reforestation programs of GIZ/GTZ, PLAE, overlaps between both programs, and recent reforestations supported by the AFAFI project.

Nombre de polygones dans les différents programmes de reboisement GIZ/GTZ, PLAE, chevauchement des deux approches, et les reboisements récents soutenus par le projet AFAFI.

	Number of Plantation Polygons	
	Boeny	DIANA
GIZ - Green-Mad (1996–2014)	437	7 128
PLAE (2014–2019)	1 597	2 112
GIZ/GTZ-PLAE overlaps (1996–2019)	84	199
AFAFI (2019–2021) *not used*	0	2 627

The different datasets did not align perfectly. We, therefore, took precautions to achieve a clean and consistent dataset. First, all geoprocessing operations were executed with a two-meter buffer. This aligned plot borders in case of smaller deviations between two datasets and improved overall consistency. Second, we removed the remaining polygons from unresolved spatial overlaps according to fixed criteria: we deleted all polygons that were smaller than one NDFI pixel. Afterward, we removed all polygons with larger boundary inconsistencies, which we defined, after manual revision, by a shape area index larger than eight and an area smaller than 1 000 m².

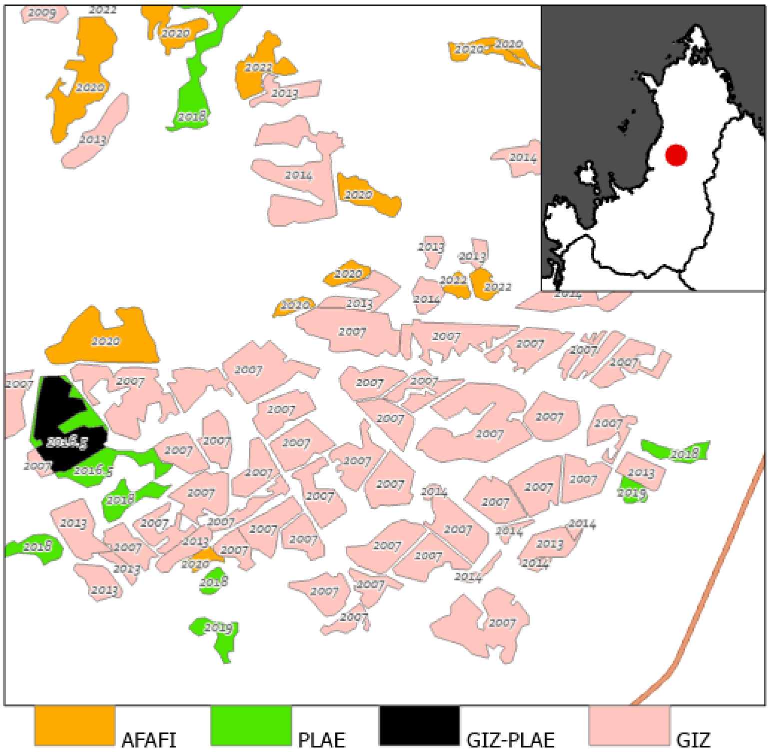


Figure 8: Example of merged plantation dataset. Different colours indicate different reforestation programs. Numbers in italics indicate the year of establishment.

Exemple d'un ensemble de données fusionnées sur les plantations. Les différentes couleurs indiquent les différents programmes de reboisement. Les chiffres en italiques indiquent l'année d'établissement.

2.5.2 Estimation of reforestation success

Compared to herbaceous vegetation, woody vegetation typically shows a lower variation between NDFI values at the beginning and end of the dry period. We utilized this information to create predictor variables for a Random Forest model (Breiman and Cutler 2022), which we used to estimate crown cover for each reforestation plot (Figure 8). We chose the Random Forest model because it is resistant to overfitting and can effectively handle large datasets. The model was trained using data from the Forest Flux Study by Sirro et al. (2021), which estimated crown cover for approximately 1 000 plots using high-resolution remote sensing images for 2015 and 2021. We used these crown cover values as the outcome variable in our Random Forest model. As predictor variables, we included NDFI at the start of the dry season, NDFI at the end of the dry season, and the difference between these values, for each year. Due to incomplete NDFI image coverage, we developed three different models based on data availability:

- For full data availability: $\text{CrownCover} \sim \text{NDFI}_{\text{start dry season}} + (\text{NDFI}_{\text{start dry season}} - \text{NDFI}_{\text{end of dry season}})$ ($R^2 = 39\%$)
- For missing end of dry season values: $\text{CrownCover} \sim \text{NDFI}_{\text{start dry season}}$ ($R^2 = 20\%$)

- For missing start of dry season values: CrownCover ~ $NDFI_{\text{end of dry season}}$ (R^2 = 19%)

Using modified values from Sirro et al. (2021), we categorized crown cover based on the condition of various reforestation plots (Figure 9). We used these estimates to quantify the area covered by each crown cover class throughout the reforestation period. In May 2024, we validated crown cover classes obtained for 2023 in the field (Section 2.2). Crown cover values for plots younger than two years were considered unreliable and thus disregarded (Sirro et al. 2021).

Low to no crown cover (0–10%)	**Low crown cover (10–20%)**
	
Almost no trees are found; any detected crown cover is probably due to the noise of existing vegetation.	Only a few individuals are found; they are detectable by remote sensing.
Moderate crown cover 20–60%	**High crown cover 60%+**
	
Denser and more mature trees; tree cover usually encompasses only part of the plot.	High-density crown and vegetation cover across the entire plot.

Figure 9: Examples of crown cover classes with corresponding crown cover values, including a short description.

Exemples de classes de couvert forestier avec les valeurs correspondantes pour le houppier, accompagnés d'une brève description.

2.5.3 Reforestation success indicated by crown cover development on RVI plots

Our analysis recognizes the high dynamics due to short rotations of approximately 5–11 years of the RVI plots (BIODEV 2020; Rasoanaivo 2014; Richter and Andriampiolazana 2023). To take this into account, we based our analysis on two proxies (Figure 10):

1. Maximum crown cover values in the first rotation (5–11 years): We assumed these values represent the crown cover before harvesting. To calculate this indicator, we averaged the two highest crown cover values recorded annually during the first rotation. We then classified these maximum values into the four crown cover classes described above and calculated the total area covered by each class. The

purpose of this indicator is to assess the extent of forest cover establishment on each plot, irrespective of growth rates and rotation length.

2. Crown cover increases: For each year, we estimated the annual percentual increase of crown cover. We replicated this for NDFI found at the start and end of the dry season. We grouped this analysis into three time steps: (a) before reforestation (only NDFI values), (b) the first seven years after reforestation, and (c) for all subsequent years. We distinguished between Boeny and DIANA as well as PLAE and GIZ reforestation. This indicator describes whether or not reforestation led to an increase in tree cover.

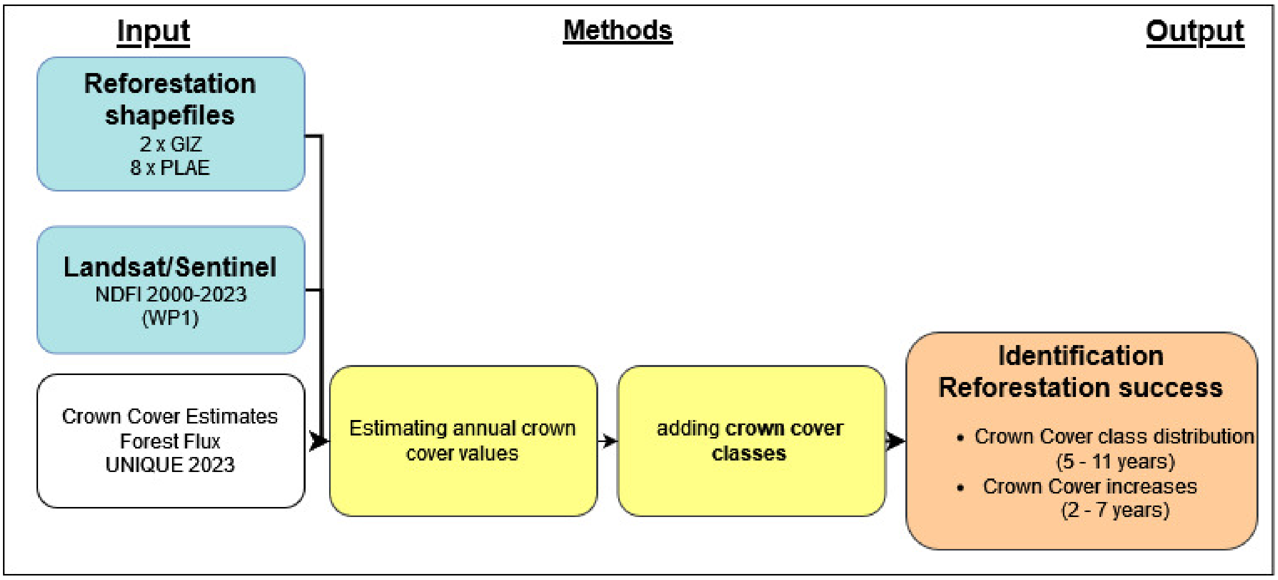


Figure 10: Simplified workflow for the quantification of reforestation success distinguishing between input data (blue), processing steps (yellow) and output (orange).

Flux de travail simplifié pour la quantification du succès du reboisement, distinguant les données d'entrée (bleu), les étapes de traitement (jaune) et les résultats (orange).

2.5.4 Identification of reforestation success drivers

We tested which environmental, socio-economic, and reforestation-related factors determined the success of reforestation and whether outcomes were different for PLAE and GIZ plantations (Figure 11). As outcome variable and proxy for plantation performance, we used crown cover and its development over time. Hence, we relied on repeated measurements and included one observation for each year for plot ages between 2 and 7 years. We chose mixed linear models that allowed us to address the dynamics of crown cover values in time and space on different levels (Zuur et al. 2009).

We replicated this model for

1) The complete dataset
2) Four subsets:
   a. GIZ plantations in DIANA
   b. PLAE plantations in DIANA
   c. GIZ plantations in Boeny
   d. PLAE plantations in Boeny

The first model informed about the overall effects found for the whole dataset. Each of the four other models informed about specific effects for the respective reforestation program and region.

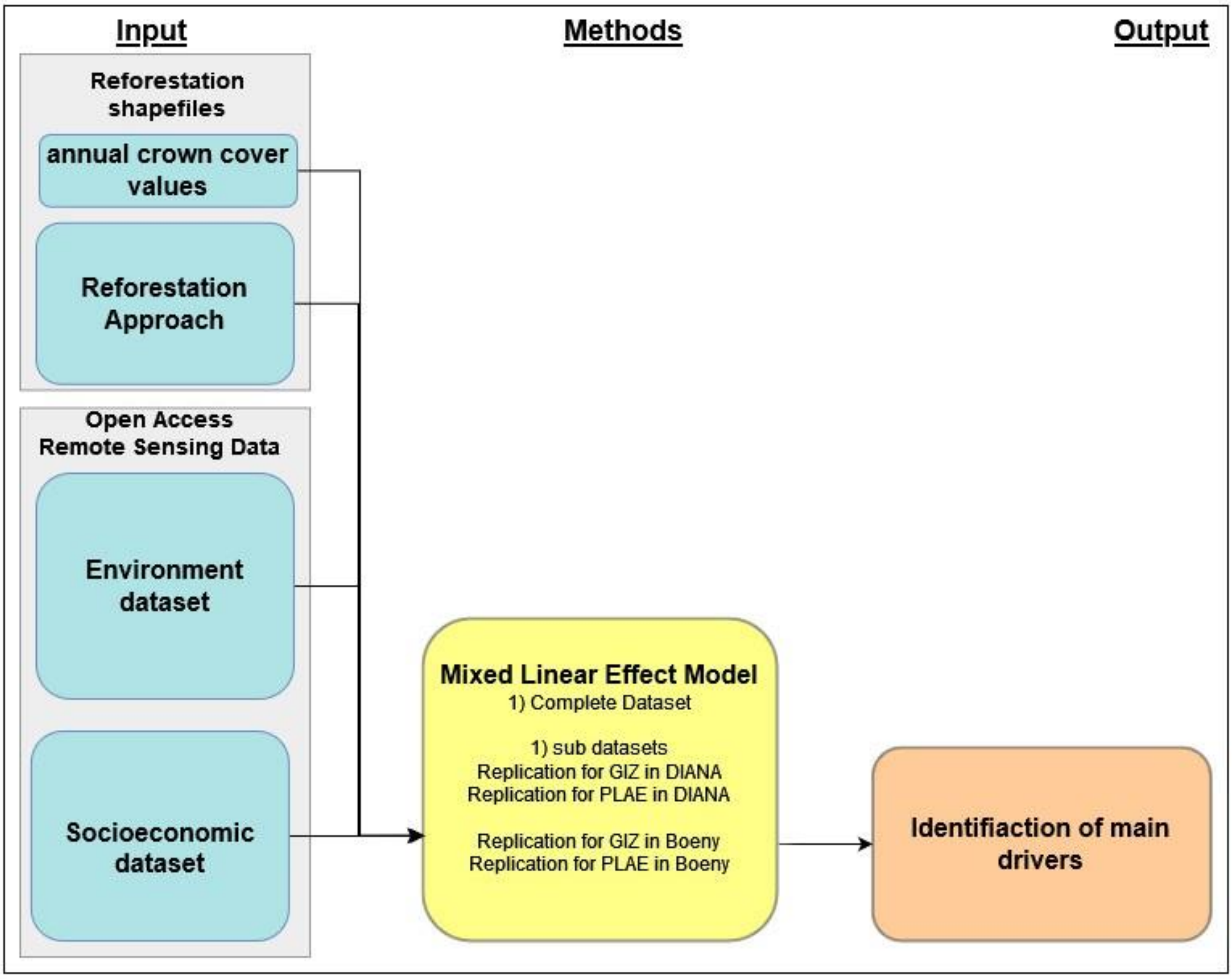


Figure 11: Simplified workflow for the identification of drivers of reforestation success distinguishing between input data (blue), processing (yellow) and output (orange).

Flux de travail simplifié pour l'identification des facteurs de succès du reboisement, distinguant les données d'entrée (bleu), le traitement (jaune) et la sortie (orange).

Prior to the analysis, we observed differences on plots in close proximity to each other. Individual landowners, for example, choose different management practices, including different rotations lengths and planting densities. To account for these dynamics in the dataset, we used mixed effect models. These mixed effect models allow to differentiate between fixed and random effects. Fixed effects describe the influence of quantifiable explaining variables (Table 4). Random effects can be used as a proxy for variables that are difficult or impossible to measure directly (Zuur et al. 2009). We included the plot as a random intercept and the plot age as a random slope. This approach allowed the model to account for variance within different plots due to specific starting conditions (random intercept), growth rates (random slope), and fluctuations in crown cover.

All variables were measured in different units, which challenges the comparison of their relative influence. To address this, we standardized all variables to a mean of zero and a standard deviation of one. Furthermore, we log-transformed slope, altitude, plot size, population density and distance from roads to approximate a normal distribution. We tested for collinearity between the different variables and excluded all variables that led to a variance inflation factor exceeding 3.

Table 4: Chosen variables to explain crown cover. Interaction variables (Age x Plantation Program[1] and Age x Second reforestation) indicate whether age's influence on the crown cover depends on a second reforestation and the program.

Variables choisies pour expliquer le couverture forestière. Les variables d'interaction (âge x programme de plantation[1] et âge x deuxième reboisement) indiquent si l'influence de l'âge sur la couverture forestière dépend d'un deuxième reboisement et du programme.

Indicator	Method	Justification and underlying questions
Socio-Economic Factors		
Population density within a 5 km buffer	Moving average of population densities in 2020 in a 5 km buffer calculated with ArcGIS and resampled to 200 m (CIESIN 2018).	A higher population increases land-use pressure and woodfuel demand. Is crown cover in populated areas higher?
Distance to roads (km)	Distance from plot to primary or secondary roads calculated with ArcGIS and resampled to 200 m (Worldbank 2017).	Proximity to primary or secondary roads indicates accessibility. Is crown cover close to roads higher?
Distance to larger cities (km)	Distance from plot to the seven largest towns calculated with ArcGIS and resampled to 200 m (SAHIMS 2006).	Short transportation distances to larger cities improve the marketability of woodfuel or timber products. Is crown cover close to larger cities higher?
Environmental Factors		
Crop water deficit (mm/year)[1]	Amount of water by which potential evapotranspiration exceeds actual evapotranspiration, resampled to 200 m (MadaClim 2014).	Does lower water availability lead to lower crown cover?
Simplified soil types	Plots were either assigned to a defined group (1. ferrallitic soils, 2. moderately developed soils, or 3. ferruginous soils; 85% of all observations) or to “other” (including vertisols, podsols, sedimentary soils; 15% of all observations) (Delenne and Pelletier 1981).	Is the crown cover influenced by the soil type and its associated characteristics?
Slope (°) and altitude (m)	Altitude (Farr et al. 2007) and derived slope resampled to 200 m.	Topographic factors indicate water storage, erosion risk, and sunlight availability. Which topographic conditions influence crown cover?
Fire frequencies	We counted a fire for the plot if it was registered on at least 25% of the plot area for that year, based on data from Long et al. (2021) if available, otherwise from Giglio et al. (2015).	Are (repeated fires) a challenge for reforestation success?
Management Factors		
Age	Age of the plot, based on reforestation shapefiles.	Does crown cover increase with time?
Plantation program[1]	Last reforestation was carried out by PLAE or GIZ.	Has the plantation been supported by PLAE or GIZ?
Age x plantation program[1]	Interaction term of age and reforestation program.	Does the annual crown cover increase depend on the reforestation program?
Second reforestation	The plot was reforested a second time by one of the two programs, based on shapefile overlaps.	Assuming reforestation was unsuccessful, does a second reforestation have positive impact?
Age x second reforestation	Interaction term of age and a possible second reforestation.	Does annual crown cover increase change after a second reforestation?

[1]Climatic water deficit and plantation program were only tested in the overall model.

We compared the quality of the different models through explained variance in crown cover as a percentage based on the statistical measure R^2. This was explained both through fixed factors alone and through the combination of fixed and random factors using the R-package MuMiN (Bartoń 2013). Additionally, we quantified the variance that environmental, socio-economic, or reforestation approach variables can each explain by running the model separately with only one subset of variables at a time.

We acknowledged that our results for fire frequency, which suggested that higher fire frequencies led to higher crown cover, are counterintuitive. Therefore, we explored this relationship in detail by examining the distribution of crown cover values of seven-year-old plots as a function of the number of fires since year zero. Additionally, in order to improve interpretation of the relationship between soil type and crown cover values, we plotted crown cover as a function of the soil type based on the model outcomes.

2.5.5 Proposition for future reforestation sites

Finally, we aimed to identify promising future reforestation zones (Figure 12). This was challenged by overall low crown cover, high variations in crown cover on small scales, and spatial predictors that only weakly explained crown cover distributions, as indicated by previous research and our model outcomes. We therefore adapted our approach by using a reduced dataset with only best performing plantations and more flexible Random Forest Models instead of the linear models. The detailed process is described below.

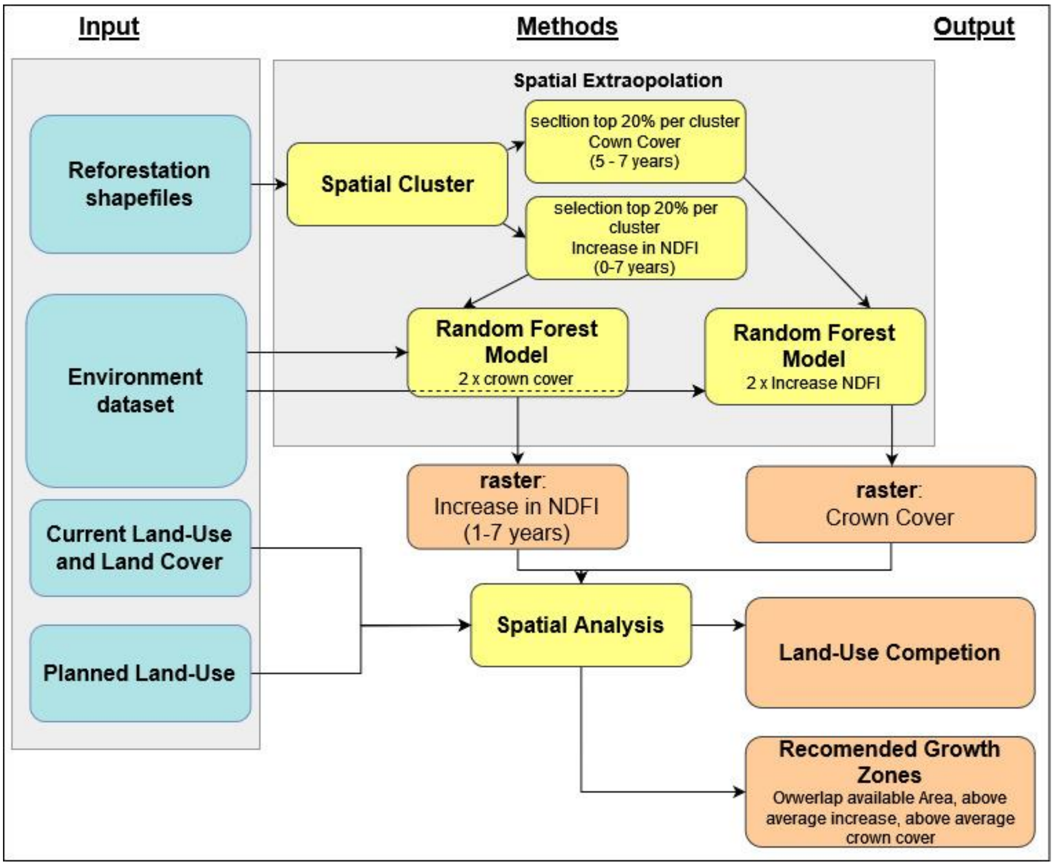


Figure 12: Simplified workflow for the extrapolation and identification of (1) reforestation potential, (2) future reforestation sites and (3) land-use competition distinguishing between input data (blue), processing (yellow) and output (orange).

Flux de travail simplifié pour l'extrapolation et l'identification (1) du potentiel de reboisement, (2) des futurs sites de reboisement et (3) de la concurrence en matière d'utilisation des terres, en distinguant les données d'entrée (bleu), le traitement (jaune) et la sortie (orange).

Step 1: Defining Area of Interest

Future reforestation aims to reduce pressure on natural forests. In alignment with this objective, we defined the direct peripheral zone of the park with a 2.5 km buffer from the park border, and the extended peripheral zone with a 2.5–7.5 km buffer (Figure 13).

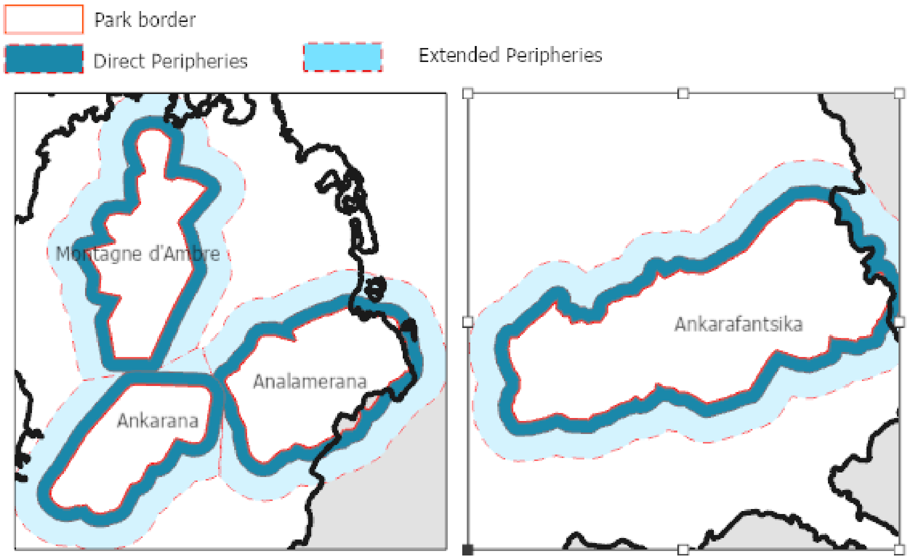


Figure 13: Priority areas for future reforestation around national parks to reduce human pressure. All priority areas were defined by 2.5 km and 2.5–7.5 km buffers.

Zones prioritaires pour le reboisement futur autour de la réduction de la pression exercée par les parcs nationaux. Toutes les zones prioritaires ont été définies par des zones tampons de 2,5 km et de 2,5-7,5 km.

Step 2: Extrapolation

We used two target variables for the extrapolation:

- **Maximum crown cover:** We estimated the maximum crown cover reached within one rotation period, assuming the plot is harvested between 5 to 7 years, followed by high dynamics. For this, we calculated the average of the two highest crown cover values recorded.
- **Increase in vegetation:** We used the increase of NDFI values at the end of the dry season for plots aged between 1 and 5 years as a proxy for crown cover increase. Plots with fewer than three observations within this timeframe were disregarded.

We aimed to identify recommendations for reforestation zones based on environmental conditions. Recognizing the large difference of crown cover within short distances, we only focused on the best-performing plantations. We grouped plots into 116 clusters based on spatial proximity and selected a subset of plots with the highest 20% of both NDFI increase and crown cover (Figure 14). Our outcomes, therefore, describe the ecological productivity in an area that could be theoretically obtained.

We used this dataset to develop models predicting crown cover and NDFI increase. For this, we used a Random Forest approach to allow for the interaction of predictor variables on multiple levels (Breiman and Cutler 2022). Extrapolations followed the workflow described by Lovelance et al. (2022). We allocated 90% of the observations in the dataset for model calibration and 10% for validation (Figure 15). Predictions were made independently for both DIANA and Boeny, resulting in four different Random Forest models—one for each region and for each target variable (i.e., crown cover and NDFI increase).

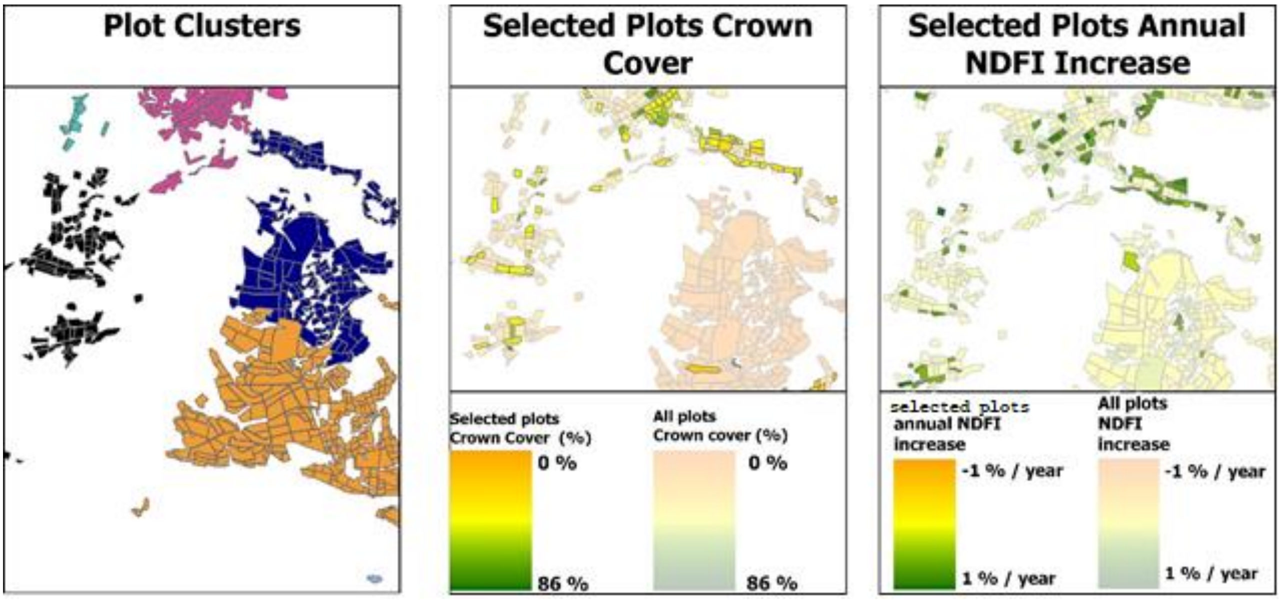


Figure 14: Example of selected best-performing plots for Boeny and DIANA (top 20%). Spatial clusters (left panel) are shown in different colours. In the mid and right panel, red to green colours indicate low to high crown cover and vegetation increase values; plots displayed in more transparent colours were rejected and plots in more opaque colours used for later modelling.

Exemple des parcelles les plus performantes sélectionnées pour Boeny et DIANA (20 % supérieurs). Les groupes spatiaux (panneau de gauche) sont représentés dans des couleurs différentes. Dans les panneaux du milieu et de droite, les couleurs rouge à vert indiquent les valeurs faibles à élevées du couvert forestrier et de l'accroissement de la végétation; les placettes affichées dans des couleurs plus transparentes ont été rejetées et les placettes dans des couleurs plus opaques ont été utilisées pour la modélisation ultérieure.

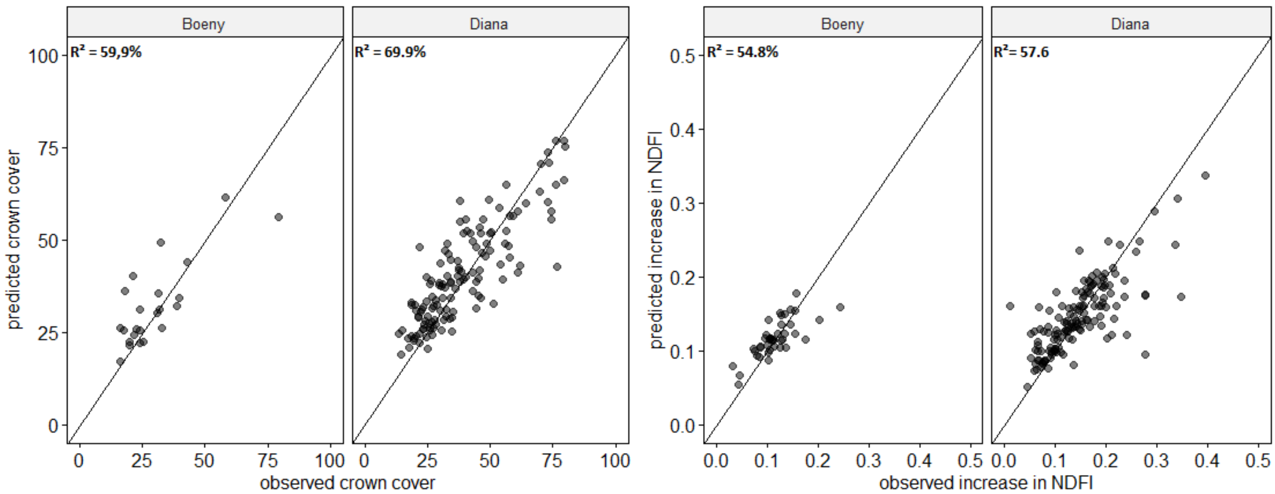


Figure 15: Validation of Random Forest models predicting canopy cover and NDFI increase in Boeny and DIANA, based on the 10% validation subsets.

Validation des modèles Random Forest prédisant le couvert forestier et l'augmentation de NDFI dans Boeny et DIANA, sur la base des sous-ensembles de validation de 10%.

After model training, we analysed the distribution of the predicted crown cover values within 1) the influence zones of the four national parks, and 2) different land use types, as established by local municipal land-use plans (Schémas d'Aménagement Communal (SAC); PGM-E/GIZ 2014).

Step 3: Exclusion of non-suitable areas

Next, we identified areas available for reforestation. We assumed that these were all areas not covered by the following land use/land cover classes:

a) All forest and tree cover (Zanaga et al. 2022)
b) Mangroves and wetlands (Zanaga et al. 2022)
c) Build-up areas (Zanaga et al. 2022)
d) Water bodies (Zanaga et al. 2022)
e) Agriculture (Potapov et al. 2022b)

All datasets were rasterized to a 200 m resolution in line with the explanatory variables (see Annex B for illustrations).

Furthermore, we identified all areas covered by a local SAC, assuming that only the following land uses specified in these plans permit future reforestation:

f) Pâturage (Pasture)
g) Savanne (Savanna)
h) Reboisement (Reforestation)

Step 4: Identification of zones with a high reforestation potential

Within the areas resulting from the previous steps, we identified zones with a high reforestation potential by finding overlaps of above-median crown cover and above-median NDFI increase in the output raster data. The median values were derived from the 20% subsets of best-performing plots, resulting in the following cut-off values:

- DIANA: 35.2% for crown cover and 0.14 per year for annual NDFI increase
- Boeny: 26.0% for crown cover and 0.11 per year for annual NDFI increase

As a guideline for future planning, we then produced maps of the location of these potential reforestation zones in Boeny and DIANA.

3 Results

3.1 Natural forests and forest landscapes

3.1.1 Potential forest degradation

The size of potentially degraded forest areas shows high annual fluctuations between 2000 and 2023, as exemplified for the region of Boeny (Figure 16, left; time series for the other research areas can be found in Annex E). To present trends more clearly, we calculated the average size of potentially degraded forest areas for two periods (2000–2010 and 2011–2023; Figure 16, middle and right). In Boeny, the size of the potentially degraded forest areas outside of national parks increased in the second time period. In DIANA, results for the first time period were unreliable due to high cloud cover, and therefore had to be excluded from the evaluation. Both regions have a similar size of potentially degraded forest areas in the second time period.

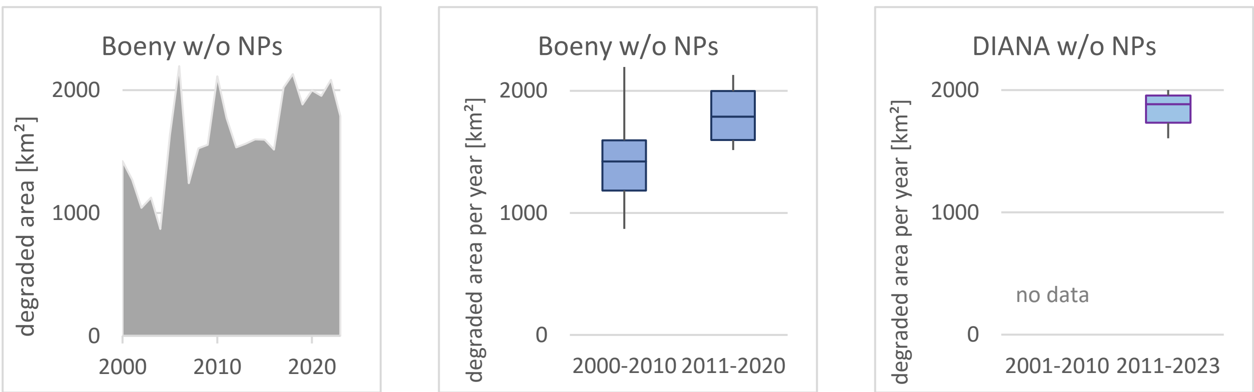


Figure 16: Time series and boxplots of the size of potentially degraded forest areas per region outside the national parks for two time periods. Boxplots show median, 1st, and 3rd quartile, whiskers show minimum and maximum.

Séries chronologiques et boîtes à moustaches de la taille des zones forestières potentiellement dégradées par région en dehors des parcs nationaux pour deux périodes. Les boîtes à moustaches indiquent la médiane, le 1er et le 3e quartile, les moustaches indiquent le minimum et le maximum.

In all national parks, the size of potentially degraded forest areas was constant between the first and second time period, with Ankarafantsika having the highest values (Figure 17). Fluctuations in the size of potentially degraded forest areas were particularly large in Boeny and Ankarafantsika during the first time period, as indicated by the large whiskers in the boxplot diagrams.

3.1.1.1 Recurring forest disturbances

Figure 18 shows the frequency classes of years with degradation events, i.e. years in which the NDFI value of a pixel was below the threshold of 0.25, for all pixels which have been classified as forest in 2000. For the centre zones, results strongly differ between national parks. In Montagne d'Ambre and Analamerana, most forest pixels in the centre zones experienced no degradation event, whereas in Ankarana, more than 50% of the forest area had three or more degradation events. Ankarafantsika's centre shows an equal distribution of the three frequency classes. Degradation events in the edges of Ankarafantsika, Montagne d'Ambre and Analamerana were more frequent than in the centres. In Ankarana, the difference between centre and edge was less pronounced.

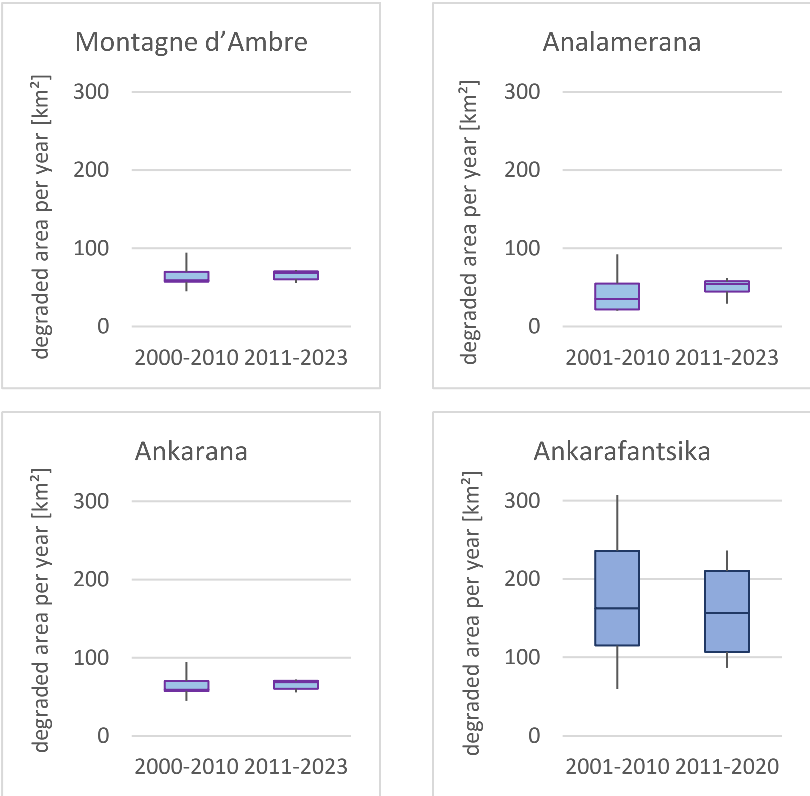


Figure 17: Boxplots of potentially degraded forest areas in national parks in two time periods. Boxplots show Median, 1st, and 3rd quartile, whiskers show minimum and maximum.

Boîtes à moustaches des zones forestières potentiellement dégradées dans les parcs nationaux sur deux périodes. Les boites à moustaches indiquent la médiane, le 1er et le 3e quartile, les moustaches indiquent le minimum et le maximum.

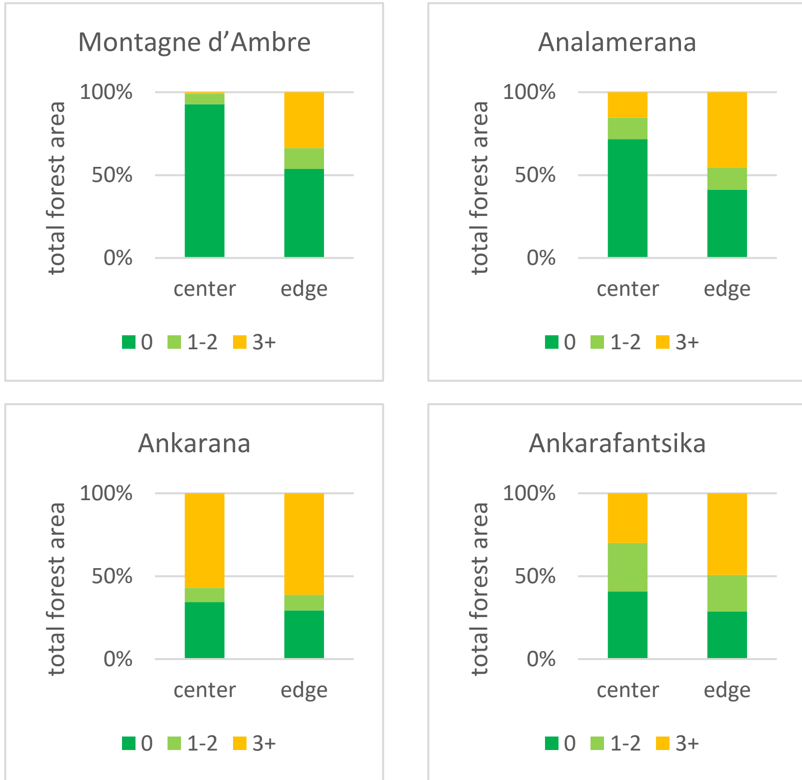


Figure 18: Frequency of years with degradation events in the centre and edge zones of national parks over 23 years (0 = zero years with a degradation event; 1-2 = one or two years with degradation events; 3+ = three or more years with degradation events).

Fréquence des années avec des événements de dégradation dans les zones centrales et périphériques des parcs nationaux sur 23 ans (0 = zéro année avec un événement de dégradation ; 1-2 = une ou deux années avec des événements de dégradation ; 3+ = trois années ou plus avec des événements de dégradation).

3.1.1.2 Post-disturbance analysis

Table 5 shows the total size of potentially degraded forest areas over all years in national parks. The area in the edge zones is larger than in the centre zones in DIANA's national parks. Ankarafantsika is largely affected by degradation events in both zones.

Table 5: Degraded areas in national parks.

Zones dégradées dans les parcs nationaux.

	Ankarafantsika		Montagne d'Ambre		Analamerana		Ankarana	
	Centre	Edge	Centre	Edge	Centre	Edge	Centre	Edge
Degraded areas [km²]	429	265	3	77	16	27	31	61

Figure 19 shows the post-disturbance analysis for all forest pixels which had 1) a degradation event, and 2) undisturbed forest in the three years previous to that event. The overall spatial and temporal trends are similar for all national parks. Degradation events were less often followed by regrowth, and more often by ongoing degradation, for edges compared to centres, and for 2012–2020 compared to 2003–2011.

In the first time period (2003–2011), most disturbance events are followed by regrowth of vegetation in the centres of Ankarafantsika and Montagne d'Ambre, with only small areas of progressive degradation and stagnation of vegetation. In contrast, there is less regrowth and more ongoing degradation and stagnation in the edge zones of all national parks. The difference between centre and edge zones is smaller in Ankarana and Analamerana than in Ankarafantsika and Montagne d'Ambre.

The second time period (2012–2020) shows much larger proportions of ongoing degradation in both centres and edges, particularly in Ankarana. Nevertheless, the trend of less regrowth and more ongoing degradation in edges compared to centres continues.

3.1.2 Forest loss

Annual forest loss showed strong fluctuations over time, as illustrated for DIANA (Figure 20, left; time series for the other research areas can be found in Annex E). To present trends more clearly, we calculated the average annual forest loss for two periods (2000–2010 and 2011–2022; Figure 20, middle and right). Outside of national parks, forest loss was higher in DIANA than in Boeny. It increased in both regions in the second decade, with a larger increase in DIANA than in Boeny.

With an area below 2 km², Ankarana, Analamerana and Montagne d'Ambre had relatively small annual forest losses (Figure 21). The loss was larger in Ankarafantsika, particularly in the second time period.

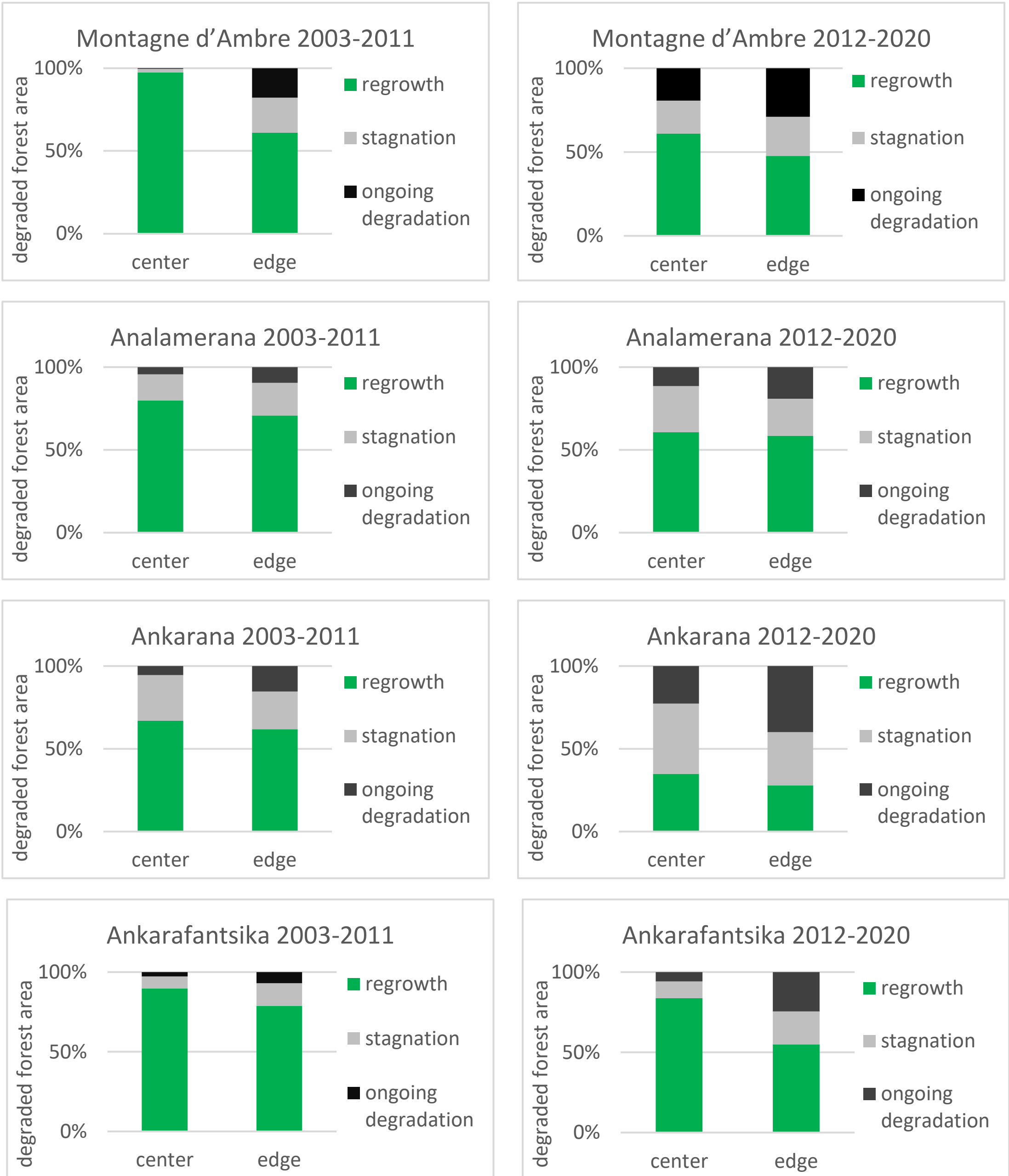


Figure 19: Development of forest areas after initial degradation events in national parks.

Développement des zones forestières après les premières dégradations dans les parcs nationaux.

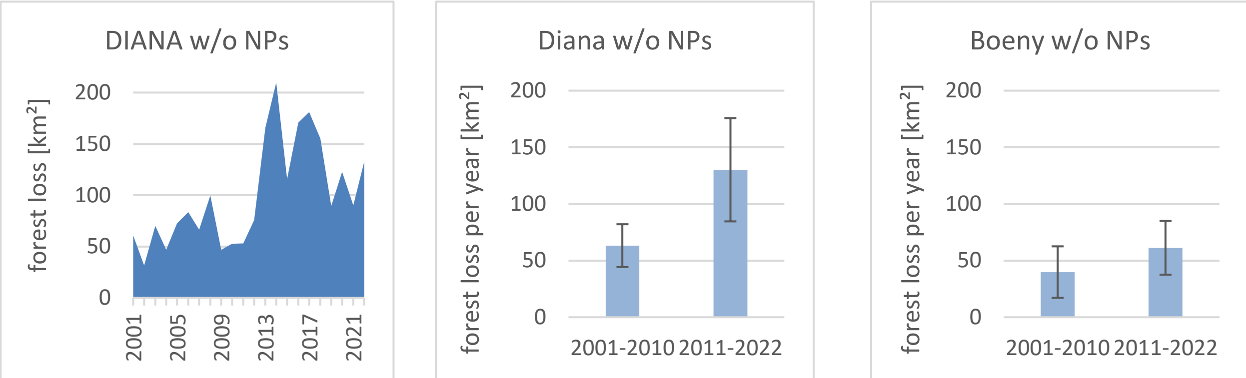


Figure 20: Time series of forest loss and average annual forest loss in regions outside the national parks for 2001–2010 and 2011–2022. Error bars show standard deviations.

Séries temporelles de la perte de forêt et de la perte annuelle moyenne de forêt dans les régions situées en dehors des parcs nationaux pour les périodes 2001-2010 et 2011-2022. Les barres d'erreur indiquent les écarts types.

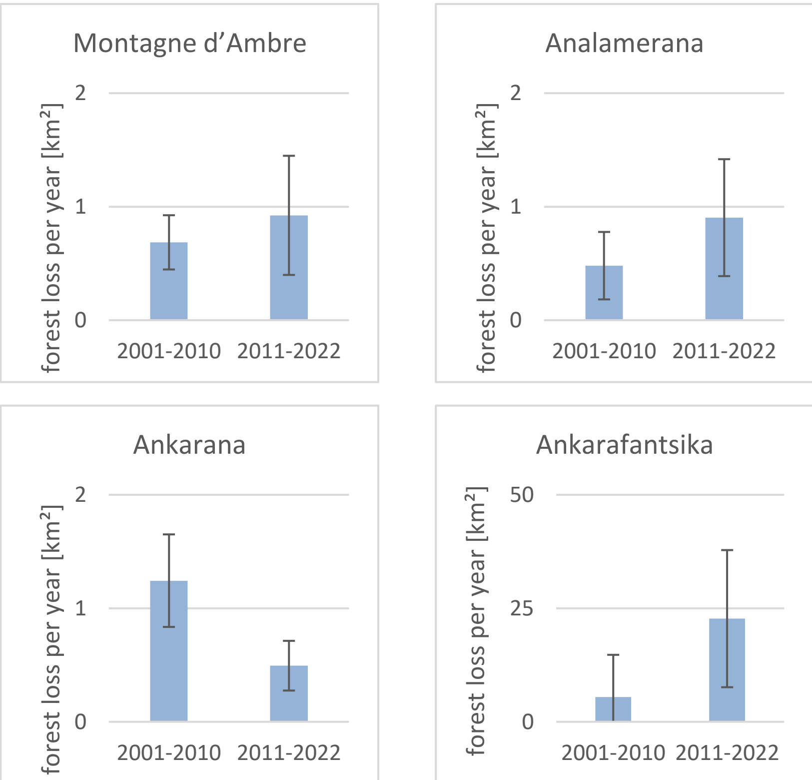


Figure 21: Average annual forest loss in national parks for 2001–2010 and 2011–2022. Error bars show standard deviations.

Perte annuelle moyenne de forêts dans les parcs nationaux pour les périodes 2001-2010 et 2011-2022. Les barres d'erreur indiquent les écarts types.

3.1.3 Forest fragmentation

Areas outside national parks had less large core forests and more small patches than areas inside national parks in both DIANA and Boeny (Table 6). In DIANA, 55% of the total forest area was found in large cores, in contrast to only 24% in Boeny. In both regions, the edge size outside national parks was large, which is typical for regions with high degradation.

Table 6: Area of forest fragment size classes [km²] and their percentages relative to the total forest area in 2000 in parentheses.

Superficie des classes de taille des fragments forestiers [km²] et leurs pourcentages par rapport à la superficie forestière totale en 2000 entre parenthèses.

Forest fragment size class	Montagne d'Ambre	Analamerana	Ankarana	DIANA w/o NPs	Ankarafant-sika	Boeny w/o NPs
core large	322 (81%)	221 (66%)	137 (63%)	3 727 (55%)	998 (86%)	1 053 (24%)
c. medium	1 (0%)	20 (6%)	3 (1%)	372 (6%)	18 (2%)	822 (18%)
core small	18 (5%)	27 (8%)	19 (9%)	731 (11%)	25 (2%)	928 (21%)
islet	8 (2%)	9 (3%)	9 (4%)	343 (5%)	5 (0%)	307 (7%)
perforation	8 (2%)	10 (3%)	19 (9%)	395 (6%)	61 (5%)	118 (3%)
edge	40 (10%)	48 (14%)	31 (14%)	1 149 (17%)	55 (5%)	1 252 (28%)

Overall, the greatest loss from 2000 to 2020 occurred in the large contiguous forest areas (Figure 22). In Boeny, the area of all forest fragment size classes decreased, indicating that larger patches are not only divided into smaller ones but that these smaller patches also eventually disappear. In DIANA, the increase of edge, small and medium core forest patches indicates that large core forests are divided, but continue to persist in smaller fragments.

In national parks, 63%–86% of the total forest area in 2000 is found in large cores, followed by the edge band (5%–14%). The largest change from 2000 to 2020 occurred in the area of large cores, which decreased by 4–51 km². Large core forest was lost or converted into more fragmented forests. In Montagne d'Ambre, the area of perforations (forest gaps enclosed by forest) increased, whereas in the other parks, the area of the fragment classes decreased or remained more or less stable.

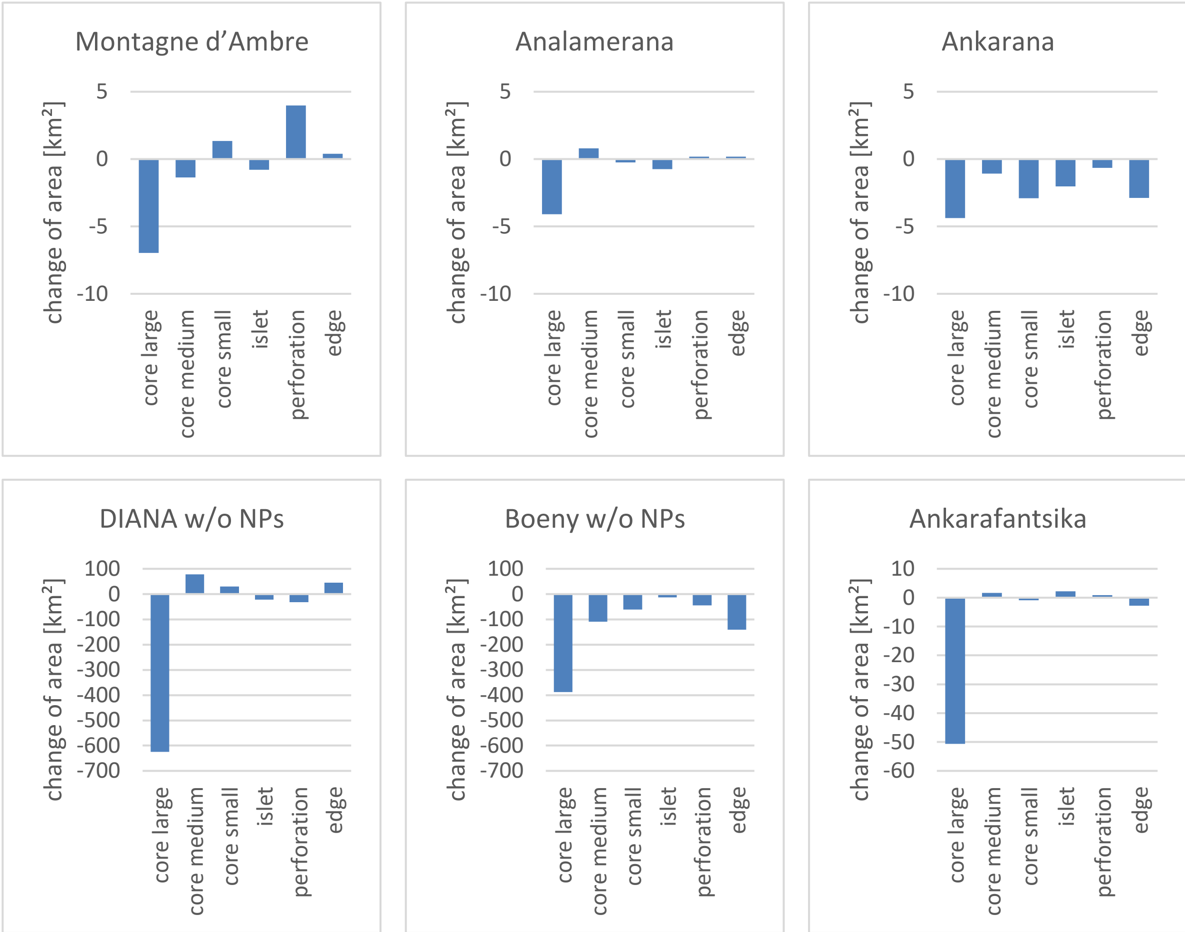


Figure 22: Area change of forest fragment size classes from 2000 to 2020 for national parks and regions without national parks.

Variation de la superficie des classes de taille des fragments forestiers entre 2000 et 2020 pour les parcs nationaux et les régions sans parcs nationaux.

3.1.4 Driver analyses for deforestation, forest loss and forest degradation

In this section, we first provide an overview of the temporal and spatial dynamics of the main drivers included in our analyses: cropland expansion, forest loss due to fire, and potential forest degradation due to fire. We then present the aggregated and summarized outcomes of our systematic approach to quantify the impact of the different drivers on forest loss and degradation. Subsequently, we translated these findings into a series of map products, detailed in Annex G, which show forest degradation and deforestation by driver for each region and national park.

3.1.4.1 Cropland expansion and forest conversion into cropland

In DIANA and Boeny, cropland expanded significantly outside national parks between 2003 and 2019, in areas previously classified as both forested and non-forested, according to the 2000 forest map. By 2019, the cropland area in previously forested land accounted for 294 km² in DIANA and for 105 km² in Boeny (Figure 23).

In Montagne d'Ambre, 71% of the total 2019 cropland area, equivalent to 8 km², was converted from previously forested land. Ankarana, which has the largest cropland area among the national parks, saw 21% of its cropland, or 8 km², also originating from forested land. In Analamerana, 13 km² of cropland existed, with one-third, or approximately 4 km², formerly forested. By comparison, in Ankarafantsika, 26% of the 2019 cropland area, amounting to 5 km², was converted from forested land (Figure 24).

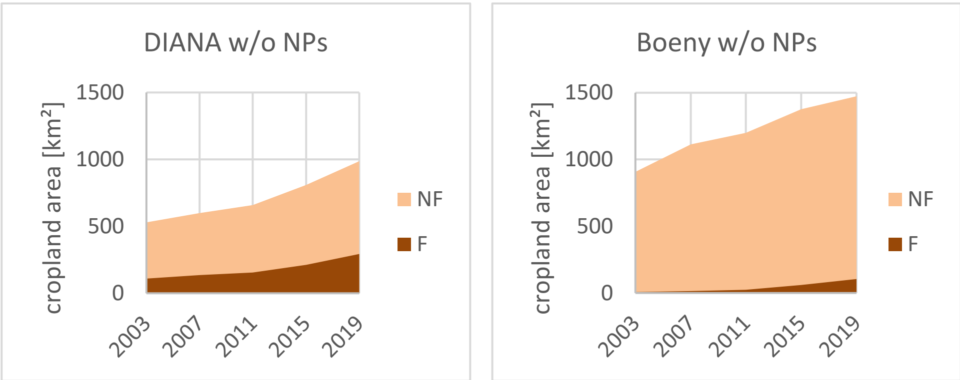


Figure 23: Cropland area outside national parks. NF = cropland on previously non-forested land, F = cropland on previously forested land.

Terres cultivées en dehors des parcs nationaux. NF = terres cultivées sur des terres précédemment non boisées, F = terres cultivées sur des terres précédemment boisées.

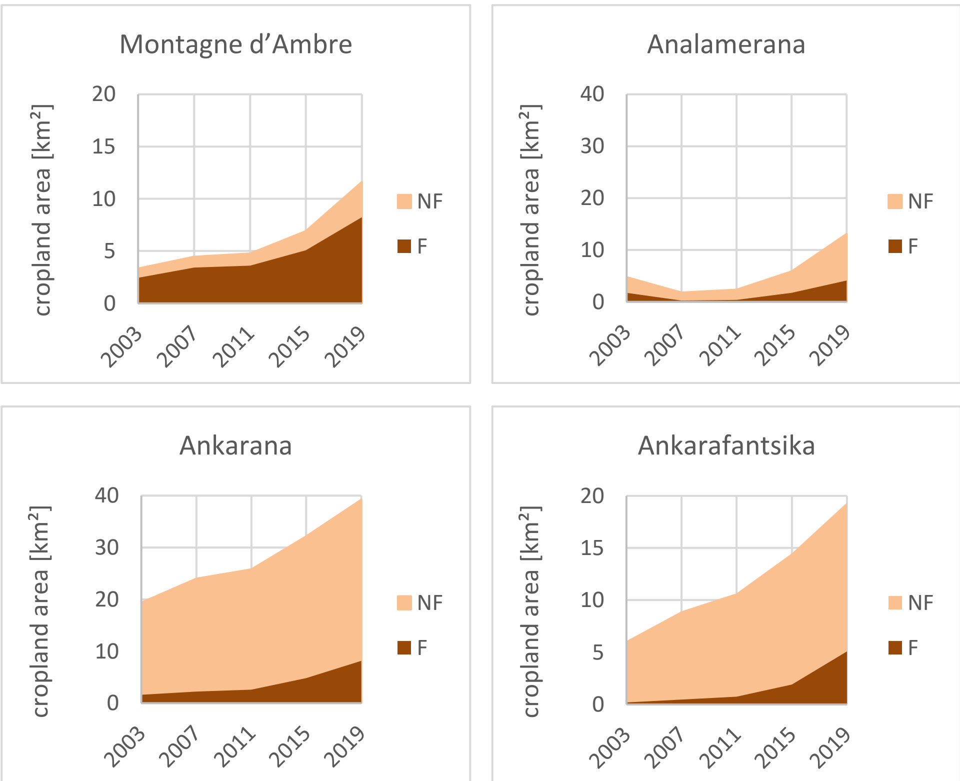


Figure 24: Cropland area in national parks. NF = cropland on previously non-forested land, F = cropland on previously forested land.

Superficie des terres cultivées dans les parcs nationaux. NF = terres cultivées sur des terres précédemment non boisées, F = terres cultivées sur des terres précédemment boisées.

For better comparability, the average annual cropland expansion between 2003 and 2019 relative to the total size of each research area is shown in Table 7. Outside national parks, the largest cropland expansion on previously non-forested land occurred in DIANA. In contrast, cropland expansion on forested land was comparable in both regions.

Compared to the cropland expansion outside national parks, the increase was notably smaller within Ankarafantsika and Analamerana, across both forested and non-forested lands. In Montagne d'Ambre, the expansion was also smaller compared to DIANA outside national parks, but the difference was less pronounced. In contrast, Ankarana experienced significantly higher cropland expansion than DIANA on non-forested lands, and slightly higher expansion on forested lands.

Table 7: Average annual cropland expansion in forest (F) and from non-forest areas (NF), relative to the land area [km²/1000 km² per year].

Expansion annuelle moyenne des terres cultivées dans les forêts (F) et dans les zones non forestières (NF), par rapport à la superficie terrestre [km²/1000 km² par an].

	Ankarafantsika	Montagne d'Ambre	Analamerana	Ankarana	Boeny w/o NPs	DIANA w/o NPs
F	0.3	0.8	0.4	1.4	1.2	1.3
NF	0.9	1.4	1.0	4.2	1.2	2.3

It should be noted that the results presented in this section are based on the global cropland dataset (Potapov et al. 2022b) to ensure comparability between regions. For the areas of the national parks and their peripheral zones, the results from our analysis of additional cropland expansion are presented in the following section.

3.1.4.2 Identification of additional cropland converted from forest

The creation of reference data for our land use classification varied in effectiveness across different national parks. In Ankarafantsika and Ankarana, it was possible to identify cropland converted from previously forested land, which was used to train the Random Forest models. In Montagne d'Ambre, we used cropland areas that were suitable for model training but were not covered by trees in the reference year of 2000. Therefore, all cropland was classified into one category. In Analamerana, we could not apply a Random Forest model because we found no additional cropland in satellite images beyond what had already been classified by Potapov et al. (2022b). The confusion matrices demonstrate that our Random Forest classification models achieved high accuracy and precision (Annex F).

Comparing the global cropland dataset of Potapov et al. (2022b) and our classification results allowed us to identify additional agricultural land that was previously unclassified. Figure 25 illustrates this for an area on the southern border of Ankarafantsika, which has a high level of agricultural activity within the national park. It should be noted that it is not possible to compare these results to cropland expansion in the entire regions of Boeny and DIANA because our Random Forest classification was conducted solely for the area of the national parks. Additionally, our reference data exclusively includes areas where forest land has been converted to cropland since 2001. However, the reference data does not inform whether these areas have been subsequently abandoned, maintained as permanent cropland, or converted to other land uses.

In Ankarafantsika and Montagne d'Ambre, the additional cropland areas identified by our Random Forest classification were particularly extensive, measuring 20.5 km² and 12.1 km², respectively. This was larger than the previously identified cropland by Potapov et al. (2022b). In contrast, the additional cropland area of 5.5 km² in Ankarana was relatively small compared to the previous classification (Table 8).

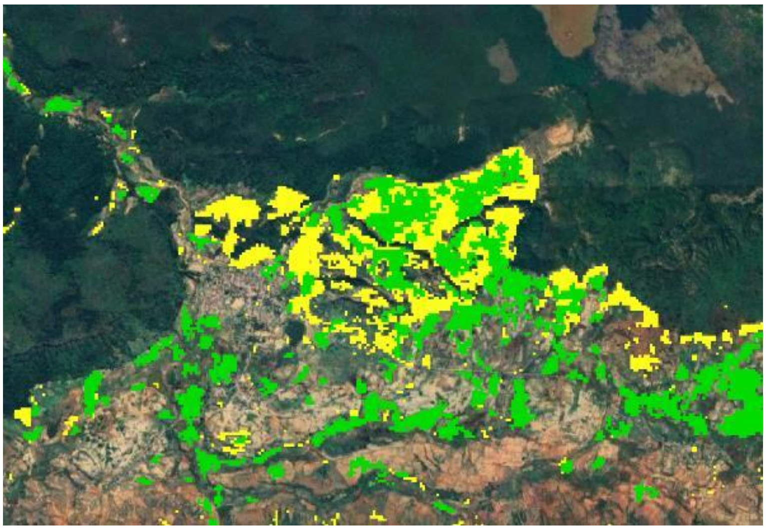


Figure 25: Illustrative comparison of areas identified as cropland (2000–2019) by Potapov et al. (2022b), shown in green, and additional cropland areas identified by our Random Forest classification (2000–2021), shown in yellow, near Andranofasika.

Comparaison illustrative des zones identifiées comme terres cultivées (2000-2019) par Potapov et al. (2022b), indiquées en vert, et des zones de terres cultivées supplémentaires identifiées par notre classification Random Forest (2000-2021), indiquées en jaune, près d'Andranofasika.

Table 9 shows the annual cropland expansion relative to 1 000 km² forest area. This relative increase translates to an annual loss of forest area due to cropland expansion amounting to approx. 1.2 km²/1 000 km² in Ankarafantsika, 0.9 km²/1 000 km² in Montagne d'Ambre, and 0.5 km²/1 000 km² in Ankarana.

Table 8: Extent of areas identified as cropland by Potapov et al. (2022b) and additional cropland areas identified by our Random Forest classification.

Étendue des zones identifiées comme terres cultivées par Potapov et al. (2022b) et zones de terres cultivées supplémentaires identifiées par notre classification Random Forest.

National Park	Total Cropland 2000–2019 [km²] (Potapov et al. 2022b)	Cropland conversion from forest [km²] (Potapov et al. 2022b)	Additional cropland 2000–2021 [km²]
Ankarafantsika	19.4	5.1	20.5
Montagne d'Ambre	11.6	8.2	12.1
Ankarana	39.2	8.1	5.5
Analamerana	13.1	4.1	Not applied

Table 9: Summary of yearly cropland increase in forests. Areas are in km² per 1000 km² of forest area per year.

Résumé de l'augmentation annuelle des terres cultivées dans les forêts. Les surfaces sont exprimées en km² pour 1000 km² de surface forestière par an.

	Ankarafantsika	Montagne d'Ambre	Ankarana
Annual increase of cropland (Potapov et al. 2022b)	0.3	0.8	1.4
Annual increase of additional cropland	0.9	1.2	0.5
Sum	1.2	2.0	1.9

3.1.4.3 Forest loss due to fire

In both regions, the forest area outside national parks lost due to fire was below 20 km² per year. In comparison, annual forest loss due to fire in Ankarafantsika was larger in multiple years, with peaks in 2007, 2016–2018, 2021, and 2022 (Figure 26). The national parks in DIANA are not displayed as their forest losses due to fire were below 0.25 km² per year.

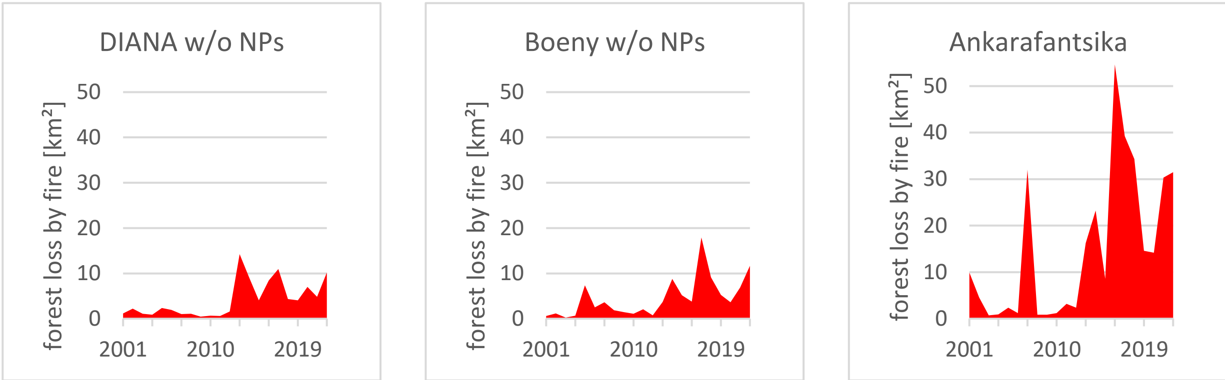


Figure 26: Forest loss due to fire.

Perte de forêts par le feu.

Only 1% to 9% of all forest losses in the observed regions and national parks were due to fire. An exception is Ankarafantsika, where fire played a major role, accounting for 57% of the forest loss (Table 10). Despite the low overall influence of fire on forest loss, there has been an increasing trend over the last decade.

Table 10: Ratio of the extent of forest loss due to fire to total forest loss. FLF: area of forest loss due to fire, FL: area of all forest loss.

Rapport entre l'étendue de la perte de forêt par incendie et la perte totale de forêt. FLF: superficie des pertes forestières par incendie, FL: superficie de toutes les pertes forestières.

	Ankarafantsika	Montagne d'Ambre	Analamerana	Ankarana	Boeny w/o NPs	DIANA w/o NPs
Ratio FLF:FL %	57%	4%	4%	4%	9%	4%

3.1.4.4 Forest degradation due to fire

The size of potentially degraded forest areas due to fire shows high annual fluctuations between 2000 and 2023, as exemplified for the region of DIANA (Figure 27, left; time series for the other research areas can be found in Annex E). To present trends more clearly, we calculated the average size of these degraded forest areas for two periods (2000–2010 and 2011–2023; Figure 27, middle and right).

Compared to DIANA, the annual forest area degraded due to fire outside national parks was larger in Boeny, along with a higher variability across years (highlighted by the wider range between the 1st and 3rd quartiles, as well as between the minimum and maximum values). An increasing trend in forest degradation due to fire is evident in both regions from the first to the second period. On average, 23% of the forest area outside national parks in DIANA was degraded by fire annually, compared to 10% in Boeny.

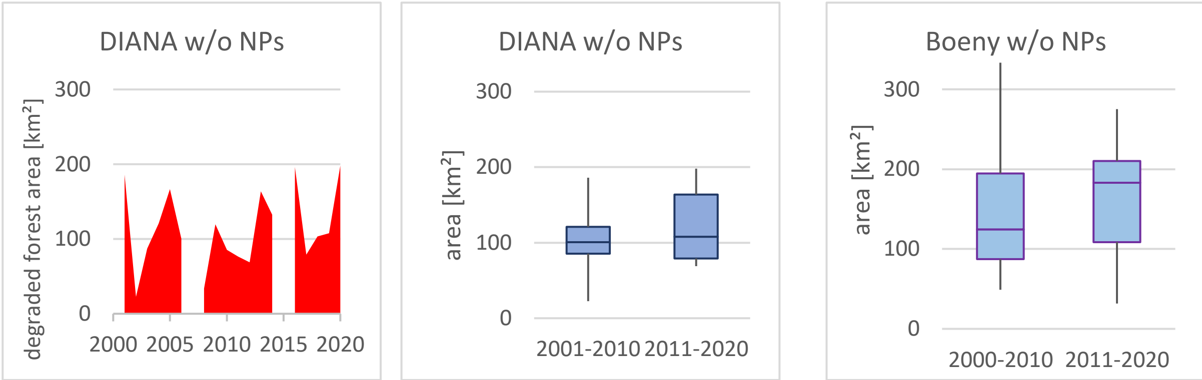


Figure 27: Time series and boxplots of the size of the forest area degraded due to fire per region outside the national parks. Boxplots show Median, 1st, and 3rd quartile, whiskers show minimum and maximum.

Séries temporelles et boites à moustaches de la taille de la zone forestière dégradée par le feu par région en dehors des parcs nationaux. Les boites à moustaches indiquent la médiane, le 1er et le 3ème quartile, les moustaches indiquent le minimum et le maximum.

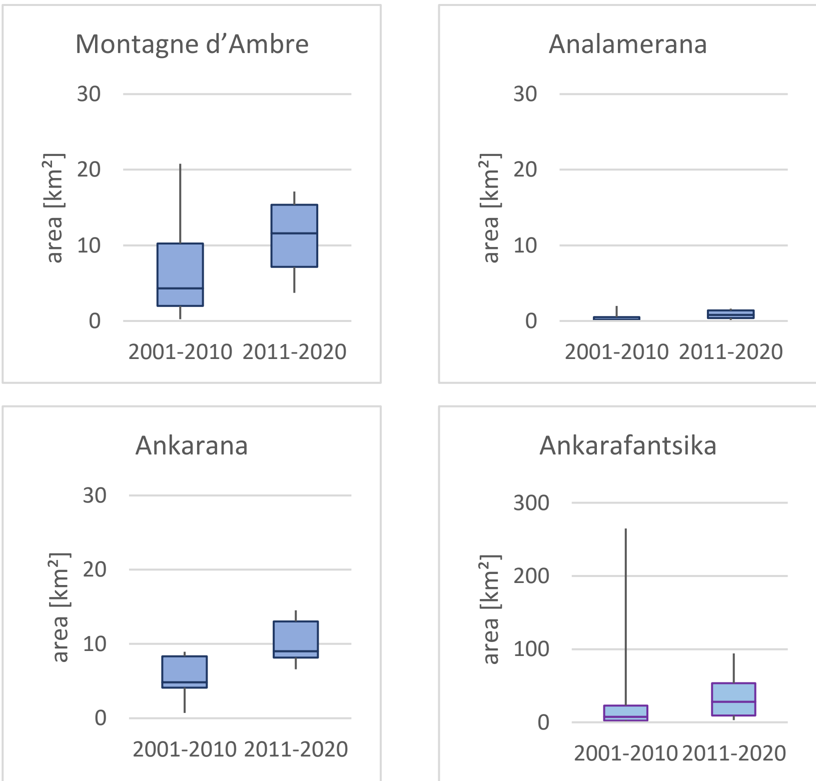


Figure 28: Boxplots of the size of the annual forest area degraded due to fire in national parks. Boxplots show Median, 1st, and 3rd quartile, whiskers minimum and maximum.

Boîtes à moustaches de la taille de la zone forestière annuelle dégradée par le feu dans les parcs nationaux. Les boites à moustaches indiquent la médiane, le 1er et le 3e quartile, les moustaches le minimum et le maximum.

Particularly in Montagne d'Ambre and Ankarana, the extent of forest degradation due to fire increased from the first to the second period. In contrast, fires played a negligible role in forest degradation in Analamerana. In Ankarafantsika, the forest burned extraordinarily in 2006, as represented by the high peak of the maximum whisker in the boxplot diagram (Figure 28).

3.1.4.5 Fire frequency in forests

In both regions, most of the forests did not burn during the observed period (81% in Boeny, 88% in DIANA; Figure 29). The proportion of forests that burned was slightly higher in Boeny than in DIANA. In Boeny, 9% of the forests burned once, 5% burned twice, and 5% burned three times or more. In DIANA, 8% of the forests burned once, while 2% burned twice, and another 2% burned three or more times.

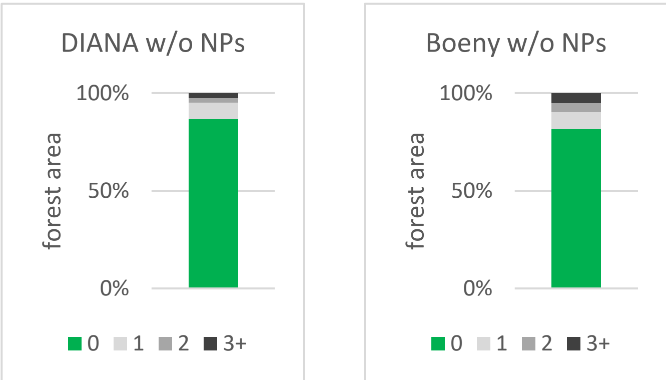


Figure 29: Fire frequency outside national parks in Boeny and DIANA between 2001 and 2019 for all pixels classified as forests in 2000 (Hansen et al. 2013). The frequency is classified as follows: 0 for never burned, 1 for once, 2 for twice, and 3+ for three or more times within the 19-year period.

Fréquence des incendies en dehors des parcs nationaux dans Boeny et DIANA entre 2001 et 2019 pour tous les pixels classés comme forêts en 2000 (Hansen et al. 2013). La fréquence est classée comme suit: 0 pour jamais brûlé, 1 pour une fois, 2 pour deux fois, et 3+ pour trois fois ou plus au cours de la période de 19 ans.

All centres of national parks show large forest areas that either did not burn or burned only once (Figure 30). In the edges of DIANA's national parks, fires occured more frequently. In Ankarafantsika, the centre has a notably larger area that burned once, primarily due to the significant fire in 2006.

The total area of forests that burned varied between the national parks (Table 11). Large areas were affected by fire in the edge zones of Ankarafantsika and DIANA's national parks. In contrast, the areas affected by fire in the central zones of DIANA's national parks were small.

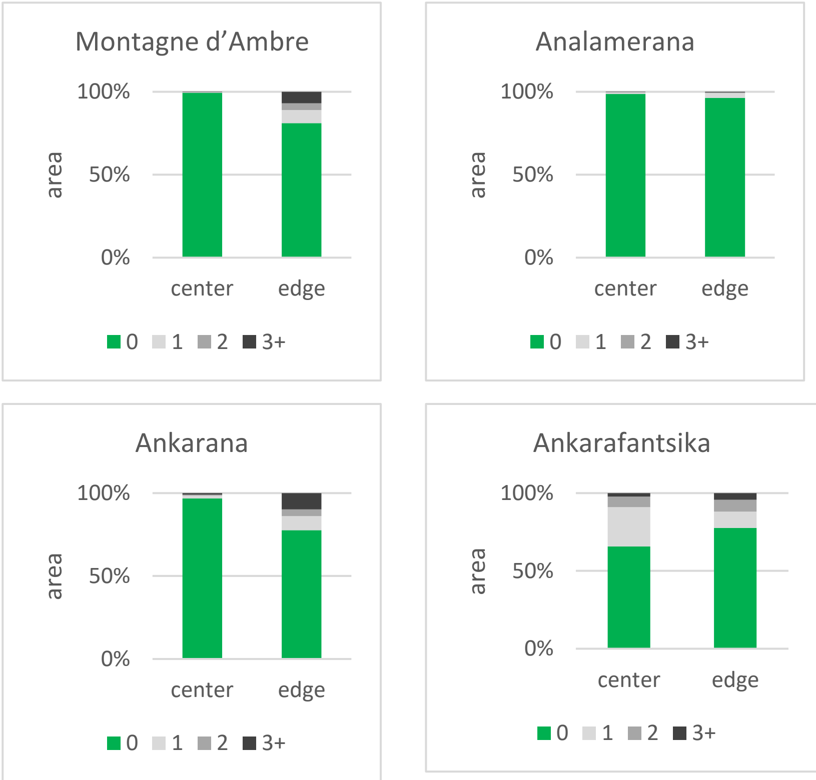


Figure 30: Fire frequency in national parks between 2001 and 2019 for all pixels classified as forests in 2000 (Hansen et al. 2013). Burned areas are distinguished between the central and edge zones. The frequency is classified as follows: 0 for never burned, 1 for once, 2 for twice, and 3+ for three or more times within the 19-year period.

Fréquence des incendies dans les parcs nationaux entre 2001 et 2019 pour tous les pixels classés comme forêts en 2000 (Hansen et al. 2013). Les zones brûlées sont distinguées entre la zone centrale et la zone périphérique. La fréquence est classée comme suit: 0 pour jamais brûlé, 1 pour une fois, 2 pour deux fois, et 3+ pour trois fois ou plus au cours de la période de 19 ans.

Table 11: Total area of forests that burned, accumulated over all available years [km²].

Superficie totale des forêts qui ont brûlé, accumulée sur toutes les années disponibles [km²].

Ankarafantsika		Montagne d'Ambre		Analamerana		Ankarana	
Centre	Edge	Centre	Edge	Centre	Edge	Centre	Edge
238	97	1	63	3	5	4	36

3.1.4.6 Summary of forest degradation and deforestation by drivers

To better interpret the influence of various direct drivers, we present an overview of the initial forest condition in 2000 (Figure 31) and the forest area that experienced forest loss or at least one degradation event (Figure 32). In our driver analyses, we aimed to exclusively include forest change which occurred between 2000 and 2022. Consequently, we excluded any forest pixels that were potentially degraded prior to this period. In 2000, all forest areas had a roughly similar proportion of undisturbed forest and potentially degraded forest, based on the NDFI threshold used in our analyses (Figure 31). Outside of national parks, 83% of the forests in DIANA and 73% in Boeny remained undisturbed. Within the national parks, the percentage of undisturbed forests ranged from 69% to 81%, with Montagne d'Ambre reporting the highest and Ankarana the lowest levels of undisturbed forests.

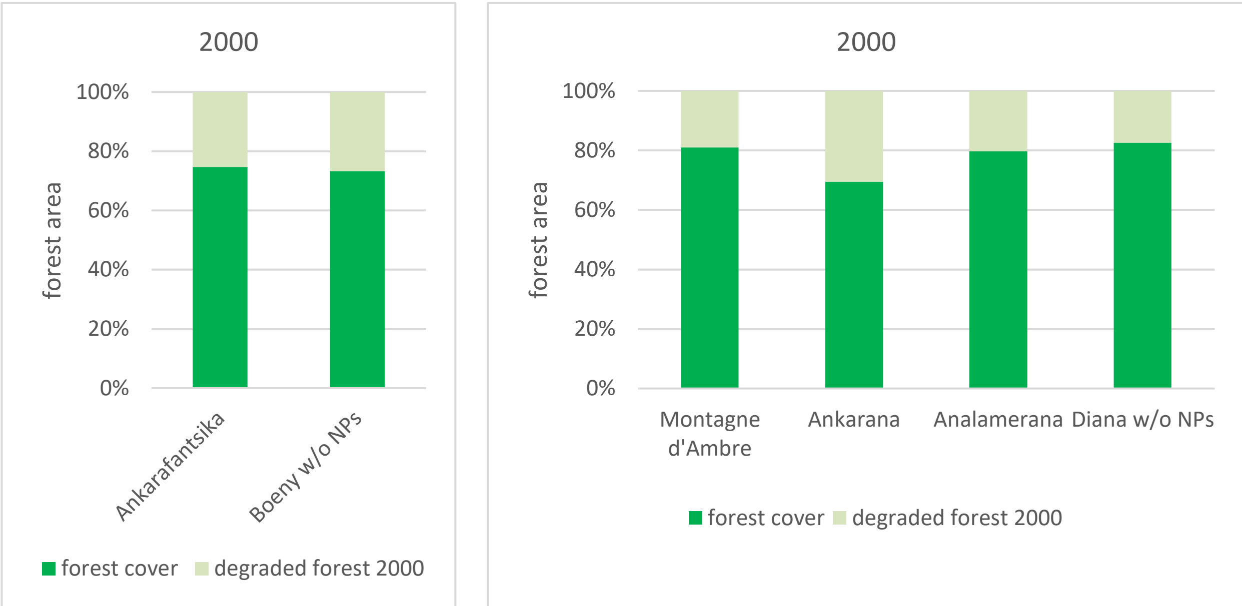


Figure 31: Initial condition of all pixels classified as forest in 2000, based on Hansen et al. (2013). Pixels with a NDFI value in 2000 below the degradation threshold used in our analyses are shown as degraded.

État initial de tous les pixels classés comme forêt en 2000, d'après Hansen et al. (2013). Les pixels dont la valeur NDFI en 2000 est inférieure au seuil de dégradation utilisé dans nos analyses sont indiqués comme dégradés.

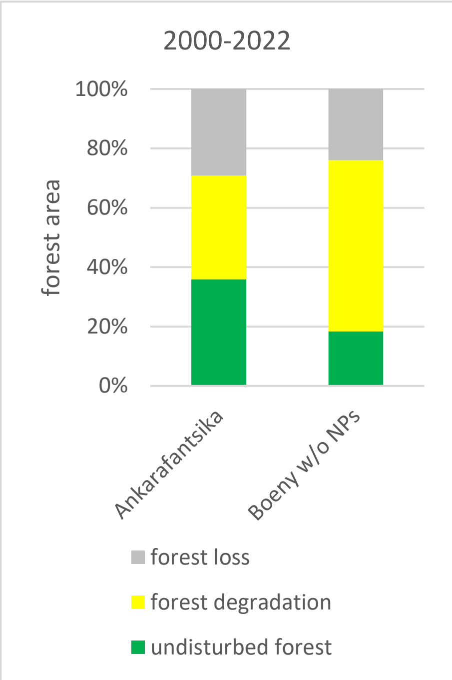
Outside national parks, both regions show large forest losses, with over 20% of the previous forest cover lost (ca. 2 000 km² in DIANA and 1 000 km² in Boeny; Figure 32). In contrast, forest loss due to fire was comparatively low, with almost 100 km² in both regions (Figure 33). Forest conversion to agriculture was more substantial, affecting nearly 300 km² in DIANA and 100 km² in Boeny.

By 2022, extensive forest areas were potentially degraded at least once, with over 3 200 km² affected in Boeny and over 4 400 km² in DIANA. Around 21% of Boeny's forest area from 2000 and 11% in DIANA were degraded by fire. A larger proportion of forest remained undisturbed in DIANA, at approximately 43%, compared to about 18% in Boeny.

In DIANA's national parks, the forest cover loss was less than 6%, significantly smaller than the losses outside the national parks. The main driver of forest loss in Montagne d'Ambre and Ankarana was agriculture, which only had a small impact in Analamerana. The forest loss in Ankarafantsika was much more extensive, with a total loss of 327 km², of which 186 km² were lost due to fire and 26 km² were converted to cropland.

The extent of areas with potential forest degradation varied considerably across national parks, ranging from 30% in Montagne d'Ambre to 67% in Ankarana. In contrast, forest degradation due to fire was more consistent, with 13–14% in all national parks, except for 2% in Analamerana.

It is important to note that the figures presented in this section do not reflect the current state of the forest but indicate whether forest loss or degradation events have been recorded in the past. In the next section, we analyse the current state of the forest in more detail.



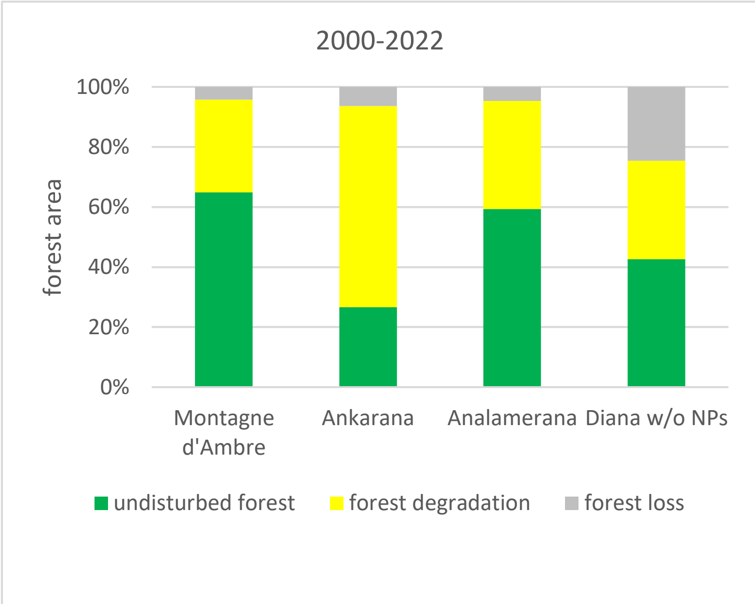
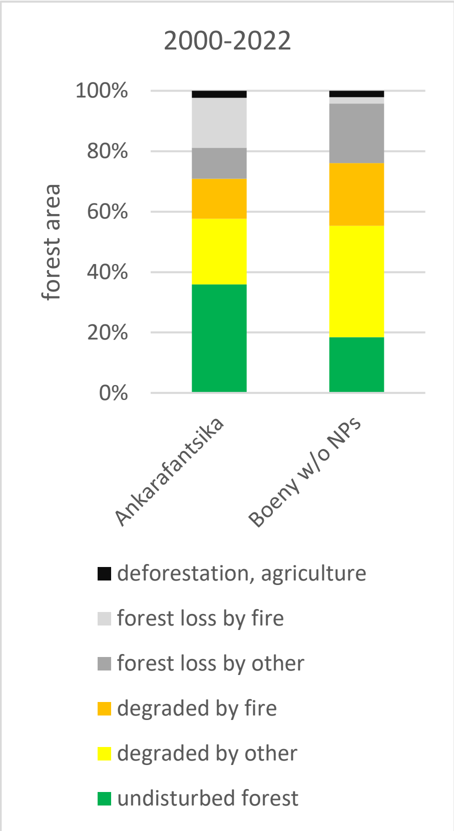


Figure 32: Potential forest degradation and forest loss until 2022. The forest area (y-axis) includes all pixels classified as forest in 2000, based on Hansen et al. (2013). Pixels without any degradation events or forest loss are marked as undisturbed forest and colored green. Pixels with recorded forest loss are depicted in grey. Pixels without forest loss but with at least one degradation event are colored yellow.

Dégradation potentielle des forêts et perte de forêts jusqu'en 2022. La superficie forestière (axe des ordonnées) comprend tous les pixels classés comme forêt en 2000, sur la base de Hansen et al. (2013). Les pixels ne présentant aucun événement de dégradation ou de perte de forêt sont marqués comme étant des forêts intactes et sont colorés en vert. Les pixels avec une perte de forêt enregistrée sont représentés en gris. Les pixels sans perte de forêt mais avec au moins un événement de dégradation sont colorés en jaune.



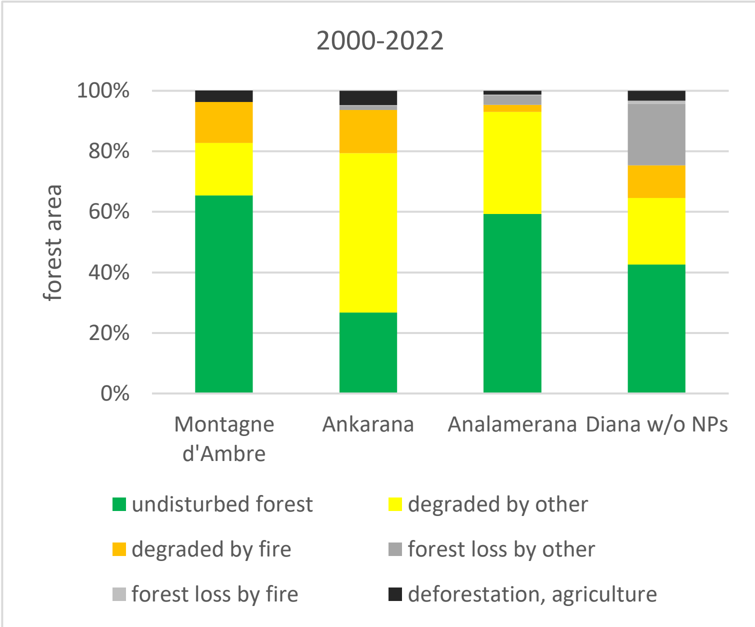


Figure 33: Potential forest degradation, forest loss and deforestation by direct driver until 2022. The forest area (y-axis) includes all pixels classified as forest in 2000, based on Hansen et al. (2013). Pixels without any degradation events or forest loss are marked as undisturbed forest and colored green. Pixels with recorded forest loss are depicted in grey or black, depending on the driver. Pixels without forest loss but with at least one degradation event are colored yellow or orange, depending on the driver.

Dégradation potentielle des forêts, perte de forêts et déforestation par facteur direct jusqu'en 2022. La superficie forestière (axe des ordonnées) comprend tous les pixels classés comme forêt en 2000, sur la base de Hansen et al. (2013). Les pixels ne présentant aucun événement de dégradation ou de perte de forêt sont marqués comme forêt non perturbée et colorés en vert. Les pixels avec une perte de forêt enregistrée sont représentés en gris ou en noir, en fonction du moteur. Les pixels sans perte de forêt mais avec au moins un événement de dégradation sont colorés en jaune ou en orange, en fonction du moteur.

3.1.5 Estimation of the forest condition in 2023

Areas that experienced potential forest degradation or forest loss between 2000 and 2022 showed substantial regrowth by 2023 (Figure 34). It is important to note, however, that a significant percentage of areas still showed no regrowth. Additionally, areas identified as having regrowth may include plantations and orchards, not solely natural forest recovery. We have produced maps that display the distribution of this regrowth in each region and within the national parks, differentiating between regrowth following forest loss and regrowth following forest degradation (Annex G).

Figure 34: Forest conditions in 2023, including the development of regrowth after potential forest degradation and forest loss.

L'état des forêts en 2023, y compris le développement de la repousse après la dégradation potentielle des forêts et la perte de forêts.

Table 12 shows estimates of the accumulated forest loss by 2023, comparing results from our analysis using NDFI thresholds with those derived from the global tree cover loss dataset (Hansen et al. 2013). In Montagne d'Ambre and Ankarana, the area of forest loss estimated using NDFI data is much larger than that estimated using Hansen's method. Conversely, this is reversed in Ankarafantsika.

Table 12: Accumulated forest loss from 2000 to 2023.

Perte cumulée de forêts de 2000 à 2023.

Forest loss estimation approach	Ankarafantsika	Montagne d'Ambre	Analamerana	Ankarana	Boeny w/o NPs	DIANA w/o NPs
Hansen 2000–2023	31.7%	4.5%	4.8%	6.5%	25.0%	25.9%
NDFI 2023	6.9%	11.1%	5.1%	10.1%	19.1%	15.1%

3.2 Reforestation and plantation development

This section first describes the development of plantations based on crown cover estimates. We then explore the various drivers that contribute to both higher and lower values of these estimates. Finally, the section addresses the identification of potential future reforestation sites and the competing land uses that may influence these efforts.

3.2.1 Estimation of reforestation success

In Boeny, more than one-third of the reforestation area failed to exceed a crown cover of 10% during the first rotation period (Figure 35). Only 26.2% of the area reached a crown cover of at least 20%, and only 0.2% of more than 60%. In contrast, in DIANA, crown cover exceeded 20% on more than 50% of the reforestation area during the first rotation period.

Throughout the entire analysis timeframe of 2000 to 2023, plantations with less than 20% crown cover were the majority in both regions (Figure 36). Plantations exceeding this threshold were primarily found after 2015, and plantations with crown cover exceeding 60% were almost exclusively found in DIANA. In both Boeny and DIANA, the area covered by higher crown cover classes increased over time, with some interannual fluctuations.

Figure 37a shows that vegetation increased after reforestation for both PLAE- and GIZ-supported plantations, as indicated by lower NDFI values in the pre-reforestation phase compared to the post-reforestation phase. In line with that, crown cover also increased in the first seven years following reforestation, by approximately 1% per year (Figure 37b). The increase was similar for both programs, but lower in Boeny compared to DIANA.

Overall, PLAE plantations had higher crown cover than GIZ plantations. It is important to note, however, that this difference was evident even before reforestation began, as indicated by higher pre-reforestation NDFI values for PLAE-supported reforestation both at the start and end of the dry season. Furthermore, the NDFI value of GIZ-supported plantations continued to increase with increasing plantation age, reaching values of 0.5 after 20 years—comparable to the NDFI value of natural forests (Section 3.1).

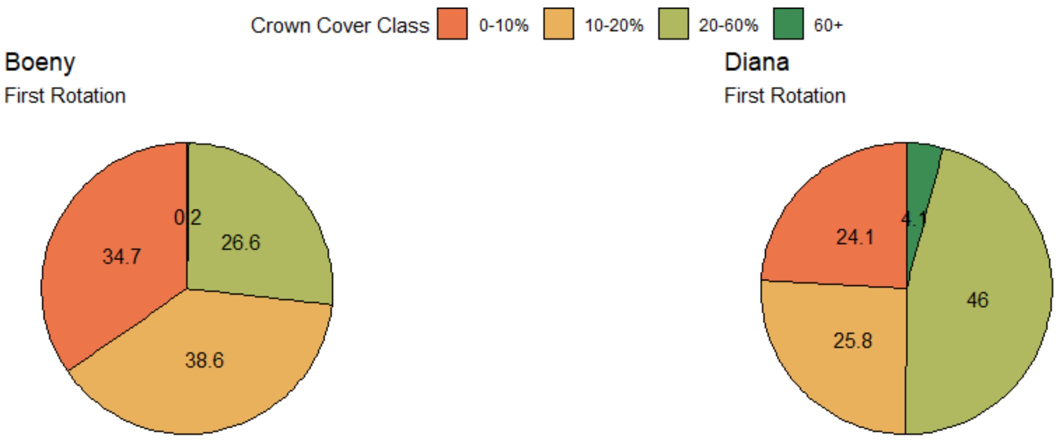


Figure 35: Proportional area covered by different canopy cover classes based on maximum values within the first rotation (5 to 11 years). Numbers indicate the proportional area in percent.

Superficie proportionnelle couverte par différentes classes de couvert forestier basée sur des valeurs maximales au cours de la première rotation (5 à 11 ans). Les chiffres indiquent la superficie proportionnelle en pourcentage.

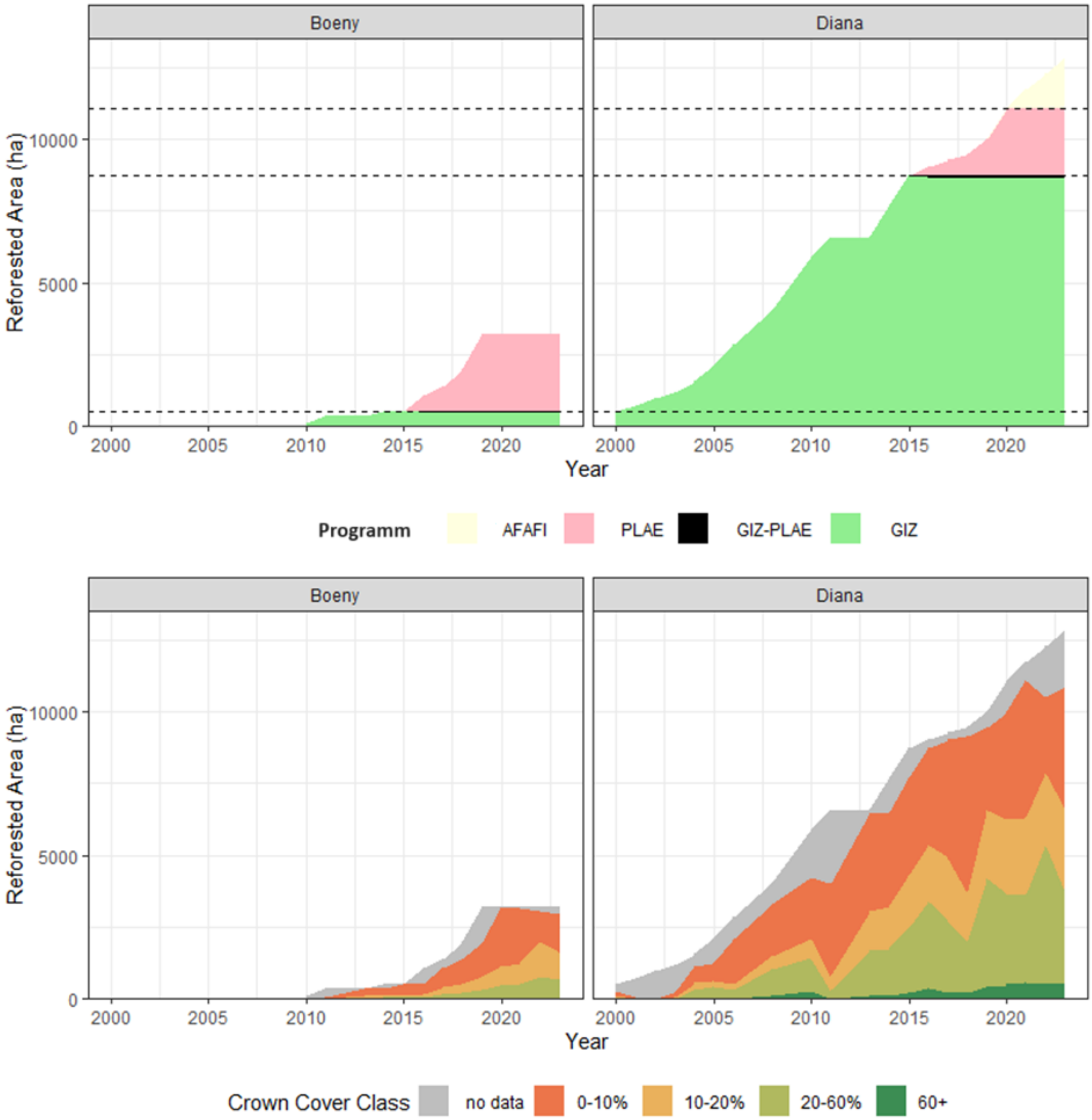


Figure 36: Upper panel: Development of RVI areas across different programs. Lower panel: The colours, ranging from orange to green, represent the different crown classes. Grey areas represent plots with no estimated crown cover, either because they were less than two years old or because satellite images of sufficient quality were not available.

Panneau supérieur: Développement des zones RVI par différents programmes. Panneau inférieur: Les couleurs, allant de l'orange au vert, représentent les différentes classes de couronnes. Les zones grises représentent les parcelles dont la couverture n'a pas été estimée, soit parce qu'elles avaient moins de deux ans, soit parce que des images satellites de qualité suffisante n'étaient pas disponibles.

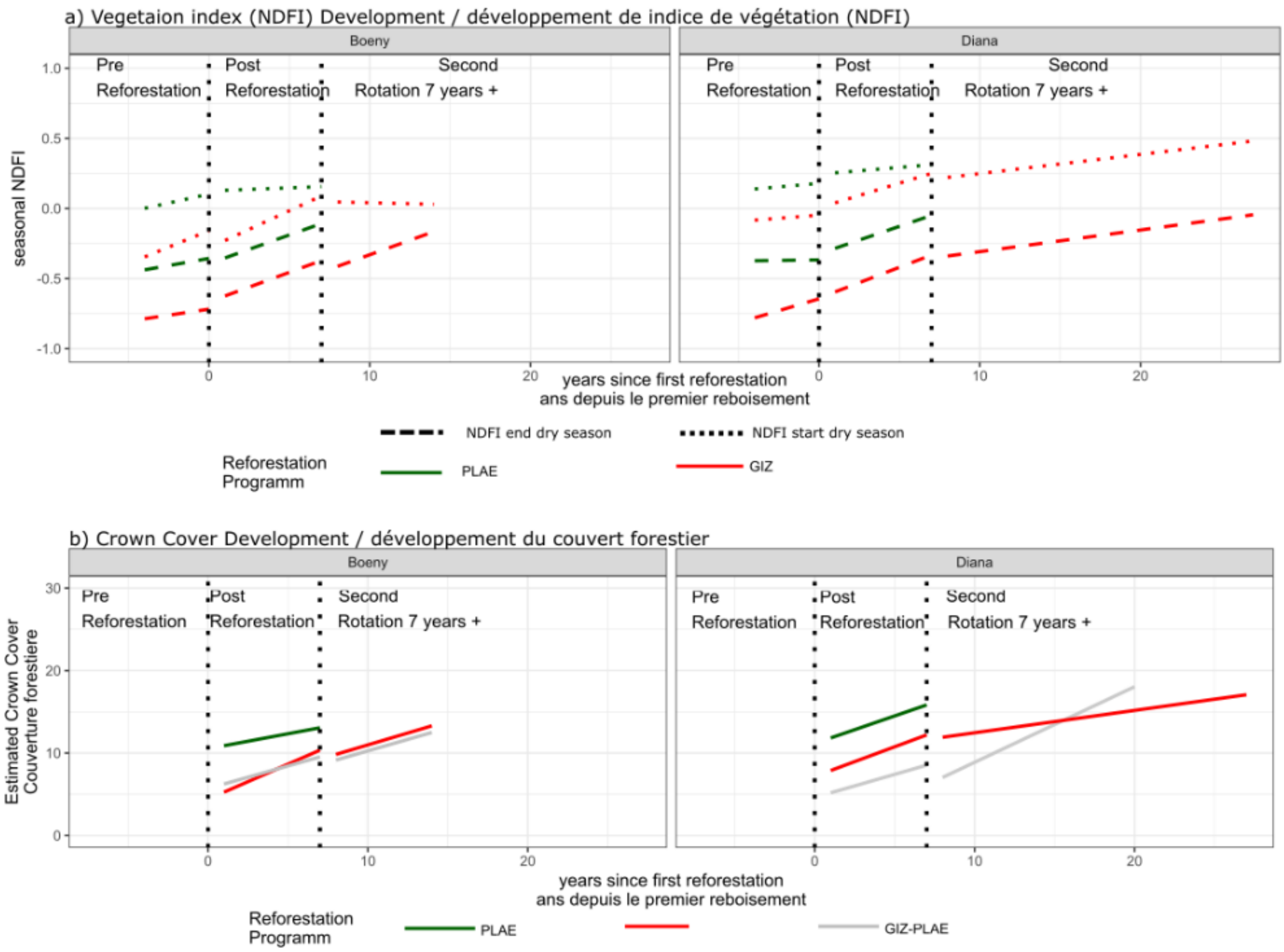


Figure 37: Comparison of vegetation development across regions and reforestation programs during three distinct phases: pre-reforestation, post-reforestation (for 2–7 year old plots), and the second rotation (for plots older than 7 years). Panel a) displays the development of NDFI values at both the start and the end of the dry season, while panel b) focuses on the aggregated increase of crown cover. Note: Crown cover values were not estimated during the pre-reforestation phase.

Comparaison du développement de la végétation entre les régions et les programmes de reboisement au cours de trois phases distinctes: pré-reboisement, post-reboisement (pour les parcelles âgées de 2 à 7 ans) et deuxième rotation (pour les parcelles âgées de plus de 7 ans). Le panneau a) montre l'évolution des valeurs du NDFI au début et à la fin de la saison sèche, tandis que le panneau b) se concentre sur l'augmentation globale du couvert forestier. Note: Les valeurs du couvert forestier n'ont pas été estimées pendant la phase de pré-reboisement.

3.2.2 Identification of drivers for reforestation success

This section presents the results of the mixed linear models, first focusing on the model based on the complete dataset, and then on reforestation program- and region-specific models. Overall, the influence of environmental and program-related variables on restoration performance was consistent across the different models. The influence of socio-economic variables, however, varied depending on the program and region.

3.2.2.1 Complete dataset

Results for the model based on the complete dataset are presented in Table 13. Overall, the combination of fixed and random factors explained 72% of the variance in crown cover, whereas the fixed effects alone only explained 9%. There was a positive correlation between random slope and intercept, indicating that reforestation plots with a high initial crown cover also had a high increase in crown cover in the subsequent years.

Table 13: Results of mixed linear models explaining plantation crown cover. Significant variables are highlighted in bold letters. R^2 (fixed effects) shows the variance explained by all environmental, socio-economic and reforestation-related variables from 2 to 7 years. R^2 (fixed + random effects) shows the variance explained by these variables, plus the plot-specific crown cover and its increase. A visualisation of the soil type effect is presented in Figure 38.

Résultats des modèles linéaires mixtes expliquant le couvert forestier des plantations. Les variables significatives sont mises en évidence en caractères gras. Le R^2 (effets fixes) montre la variance expliquée par toutes les variables environnementales, socio-économiques et liées au reboisement de 2 à 7 ans. Le R^2 (effets fixes + aléatoires) montre la variance expliquée par ces variables, plus le couvert forestrier spécifique à la parcelle et son augmentation. Une visualisation de l'effet du type de sol est présentée dans la Figure 38.

	Complete Dataset
Population Density / *Densité de la population*	**-0.03*** (0.01)**
Distance settlement / *Distance par rapport aux plus grandes agglomérations*	**-0.09*** (0.01)**
Distance road / *Distance aux routes*	0.00 (0.01)
Soil type *(ferrallitic soils, sols ferrallitiques)*	**0.45*** (0.03)**
Soil type *(ferruginous soils, sols ferrugineux)*	0.01 (0.02)
Soil type *(poorly developed soils, sols peu évolués d'apport)*	**0.19*** (0.03)**
Altitude / *Altitude*	**-0.11*** (0.01)**
Slope / *Inclination*	**0.10*** (0.01)**
Climatic water deficit / *Déficit hydrique climatique*	**-0.20*** (0.01)**
Plot size / *Taille de la parcelle*	**-0.09*** (0.01)**
Fire frequency / *Fréquence des incendies*	**0.02* (0.01)**
Plot age / *Âge de la parcelle*	**0.09*** (0.01)**
GIZ promoted reforestation / *Promoteur GIZ*	**-0.46*** (0.02)**
Second reforestation / *Deuxième reboisement*	**-0.25*** (0.05)**
Age x program / *âge x programme*	0.01+ (0.01)
Age x second reforestation / *âge x second reforestation*	0.06+ (0.03)
(Intercept)	0.21*** (0.04)
Number of observations	52877
Cor (Intercept~age plot)	0.32
R^2 (fixed effects)	0.087
R^2 (fixed + random effects)	0.718
RMSE	0.57

Environmental variables explained 6.7% of the variance in crown cover. Within these variables, soil type was the most influential. Plots located on "other" soil types had the highest crown cover values, while those on ferralitic soils showed intermediate values (Figure 38). The climatic water deficit was identified as the second most significant environmental variable, with higher crown cover observed under conditions of low water stress. Additionally, plots situated at lower altitudes and on steeper slopes also demonstrated higher crown cover. The model outcomes indicated further that increased fire frequencies were associated with higher crown cover values. We explore this relationship in the following section.

Socio-economic variables accounted for only 0.6% of the variance in crown cover. Nevertheless, the two socio-economic variables included in the model were significant: plantations located closer to large cities and in areas with lower population densities tended to have higher crown cover.

Variables related to the reforestation approach explained 6.0% of the variance in crown cover. The reforestation program was the most influential of these variables, with GIZ-supported plots having lower crown cover than PLAE-supported plots. Additionally, plots with a second reforestation and larger plots had lower crown cover. None of the interaction terms proved significant, suggesting that growth rates were not significantly impacted by a second reforestation or the reforestation program.

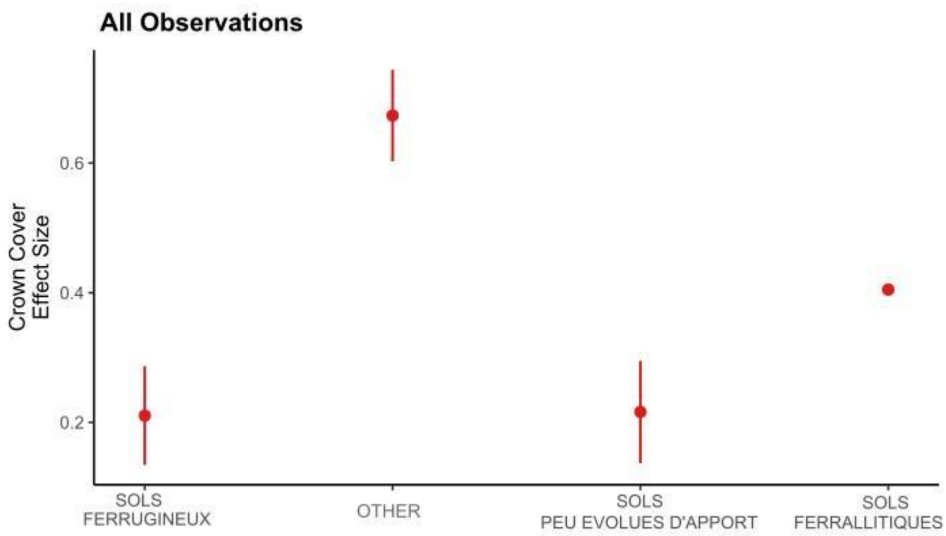


Figure 38: Crown cover plotted as a function of the most frequent soil types for the complete dataset. Y-axis values were standardized. Ferruginous soils and poorly developed soils had lowest values, whereas ferralitic soils showed intermediate values. These three soil types account for 85% of all plots analysed.

Représentation graphique du couvert forestier en fonction des types de sol les plus fréquents pour l'ensemble des données. Les valeurs de l'axe Y ont été normalisées. Les sols ferrugineux et les sols peu évolués d'apport présentent les valeurs les plus faibles, tandis que les sols ferralitiques présentent des valeurs intermédiaires. Ces trois types de sol représentent 85% de toutes les parcelles analysées.

3.2.2.2 Fire Frequencies

Fire scars or burned areas were detected on 20% of all reforestation plots. We found a weak trend of higher crown cover under increased fire frequencies. This effect, however, was unevenly distributed: plots with crown cover values of 10% and 20% were more often found under higher fire frequencies, whereas crown cover values exceeding 60% were absent under higher fire frequencies. Only plots that experienced less than two fires had crown cover values exceeding 60%.

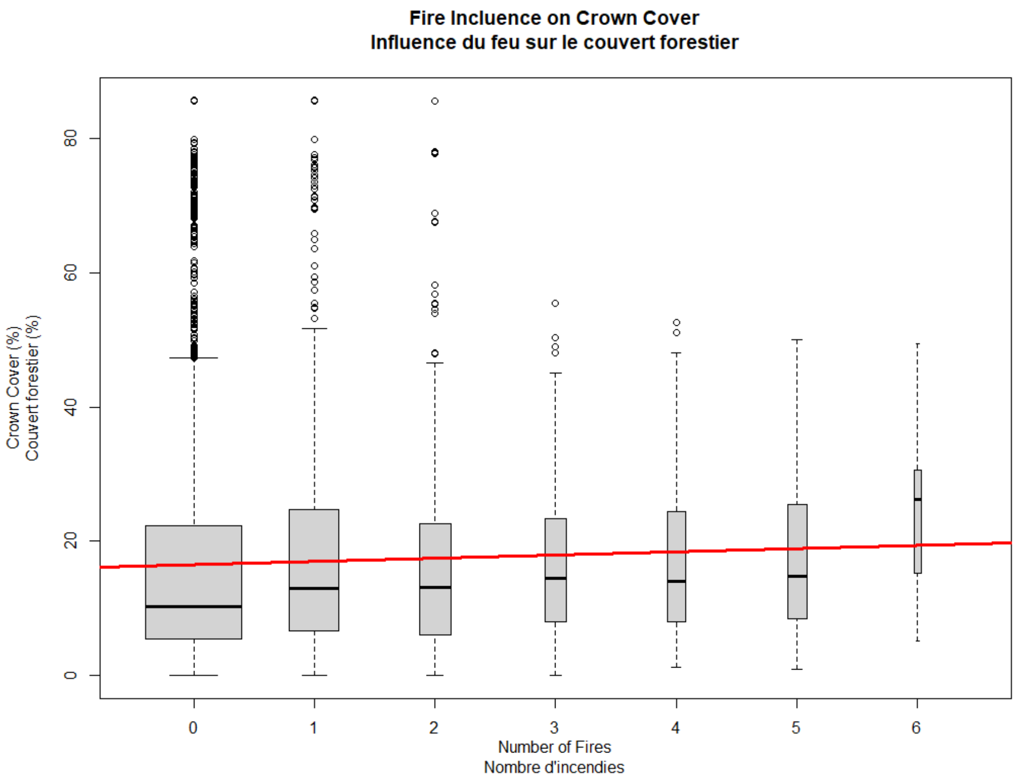


Figure 39: Distribution of crown cover values of seven-year-old plots as a function of the number of fires since year 0. Boxplot widths correspond to the number of observations in each group. The red line indiates the linear increase of crown cover with each extra fire.

Répartition des valeurs de couvert forestier des parcelles âgées de sept ans en fonction du nombre d'incendies depuis l'année 0. La largeur des boîtes à moustaches se rapporte au nombre d'observations dans chaque groupe. La ligne rouge indique l'augmentation linéaire de la couverture du houppier à chaque incendie supplémentaire.

3.2.2.3 Region- and program-specific results: GIZ versus PLAE

The distribution of random and fixed effects in program- and region-specific models were similar to the overall model (Table 14). The fixed effects only explained 9–12% of the variance in crown cover, whereas the combination of fixed and random factors explained 46–72% of the variance.

Overall, it was mostly the significance of environmental variables which differed between the two regions, whereas the direction of their influence was generally consistent. Notably, the soil type was not significant for GIZ-supported plantations in Boeny, unlike in the other three models. For PLAE-supported plots, fire frequency was insignificant in Boeny, whereas in DIANA, increased fire frequencies were associated with lower crown cover.

The effect of socio-economic variables was heterogeneous. For example, in line with the overall trend, GIZ-supported plantations in DIANA had higher crown cover under lower population densities. Conversely, GIZ-supported plots in Boeny showed higher crown cover under higher population densities. Population density and distance to settlements were insignificant for PLAE-supported reforestation plots in Boeny.

The effect of variables related to the reforestation approach was mostly consistent with the complete dataset model. A second reforestation was significant only for PLAE-supported reforestation in Boeny, indicating that a repeated reforestation leads to lower crown cover. However, for these plots, the interaction between age and a second reforestation was significant and positive. This suggests that after a second reforestation crown cover is first lower, but increases at a faster rate compared to plots with only one reforestation.

Table 14: Results of mixed linear models explaining plantation crown cover in Boeny and DIANA for both the GIZ and PLAE program. Significant variables are highlighted in bold letters. R^2 (fixed effects) shows the variance explained by all environmental, socio-economic and reforestation-related variables from 2 to 7 years. R^2 (fixed + random effects) shows the variance explained by these variables, plus the plot-specific crown cover and its increase.

Résultats des modèles linéaires mixtes expliquant la couvert forestier des plantations dans le Boeny et la DIANA pour les programmes GIZ et PLAE. Les variables significatives sont mises en évidence en caractères gras. R^2 (effets fixes) montre la variance expliquée par toutes les variables environnementales, socio-économiques et liées au reboisement entre 2 et 7 ans. R^2 (fixed and random effects) montre la variance expliquée par ces variables ainsi que la couverture végétale spécifique à la parcelle et son augmentation.

	DIANA		**Boeny**	
	GIZ	PLAE	GIZ	PLAE
Population Density / *Densité de la population*	**-0.05*** (0.01)**	**-0.04* (0.02)**	**0.22*** (0.04)**	0.03 (0.02)
Distance settlement / *Distance par rapport aux plus grandes agglomérations*	**-0.16*** (0.01)**	**-0.14*** (0.02)**	**-0.23*** (0.05)**	0.00 (0.03)
Distance road / *Distance aux routes*	**0.09*** (0.01)**	**-0.09*** (0.02)**	**-0.09* (0.04)**	**-0.12*** (0.03)**
Soil type (ferrallitic soils */ sols ferrallitiques)*	**0.39*** (0.03)**	**0.29*** (0.07)**		
Soil type (ferruginous soils*/ sols ferrugineux)*	**-0.09** (0.03)**	**0.22*** (0.05)**	-0.05 (0.17)	-0.12 (0.09)
Soil type (poorly developed soils / *sols peu evolues d'apport)*	**0.26*** (0.05)**	**0.20** (0.06)**	0.09 (0.18)	0.11 (0.10)
Altitude / *Altitude*	**-0.06*** (0.01)**	0.03 (0.03)	**-0.28*** (0.04)**	**-0.19*** (0.03)**
Slope / *Pente*	**0.06*** (0.01)**	**0.16*** (0.02)**	**-0.09** (0.03)**	**0.18*** (0.02)**
Climatic water deficit / *Déficit hydrique climatique*	**-0.11*** (0.01)**	**-0.38*** (0.02)**	nt	nt
Plot size / *Taille de la parcelle*	**-0.08*** (0.01)**	**-0.05** (0.02)**	0.00 (0.03)	**-0.13*** (0.02)**
Fire frequency / *Fréquence des incendies*	**0.04*** (0.01)**	**-0.03** (0.01)**	**0.10*** (0.02)**	0.00 (0.01)
Plot age / *Âge de la parcelle*	**0.13*** (0.00)**	**0.09*** (0.01)**	**0.12*** (0.02)**	**0.11*** (0.01)**
Second reforestation / *Deuxième reboisement*	-0.18+ (0.10)	-0.15 (0.14)	-0.20 (0.12)	**-0.19** (0.06)**
age x second reforestation / *âge x second reforestation*	0.04 (0.07)	0.04 (0.07)	0.11 (0.10)	**0.10** (0.03)**
(Intercept)	-0.11***	-0.15***	0.00	0.05
Number of observations	34294	9659	2657	7668
R2 (fixed effects)	0.09	0.16	0.12	0.10
R2 (random + fixed effects)	0.48	0.75	0.46	0.72

3.2.3 Recommendation of growth zones

In this section, we describe the distribution of potential and promising growth zones in DIANA and Boeny.

3.2.3.1 Extrapolation and spatial analysis

The potential crown cover predicted by our Random Forest models was highest around Montagne d'Ambre, followed by the northern sides of Analamerana and Ankarafantsika (Figure 40). In contrast, lower values were observed to the south of Ankarana and Analamerana. The surroundings of Ankarafantsika in Boeny had the lowest values, with slightly higher crown cover on the southern and western sides, compared to the northern side.

Predicted NDFI increases were more evenly distributed among all three parks in DIANA. The values in Boeny were generally lower than in DIANA. The NDFI increase on the southern side of Ankarafantsika was slightly higher than on the northern side (Figure 41).

The distribution of predicted crown cover pixel values in the peripheral zones of the national parks confirms that Montagne d'Ambre had the highest values, followed by Analamerana, Ankarana and Ankarafantsika (Figure 42). The differences between the direct peripheral zones (2.5 km buffer) and extended peripheral zones (2.5–7.5 km buffer) were negligible (Figure 42).

The predicted crown cover showed substantial variation within the designated land uses as planned in local SACs (Figure 43). It was highest for commercial agriculture, with a median of 56% in DIANA and 36% in Boeny. This was followed by zones designated for local agriculture, with similar values for savanna and pastures and natural forest. Predicted crown cover was lowest in designated reforestation zones.

3.2.3.2 Excluded areas

Using remotely sensed land use and land cover data (Potapov et al. 2022a; CIESIN 2023; Zanaga et al. 2022), we found that, on average, 42% of the areas within the peripheral zones of the national parks are covered by land-use types that prohibit reforestation (Figure 44; maps in Annex D). The primary reasons for this exclusion are agricultural production in Ankarafantsika and Ankarana, and forest and tree cover in Montagne d'Ambre and Analamerana.

3.2.3.3 Identification of zones with a high reforestation potential

We categorized reforestation sites into two types: potential and promising. Potential reforestation sites include all areas not identified as excluded in previous section. Promising reforestation sites are potential sites with an above-median predicted crown cover and NDFI increases. Figure 45 shows outcomes for the national parks and their surrounding areas. Figure 46 presents the results from an analysis limited to locations where a local SAC was available, and excludes all areas not designated as pasture, savanna, or reforestation zones.

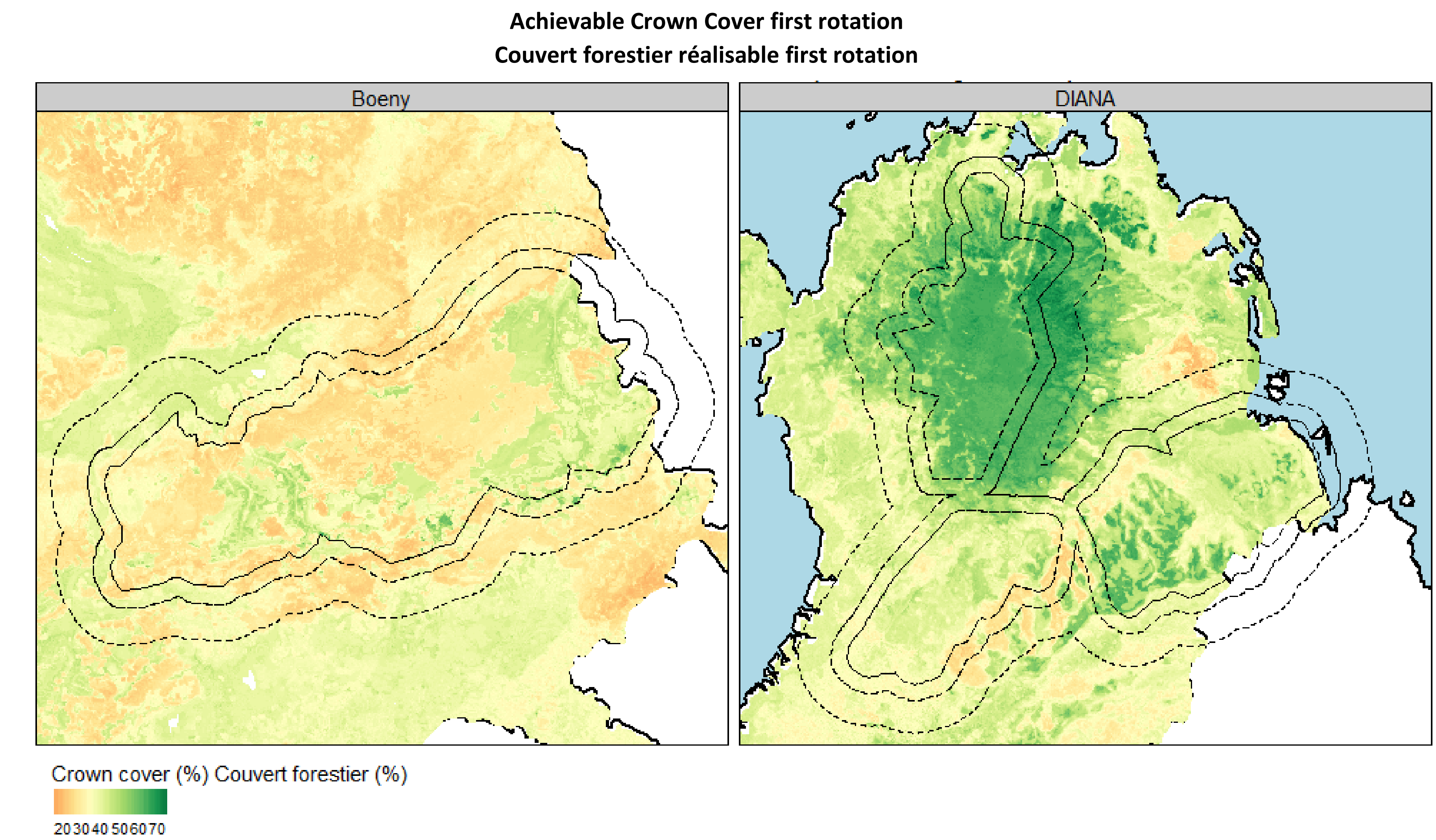


Figure 40: Crown Cover predictions in the peripheral zones of the national parks based on the best performing plantations in Boeny and DIANA. Colours represent the crown cover reached within the minimum rotation length (4–7 years).

Prévisions de couvert forestier dans les zones périphériques des parcs nationaux sur la base des plantations les plus performantes de Boeny et DIANA. Les couleurs représentent le couvert forestier atteint pendant la durée minimale de la rotation (4 à 7 ans).

NDFI Increase First Rotation (1-6 years)
Augmentation du NDFI lors de la première rotation (1 à 6 ans)

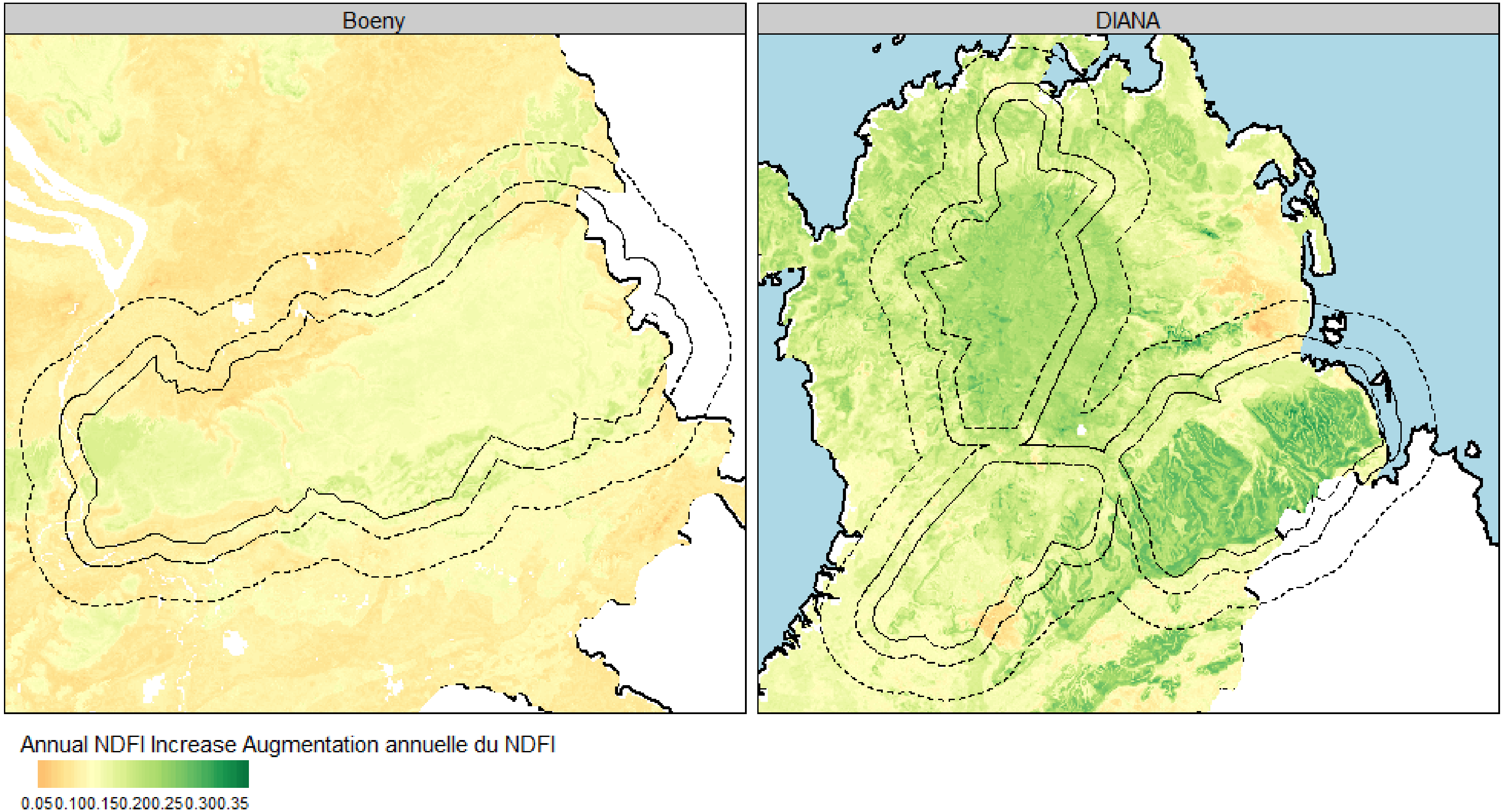


Figure 41: NDFI increase predictions in the peripheral zones of the national parks based on the best performing plantations in Boeny and DIANA. Colours represent a dimensionless vegetation increase at the end of the dry season from the first to the sixth year after reforestation.

Accroissement du NDFI dans les zones périphériques des parcs nationaux sur la base des plantations les plus performantes de Boeny et DIANA. Les couleurs représentent un accroissement de la végétation sans dimension à la fin de la saison sèche, de la première à la sixième année après le reboisement.

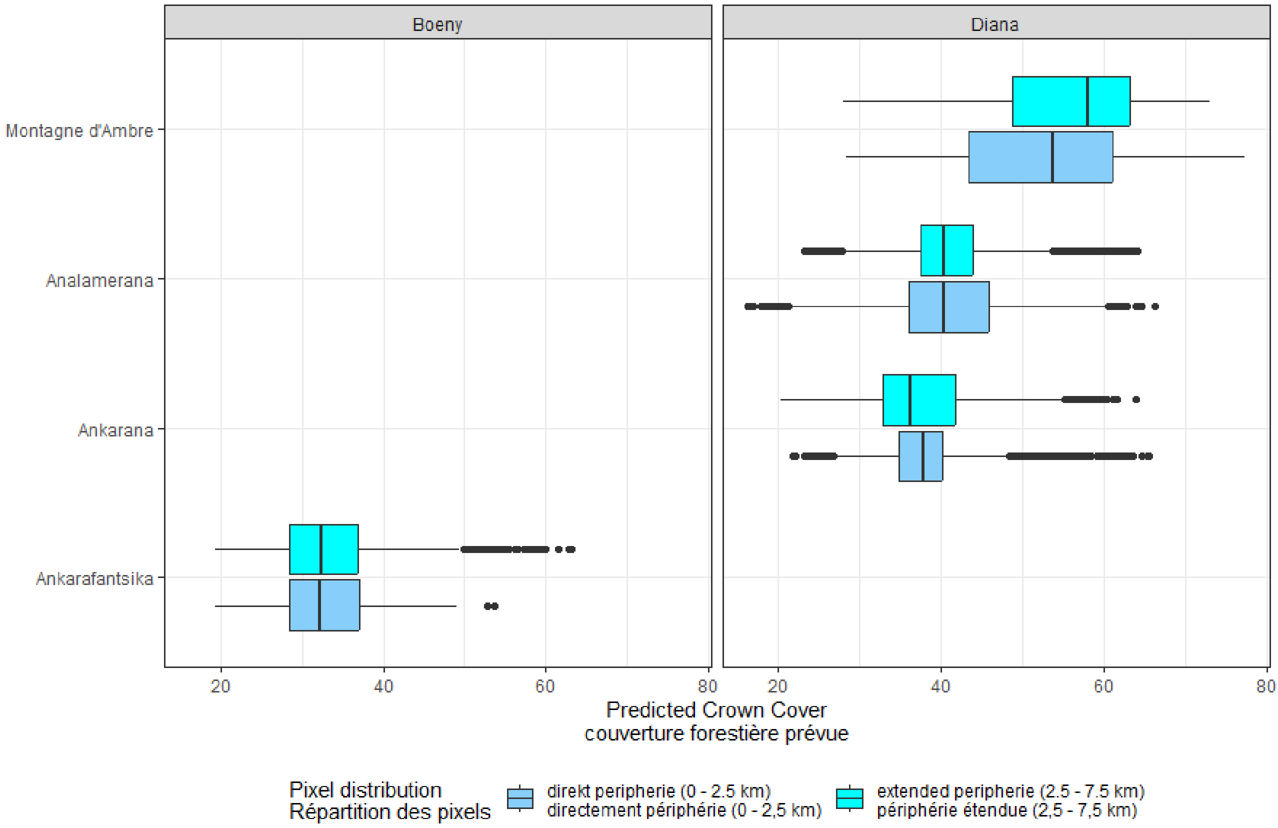


Figure 42: Distribution of predicted potential crown cover in all four national parks distinguishing between a 2.5 km buffer (direct peripheral zone) and 2.5–7.5 km buffer (extended peripheral zone).

Distribution du couvert forestier potentiel prédit dans les quatre parcs nationaux, avec une distinction entre une zone tampon de 2,5 km (zone périphérique directe) et une zone tampon de 2,5 à 7,5 km (zone périphérique étendue).

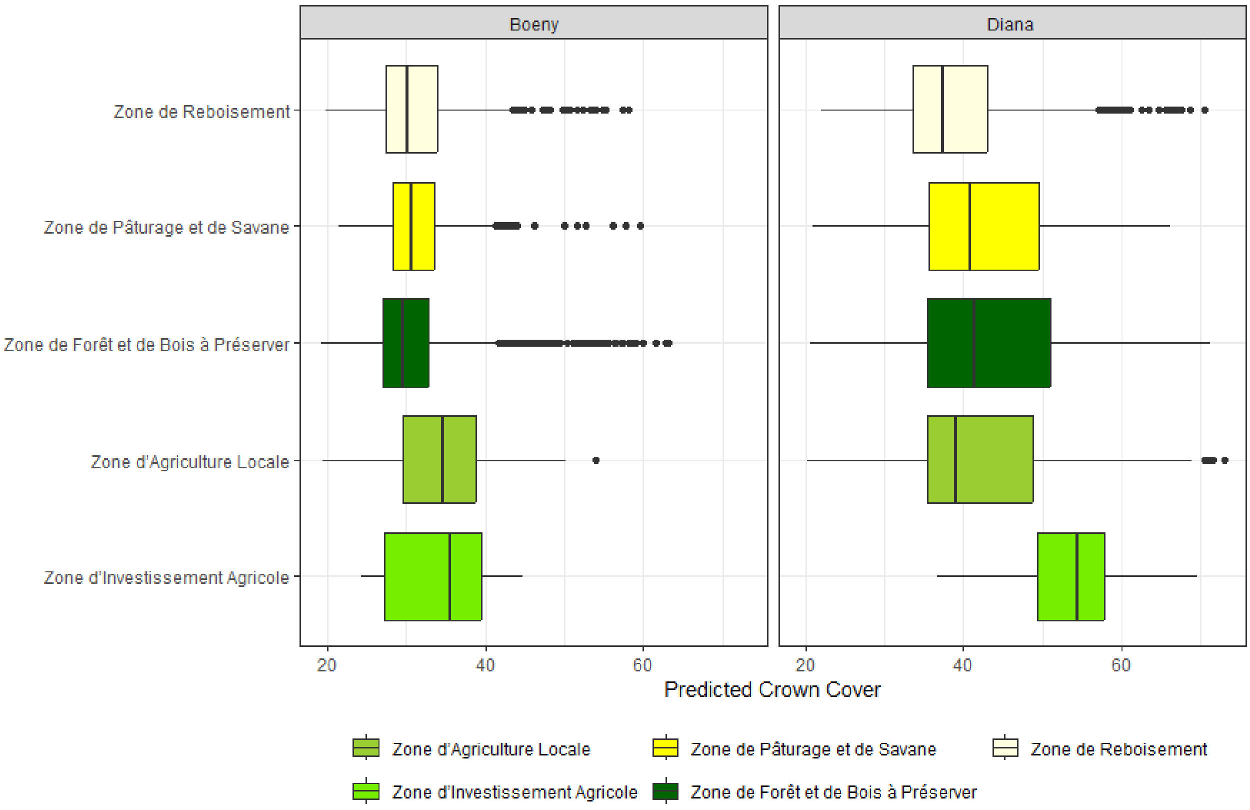


Figure 43: Distribution of predicted potential crown cover within the designated land uses as planned in local SACs.

Distribution du couvert forestier potentiel prédit dans les utilisations des terres désignées, comme prévu dans les SAC locales.

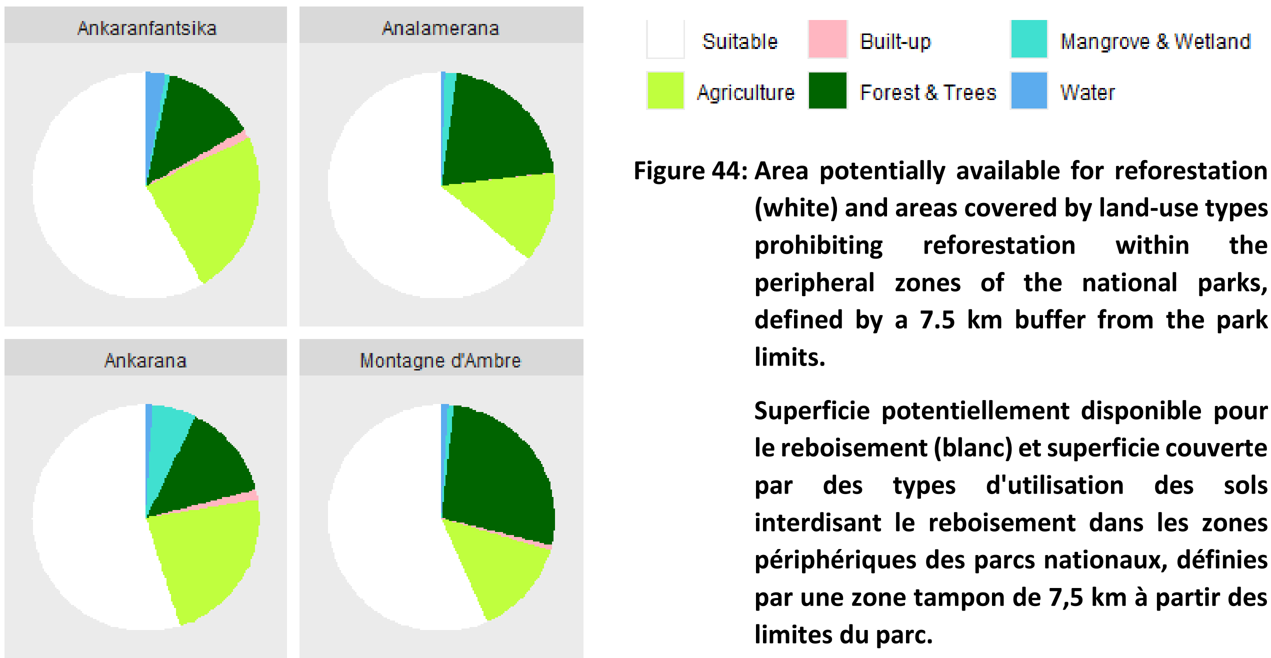


Figure 44: Area potentially available for reforestation (white) and areas covered by land-use types prohibiting reforestation within the peripheral zones of the national parks, defined by a 7.5 km buffer from the park limits.

Superficie potentiellement disponible pour le reboisement (blanc) et superficie couverte par des types d'utilisation des sols interdisant le reboisement dans les zones périphériques des parcs nationaux, définies par une zone tampon de 7,5 km à partir des limites du parc.

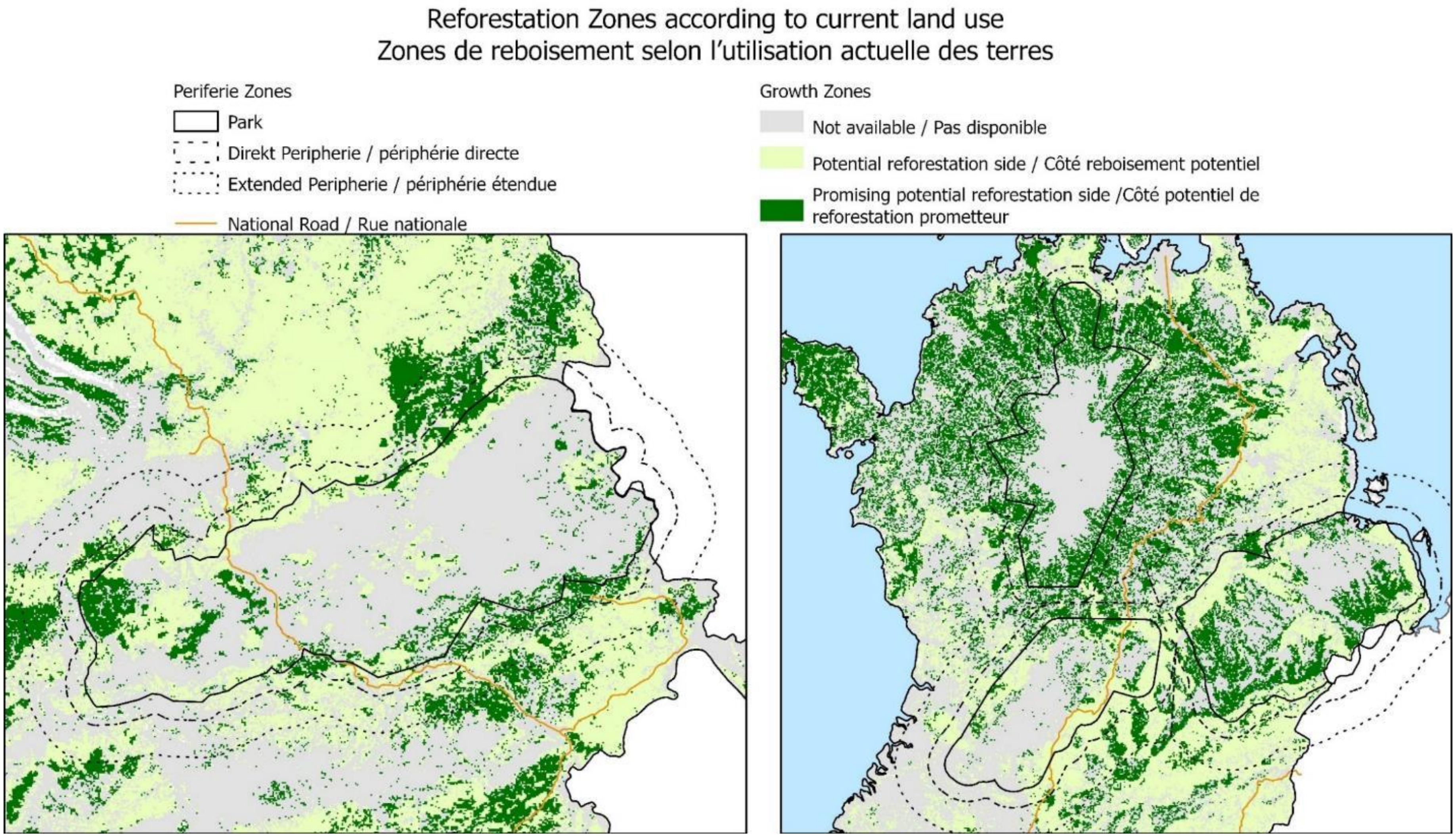


Figure 45: Potential reforestation sites (all areas not identified as excluded) and promising reforestation sites (potential sites with above-median crown cover and vegetation increase) in national parks and their surrounding areas.

Sites de reboisement potentiels (toutes les zones non exclues) et sites de reboisement prometteurs (sites potentiels avec un couvert forestier et une augmentation de la végétation supérieurs à la médiane) dans les parcs nationaux et les zones environnantes.

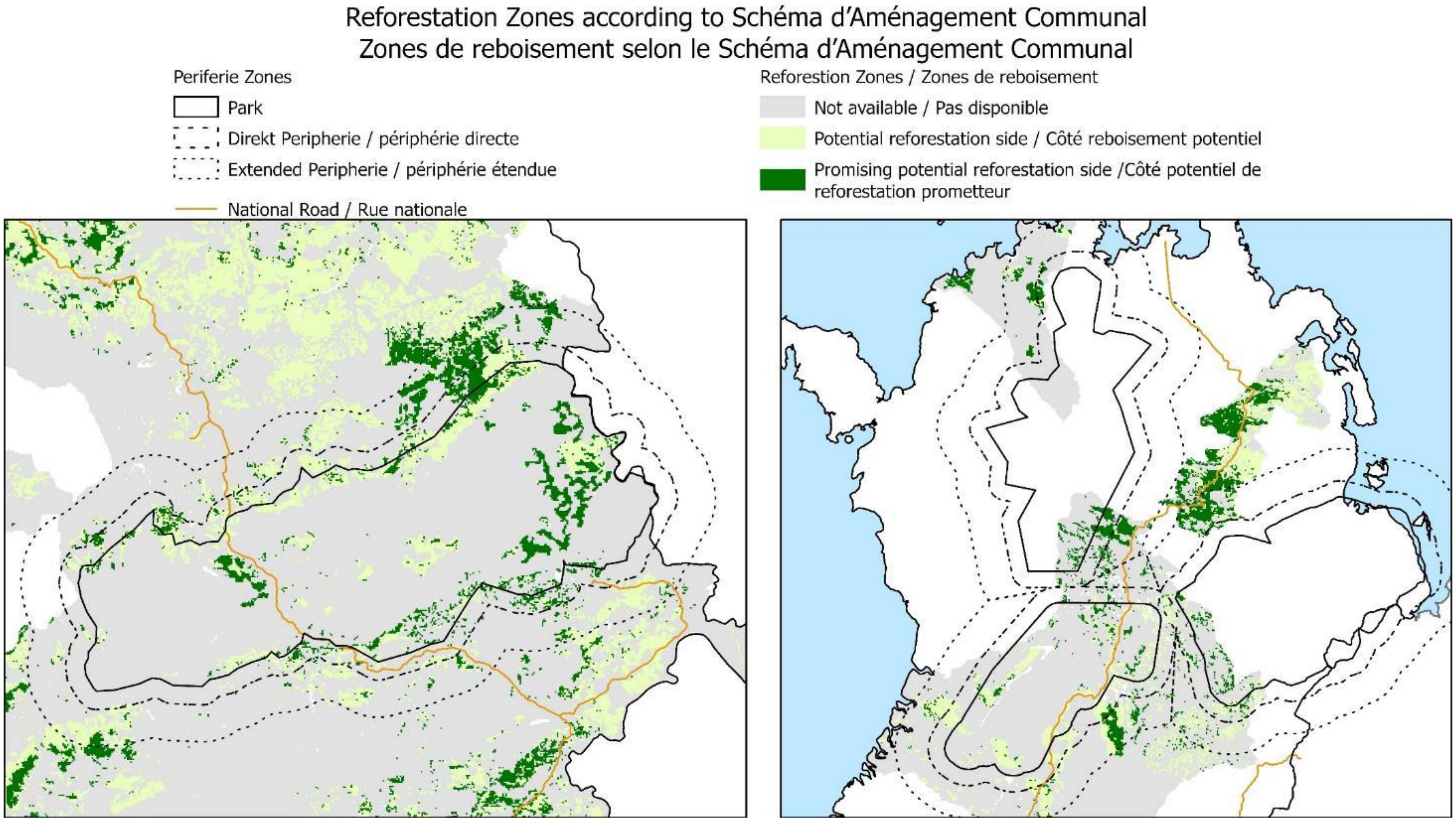


Figure 46: Potential reforestation sites (all areas not identified as excluded) and promising reforestation sites (potential sites with above-median crown cover and vegetation increase) for areas where a local SAC was available. All areas not designated as pasture, savanna, or reforestation zones were excluded.

Sites de reboisement potentiels (toutes les zones non exclues) et sites de reboisement prometteurs (sites potentiels avec un couvert forestier et une augmentation de la végétation supérieurs à la médiane) pour les zones où un SAC local était disponible. Toutes les zones non désignées comme pâturages, savanes ou zones de reboisement ont été exclues.

4 Discussion

4.1 Natural forests and forest landscapes

In this work package, we focused on potential forest degradation and deforestation and their drivers in Boeny and DIANA, differentiating between protected and non-protected areas. We identified when and where potential forest degradation and deforestation occurred and showed forest fragmentation dynamics. In our driver analysis, we attributed all forest losses either to cropland expansion, fire, or to the category of other drivers. For forest degradation drivers, we differentiated between fire-related and other causes.

4.1.1 Potential forest degradation, deforestation and fragmentation

Our findings draw a rather bleak picture: over 20% of the forest area in 2000 has been lost in Boeny and DIANA, with an increasing trend over time. Of the remaining forest area, more than 40% was classified as potentially degraded in DIANA and more than 75% in Boeny. Furthermore, our fragmentation analysis revealed a decline in the continuity of large forest areas. Additionally, small and tiny forest fragments are in decline, too, which will eventually lead to forest loss.

Our forest loss and fragmentation results are coherent with the studies of Harper et al. (2007) and Vieilledent et al. (2018), who observed a continuous increase in fragmentation in Madagascar between 1953 and 2014. At the local level, Eckert et al. (2011) reported strong fragmentation of the lowland rainforest in the Analanjirofo region in the north-east of Madagascar, accompanied by an increase of forest loss and degradation. For the same region, Zaehringer et al. (2015) showed that deforestation mostly affects small forest fragments that are interspersed in the agricultural landscape.

Our findings indicate that forest degradation is spatially many times larger than deforestation. For the interpretation it is important to keep in mind that our methodological approach quantified the extent of forest disturbances as a proxy for potential forest degradation. However, not all of the disturbances lead to actual forest degradation. Additionally, it should be noted that our approach does not differentiate between anthropogenic and natural causes of forest disturbances. Focussing on specific areas with a high occurrence of potential forest degradation allows for a better interpretation of our findings. For example, in Ankarana, it is evident that here is high spatial correlation between our findings and the karst topography: most of the dry vegetation on the limestone plateaus was mapped as degraded, whereas a large share of the vegetation in the more humid valleys was classified as undisturbed. In Montagne d'Ambre, the areas we mapped as potentially degraded have been predominantly classified as either "Western dry forest" or "Wooded grassland-bushland mosaic" by Duncan (2008), while the forest areas we mapped as undisturbed have been mostly classified as "Humid forest". These observations indicate that our methodological approach is particularly sensitive to areas with dry, open forests or woodlands. In consequence, our findings about the absolute extent of the degraded forest areas are challenging to interpret. This underlines the methodological challenges for the quantification of forest degradation, especially in dry and open forest areas (Fremout et al. 2022). It is therefore more meaningful to focus on the temporal and spatial trends in potential forest degradation we revealed.

With these caveats in mind, how did the national parks hold up against the overall trend of deforestation, fragmentation and forest degradation, and to what extent did they contribute to the protection of native forests in the project regions? Our findings do not allow us to provide a conclusive answer, because the proportions of undisturbed forest, potential forest degradation and deforestation showed context-specific situations for each national park and region. While there were substantially more large-scale forest patches inside national parks than outside, in both DIANA and Boeny, the findings for deforestation and potential forest degradation are more conflicting. In DIANA, there was significantly less deforestation inside national parks than outside, relative to the forest area in 2000. In contrast, potential forest degradation was considerably higher inside Ankarana than outside. While this can be partially explained by the influence of the geological formation in this national park, the other two national parks in DIANA also show high potential forest degradation, with similar rates inside and outside the park limits. In Boeny, the deforestation rate inside Ankarafantsika National Park was higher than outside, whereas potential forest degradation was higher outside than inside.

With the exception of Ankarana, the centre areas of national parks experienced significantly less potential degradation than the edge areas. Additionally, when disturbances occur in the centre areas, quick regeneration is common. In contrast, the edges of national parks are much more affected by frequent disturbances, which eventually lead to forest degradation. This illustrates that human activity and pressure is much stronger on the edges of national parks than in their central areas, likely due to the local population's demand for wood and forest products. In Ankarana, there was only a small difference between the edge and centre area. This finding can be, at least partially, explained by the influence of the karst topography on our mapping of potential forest degradation, as discussed above.

At first glance, it could seem promising that the size of potentially degraded forest areas inside national parks did not increase between the first and second time period, particularly in contrast to the increase of potential forest degradation which was observed in Boeny’s forests outside national parks. However, our post-disturbance analysis indicates that potentially degraded forest areas in all national parks had less regrowth and more ongoing degradation in the second time period compared to the first, in both edge and centre areas. This indicates that forest disturbances lead more often to forest degradation now than in the past.

In summary, our findings only partially support the conclusion that national parks still had a protecting function. This shows that efforts to protect the parks have not been sufficient to prevent losses and disturbances. To improve forest protection strategies, it is crucial to discuss in more detail the extent to which different direct drivers negatively impacted natural forests in Boeny and DIANA.

4.1.2 Driver analyses for deforestation, forest loss and forest degradation

The importance of the direct deforestation drivers we analysed showed substantial differences, both between regions and national parks. Despite these varied results, it is possible to identify some overall trends: with the exception of Montagne d’Ambre and Ankarana, deforestation with subsequent cropland use was relatively low. Fire was only responsible for a small part of the forest loss, with the exception of Ankarafantsika. In contrast, the importance of fire for potential forest degradation was substantial. Overall, there was a large importance of the group of “other” drivers for both forest loss and potential forest degradation.

4.1.2.1 Cropland expansion

At first glance, our findings that cropland expansion had a low importance as a driver of forest loss seem to be in contrast with reports from literature. For example, in a global study, Masolele et al. (2024) analysed land uses following deforestation across Africa with high spatial resolution for 2000–2020. According to their analysis, 88.3% of deforestation in Madagascar was followed by small-scale cropland (the highest share of all African countries). Similarly, Curtis et al. (2018) reported that small-scale agriculture was the main driver for deforestation in Madagascar. How can we explain these differences in the importance of deforestation drivers between these analyses and our study? To answer this question, it is important to discuss the methodological approach we used for the analysis of direct drivers: any forest loss without evidence for fire or cropland as the primary driver was attributed to the category of “other”. This is a plausible assumption that allowed us to make best use of the available data. However, our approach is sensitive to the quality of the fire and cropland datasets; underestimations of these drivers result in an overestimation of the category of “other” drivers.

The global data product we used to quantify cropland expansion could be the cause of a significant potential underestimation. While the product has a high overall accuracy, the authors observed an underestimation of the cropland extent for Africa (Potapov et al. 2022b). Furthermore, the global cropland product intentionally excluded slash-and-burn agriculture. Our analysis of additional cropland, which also included slash-and-burn agriculture in its reference data, resulted in a cropland extent 60%–200% larger than identified by Potapov et al. (2022b). An additional potential source for an underestimation of the importance of cropland as a deforestation driver is a temporal mismatch between the datasets we used. The cropland dataset of Potapov et al. (2022b) was only available until 2019. However, of the forest loss registered between 2000 and 2022, ca. 20% in Boeny and ca. 16% in DIANA occurred after 2019. In our analysis, none of these post-2019 forest losses could have been attributed to cropland expansion. This is particularly relevant as cropland expansion has accelerated in all of our study regions in recent years, showing a potentially exponential increase in some of the areas.

It was not feasible to carry out the additional cropland analysis for the complete extent of the regions of Boeny and DIANA, but only for the areas of the national parks. In consequence, it is plausible to assume that in the regions outside the national parks, the importance of cropland, and particularly slash-and-burn agriculture, as a deforestation driver was significantly underestimated, and in turn the importance of the "other" drivers overestimated. This can be illustrated by scrutinizing our findings for the Ampasindava Peninsula, located to the Southwest of Nosy Be, on the border between DIANA and Sofia. There, a large area was mapped as forest loss, most of it classified as being caused by the category "other". However, a visual assessment using high-resolution images in Google Earth Pro suggests that slash-and-burn agriculture is wide-spread on the entire peninsula, and likely responsible for a large share of the forest loss. This is supported by our analysis of the forest condition in 2023, which shows that many of the forest areas on the peninsula we classified as lost were covered by secondary forest in that year. Our findings about the importance of cropland as a deforestation driver for the national parks, on the other hand, are much more reliable, as they are based on our analysis of additional cropland. The fact that cropland expansion was the direct driver for almost all forest loss in Montagne d'Ambre and Ankarana therefore illustrates that our findings are not necessarily a contradiction to the previous reports from the literature about the high importance of agriculture for deforestation in Madagascar.

4.1.2.2 Fire

For the interpretation of fire as a driver of forest loss, it is important to consider that the data product we used for this analysis focused on forest loss due to natural or accidental wildfires. Forests lost in areas intentionally burned for shifting cultivation, on the other hand, were excluded (Tyukavina et al. 2022). This explains why across Africa, only 2% of the total 2001–2019 forest loss was due to fire, despite the widespread occurrence of fire on this continent. In Madagascar, 6% of the forest loss was due to fire (Tyukavina et al. 2022). With 4%, this rate was slightly below the national average in DIANA and its national parks. In Boeny, it was slightly higher, with 9%. The higher rate in Boeny can most likely be explained by its drier climate and the higher prevalence of dry forest. This is also evident from the work of Frappier-Brinton and Lehman (2022), who showed that dry forests burned significantly more often than humid and lowland forest in Madagascar.

In comparison with our other research areas, it was extraordinarily high that 57% of all forest loss in Ankarafantsika was due to fire. This can be partially explained by a large fire in 2006, when approx. 20% of the national park's entire forest area burned, but also by an increase of the annual forest loss due to fire after 2012. This is supported by Percival et al. (2024), who report that the fire-affected forest area in Ankarafantsika grew exponentially after 2014. They further reported that post-fire vegetation recovery was negligible, and that initial burns are likely to trigger subsequent fires. They conclude that the national park's dry forests exhibit high vulnerability and low resilience to anthropogenic fires.

Fire was overall a much more important driver for forest degradation than for forest loss, both in absolute terms (i.e. the total area affected) and in relation to the total forest degradation. How can it be explained that more than 30% of the total potential forest degradation in DIANA was caused by fire, more than 35% in Boeny, and more than 40% in Montagne d'Ambre, whereas forest loss due to fire was very low in these areas? A partial explanation can be found in methodological differences: the data product by Tyukavina et al. (2022) only registered fire as a driver of forest loss if there was a temporal link between a fire and the forest loss. In contrast, we recorded fire as the degradation driver if at least one fire was registered during the analysis period in the forest areas we mapped as potentially degraded, whether there was a temporal overlap or not. A visual assessment of areas with forest loss neither due to fire nor cropland expansion indicates that a significant part of these areas had burned at least once during the analysed time period, according to the burned area data product (Long et al. 2021). It is thus likely that the difference between the importance of fire as a driver of forest loss and potential forest degradation would have been smaller if the same methodological approach had been used for both.

Investigating hotspots of forest degradation due to fire in our research areas can further explain our findings. In Montagne d'Ambre, for example, such a hotspot can be found in the northern part of the national park. Historical satellite images from Google Earth Pro reveal that this area has been a human-modified forest landscape since our analysis began, with small-scale agriculture interspersed by forest fragments. In line with this observation, the vegetation of this area has been mostly classified as "Wooded grassland-bushland mosaic" by Duncan (2008). In contrast, the areas classified as humid forest by these authors were rarely mapped as degraded due to fire in our analysis. Similarly, for the regional level of DIANA and Boeny, a large share of the area classified as degraded due to fire are dry forests in human-modified forest landscapes. In these landscapes, fire is an integrated and traditional part of land use which is predominately used for pasture management (Bloesch 1999; Jacquin and Goulard 2013). This is supported by the observation that the areas with high levels of forest degradation due to fire are generally in areas with an overall high fire occurrence (Frappier-Brinton and Lehman 2022). It is thus plausible to assume that land-use activities are a significant contributor to the high importance of fire as a driver for forest degradation.

In summary, determining the exact role of fire in forest loss and degradation is methodologically challenging due to complex land use dynamics. This observation is in line with the literature, which has debated the extent to which fire is actually a driver for deforestation and degradation in Madagascar (Bloesch 1999; Phelps et al. 2022; Kull 2002). While our study cannot resolve this longstanding debate, it is worth noting that the extent of both forest loss and forest degradation due to fire has increased over time in almost all of our research areas. This is in line with Frappier-Brinton and Lehman (2022), who reported that fire frequency was increasing over time in most of the forest areas in Madagascar. Higher temperatures, more temperature extremes and reduced water availability are projected for the north-western part of the country under future climate change (Tomalka et al. 2021). The remaining natural forests in our research areas will therefore have to increasingly cope with the impacts of climate change, in addition to direct human pressures. In consequence, it is likely that the importance of fire will continue to increase.

4.1.2.3 Other drivers

The importance of the category of "other" drivers for forest loss and degradation was remarkable large. In the regions of Boeny and DIANA, it was responsible for more than 80% of the forest loss, and for more than 60% of the forest degradation. In the national parks, the category of "other" drivers caused between 55–95% of all potential forest degradation. This raises two important questions: which direct drivers are included in the category of "other", and what is their importance?

The first question can be readily answered: logging, charcoal production, firewood collection, and, to a lesser extent, pasture management have been reported as significant threats for forests in Madagascar (e.g., Eckert et al. 2011; Zaehringer et al. 2015; Phelps et al. 2022; Neugarten et al. 2024; PREB 2015a; PREB 2015b; Masolele et al. 2024). Charcoal production has been a longstanding threat to the natural forests of Boeny and DIANA, and addressing it has been a principal motivation for the development of the RVI approach (Lacroix et al. 2016). Due to the growing population, it can be exported that the demand for charcoal will continue to increase in the future

(PREB 2015a; PREB 2015b; MEDD 2020). Firewood collection and charcoal production are often cited as a single direct driver, lumped together under the term fuelwood. However, as mainly dry wood is collected for firewood, its impact on native forests is generally less severe (Randriamalala et al. 2021).

Since the 80s, logging of precious hardwoods has been a major issue in Madagascar's natural forests. This issue stems from a combination of weak governance, poor law enforcement, and a prevalence of corruption in the forestry sector (Waeber et al. 2019). An increase of illegal logging in protected areas has been reported (Waeber et al. 2016). Particularly the genera *Dalbergia* (rosewood and palisander) and *Diospyros* (ebony) have been logged, mostly to meet the demand of international markets. As a result, the two genera were placed under Appendix II of CITES, which aims to control trade in order to avoid utilization incompatible with their survival. There have been recent calls to move these species to Appendix I, which includes the most endangered CITES-listed species and does not permit any commercial trade (Waeber et al. 2019). During our field visit, we witnessed that illegal logging has been ongoing at a high rate in Montagne d'Ambre, and that other hardwood species than *Dalbergia* and *Diospyros* were also harvested, such as *Canarium madagascariensis*. Most of the timber produced in the national park is transported to Antsiranana and consumed in the domestic market (personal communication with MNP agents).

Extensive cattle production is widespread in the wooded savanna of Boeny (Randrianasolo et al. 2022), and fire is frequently used as a tool for pasture maintenance (Frappier-Brinton and Lehman 2022). It is plausible to assume that the frequent burning in the savanna can have a negative impact on adjacent forests, even in cases where we did not record fire as the primary driver for forest loss or potential forest degradation. Additionally, the follow-up land use of 6.4% of all forest loss between 2000–2020 in Madagascar was pasture, which was second only to small-scale cropland (Masolele et al. 2024). However, it is not clear to what extent this applies to Boeny and DIANA.

The second question, about the importance of the different drivers, is much more challenging to address for multiple reasons. First, the Analysis Ready Data products and NDFI time series we used for our analyses had a spatial resolution of 30 m. This resolution provided enough details to identify cropland expansion, individual fires, forest loss and potential forest degradation, but not enough to further differentiate between the "other" direct drivers. Using datasets with higher spatial resolution would have incurred additional costs and required higher computational resources for wall-to-wall analyses on the regional level (Section 4.3.1.4.3). Second, as discussed above, it is plausible to assume that the importance of agriculture has been underestimated in our analysis, particularly for slash-and-burn practices. In consequence, it is likely that the importance of the category of "other" drivers for forest loss has been overestimated. Third, as discussed above, the extent of potential forest degradation was possibly overestimated in the dry and open human-modified forest landscapes, which are widespread in Boeny and DIANA (see also Section 4.3.1.1). As we attributed any potentially degraded forest pixel without a recorded fire to the "other" driver, the importance of this category would also have been overestimated. Fourth, deforestation and forest degradation are often a complex process, with spatial and/or temporal links between different direct drivers. For example, charcoal or timber may be produced as a by-product of forest conversion for agriculture. Another example would be a gradual transition from an intact natural forest to a degraded forest, e.g. due to selective logging or charcoal production, and then, after multiple years, to cropland. These interlinkages do not only favour integrated approaches to address these drivers (Section 5), but they also make any attribution of direct drivers challenging, even if the above-described limitations were not present.

In summary, there is ample evidence for the production of timber and fuelwood in natural forests, and it can therefore be assumed that a substantial part of the category of "other" drivers is linked to the demand for wood products. However, the absence of evidence for agriculture or fire cannot be equated to evidence for charcoal production or selective logging as the direct drivers for forest loss and forest degradation. Assessing the importance of the different direct drivers from the category of "other" therefore remains challenging. In Section 4.3.1.4.3, we discuss potential methodological approaches to reduce this uncertainty.

4.2 Reforestation and plantation development

Our study represents the first evaluation of 13198.89 ha reforestation by 10459 plots promoted by two different programs in two regions covering a 23-year analysis period. The findings show that crown cover was low during the first rotation; however, it showed an upward trend throughout the analysed period. We identified several factors that contributed to the development of crown cover, accounting for known and unknown variables. While the influence of environmental factors such as topography and soil was comparable across regions and programs, the influence of socio-economic factors was program- and region-specific.

4.2.1 Estimation of reforestation success

More than half of the plots did not develop crown cover exceeding 20%. This is lower than expected, considering that many natural forests in Boeny and DIANA have crown cover values above 50% (Hansen et al. 2013). Our findings are in line with previous inventories in the study regions. The average stand volume was ca. 10.8 m^3/ha in selected basins in DIANA (Richter and Andriampiolazana 2023) and 3,96 m^3/ha in Boeny (Rasoanaivo 2014). In comparison, an average stand volume of ca. 325 m^3/ha at an age of 4—6 years was reported for highly-productive *E. urophylla* x *E. grandis* plantations in Minas Gerais, Brazil (Leite et al. 2020). For South African plantations in Zululand, Dube et al. (2015) reported an average volume of ca. 164 m^3/ha for predominantly 4–11-year-old stands of *Eucalyptus* spp. On degraded land in a semi-arid region in North-eastern Mexico, *E. camaldulensis* reached a stand volume of 59 m^3/ha after 20 years (Foroughbakhch et al. 2017). These examples show that the stand volumes in DIANA and Boeny are considerably lower than in other regions. This can be explained by several reasons. The main objective of the reforestation plots is the production of energy wood; they are managed in short rotations and often harvested for charcoal after around 5 years (Rasoanaivo 2014). This prevents the development of higher and more closed canopies. Furthermore, our results confirmed the pattern reported by Rasoanaivo (2014) of a low percentage of well performing plots in Boeny: Of the plots established in 2009/2010, 23% had a stocking rate of 0% four to five years later. Additionally, 45% of the inventoried area had a stand volume of 0 m^3/ha for trees with a DBH exceeding 8 cm, and only 5% achieved a stand volume exceeding 20 m^3/ha. In DIANA, the results of Richter and Andriampiolazana (2023) confirmed the high percentage of damaged RVI plots (ca. 90%), due to diseases, intrusion of livestock, fires and windthrow, that was even reported in selected flagship basins. In addition to previous studies, we observed frequent establishment of agriculture within plot boundaries during our field visits. However, for the interpretation of our findings, it is important to keep in mind that our presented crown cover values are plot averages. While many plots had low crown cover, others developed either a closed canopy or high stocks, at least on parts of the plot. In line with that, Richter and Andriampiolazana (2023) reported average stand volumes of up to 68 m^3/ha for the stratum of well performing reforestation plots.

Reforestation plots established by PLAE had overall higher crown cover than those by the GIZ. This can be explained by the difference between both programs in terms of planted species, objectives and soil preparation. On average, PLAE plots had a higher vegetation cover prior to the establishment of the RVI plots. This reflects the objective of erosion control of PLAE plots: erosion sensitive areas on inclined terrain likely already have shrub and other vegetation cover and are located at higher and thereby cooler sites. Erosion control depends on continuous vegetation cover (Morgan 2005; Bauhus et al. 2010). Hence, plots were largely prepared with manual labour and as a result, remnant vegetation was only partially removed, and contour strips were established. Higher NDFI and lower inner-annual differences due to a higher vegetation cover with a likely higher shrub proportion further leads to higher crown cover (Jones and Vaughan 2010; Abelleira Martínez et al. 2016). In contrast, in case of the GIZ approach, plot preparation was largely executed with mechanized labour, resulting in complete vegetation removal. Additionally, PLAE plots were mainly planted by various combinations of *Acacia* spp. and *Eucalyptus* spp. while GIZ plots were mainly covered by *Eucalyptus camaldulensis*.

We found continuous increase in crown cover over time for both the GIZ- and PLAE-supported reforestation. However, the total average growth rate is slow, with only ca. 1% crown cover increase per year per plot. We found no significant differences in crown cover increase (in %/year) between both programs. However, in contrast to GIZ-supported plots, PLAE-supported plots showed almost no increase in NDFI values at the start of the dry season, particularly in Boeny. Possibly, this finding was influenced by grass or undergrowth, as NDFI-values are sensitive to non-woody vegetation. Crown cover and NDFI values at the end of the dry season are therefore better suited to show the development of plantation plots to compare both PLAE and GIZ plots.

Throughout the analysed period, crown cover values continuously increased after the first reforestation resulting in an average tree cover of 20% in 2023. This finding can be explained by multiple factors. Coppicing and selective cuts are often used in the plots for charcoal production. In contrast to clear cuts, part of the tree cover remains on the plots afterwards. This allows for an long-term increase of crown cover (Ferraz Filho et al. 2014; Hegde et al. 2013). Additionally, farmers use the reforestation to produce not only charcoal, but also timber poles, resulting in longer rotation periods. Moreover, we observed proactive recent reforestations on previously unsuccessful reforestation plots.

In summary, our findings highlight that both projects achieve to establish tree cover in the long term, however there is potential for the improvement of the success rate. The following section will address factors that contributed to success and failure of reforestation initiatives.

4.2.2 Identification of reforestation success drivers

The mixed model approach we used to explain the development of crown cover allowed us to account for success drivers on different levels. As fixed factors, we used 11 environmental, socio-economic and reforestation-related variables which were available across the different programs and regions. The fixed effect variables only explained 8.7% of the variance in crown cover values; in contrast, 72% of the variance was explained when including both fixed and random effects. The high influence of the random effects, i.e. plot as a random intercept and plot age as a random slope, shows that crown cover varies substantially at small scale and barely relates to spatial gradients, and that the increase of crown cover depends considerably on the individual plot. The random effects thus serve as a proxy for those environmental and socio-economic factors which differ between plots, but which we could not include as fixed factors into the model due to data limits. Such factors can include the influence of remnant vegetation, planting densities, survival rates, planted species, fire management, presence of diseases, management objectives of the owner, and others. The high influence of non-quantifiable factors on forest restoration success has been confirmed by cross-country analyses and other case studies (Wells et al. 2020).

Although fixed effects do not explain much of the variance, the information they provide is still valuable and should be discussed. Of the fixed effects, environmental gradients, and particularly soil type and climatic water deficit, explained most of the variation in crown cover. The soil maps we used grouped soil types at a macro scale (Delenne and Pelletier 1981). In line with the RVI approach, most reforestation plots were established on soils that were considered less suitable for agriculture, such as ferrallitic soils and ferruginous soils (see Figure 38 and Annex B). However, highest crown cover values were found on the category “other”, which included all soil types that did not belong to the three most frequent classes. The most common “other” soil types were lithosols, vertisoils and podsols. We also found differences within oxidized soils: ferruginous soils had higher crown cover than ferralic soils. In DIANA, these ferralitic soils were mostly yellowish sandy soil groups located at lower altitudes and in Boeny, these were grouped as highly eroded. The ferruginous soils belonged to more humus forming soils at higher altitudes (see Annex B). These characteristics are especially important in tropical soils as a water reservoir, but they also make these soils more susceptible to erosion (Obame et al. 2022). In Boeny, where overall crown cover was lower, the ferruginous soils were mapped as eroded and sandy. The distribution and influence of the different soil types confirms that RVI is often executed on sites where more profitable forms of agriculture are less viable, even at the cost of lower plantation performance. Furthermore, this suggests that tree cover develops better on non-degraded soils. This highlights the need to prevent soil degradation from the outset, as restoring degraded soils tends to result in reduced productivity.

The climatic water deficit particularly described differences between DIANA and Boeny. Overall, the drier climate can cause higher mortality of saplings, higher fire frequencies, and development of lower canopy to adopt to water stress (Bonell and Bruijnzeel 2010). In light of this finding, we would expect higher crown cover at higher altitudes, which have cooler temperatures. However, crown cover was higher at lower altitudes. Our results can thus be interpreted as another indicator that water stress limits plantation development. Water availability is often higher in sedimentary zones due to increased water accumulation and nutrient-richer soils (Morgan 2005; Bonell and Bruijnzeel 2010). Higher crown cover on steeper slopes can be related to the objective of erosion control and lower competition with other land uses.

Our finding that higher fire frequencies led to higher crown cover is in line with findings for savannah ecosystems in Africa and Australia (Volkova et al. 2019; Russell-Smith et al. 2010; Gordon et al. 2017). This also confirms that the two main species are resilient to fires: natural regeneration of acacia is supported by forest fires (Gordon et al. 2017; Saharjo and WATANABE 1997) and *Eucalyptus sp.* is fire-resistant to some degree (Russell-Smith et al. 2010; Volkova et al. 2019). In addition, forest fire can have a fertilisation effect (Volkova et al. 2019), which could lead to higher crown cover on reforestation plots. It is also noteworthy that, despite the overall positive influence of fire frequency on crown cover, high crown cover classes were only found in plots with reduced fire frequency. This suggests that the desired high crown cover values are not viable once fire frequency passes a critical level. It should be emphasized that overall, fire frequency had a low influence on forest cover. In summary, the weak and diverse influence of fire frequency suggests that adverse environmental conditions and poor sites hinder the growth of plantations rather than fires on plot with low crown cover. However, to increase the proportion of plots with high crown cover, adapted fire management strategies might be necessary.

On its own, the variables related to the reforestation approach (reforestation program, number of reforestations, age and plot size) explained 6% of the variance in crown cover and were thus one of the most determining group of factors. The model outcomes indicated that PLAE-supported plots had significantly higher crown cover than GIZ-supported plots. This finding can most likely be explained by the fact that GIZ-supported plots had lower crown cover values before the establishment of reforestation, as discussed earlier. The increase in crown cover per year was comparable for both the GIZ and PLAE program, as indicated by the non-significant interaction between the reforestation programs and the annual crown cover increases. Hence, there is little evidence for one program being more effective than the other in restoring forest cover, and differences are likely rather related to reforestation objectives.

Plot size was also a significant factor, with most higher crown cover plots being ca. 1 ha or smaller. These smaller plots performed better, which could be caused by their easier maintenance, less labour, and a lower incentive to convert the plantations to other land uses. Whether or not a plot was reforested a second time only had a significant effect on PLAE-supported plots in Boeny. There, plots with a second reforestation had a lower crown cover than those without. This can be explained by the fact that a second reforestation would only occur in plots where tree cover had not been successfully established. These plots are likely on poorer sites; hence a second reforestation would meet the same challenges as the first. Additionally, the reduction in crown cover might result from clearing any remaining vegetation as preparation for a second reforestation. These results suggest focussing reforestation efforts on overall smaller plots and discouraging repeated supported reforestation on the same plot.

Three out of four linear mixed models indicated higher crown cover values close to roads and the overall model showed higher crown cover closer to larger settlements. Excluding outliers, most of the distances from roads to reforestation plots were in the range between 0 and 18 km. The distribution of crown cover along this distance gradient suggests a high variation in the first ca. 3 km from the included roads. This could indicate that easy access for preparation, maintenance and harvesting is an important factor. Higher crown cover in proximity to cities can be explained by their higher charcoal demand and lower transport costs (PREB 2015b; PREB 2015a). These findings are in line with the motivations of charcoal producers from Zambia (Kazungu et al. 2020). An additional explanation is the improved institutional support of reforestation activities and value chains in proximity to urban centres and project offices.

It must be noted that these results, however, were inconsistent for the different programs and across regions. For example, in DIANA, crown cover was higher in regions with low population density, while in Boeny, the opposite was true. Additionally, in contrast to the other three models, GIZ-supported reforestation in DIANA had higher crown cover with increasing distance to roads. It is likely that the higher accessibility and population density lead to increased land-use pressure, resulting in adverse effects on reforestation. With higher demand for charcoal, reforestation plots closer to roads and cities are likely to be harvested earlier and more frequently compared to the remote plots.

Although the GIZ- and PLAE-supported programs had similar objectives and target groups, depended on the same species and overlapped spatially, socio-economic influences were weak in the overall model and heterogeneous in the program- and region-specific models. This highlights the difficulties to generalize socio-economic patterns and scale up lessons learned from one region or project to another. For example, Ranjatson et al. (2019) highlights different tenure systems in Boeny and their implication for forest restoration. Ahimbisibwe et al. (2024) showed the influence of labour input, training, tenure status and silvicultural practices on home garden and woodlot performance in Ethiopia. Other important factors for reforestation success include motivation of farmers (Kubo et al. 2022), the dependency on forests products and reduced access to forest resources (Lambin and Meyfroidt 2010).

4.2.3 Recommendation of growth zones

As discussed in the previous section, the environmental drivers for the success of reforestation were consistent across programs and regions. This allowed us to use them as independent variables for the prediction of maximum crown cover values and annual increases in NDFI in Random Forest models. However, it was crucial to consider the small proportion of the total variance in the linear mixed models which was explained by the fixed effects. To address this, we only used the best performing reforestation plots as training data in the random forest models. This not only considerably improved model quality, but it also made the predictions relevant for practice: the resulting maps describe the potential productivity in an area that could be theoretically obtained from an ecological point of view. These maps can guide the identification of promising zones for future reforestation in general, and Eucalyptus- and Acacia-based reforestation in particular. However, this is limited to supporting macro-scale planning. For an application on a local scale, further validation and confirmation are required.

The two maps we produced are complementary. The first map ("crown cover raster"), can serve as a guideline which shows the crown cover values that can be expected under favourable conditions after seven years. Future more advanced analyses should rely on this prediction due to its high model quality and straightforward interpretation of crown cover values. The second map ("NDFI development raster") shows the increase of NDFI in the dry season as a proxy for an increase in vegetation cover. It therefore describes the expected change of NDFI after a reforestation. However, due to the nature of the NDFI, this map is more challenging to interpret: a low increase can either be due to an NDFI saturation by permanent non-tree vegetation or due to low canopy growth rates. Additionally, the quality of this map is poorer (Figure 15). In DIANA, zones of higher ecological potential are located at higher altitude and under lower water deficit around Montagne d'Ambre. This is in line with predictions for biomass in natural forests for Madagascar (Vieilledent et al. 2013). In Boeny, the highest ecological potential is south of Ankarafantsika National Park and around the Betsiboka river, which overlap with areas for agricultural production potential (Delenne and Pelletier 1981).

It is important to emphasize that the ecological predictions do not take competing land use or socio-economic constraints into account. Our analysis of excluded areas indicates that, based on current land use, around 70% of the area of the park buffer zones would be available for reforestation. This estimate, however, is based on global remote sensing products. It is a likely an overestimation, since not all areas of small-scale agriculture and shifting cultivation were identified by these products (see Section 3.1.4.2). We could confirm this for areas where a SAC was available; in these areas, only a fraction of the sites with high ecological potential is not dedicated to competing land uses. Furthermore, the distribution of sites with high potential is uneven. The overlap between planned reforestation sites and areas with low productivity likely contributes to the low success rates of reforestation sites. This highlights the conflicts between reforestation and agricultural activities on the one hand and firewood provision and conservation on the other hand. It confirms diverse and interconnected links between reforestation and livelihoods (Harvey et al. 2014).

We additionally generated two maps which show high potential zones for reforestation while taking current or future land use into account. The first one ("planned land use") can be applied to areas with existing SACs in Boeny and DIANA. It provides information in three categories: 1) planned land use allows for reforestation-related activities, 2) planned land use allows for reforestation and the ecological potential is above average for an RVI approach, and 3) planned land use prohibits reforestation. If a project zone is covered by a SAC, this map should be used, as it likely gives a better recommendation for future reforestation areas. The second map ("existing land use") can be used for areas not covered by a SAC. It contains three distinct classes: 1) current land use allows for reforestation, 2) current land use allows for reforestation and the ecological potential is above average, and 3) current land use prohibits reforestation. While this map can be applied to the entire area of Boeny and DIANA, its reliability likely decreases with increasing distance from past reforestation sites.

4.3 Validation, limitations and future research

In this section, we discuss aspects related to the validation and limitations of our findings. Furthermore, we propose future research directions which can either address some of these limitations, or answer additional questions raised by our findings. For these recommendations, it is relevant that land use analyses and remote sensing are highly dynamic fields of research. Ongoing technological and analytical improvements, often fuelled by the latest development in AI research, have contributed to the frequent development of new large-scale or global products. This includes, for example, the analysis of diversity of land uses following deforestation across Africa by Masolele et al. (2024) and forest canopy height maps by Tolan et al. (2024), the latter with a very high spatial resolution of 1 m. These two products have not been available at the beginning of the project and could therefore not be used for our analyses, but they illustrate that technological innovations can have a large potential for many of the future research directions we suggest below.

An overall limitation for both natural forest and restoration is related to the datasets we used in the remote sensing-based analyses. The open access and global availability of these datasets allowed us to produce regional-level findings without additional costs for data purchase. The ease of data access is a significant advantage if our analyses should be transferred to other regions of Madagascar or upscaled to the national level. Additionally, the satellites which provided the images we used to calculate the NDFI time series had a frequent revisit time of approx. 16 days, resulting in a high likelihood of cloud-free images. This, in combination with an annual temporal resolution of most of the ready-for-analysis data products, allowed us to track forest loss, potential forest degradation, their direct drivers, as well as crown cover development of reforestation plots over the entire analysed time periods. Therefore, the use of these open access data proved valuable to reach the goals of AFOB within the project duration; generating our own data, e.g. for burned areas, would otherwise have required too significant efforts in ground-truthing and data analyses. Despite these advantages, there is also an important limitation that resulted from the use of the ready-for-analysis data products. For their generation, elaborated analytical processes have been employed, calibrated with reference data spanning over a wide range of forest ecosystems, forest types and geographic regions. In consequence, most of the data products have a relatively high overall accuracies on the global level, but this does not always translate to high accuracies in specific areas. On the positive side, these ready-for-analysis data products typically underwent a thorough validation procedure before publication and their quality were subsequently critically assessed by the scientific community (e.g., Ferrer

Velasco et al. 2022). Therefore, the level of uncertainty is typically known. We use this information to discuss limitations of our findings in the following sections.

4.3.1 Natural forest

Our field trip for verification provided insights to assess the accuracy of the data products and our findings. With the help of local experts, we visited different spots that were mapped as either undisturbed forest, forest-to-cropland conversion, forest loss due to fire or other drivers, or potential forest degradation due to fire or other drivers. In Ankarafantsika, all visited spots were correctly classified, indicating a high degree of overall accuracy for this dry forest ecosystem. Furthermore, personal communications with colleagues from GIZ and local guides who accompanied us during the field visit confirmed that the year of occurrence of forest loss or degradation was correctly recorded in our data.

In Montagne d'Ambre, all locations mapped as potential forest degradation or forest loss were also correctly classified. However, multiple locations mapped as undisturbed forest were in reality either degraded or converted, and some cropland areas were falsely mapped as other land cover. This indicates that the data products and our findings underestimated forest loss, potential forest degradation and cropland expansion in humid forest ecosystems.

It should be noted that due to the limited duration of AFOB, it was not feasible to employ a systematic approach for the collection of ground-truth data or to validate our findings outside of the two national parks we visited. Therefore, our field trip cannot be considered as a complete and scientifically sound validation of our findings, particularly with regards to the large swaths of human-modified dry forest landscapes outside of the analysed national parks. Reports from literature indicate that mapping forest cover, forest loss and forest degradation is challenging in sparse forests of dry ecosystems associated with woodlands or savannas (Gao et al. 2020; Mullissa et al. 2023), especially in advanced deforestation stages (Ferrer Velasco et al. 2022). This can be explained by the fact that, in contrast to tropical humid forests, tropical dry forests consist of open canopy cover with a significant herbaceous under-story and strong seasonal effects (Mullissa et al. 2023). In consequence, we assume that our findings are associated with larger uncertainties and errors in the areas outside national parks, both in Boeny and DIANA.

4.3.1.1 Potential forest degradation

We identified potential forest degradation based on an empirically defined NDFI threshold of 0.25, which we estimated by visually assessing a large number of pixel trajectories and comparing them to historical images on Google Earth Pro. Each year, we classified all forest pixels with a dry season NDFI value below this threshold as potentially degraded. However, the value of this threshold has a large influence of the outcomes of this analysis (Souza et al. 2024). The fact that our threshold definition does not take the ecological differences between different forest types into account can explain the underestimation of forest degradation in the humid forest of Montagne d'Ambre, which we observed during our field trip. These forests naturally have high NDFI values, with only small variations between the dry and wet season. In an area where forest degradation causes only a minor loss of tree cover, it is likely that the NDFI value remains above the threshold of 0.25, and that in consequence, we would classify this area as undisturbed. We therefore used an adapted NDFI threshold of 0.5 to identify potential forest degradation in humid forests to estimate the forest condition in 2023; time constraints did not allow it to recalculate our analysis for the entire time period. It should be noted that the threshold of 0.5 was based on our limited field observations and should be considered as preliminary.

In Ankarafantsika, the forest areas we visually assessed as degraded during our field trip were generally classified as potentially degraded in our findings. This indicates that the threshold value of 0.25 was adequate for the dry forest of this national park. However, not all dry forests in Boeny and DIANA have the same ecological characteristics. In undisturbed forest areas where the tree cover is lower or the seasonal amplitude between minimal and maximal NDFI higher than in Ankarafantsika, it is possible that natural processes, such as years with a prolonged dry season, lead to temporarily low NDFI values. This would then be falsely classified as potential forest degradation in cases where the NDFI falls below the threshold value of 0.25. This might have been the case in Ankarana, for example, where almost the entire forest area on the limestones plateaus was classified as potentially degraded. Similarly, the predominance of dry and open forest types in Boeny and DIANA, with their characteristic dry forest-savannah dynamics, could partially explain why large swaths of forest land were classified as potentially degraded in these regions.

We used the NDFI-threshold approach because it was pragmatic and allowed us to address our research questions within the limited project duration. Future research could employ more elaborate approaches for the analysis of NDFI time series which could address the limitations of the threshold approach discussed above, therefore likely producing more reliable findings (e.g., Bullock et al. 2020, Souza et al. 2024). These approaches first determine the typical temporal patterns of seasonal NDFI fluctuations for each forest pixel and then use this information to classify significant deviations from the natural seasonal patterns as forest degradation.

The NDFI-based approach we used requires in-depth expertise in spatial analysis and programming. Using this approach in an operational setting—such as for ongoing monitoring of forest degradation by national park managers—would therefore require substantial investments in capacity building. However, there have been ongoing scientific advances, such as a recently developed method by Mullissa et al. (2023) that can be used to generate large-area and near real-time disturbance alerts in the dry tropics using deep learning models. Therefore, it can be expected that ready-for-analysis data products mapping forest degradation will be released in the near future, opening up new possibilities on the operational scale.

It is important to emphasize that NDFI is influenced by tree canopy structure and vegetation greenness. Using NDFI changes as an indicator for forest degradation therefore mostly detects structural changes; however, forest degradation can also be caused by large shifts in species composition (Vásquez-Grandón et al. 2018). For example, during our field trip we witnessed that species such as banana or papaya have been introduced into the natural forests of Montagne d'Ambre. If the NDFI values of these forests and undisturbed natural forest are similar, we wouldn't classify them as potential forest degradation. Forest degradation due to changes in species composition is currently almost undetectable (Gao et al. 2020).

4.3.1.2 Forest loss

A study from the Masoala National Park in north-eastern Madagascar, which compared the tree cover loss from Hansen et al. (2013) to an object-oriented classification method trained with local ground-truthing data, concluded that the Global Forest Change dataset is a valuable resource in detecting small-scale and diffuse deforestation caused by slash-and-burn agriculture and landslides. However, during our field trip in Montagne d'Ambre, we noticed that most of the forest loss which was incorrectly mapped as forest cover was caused by illegal logging or small-scale agriculture. This is in line with previous reports that the Global Forest Change dataset of Hansen et al. (2013), which was the basis for our estimates, underestimates forest loss driven by small-scale disturbances (Tyukavina et al. 2015; Milodowski et al. 2017). Additionally, it should be pointed out that the forest loss data from 2011 to 2023 has been recently updated with an improved method that more reliably detects smallholder rotation agricultural clearings in dry and humid tropical forests and selective logging. As the years preceding 2011 have not yet been reprocessed, comparisons between 2000–2010 and 2011–2023 should be performed with caution (GLAD 2024). The increase in forest loss from the first period (2001–2011) to the second (2012–2022) in all our research areas could be in part linked to this improvement of the data product. Updating our analysis with reprocessed forest loss data back to the year 2000, which is planned in an upcoming update by GLAD (2024), could provide further insight about the importance of this limitation.

For the design of future forest conservation strategies, it would be important to have more robust knowledge about the relationship between forest loss and degradation. For example, interventions should take into account the extent to which deforestation occurs in previously degraded forest or intact forest, spatial and temporal trends in these processes, and whether forest loss or degradation has more severe impacts. However, generating this knowledge based on our findings would be challenging because we relied on Hansen et al. (2013) for forest loss and on NDFI time series for potential forest degradation, based on a method we adapted from Souza et al. (2005). This approach was practical, but the methodological differences could potentially obscure true relationships between forest loss and degradation. Using the same methodological approach for mapping both phenomena could allow for a more robust linkage. In view of that, it is relevant that reports from literature suggest that NDFI time series can also be a suitable data basis for mapping tropical deforestation (Schultz et al. 2016; Bullock et al. 2020). We started to explore this potential by estimating NDFI thresholds that correspond to forest loss based on the observations we made during our field trip. We then used these thresholds to estimate the forest condition in 2023. These results should be considered as preliminary; a more robust analysis would require additional ground-truthing and validation. Nevertheless, exploring the differences in forest loss estimates between Hansen et al. (2013) and our NDFI-based approach can provide further insights. The largest difference was found in Ankarafantsika, where the NDFI-based forest loss was more than four times lower. This can likely be explained by the large-scale fires in this national park. Forest areas that burned after 2000, but then regenerated before 2023, would have been recorded as forest loss by Hansen et al. (2013), but not by the NDFI-based analysis. In contrast, the NDFI-based analyses recorded more than twice as much forest loss in Montagne d'Ambre than Hansen et al. (2013), supporting our field observations that the latter underestimated forest loss. In DIANA and Boeny, NDFI-based finding were 41% and 23% lower, which indicates that forest loss based on Hansen et al. (2013) might have been overestimated in the human-modified dry forest landscapes outside of the analysed national parks. In Ankarana, the karst topography, which likely artificially inflated our findings for potential forest degradation, might also explain why the forest loss based on NDFI was almost twice as high as by Hansen et al. (2013).

4.3.1.3 Fragmentation

It should be pointed out that our analysis compares the state of fragmentation in 2000 and 2020. In consequence, it does not account for tree cover changes which occurred after 2000, but were subsequently reversed by 2020. This is the case, for example, in Ankarafantsika, where most of the large forest areas lost to fire in 2006 in the national park's centre were recorded as forest in 2020 due to the natural regeneration that occurred after the initial tree cover was lost.

4.3.1.4 Driver analysis

4.3.1.4.1 Cropland

We identified a substantially larger extent of cropland than Potapov et al. (2022b) in their global map product. However, our analysis of additional cropland only applies to the national parks and their peripheral zones. As a result, our findings regarding the importance of cropland as a driver for forest loss are less reliable at the regional level in Boeny and DIANA. Therefore, the analysis of additional cropland not only provides new insights into the actual importance of cropland, but also illustrates that high data quality is crucial in analyses of deforestation drivers.

During our field visit, we were able to exemplarily compare the outcomes of our analysis of additional cropland with the ground-truth. We noticed that our model demonstrated high specificity, i.e., most actual non-cropland areas were correctly predicted as non-cropland. We only found a few pixels misclassified as cropland, for example, in the centre of the national park of Ankarafantsika. However, the model exhibited low sensitivity, as it failed to detect several instances where cropland actually existed. This suggests that even the extent of our additional cropland areas is likely underestimated, which in turn indicates that the global estimates of Potapov et al. (2022b) were even more underestimated. An explanation for the underestimation of the cropland extent in our analysis could be partly the change from vegetable and rice to khat cultivation, a perennial shrub. From a remote sensing perspective, the detection of these areas is more difficult, because the reflectance values of shrub vegetation can more closely resemble those of tree-covered areas. Additionally, we did not add khat areas to the cropland reference dataset we created using Google Earth Pro, due to uncertainty about whether these areas were indeed agricultural or not. Furthermore, we observed encroachment in the natural forest of Montagne d'Ambre during our field trip. The agricultural fields inside the forest had a very small extent. The forest understory was cleared, but a number of adult trees still persisted. This type of small-scale agriculture is very challenging to detect using remote sensing approaches. It is likely that neither the global cropland analysis nor our additional cropland analysis would have detected such a pixel.

To gain a more comprehensive picture of the importance of cropland as a deforestation driver, future research should address some of the limitations described above. At the regional level, conducting an analysis of additional cropland similar to our approach for the national parks would likely reveal a larger cropland extent, particularly if slash-and-burn agriculture is considered. The latter could be achieved using a dedicated time series analysis of remote sensing imagery which takes the different phases of the swidden agriculture cycle into account (land clearance, crop cultivation for several years, and fallow; Jiang et al. 2022). Chen et al. (2023) recently demonstrated that NDFI time series can be used for that purpose; the authors did not only detect forest degradation and deforestation in Laos, but also shifting cultivation. For khat, our field observations in Montagne d'Ambre confirmed that large forest areas have been converted for its cultivation over the last years. A study focusing specifically on the extent of khat could reveal its importance as a deforestation driver. For this, suitable remote sensing methods can be found in Dessie and Kinlund (2008) and Baariu and Mulaku (2015). Improved methods for the mapping of slash-and-burn agriculture and khat cultivation would likely also address the underestimation of cropland in our analysis. However, it should be noted that such studies would require substantial efforts to create reference data, either through visual interpretation of high-resolution satellite imagery or ground-truthing using, for example, camera-equipped drones.

4.3.1.4.2 Fire

As discussed above, our findings showed that the overall importance of fire as a driver for forest loss and degradation has increased over the time period we analysed, and will likely continue to do so in the future. This is particularly true in Ankarafantsika, where large forest areas have been lost due to fire. A recent study by Percival et al. (2024) indicates that the native old-growth dry forests of this national park only have a low fire tolerance and that a single fire transforms them into a degraded savannah state with low biodiversity. This is only partially supported by our field observations, which suggest that diverse secondary forests have established in some forest areas previously lost due to fire. The impact of fire on the flora and fauna therefore warrants further research. For example, identifying which factors favour or prevent natural regeneration after forest loss due to fire could provide insights that are relevant for the design of intervention strategies.

Furthermore, fire prevention and control will become even more crucial in the future. For prevention, fire breaks have been established in the peripheral zones of Ankarafantsika, but they could not completely prevent the spread of fires into the national park (personal communication with colleagues from GIZ). Further research on fire breaks should focus on efficient methods for their establishment, e.g. through prescribed burning, their optimal allocation in the buffer zone, as well as the potential role of wider trails in the natural forest that can double as a fire break and an ecotourism infrastructure (Percival et al. 2024). Additionally, the use of automatic alert systems for notifying national park managers about active fires could enhance fire control. For this, the near-real time VIIRS active fires data (Giglio 2024), which can be accessed, for example, through Global Forest Watch (NASA FIRMS 2024), has a high potential.

4.3.1.4.3 Other drivers

Our findings provide overall importance values for the category of “other” drivers, but do not distinguish between different direct drivers within that group, such as logging, collection of fuel wood, charcoal production, mining or extension of settlements and roads.

As discussed above, reports from the literature indicate that charcoal production contributes significantly to forest degradation and deforestation in Madagascar. Remote sensing approaches can be used to estimate the importance of this driver. For example, Dons et al. (2015) employed a supervised classification approach to delineate burn marks from charcoal production in Tanzania, using a QuickBird satellite scene (resampled to a spatial resolution of 0.6 m) and reference data from 45 charcoal kilns as input data, monitored in the field over multiple months. Sedano et al. (2020) mapped kiln scares in Mozambique, using an image segmentation approach based on Sentinel 2 images with 10 m spatial resolution, reference data created from field measurements of kiln parameters and very high-resolution PlanetScope images (3 m spatial resolution) for the validation of their findings. Recently, Verhegghen et al. (2023) used computer vision to detect kilns in a 42 000 km^2 area in Somalia with a high accuracy. Their deep learning model was trained with DigitalGlobe images (0.5 m spatial resolution) and a manually delineated reference data set consisting of 110 000 known kiln locations. These examples illustrate that remote-sensing based approaches for detection of charcoal production require very high-resolution satellite images, which have typically high acquisition costs, and reference data that is time-consuming to collect. Due to these requirements, it was not feasible for us to detect charcoal production within the limited project duration of AFOB. It can be expected that very high-resolution remote sensing data and advanced analytical methods will be increasingly available and accessible, making it less challenging for future studies to gain more detailed knowledge about the importance of charcoal production in natural forests in Boeny and DIANA.

The number of studies that use remote sensing to monitor selective logging activities has been steadily grown over the last years (Jackson and Adam 2020). At first glance, this suggests that remote sensing-based methods are readily available to quantify the extent of illegal logging in the natural forests in our research areas, and therefore estimate its importance as a driver of forest degradation. However, despite the growing number of studies, it remains challenging to map the areal extent or impacts of selective logging utilizing remote sensing imagery (Jackson and Adam 2020). Furthermore, the available studies most often analyse selective logging in large-scale industrial forest concessions. There, information about the location, timing and intensity of logging as well as detailed forest inventory data are often available, which constitute valuable reference data for remote sensing analyses. In the context of small-scale illegal logging in Boeny and DIANA, such detailed ground information is typically not available and would have to be created first. This would involve intensive field monitoring and/or visual interpretation of very high-resolution satellite imagery (Jackson and Adam 2020). This was not feasible for the AFOB project, but could be a worthwhile investment for future studies. As with charcoal production, we expect that ongoing scientific developments will considerably improve our ability to monitor logging in tropical forest landscapes. For example, when time series of the recently released very high-resolution global tree height map by Tolan et al. (2024) become available, they could be utilized to detect the removal of individual trees in natural forests in Boeny and DIANA.

4.3.2 Reforestation

4.3.2.1 Field data quality

The comparison of GIZ- and PLAE-supported reforestation revealed different main drivers of restoration success. However, the fixed factors we included in the mixed effect model had limited explanatory power, as they only explained a small part of the total variance in the crown cover of reforestation plots. These substantial uncertainties make it challenging to transfer the lessons learned between these different reforestation programs and therefore limit their extrapolation and upscaling potential. The uncertainties are in part due to crown cover varying substantially at small scales and barely relating to spatial gradients. However, they were also caused by limitations related to data quality. Initially, we aimed to use the existing inventory data of reforestation plots as a calibration dataset for our remote sensing-based analyses, allowing us to estimate standing volumes over all research areas. However, data homogenization proved to be too challenging due to inconsistent quality of the forest inventory datasets. Instead, we used crown cover data reported by Sirro et al. (2021) in their ForestFlux study for calibration. While this allowed us to make best use of the available data, it also introduced two sources of potential uncertainty. First, the ForestFlux study only included a subset of all GIZ- and PLAE-supported reforestation plots in DIANA and none in Boeny, making our crown cover predictions beyond these areas less reliable. Second, larger crown volumes are generally related to higher wood volumes, but the correlation between the two can be weak (Rodríguez-Solís et al. 2015). Therefore, crown cover may be a proxy for the success of reforestation, but fails to quantify the provision of wood for charcoal production, which is the primary objective of most of the reforestation plots included in our analyses.

Additionally, we relied on the NDFI time series to predict crown cover of reforestation plots, because the full spatial coverage for all our research areas and availability for each year between 2000 and 2021 constituted a considerable advantage. However, NDFI values of reforestation plots with low tree cover can be high if the cover of herbaceous vegetation is high, thus potentially introducing further uncertainties into our crown cover estimates. We tried to reduce this uncertainty by including the difference between NDFI values at the start and end of the dry season in our random forest model. Despite these efforts, we cannot entirely rule out that crown cover estimates for plots with an abundant herbaceous layer are less reliable.

These limitations illustrate that there is a need for high-quality field data to close knowledge gaps about optimal silvicultural practices to achieve best reforestation results. We therefore recommend to implement more systematic field trials. Their establishment should be guided by an experimental design geared towards learning from restoration successes and failures, thus informing future strategies. These trials should ensure ongoing monitoring to generate comprehensive data pools of biophysical and silvicultural variables which serve as a basis for long-term planning beyond project timelines. Additionally, it is crucial to also include socio-economic variables, as discussed in the following section.

4.3.2.2 Socio-economic factors

Our findings that socio-economic influences were weak in the overall model and heterogeneous in the program- and region-specific models makes it challenging to scale up lessons learned from one region or program to another. In contrast to our findings, reports from the literature indicate that socio-economic factors can be a significant determinant for the success or failure of reforestation and FLR projects. For example, Höhl et al. (2020) reported that lack of local stakeholder involvement and a mismatch between goals of local communities and restoration managers can constitute major obstacles to forest restoration, whereas perceived direct benefits for local communities can contribute substantially to success. In Zambia, education, landholding size, the share of forest income, cash crops and non-farm income, and access to markets all had an impact on participation in forest support programmes (Kazungu et al. 2021). It is plausible to assume that these factors also influence to what extent reforestation plot owners in our research areas were willing and able to allocate the workforce and resources necessary for success. The ready-for-analysis data products we used as proxies for socio-economic dynamics (population density, distance to roads and distance to large settlements) did probably not completely capture all these different aspects. This can partially explain the low importance and inconsistency of socio-economic influences in our findings. Despite this limitation, the use of the data products was reasonable, because the fact that they are spatially explicit allowed us to assign for each variable a specific value for the location of each reforestation plot.

Future research should address the limitations by collecting socio-economic field data which can be better linked to silvicultural outcomes of reforestation plots. For example, Zhunusova et al. (2019) used focus group discussions and a household survey to capture the wider socio-economic situation of small-scale plantation owners in central Vietnam, which was then used to analyse the probability that they adopt long rotation periods. Additionally, a better understanding of the perception of local communities towards restoration activities should be gained (Höhl et al. 2020), particularly with regards to species diversification (see below). The socio-economic data would be complementary to the biophysical and silvicultural variables discussed above, and they should therefore also be subject to a data management strategy which allows for long-term storage beyond project timelines.

4.3.2.3 Fire

On the one hand, our analysis of restoration success drivers indicates that higher fire frequencies lead to higher crown cover values. On the other hand, high crown cover classes can only be found on plots with low fire frequency, and the overall effect of fire frequency was low. It is possible that this seeming contradiction can be partially explained by the approach we used to determine fire frequency of reforestation plots. A higher number of forest fires was observed in field inventories than in the ready-for-analysis remote sensing data product we used for our analyses; according to the latter, 22% of plots burned at least once in 23 years, whereas Richter and Andriampiolazana (2023) reported fires scars in ca. 50% of all plots. This difference can be explained by the fact that wildfires depend on the accumulation of biomass. Hence, only fires on plots with a high biomass stock can be reliably detected, whereas smaller fires on plots with no or low tree cover are possibly undetected by remote sensing. This can result in a spurious relationship between crown cover and fire frequency (Long et al. 2021). Our finding that higher fire frequencies led to higher crown cover, which was particularly the case in zones where the overall crown cover was low, could partially be explained by this relationship.

The overall positive effect of fire on crown cover development indicates, despite the associated uncertainty, that a fire management strategy needs to be considered which should go beyond the creation of firebreaks. Future research based on field data should lead to a better understanding of fire dynamics and the required actions, thus facilitating the development of adapted strategies. Without fire management strategies, there might be a trend towards savannah-like systems with scattered trees and low crown cover of ca. 10-20%.

4.3.2.4 Species diversification and land use planning

Reforestation so far has focussed on the production of energy wood and timber using two exotic species. In addition to providing these forest-based resources, reforestation will have to increasingly fulfil other societal needs, such as the conservation of biodiversity, the provision of water resources, as well as other ecosystem services. Future reforestation activities should therefore be embedded in a wider FLR approach. For this, a number of important knowledge gaps still exist, including aspects related to land use competition, species diversification, and the inclusion of FLR activities in diverse livelihood portfolios. Our results can only provide partial answers to these gaps, as our recommendations for growth zones were calibrated for the two species currently in use and extrapolation to other species should therefore be treated with caution. Additionally, we could only include a limited consideration of land use conflicts in our analyses. To address these knowledge gaps, we therefore recommend different research directions.

Species diversification requires the identification of locally significant tree species which do not only have satisfactory wood production potential, but also fulfil other ecosystem services. For this, both communities and stakeholders at various levels should be involved, for example utilizing semi-structured interviews in multiple villages to document ecosystem services provided by specific tree species. Subsequently, field trials should be established which allow to gain knowledge about germination, survival and growth rates of different promising native species under different environmental conditions. This would be a valuable asset for the development of optimal silvicultural methods for the establishment of forest restoration that uses community-supported native species. Additionally, an alternative source for charcoal could be perhaps made from savannah grass, as trialled successfully in a pilot project in Ghana (FAO 2023).

Our findings suggest that sites with a high ecological potential for reforestation in national park proximity are largely occupied or designated for land-use types not compatible with the RVI approach. Additionally, our field observations suggest that competition with other land uses, such as grazing and crop production, frequently contributed to the failure of reforestation sites. This illustrates the need for future research to identify potential synergies and conflicts among different actors regarding the spatial distribution and types of FLR measures in the landscape context. The research could provide the basis for spatial planning that minimizes land-use conflicts and maximises ecosystem service delivery by taking the ecological site potential, existing land uses and other socio-economic parameters into account. Additionally, integrative land-use systems, such as agroforestry, silvopastoral or alternative silvicultural systems (e.g. pollarding), can be an important element in the portfolio of future reforestation programs.

5 Conclusions and implications

For multiple decades, reforestation efforts have been made to meet the growing demand for energy wood and, to a lesser extent, construction wood for the local population. Reforestation plots supported by the GIZ or PLAE now cover over 110 km² in DIANA and 32 km² in Boeny (Table 15). Our findings show, that, despite these efforts, deforestation and forest degradation have been ongoing at high rates. Between 2000 and 2022, over 2 000 km² of the year 2000 forest cover has been lost in DIANA, and over 1 000 km² in Boeny. Additionally, by 2022, over 4 400 km² of forest areas were potentially degraded at least once in DIANA, and over 3 200 km² in Boeny (Table 15). This indicates that the existing reforestation plots were not able to meet the wood demand, and that the supply deficit was largely harvested informally and unsustainably (PREB 2015a; PREB 2015b). This can be in part explained by our finding that crown cover remained low on a large part of reforestation plots (Table 15). The low crown cover suggests that most plantations have only been partially reforested and therefore stayed behind their full potential, or outright failed, indicating that the success of the reforestation efforts has only been limited.

Table 15: Accumulated forest loss and reforestation areas.

Perte cumulée de forêts et zones de reboisement.

Size [km²]	Boeny	DIANA
Forest loss 2000–2022	> 1 000	> 2 000
Forest areas potentially degraded at least once by 2022	> 3 200	> 4 400
Reforestation 1996–2019	32.1	110.7
Reforestation 1996–2019 with exceeding 20% Crown Cover in 2023	6.8	36.5

Our study also provides insight into the importance of different direct drivers for deforestation and forest degradation. The extent of cropland has substantially increased over the last two decades, with an acceleration of the increase over the last few years. The annual increase of cropland within the forests in DIANA and Boeny revealed similar trends, indicating that forests in both regions face comparable pressures, regardless of their protection status. Additionally, fire plays an important role for forest loss in Ankarafantsika, and for forest degradation in nearly all research areas. Our findings also illustrate that some of the direct drivers are more challenging to detect using remote sensing than others. This is particularly the case for charcoal production and logging of precious hardwoods, which are known to be important drivers, but their exact quantification was not feasible during the duration of AFOB.

The methodological challenges related to the quantification of direct drivers should not distract from the importance of the underlying, indirect drivers. In order to be successful, strategies and interventions need to address both direct and indirect drivers of deforestation and forest degradation. For our research areas, the main indirect drivers are well-known. The population in Boeny and DIANA have approximately doubled over the last 20 years. This population growth, which includes substantial immigration mainly from Southwest Madagascar, has been driving increased demand for food and energy resources in both rural and urban areas (Percival et al. 2024). Further critical indirect drivers are widespread poverty, insecure land tenure, weak forest sector governance and institutions as well as weak enforcement, which lead, in combination with population growth, to complex interactions with the direct drivers. We recommend to further study the links between forest dependency, livelihoods, migration and socio-economic drivers of deforestation and forest degradation.

The population is projected to grow at a high rate in the coming decades, highlighting the need for careful planning and resource management to accommodate the expanding population and ensure sustainable development. Unless there are significant improvements in agricultural intensification or a reduction on the reliance on wood products, the increased population will translate to substantial higher future demands for cropland as well as energy and construction wood. For example, PREB (2015a) and PREB (2015b) project that the energy wood deficit will almost be twice as high in 2030 than in 2015 in DIANA, and almost three times as high in Boeny, if no additional reforestation actions are taken between 2015 and 2030 (Table 16).

Table 16: Estimated annual demand, supply and deficit of energy wood for 2015 and predicted values for 2030 (PREB 2015a, PREB 2015b).

Estimation de la demande, de l'offre et du déficit annuels de bois pour l'énergie en 2015 et prévisions pour 2030 (PREB 2015a, PREB 2015b).

Energy wood [m^3 per year]	Boeny 2015	Boeny 2030	DIANA 2015	DIANA 2030
Demand	2 020 000	3 040 000	1 040 000	1 570 000
Supply	517 000	307 000	270 000	190 000
Deficit	1 053 000	2 733 000	770 000	1 380 000

In the following, we draw our implications based on the current threats and expected future demands.

5.1 Natural forests

Deforestation and forest degradation should be considered as two distinct, but related, threats, with different underlying processes. In consequence, the conservation of protected forest areas should be addressed with two different strategies, one focusing on reducing the deforestation pressure in the buffer zones of national parks, and the other addressing forest degradation within the parks' limits.

In the buffer zones, the ongoing efforts for advanced cropland management are essential and should continue, with the aim to avoid further clearing for cropland. However, sustainable agricultural intensification will not be able to address all of the deforestation threats. Our field observation showed that particularly khat cultivation is a widespread and fast-growing deforestation driver in Montagne d'Ambre. There is a need for additional research and development of targeted strategies.

The extent of forest degradation is substantially larger than that of deforestation, with remarkably low percentages of undisturbed forests in Ankarana and Ankarafantsika. Forest degradation will likely significantly disturb the population structures of many tree species in the national parks, particularly those with high economic potential. Our field observation showed that the local national park rangers have little legal room and few resources to address illegal logging and charcoal production within the park limits. This indicates that ex-situ conservation measures for the most threatened populations will become increasingly important in the future. We therefore recommend the promotion of seed collection and the establishment of seed orchards and tree nurseries by the local authorities. We furthermore suggest to involve the local population in the value chains, for example through employment in seed tree monitoring, seed harvesting, and nursery management. This strategy would lead to the generation of a valuable gene pool of tree species that can be preserved ex-situ, while at the same time contributing to local development, achieving ongoing monitoring of genetic resources, and adding economic value to natural forests.

5.2 Reforestation

Madagascar has committed to restoring four million hectares of forest by 2030. There will therefore not only be an increased demand for cropland and wood, as discussed above, but also a large demand for forest restoration areas. Meeting these different demands will increasingly require integrative landscape approaches, such as FLR. The large reforestation efforts in Boeny and DIANA over the last decades have the potential to provide valuable insights on factors for success and failure, not only for future reforestation, but also for wider FLR activities. To be able to fully realize this potential, it is crucial to be able to extract the most important lessons learned from past activities. For example, data exchanges between GIZ- and PLAE-supported programs served as a basis for the results presented in this study. However, we experienced problems to harmonize the database regarding species composition, planting densities and survival rates. The potential for joint analyses could be significantly enhanced by adopting a comprehensive monitoring and data management approach across a wider range of development cooperation and reforestation programs.

Our findings suggest that dynamics on the plot-level largely determined the reforestation success. Capacity building and good silvicultural practices are therefore crucial, but require further research which should be underpinned by field trials. This should include, for example, an in-depth analysis of the response of crown cover to increasing fire frequencies, which can then inform the development of an adapted fire management strategy.

For the integration into a wider FLR-context, it is important to more explicitly consider that reforestation can have different objectives and provide multiple ecosystem services. If ecosystem services which are linked to higher crown cover, such as the provision of habitat corridors or water cycling, should be prioritized, improved reforestation strategies would have to be in the focus of research and implementation. This also includes trade-offs between fast-growing, often exotic, species with commercial value managed in short rotations and slow-growing long-rotation systems with mixed and native species.

Additionally, due to the increasing land-use pressure and importance to provide livelihoods which do not result in deforestation and forest degradation, the sustainable development of local communities will be even more in the focus of reforestation activities. These issues require careful land-use planning and the implementation of sustainable agricultural and forestry practices that prevent displacement and leakage, and promote the coexistence of different land uses. Therefore, reforestation should be designed, managed and evaluated in a landscape approach, under the perspective of a diverse livelihood portfolio which also include integrative land-use systems such as agroforestry, silvopastoral or alternative silvicultural systems (e.g. pollarding), and not as a single activity isolated from other portfolio components.

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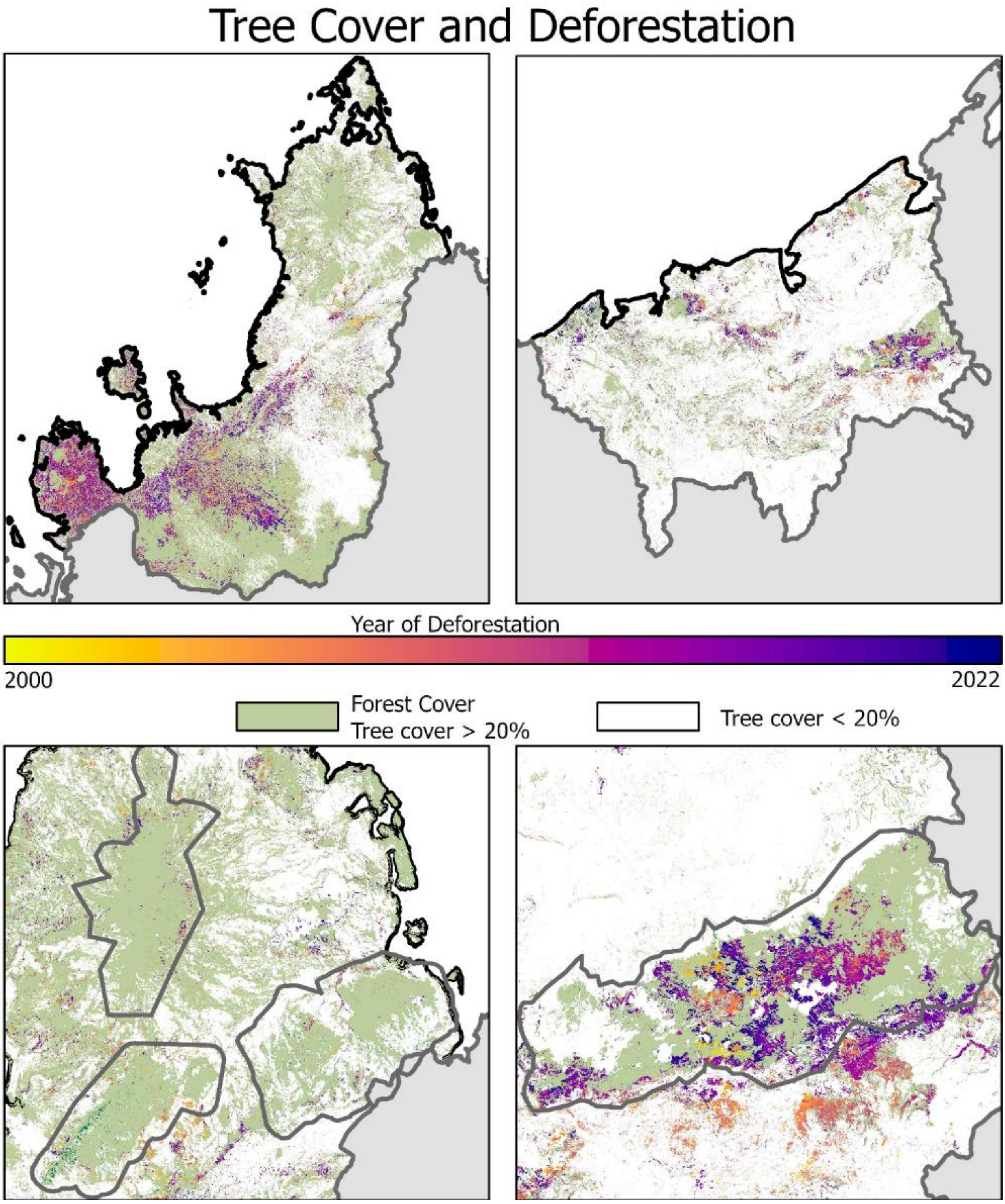
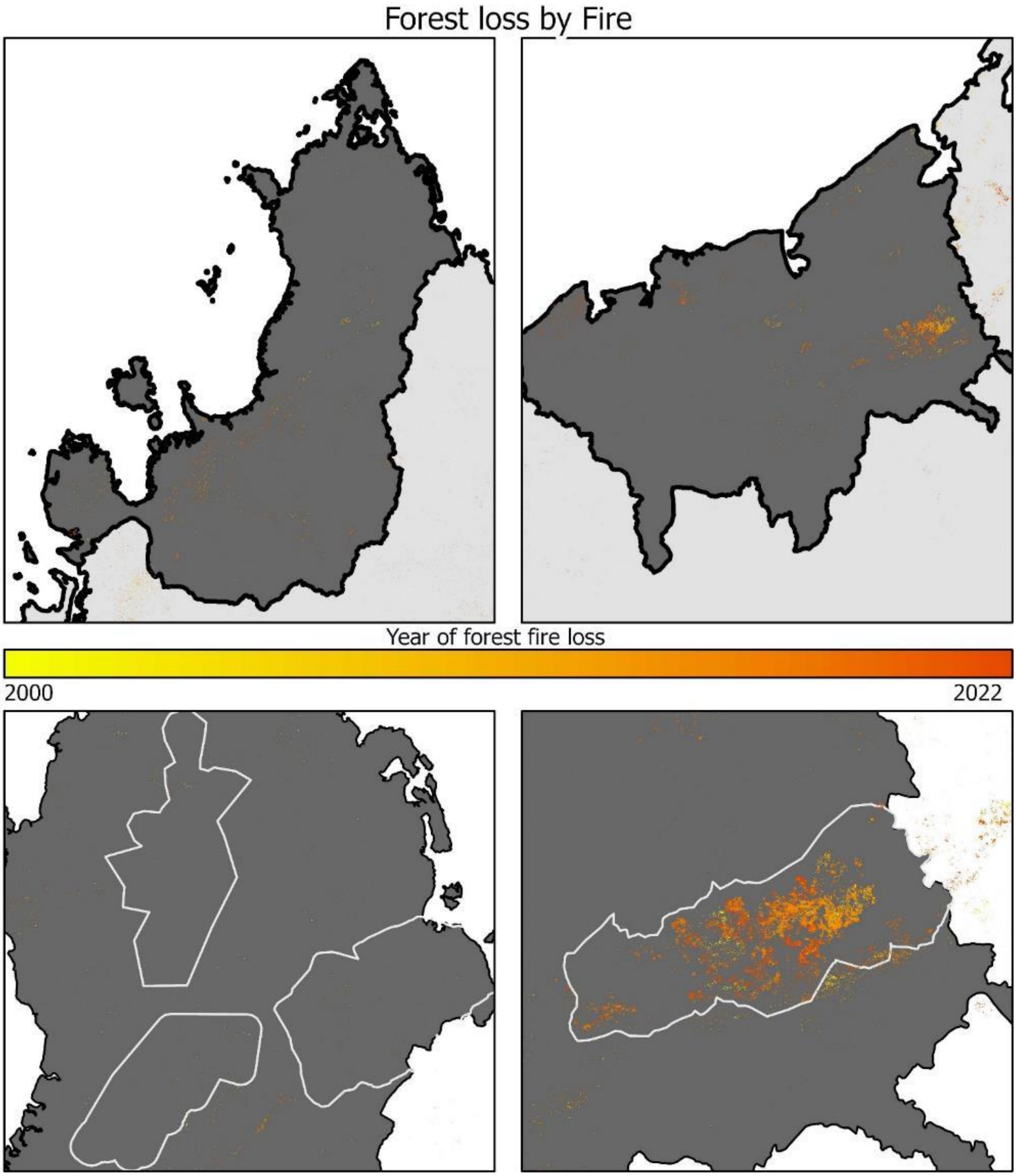
7 Annexes

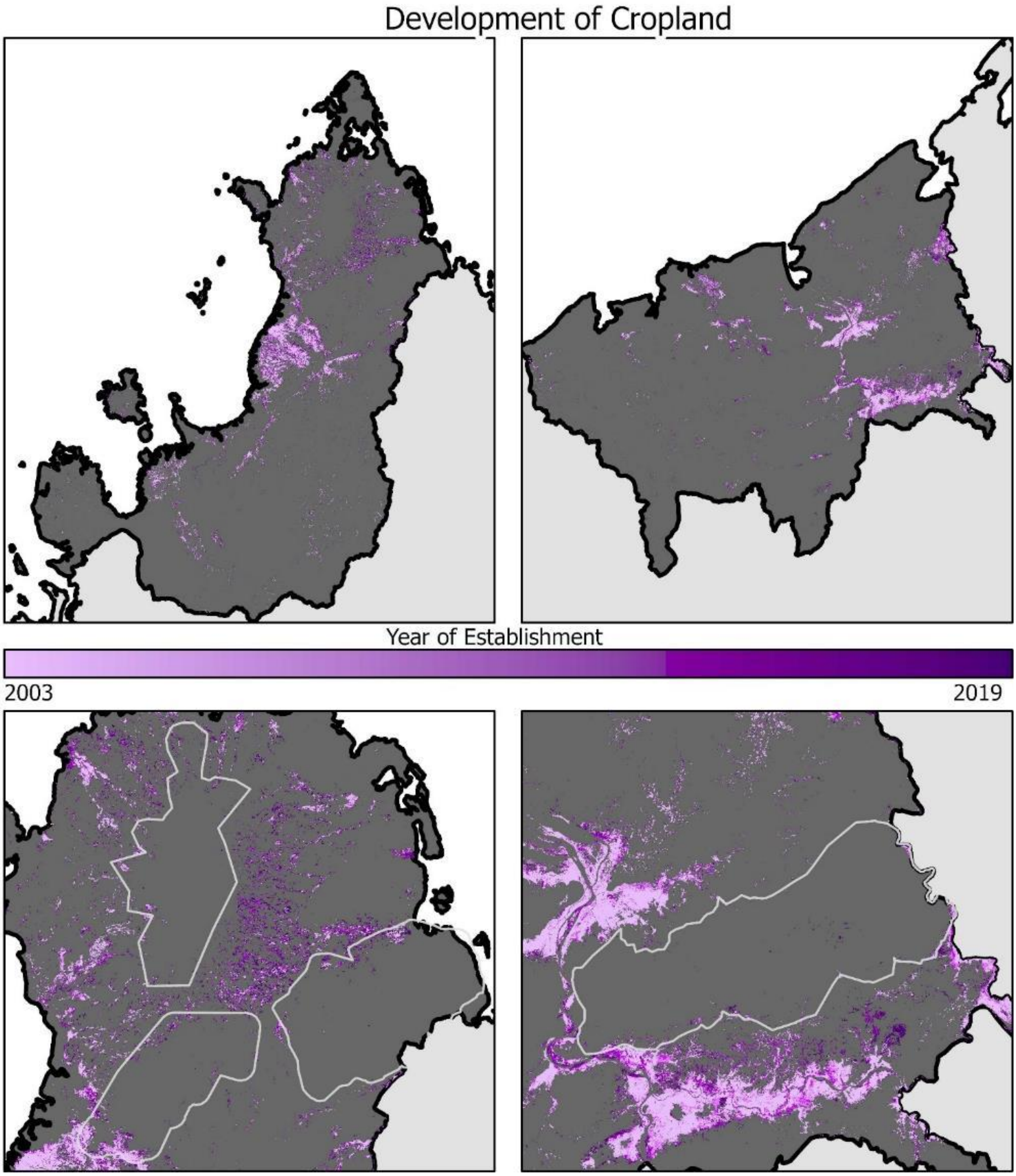
Annex A Data product maps



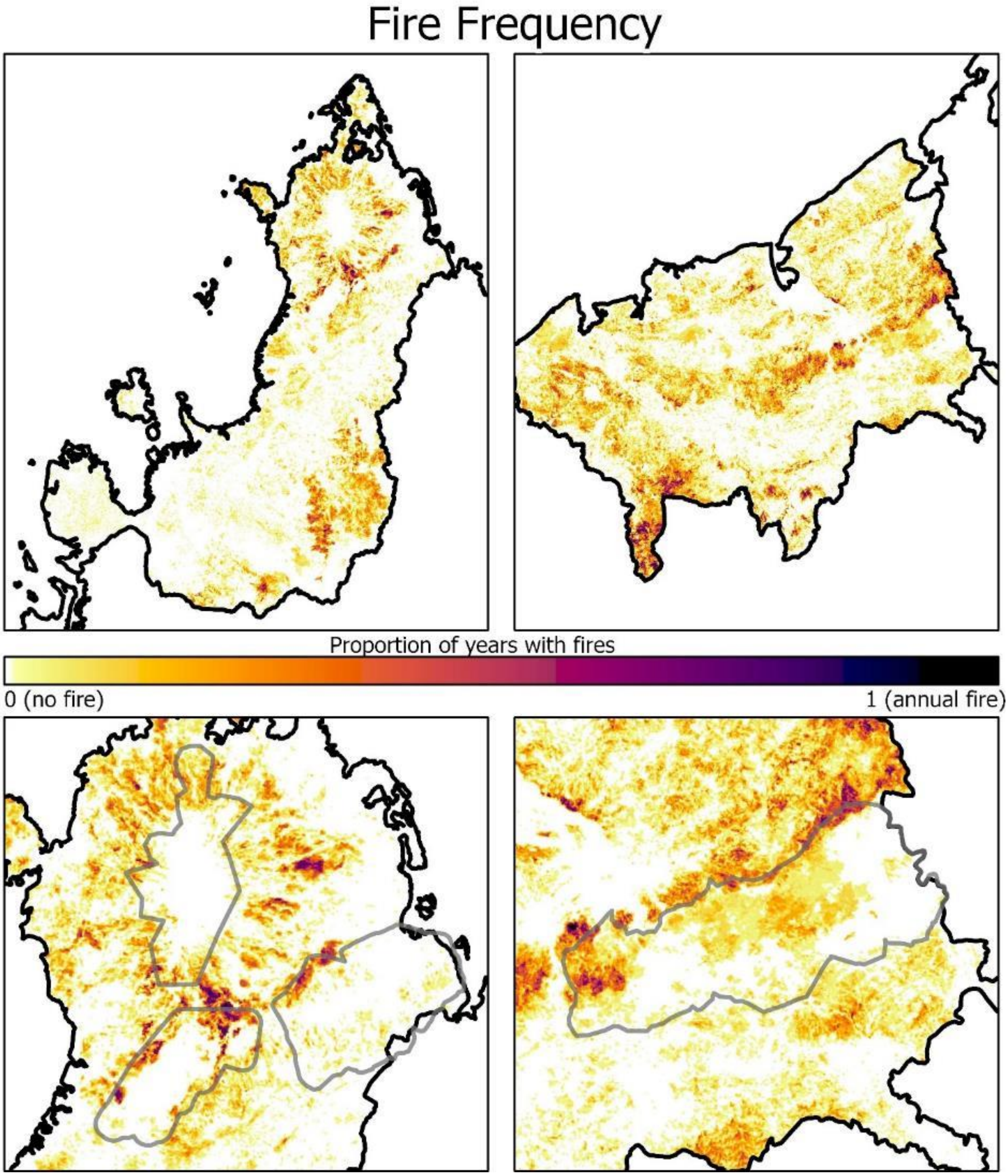
Tree cover 2000 and forest loss.



Forest loss by fire.

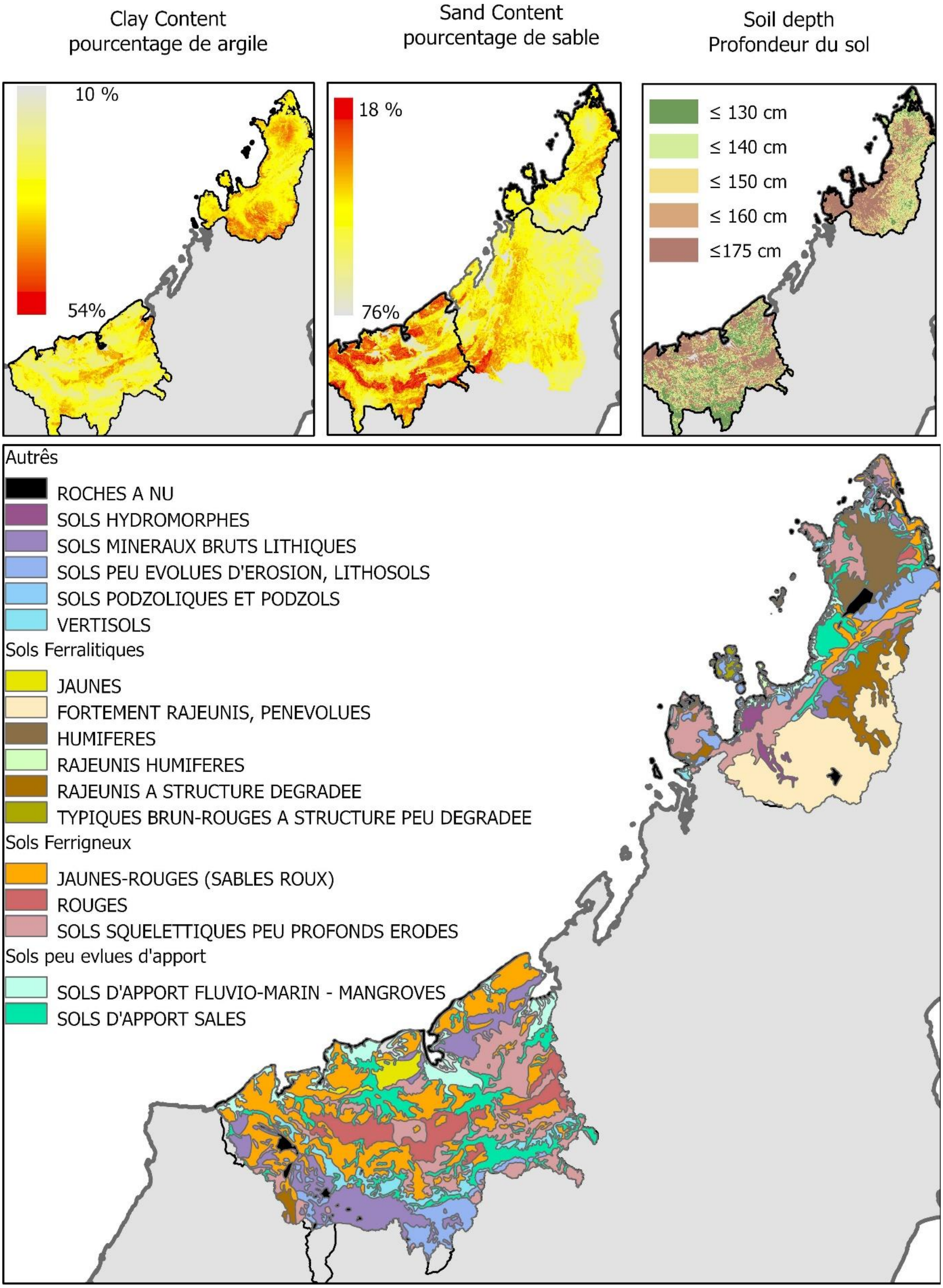


Total cropland development.

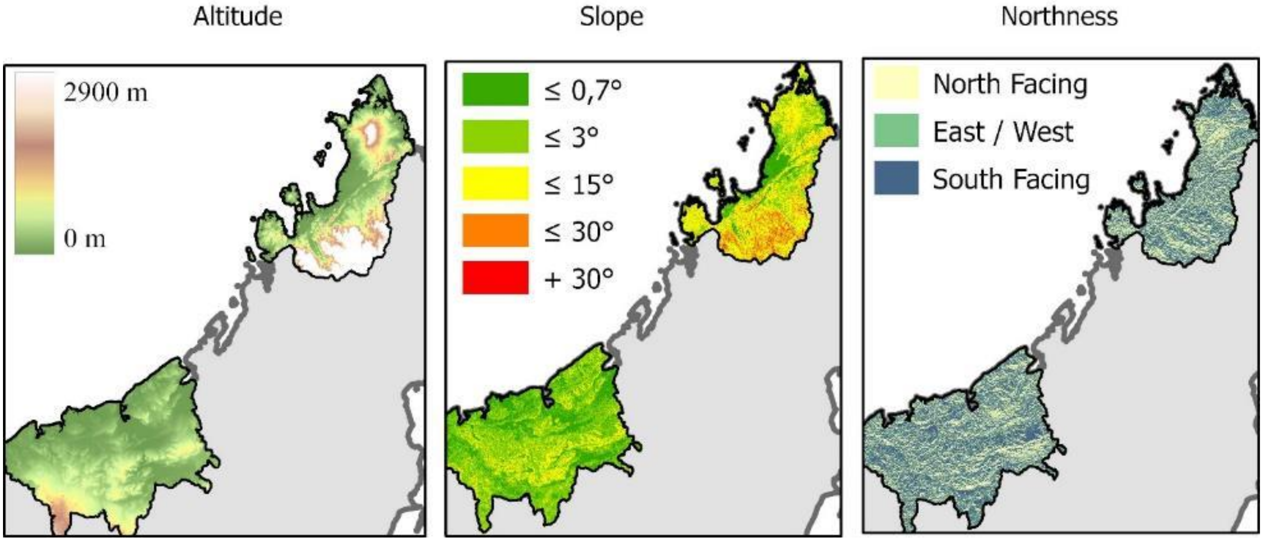


Total fire frequency.

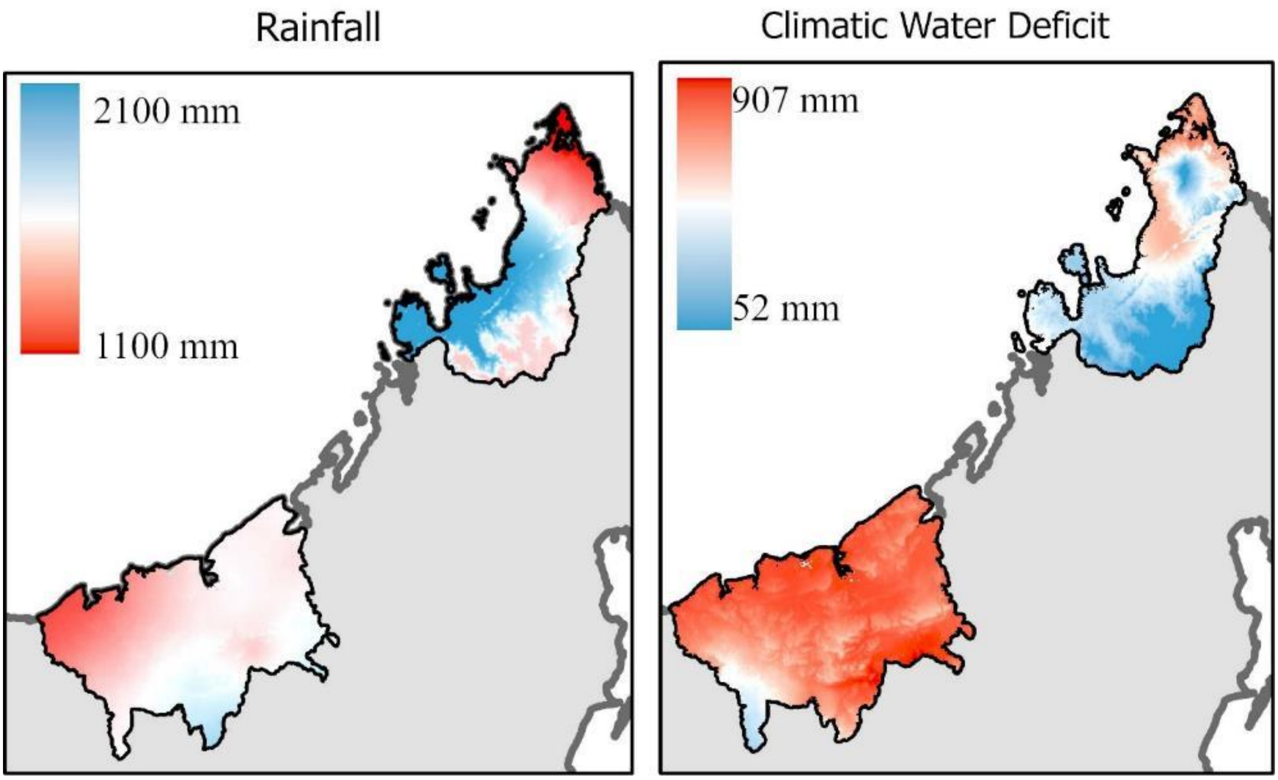
Annex B Descriptive variables



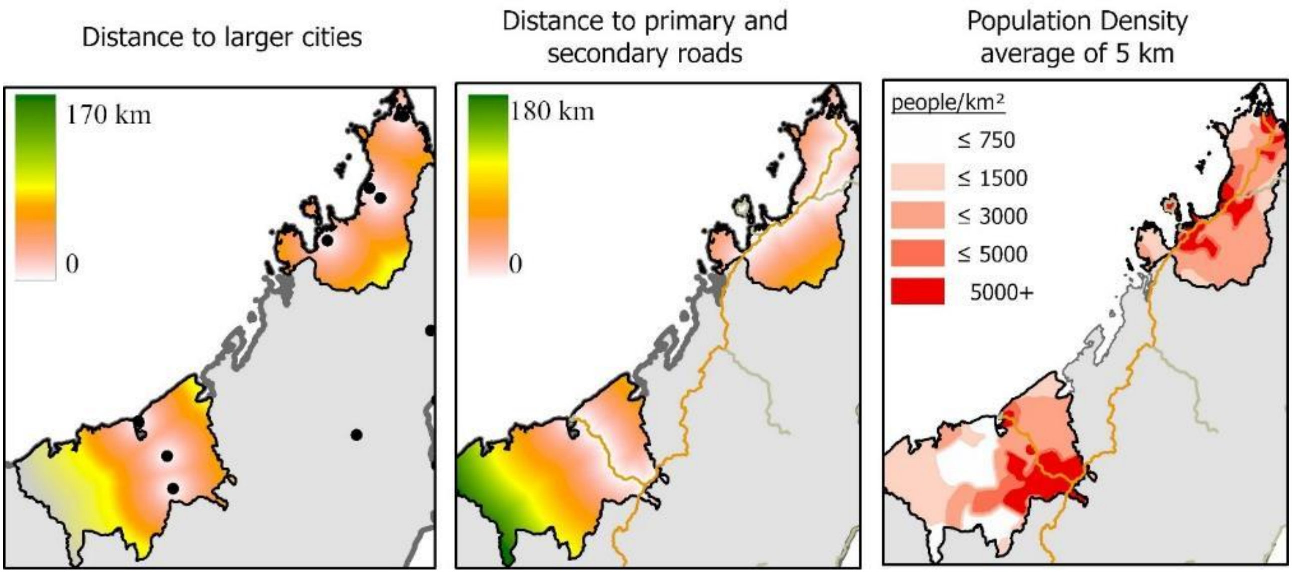
Soil.



Topography.

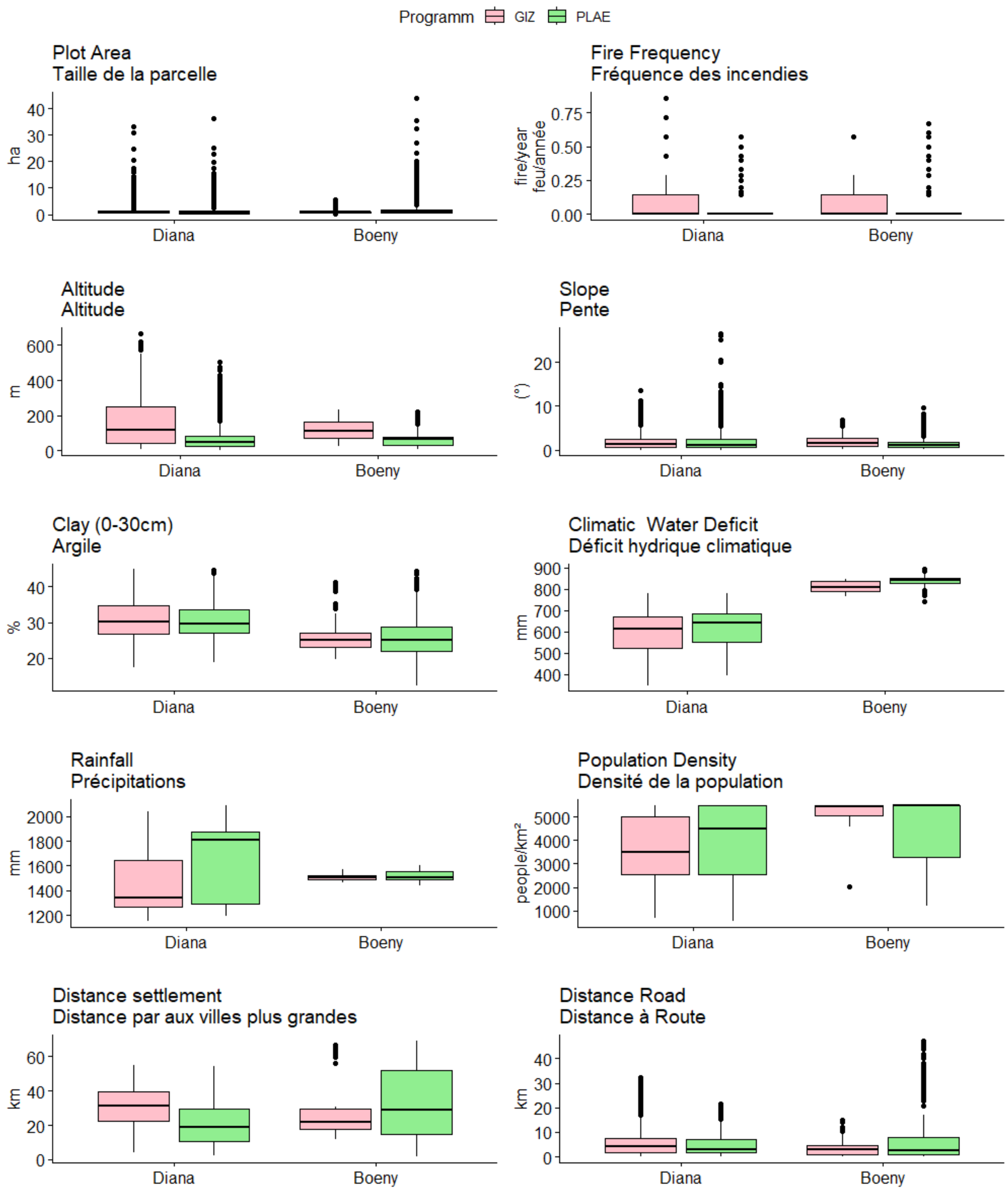


Climate.



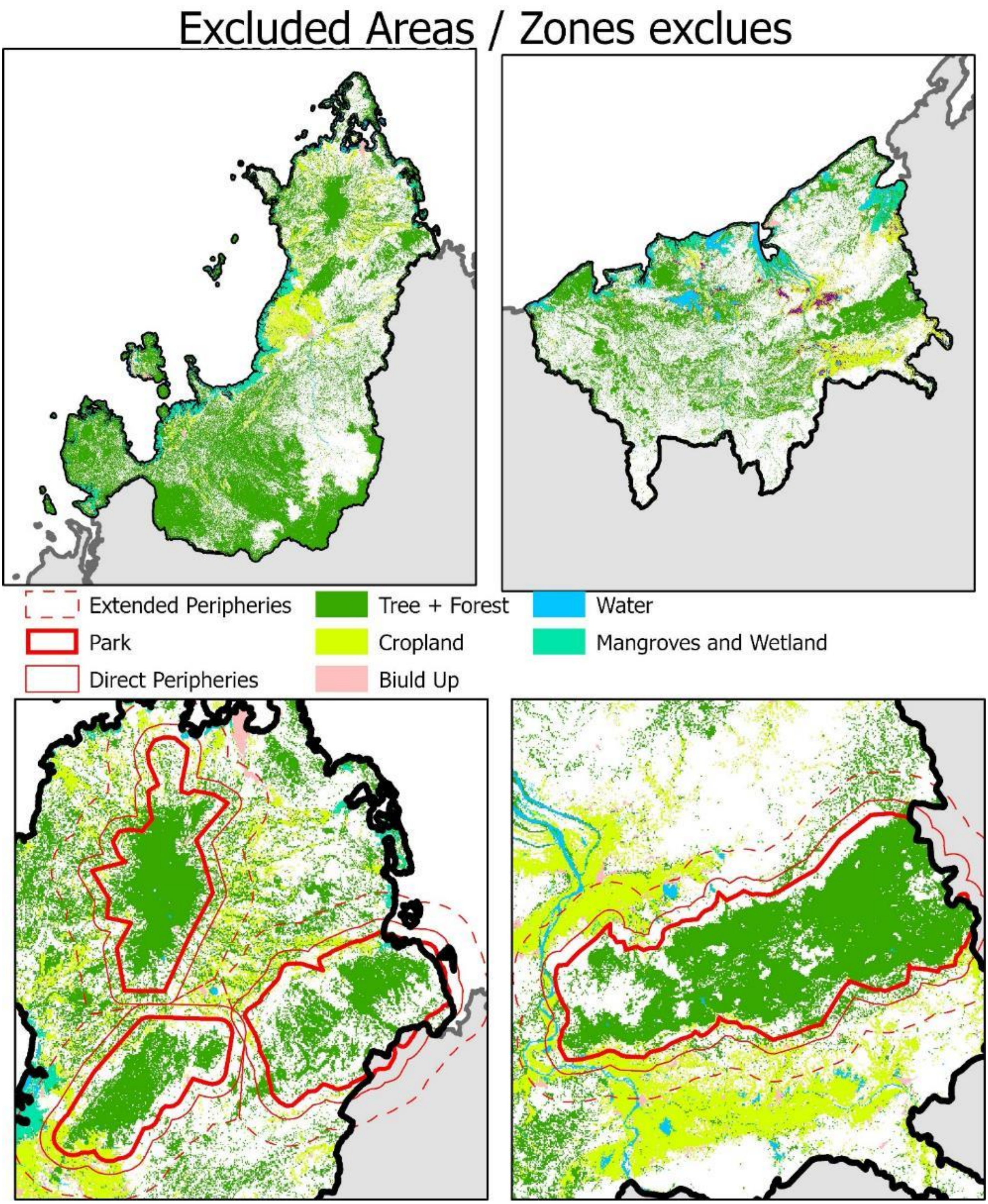
Anthropogenic.

Annex C Range of input data of mixed effect models



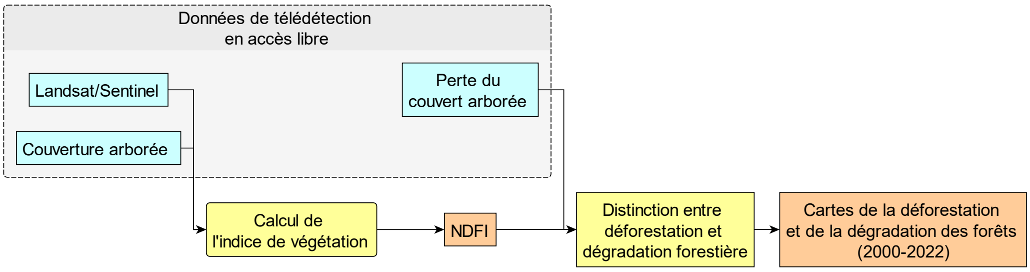
Range of input variables used in mixed effect models.

Annex D Excluded areas for reforestation

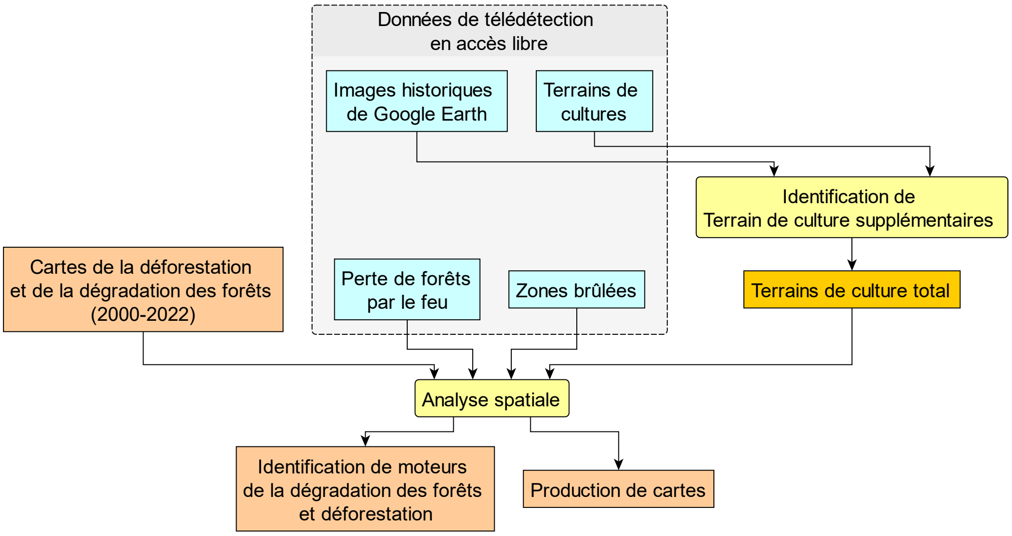


Areas exlcuded from reforestation.

Annex E Forest loss and degradation time series



Workflow for separation of forest degradation and loss (in French).



Workflow of driver analysis for forest degradation and forest loss (in French).

Tree cover, annual degraded areas, fire degraded areas, forest losses, forest fire losses, and cropland development in DIANA and national parks.

areas in km²		**Montagne d'Ambre**	**Analame-rana**	**Ankarana**	**Manonga-rivo**	**Tsaratanana**	**DIANA w/o NPs**
Total area		587.3	712.6	485.3	494.8	1420.7	16311.8
TC2000>25		478.6	335.7	288.4	491.6	1324.3	8920.0
Yearly degradation							
2000-2010	Mean	65.7	43.2		3.7	42.6	
	SD	7.6	13.2		4.4	11.0	
2011-2022	Mean	67.9	53.3	120.1	6.7	63.5	1852.2
	SD	9.8	12.3	17.9	3.0	15.3	152.1
Yearly degradation by fire							
2001-2010	Mean	6.5	0.4	5.3	0.6	8.9	102.6
	SD	6.2	0.6	2.8	0.5	6.5	50.9
2011-2020	Mean	11.2	0.8	10.1	0.9	13.6	125.1
	SD	4.3	0.5	2.8	0.9	7.2	47.5
Yearly forest loss							
2001-2010	Mean	0.7	0.5	1.2	1.2	5.6	63.2
	SD	0.2	0.3	0.4	0.6	3.2	18.9
2011-2022	Mean	0.9	0.9	0.5	5.0	14.6	130.2
	SD	0.5	0.5	0.2	2.6	4.1	45.6
areas in km²		**Montagne d'Ambre**	**Analame-rana**	**Ankarana**	**Manonga-rivo**	**Tsaratanana**	**DIANA w/o NPs**
Yearly forest loss by fire							
2001-2010	Mean	0.02	0.01	0.05	0.02	0.24	1.30
	SD	0.01	0.01	0.04	0.02	0.25	0.63
2011-2022	Mean	0.02	0.05	0.01	0.29	0.53	6.62
	SD	0.01	0.06	0.01	0.55	0.40	3.90
Cropland conversion from forest							
2003		2.4	1.8	1.6	0.0	0.0	110.8
2019		8.2	4.1	8.1	0.0	0.4	293.5
Cropland development in non-forest							
2003		0.9	3.0	17.8	0.0	1.5	419.5
2019		3.4	9.0	31.1	0.0	2.4	693.3

Tree cover, annual degraded areas, fire degraded areas, forest losses, forest fire losses, and cropland development in Boeny and national parks.

areas in km²		**Ankarafant-sika**	**Namoroka**	**Baie de Baly**	**Boeny w/o NPs**
Total area		1693.5	379.2	1020.4	28160.8
TC2000>25		1124.2	149.9	450.9	4776.8
Yearly degradation					
2000-2010	Mean	175.7	63.6	76.1	1458.8
	SD	80.0	20.8	31.4	399.1
2011-2022	Mean	160.2	66.4	95.6	1807.7
	SD	52.8	8.4	39.3	215.1
Yearly degradation by fire					
2001-2010	Mean	37.1	4.3	6.7	152.4
	SD	76.8	4.1	6.1	96.2
2011-2020	Mean	34.2	2.4	20.6	166.9
	SD	28.1	1.5	23.1	70.8
Yearly forest loss					
2001-2010	Mean	5.48	0.09	0.75	39.83
	SD	9.27	0.07	0.40	22.72
2011-2022	Mean	22.71	0.23	7.34	61.32
	SD	15.10	0.16	8.32	23.74
Yearly forest loss by fire					
2001-2010	Mean	1.41	0.01	0.05	2.05
	SD	2.87	0.00	0.04	2.01
2011-2022	Mean	14.32	0.01	1.65	6.56
	SD	12.56	0.01	2.67	4.56
Cropland conversion from forest					
2003		0.2	0.1	0.0	6.3
2019		5.1	0.2	0.2	99.4
Cropland development in non-forest					
2003		5.9	0.8	3.1	891.1
2019		14.3	1.4	4.0	1349.0

Total areas of undisturbed and degraded forests in national parks.

areas in km²	Ankarafantsika		Montagne d'Ambre		Analamerana		Ankarana	
Count of degradation events	Centre	Edge	Centre	Edge	Centre	Edge	Centre	Edge
0	278	122	132	181	142	57	47	51
1-2	201	93	9	42	25	18	12	16
3+	205	208	1	113	31	63	78	106

Fire frequency in forests in DIANA and national parks.

areas in km²	**Montagne d'Ambre**		**Analamerana**		**Ankarana**	
	Centre	Edge	Centre	Edge	Centre	Edge
0	141.1	273.2	195.7	132.4	121.5	125.9
1	0.5	26.6	1.7	4.0	2.2	13.7
2	0.1	13.6	0.5	0.8	0.6	6.5
3+	0.3	23.2	0.3	0.4	1.3	15.9
areas in km²	**Manonga-rivo**	**Tsaratanana**	**DIANA w/o NPs**			
0	479.8	1204.2	7862.2			
1	10.4	81.8	672.7			
2	1.3	20.7	180.4			
3+	0.1	17.6	204.7			

Fire frequency in forests in Boeny and national parks.

areas in km²	**Ankarafantsika**		**Namoroka**	**Baie de Baly**	**Boeny w/o NPs**
	Centre	Edge			
0	454.5	335.5	118.9	360.8	3693.3
1	176.2	45.8	18.4	38.0	517.3
2	46.1	32.7	5.6	33.8	280.0
3+	15.8	18.4	7.1	18.3	286.1

Post-disturbance areas in Montagne d'Ambre, Analamerana and Ankarana.

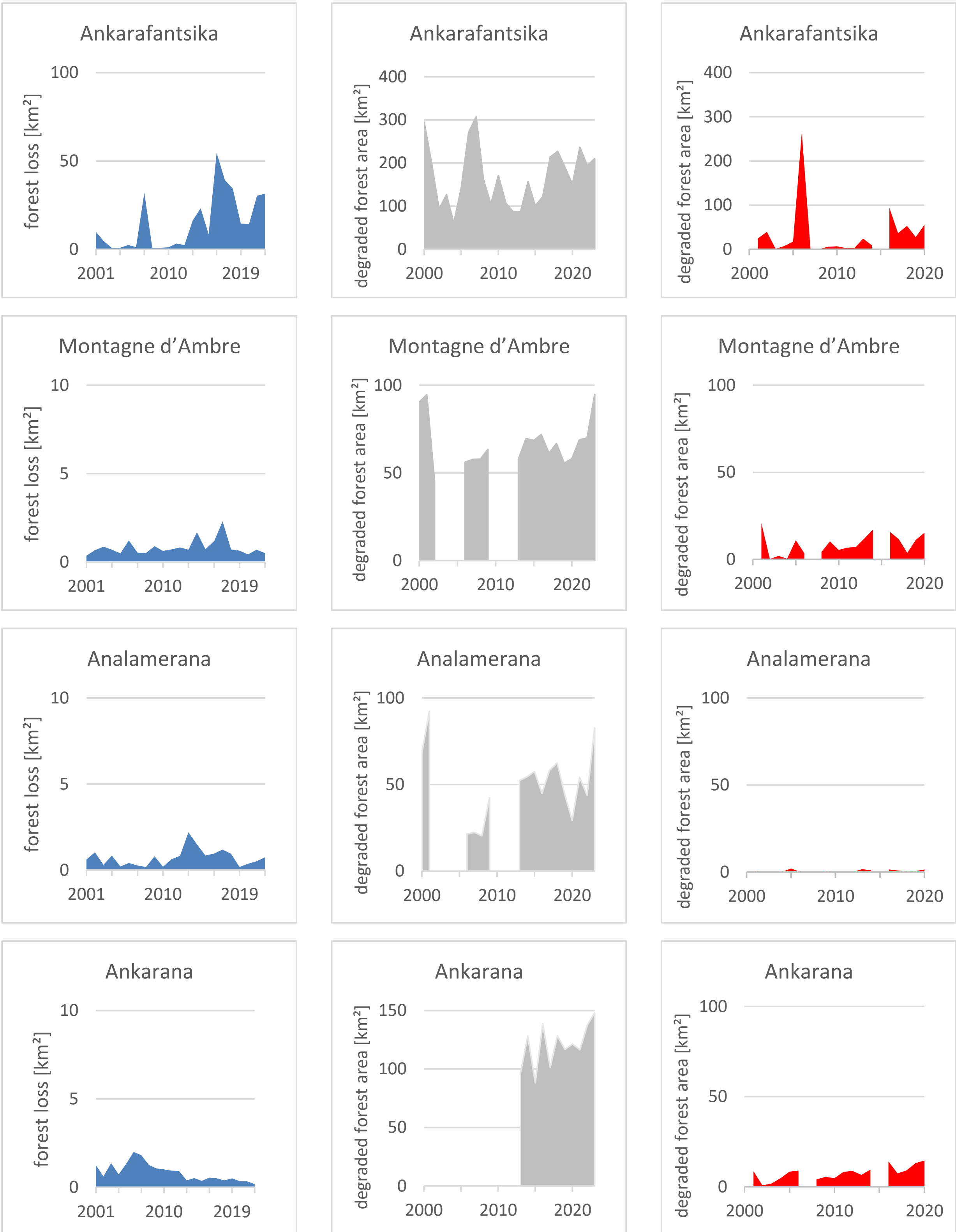
areas in km²		**Montagne d'Ambre**		**Analamerana**		**Ankarana**	
		Centre	Edge	Centre	Edge	Centre	Edge
2003-2011	ongoing degradation	0.0	7.5	0.2	1.0	1.0	5.6
	stagnation	0.0	8.9	0.7	2.1	5.0	8.2
	regrowth	2.3	25.7	3.5	7.4	12.2	22.4
2012-2019	ongoing degradation	0.1	10.0	1.4	3.1	3.0	6.9
	stagnation	0.1	8.0	3.3	3.7	5.6	7.9
	regrowth	0.2	16.5	7.1	9.6	4.6	9.8

Post-disturbance areas in Ankarafantsika.

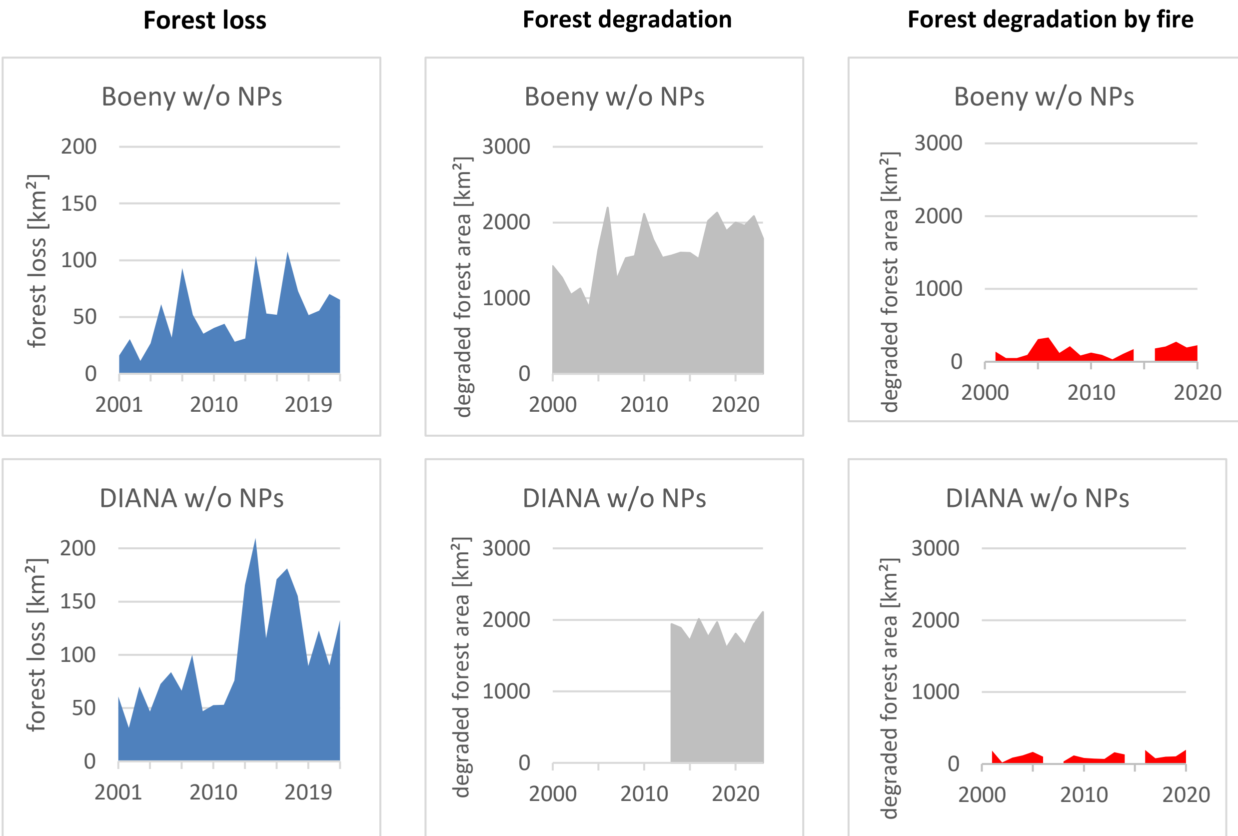
areas in km²		Centre	Edge			Centre	Edge
2003-2011	ongoing degradation	6.9	10.2	2012-2019	ongoing degradation	10.4	29.6

	stagnation	18.6	20.4		stagnation	18.8	24.7
	regrowth	223.2	113.7		regrowth	150.8	66.5

Forest loss **Forest degradation** **Forest degradation by fire**



Total forest loss, total degradation and degradation due to fire over time for national parks.



Total forest loss, total degradation and degradation due to fire over time for regions without national parks.

Annex F Random Forest quality metrics

A confusion matrix is a way of expressing how many predictions of a class were correct. In the following confusion matrices, the rows represent the true classifications based on the reference data, and the columns represent the predicted classifications. The values on the diagonal indicate the percentage of cases in which the predicted matches the true classification. The values in the other cells represent cases in which the classifier incorrectly classified an observation.

Confusion matrix Ankarafantsika (%)

	Predicted							
True	additional cropland	permanent cropland	barren land	forest	degraded forest	water	sand	shrub
additional c.	95	0	0	0	4	0	0	0
permanent c.	0	93	0	0	2	0	0	0
barren land	0	0	99	0	0	0	0	0
forest	0	0	0	98	2	0	0	0
degraded f.	0	1	0	0	98	0	0	0
water	0	3	3	0	6	88	0	0
sand	0	0	20	0	0	0	80	0
shrub	0	0	1	0	9	0	0	90

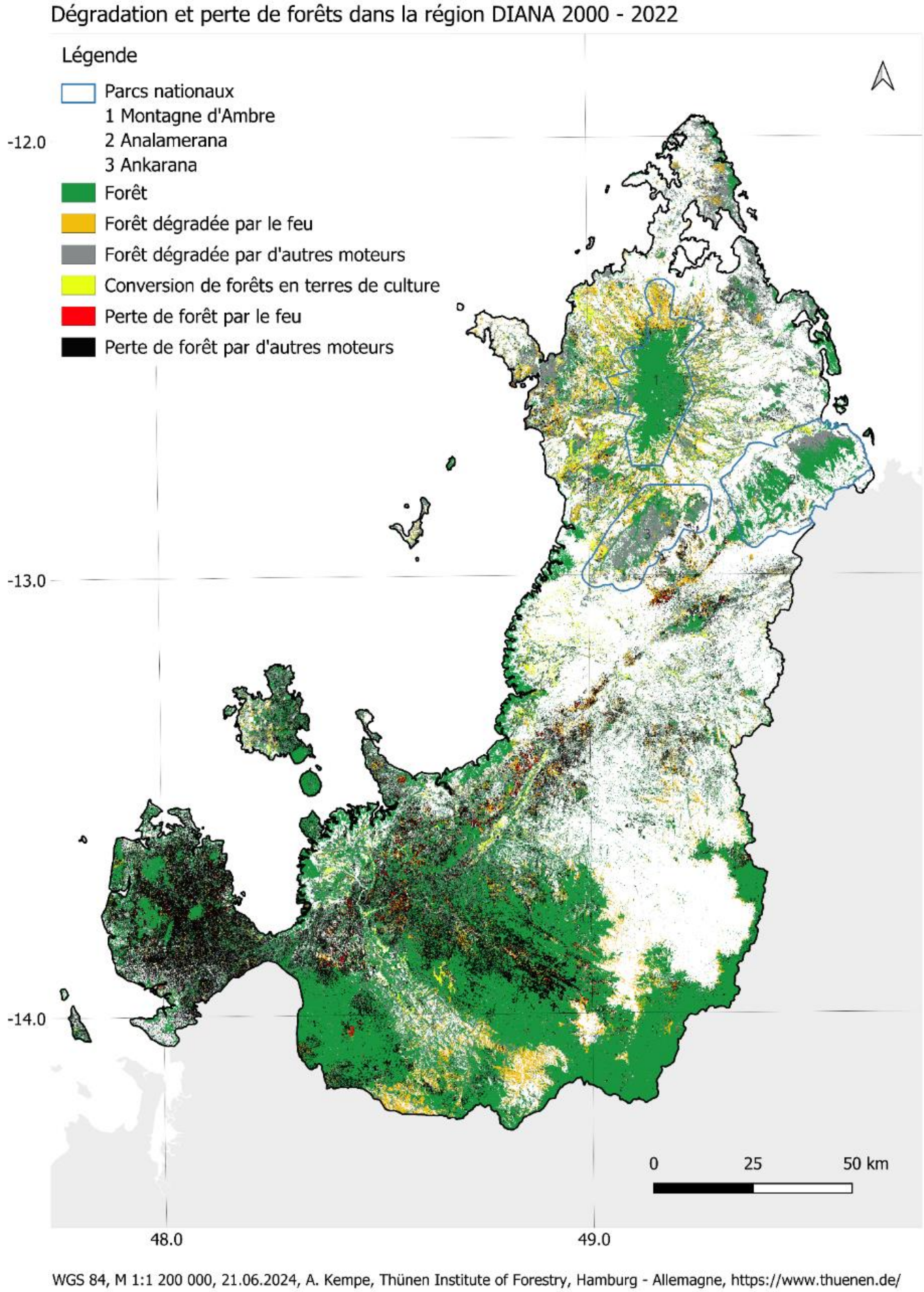
Confusion matrix Montagne d'Ambre (%).

	Predicted					
True	forest	barren land	cropland	water	shrub	rock
forest	100	0	0	0	0	0
barren land	0	99	0	0	0	0
cropland	0	10	89	0	1	0
water	1	2	0	97	0	0
shrub	0	4	0	0	95	0
rock	0	19	0	0	0	81

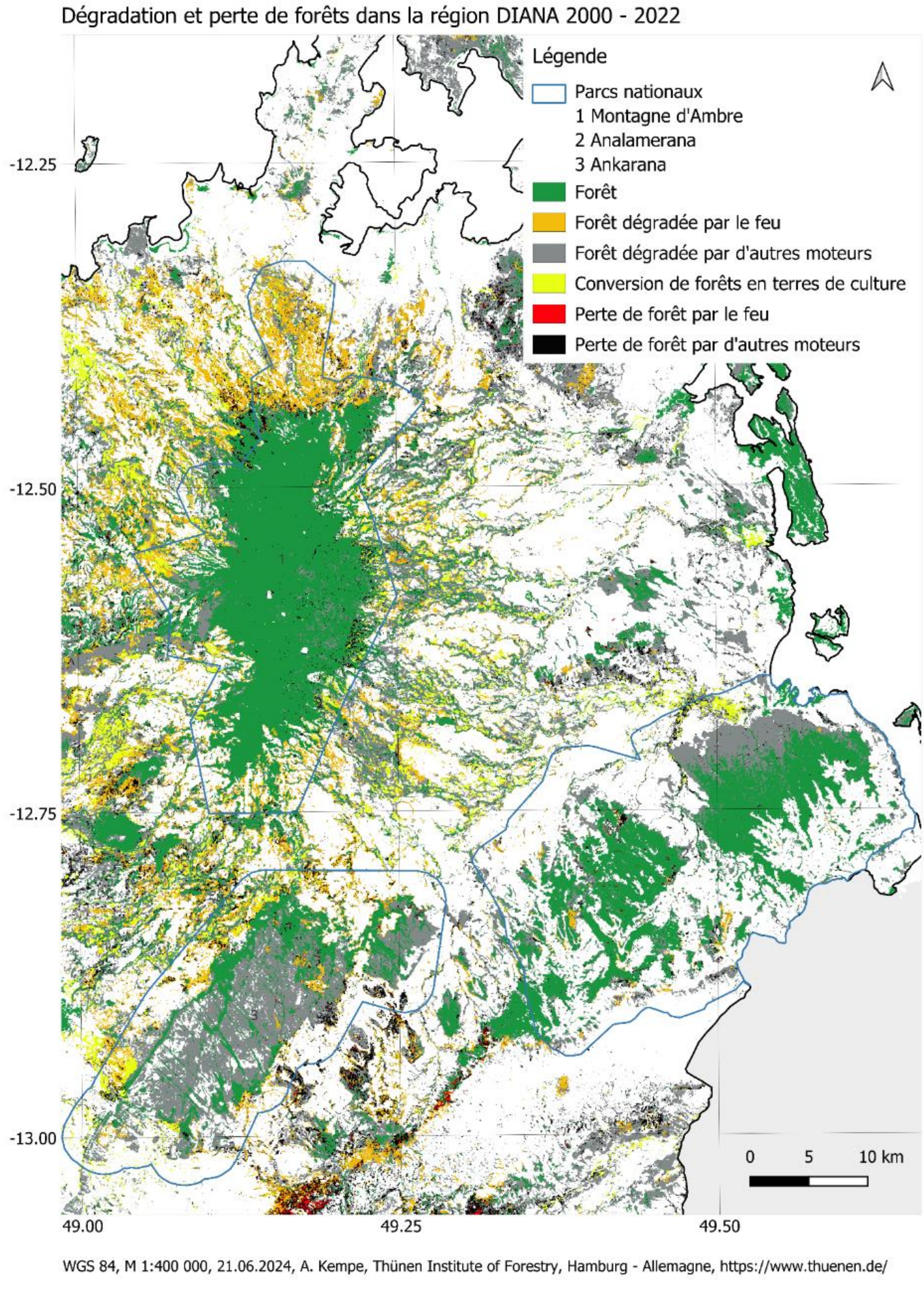
Confusion matrix Ankarana (%).

	Predicted							
True	additional cropland	permanent cropland	barren land	forest	degraded forest	water	sand	shrub
additional c.	95	0	0	0	4	0	0	0
permanent c.	0	93	0	0	2	0	0	0
barren land	0	0	99	0	1	0	0	0
forest	0	0	4	98	2	0	0	0
degraded f.	0	1	1	0	98	0	0	0
water	0	3	3	0	6	88	0	0
sand	0	0	2	0	0	0	80	0
shrub	0	0	1	0	9	0	0	90

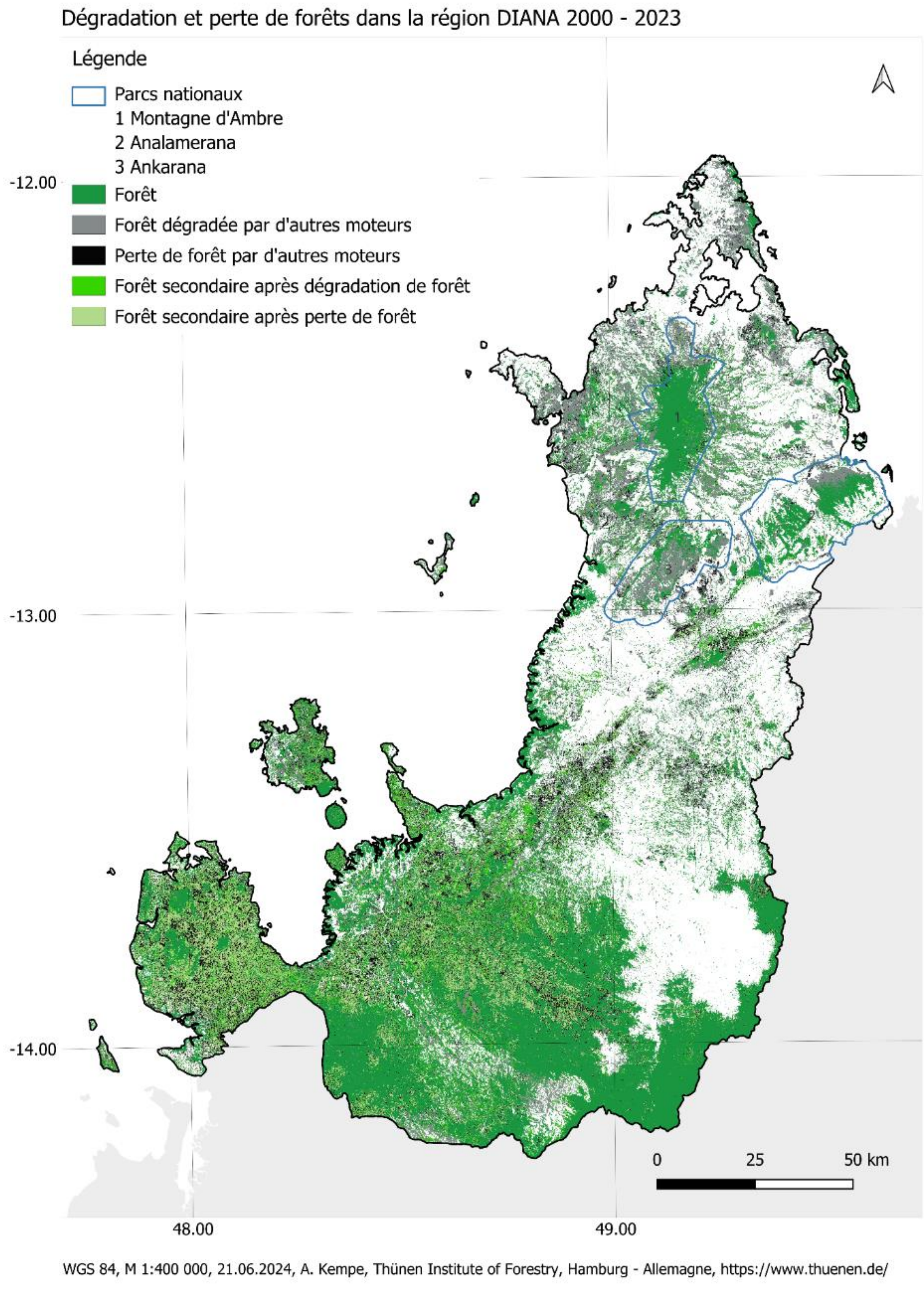
Annex G Forest degradation and deforestation maps



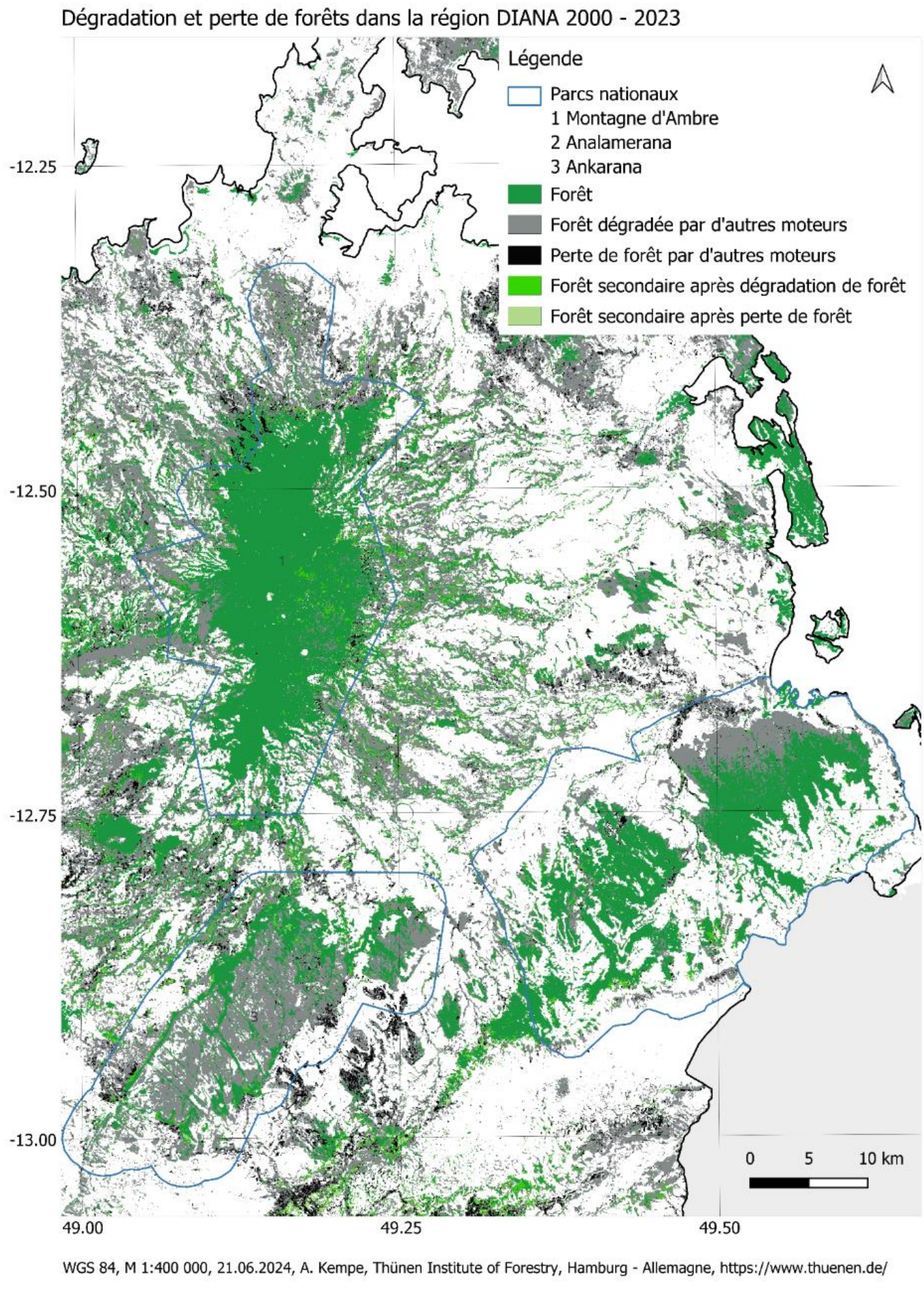
Map of forest degradation and deforestation by driver in DIANA.



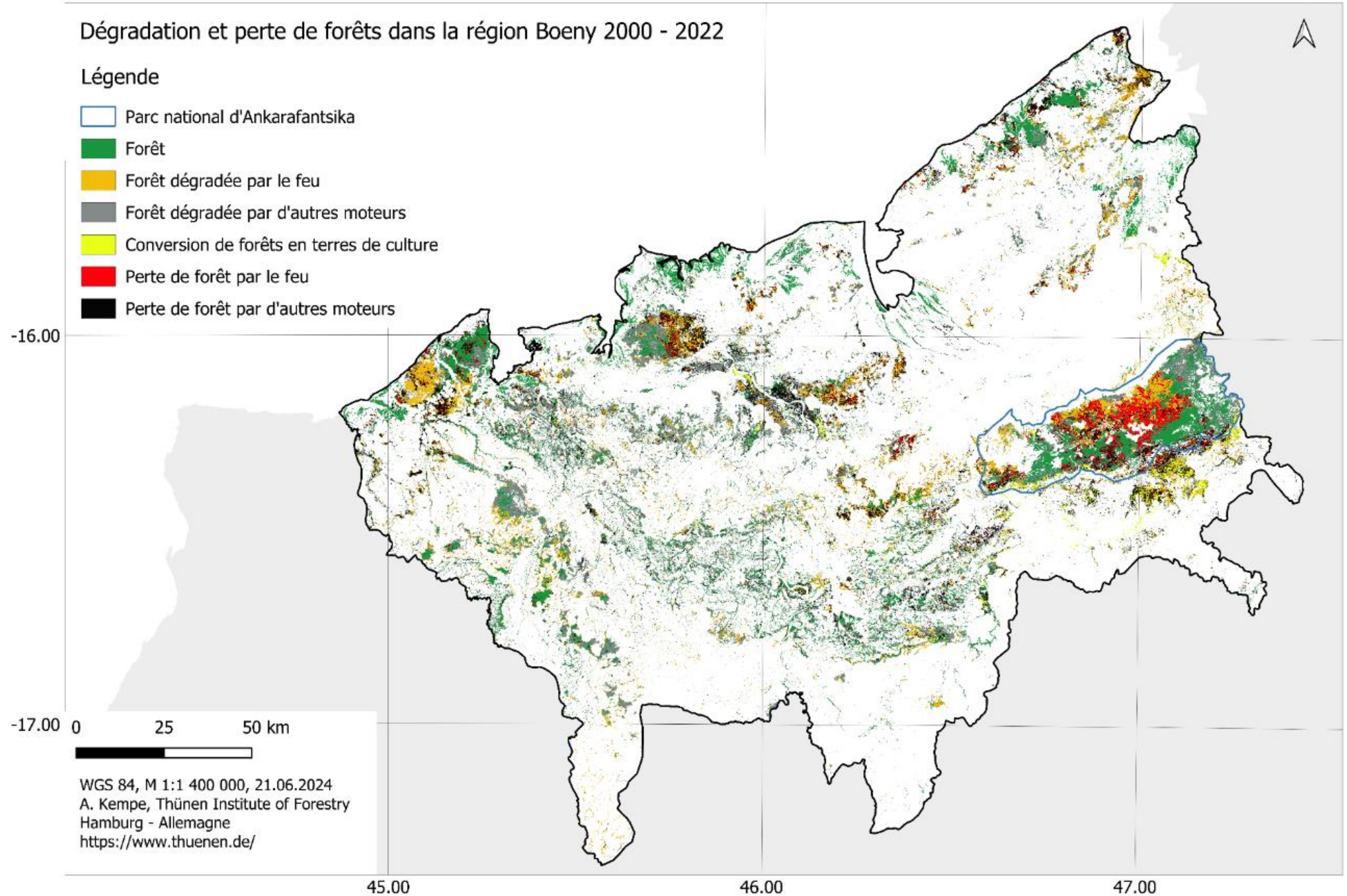
Map of forest degradation and deforestation by driver in DIANA, national parks.



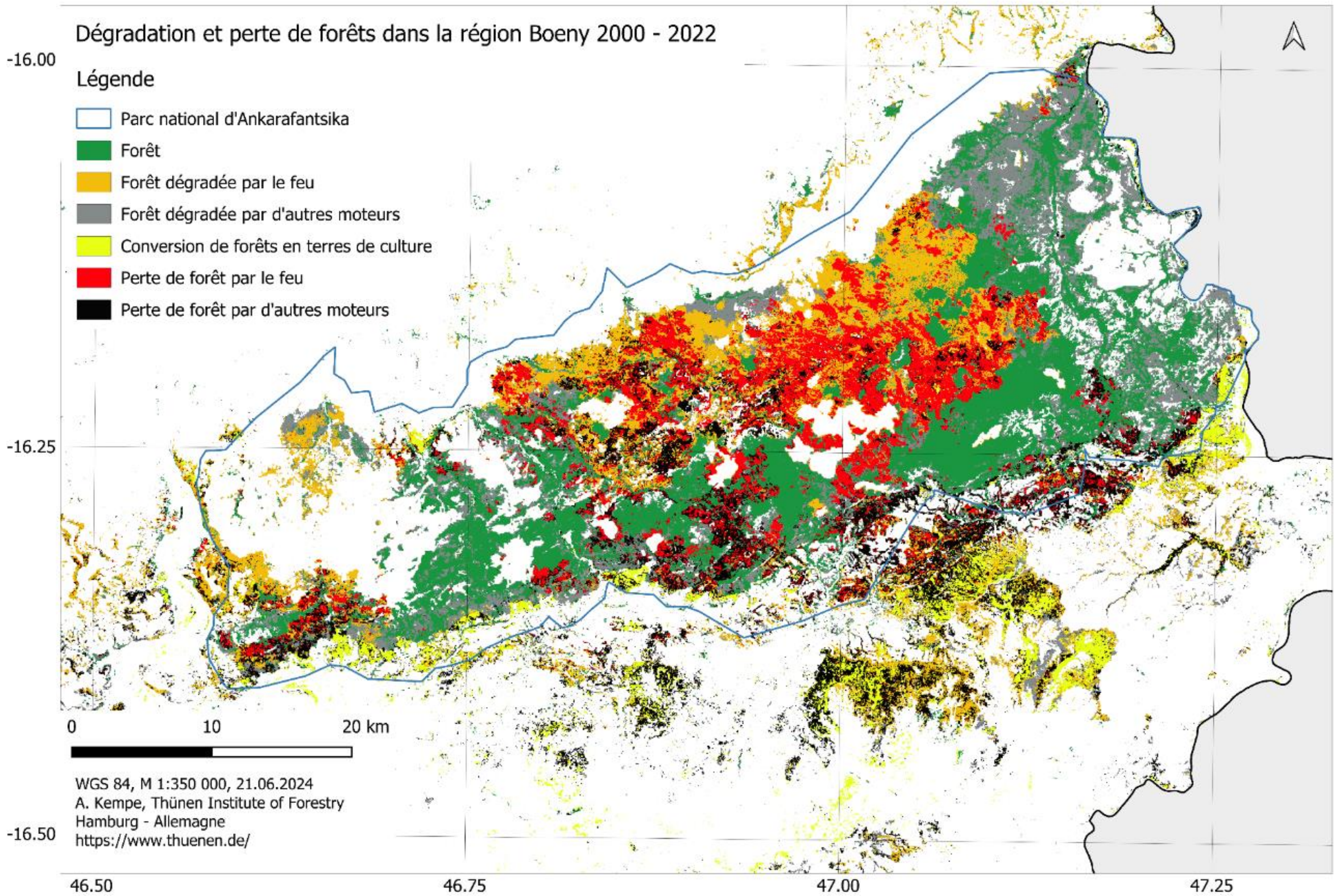
Map of forest situation in DIANA in 2023.



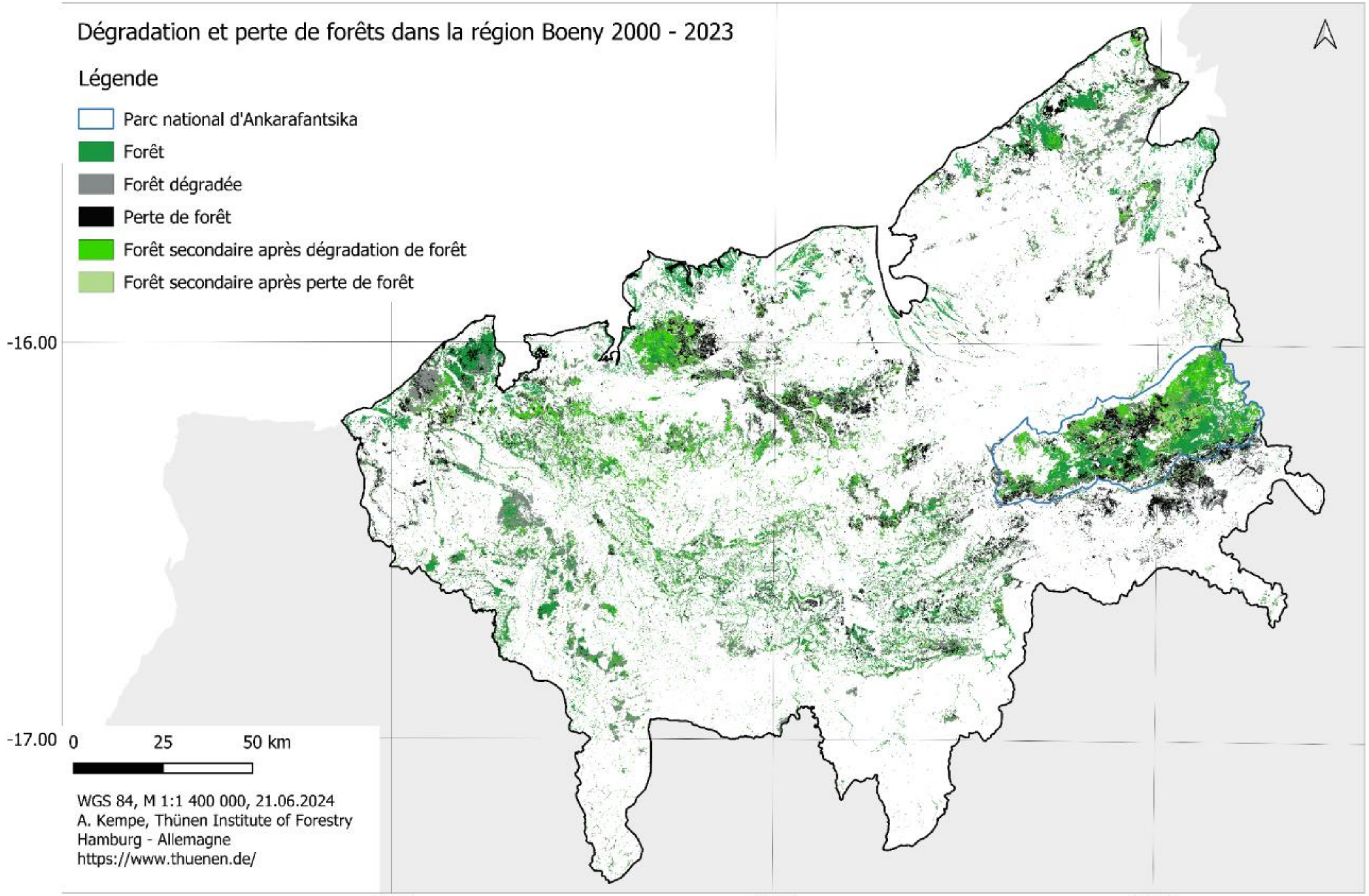
Map of forest situation in DIANA's national parks in 2023.



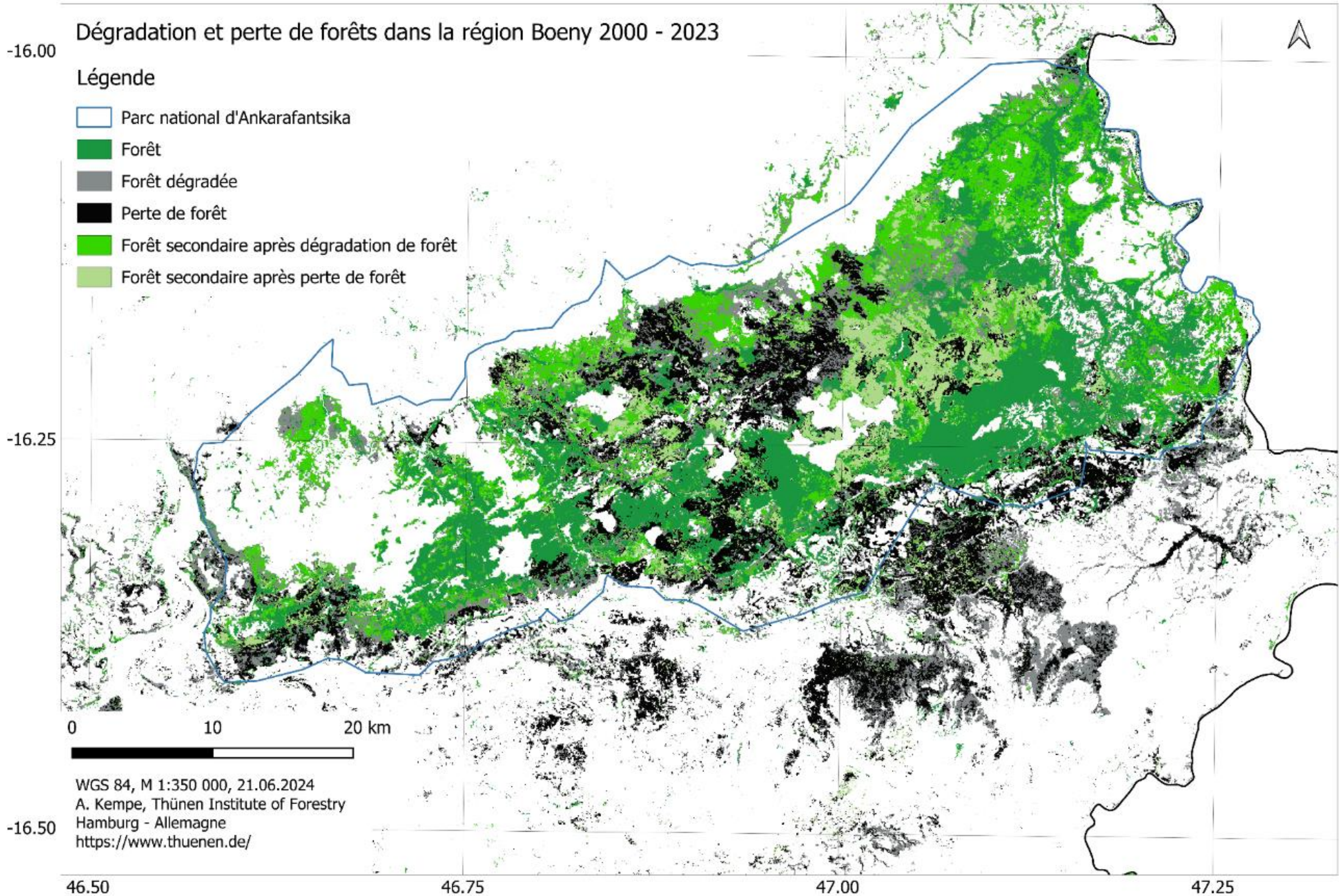
Map of forest degradation and deforestation by driver Boeny.



Map of forest degradation and deforestation by driver in Ankarafantsika.



Map of forest situation in Boeny in 2023.



Map of forest situation in Ankarafantsika in 2023.

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thuenen-working-paper@thuenen.de
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