ABSTRACT

Title of Dissertation:	FORREST LOSS TRAJECTORIES AND PALM OIL EXTENT IN INDONESIA
	Diana Parker, Doctor of Philosophy, 2022
Dissertation directed by:	Professor Matthew Hansen, Department of Geographical Sciences

Tropical forests provide critically important ecosystem services, and they are particularly important for their levels of biodiversity and for the carbon that they store. Yet despite global efforts to slow or halt deforestation, natural forests in the tropics continue to be cleared, primarily for agricultural expansion. Indonesia contains the world's third largest humid tropical forest area, and for much of the past several decades has experienced alarmingly high rates of deforestation. This began to change in 2017, when deforestation rates dropped precipitously and have since remained low. To better understand how this recent trend compares to historical deforestation patterns, this study used a sample-based approach to estimate annual primary forest loss in Indonesia over a 30-year period, from 1991-2020. Since 1990, Indonesia has lost 28.4 (standard error of +/-0.7) Mha of primary forest – roughly one quarter of its total primary forest area in 1990. One fifth of this area (19.7% +/-1) was cleared during a single two-year period, 1997 and 1998, when millions of hectares of primary forest were burned during a severe El Niño event. I also tracked land use after forest clearing to better understand what drives deforestation in Indonesia and found that more than half of all forests were left idle after clearing, often for

years at a time. While some of this was caused by forest fires, like those that occurred during the 1997/98 El Niño event, the majority, 8.5 (+/-0.4) Mha, was actively cleared. Large areas of actively and fire-cleared land remained unused at the end of the study period (4 +/-0.3 and 4.8 +/-0.3 Mha, respectively). However, by 2020, an estimated 40.7% (+/-1.7) of initially unproductive land had also been converted to productive land uses, primarily palm oil production, which covered 16 (+/-0.5) Mha of land in Indonesia in 2020. This included 2.5 (+/-0.2) Mha of land used to cultivate oil palms that directly replaced primary forests and another 5.3 (+/-0.3) Mha that expanded into previously forested areas one or more years after forest conversion. In the last few years of the study, my sample-derived estimates also confirmed a decline in deforestation after 2016, which had previously been seen in forest loss estimates derived from map pixel counting. From 2017-2020 Indonesia experienced the lowest rates of primary forest clearing observed during the study period. This drop in deforestation occurred after years of increasingly tight restrictions related to primary forest conversion, peatland use, and palm oil expansion, and during a period of heightened public concern about deforestation and land fires following the 2015 El Niño event. It also occurred during a time when palm oil prices were relatively low, and after millions of hectares of idle land had been intentionally created, a phenomenon that is likely closely tied to speculation and land banking. This study provides the most detailed information currently available about historic deforestation trends and land use trajectories after forest clearing in Indonesia, shedding new light on forest change patterns and providing a dataset that could potentially be used in future studies, including for econometric research to quantify the extent to which political and economic factors may have influenced land cover change.

FOREST LOSS TRAJECTORIES AND PALM OIL EXTENT IN INDONESIA

by

Diana Parker

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2022

Advisory Committee:
Dr. Matthew Hansen, Chair
Dr. Peter Potapov
Dr. Christopher Justice
Dr. Fred Stolle
Dr. Joseph Sullivan

Acknowledgements

The questions explored in this dissertation include many of the questions that sparked my interest in this field. However, I never imagined that I would be able to answer them to the extent that I have here, and that would never have been possible without the support and mentorship of my collaborators. Most importantly, I would like to thank my advisor, Matt Hansen. Your global tree cover loss product is why I applied to Maryland, and I am constantly amazed and grateful that I have the opportunity to work with and learn from a scientist of your caliber and from someone with such a strong commitment to produce research that is accessible beyond academic communities. Along those same lines, I would also like to thank Peter Potapov, whose Analysis Ready Data provides the backbone of this and many other projects, and who first brought me into the Global Land Analysis and Discovery (GLAD) group as his teaching assistant for an introductory remote sensing course, despite my, at the time, extremely limited knowledge of remote sensing. Working with you on that class was one of the highlights of my time in graduate school, and I could not have imagined a better introduction to the field.

I would also like to thank my other GLAD colleagues, in particular Viviana Zalles and Amy Pickens. You both helped me at critical points and I would not have been able to complete this dissertation without you.

Beyond my community at Maryland, I was fortunate to be able to work with many amazing collaborators at Indonesia's National Institute of Aeronautics and Space (LAPAN), the Indonesian Ministry of Environment and Forestry (KLHK), and

World Resources Institute (WRI) Indonesia. I would like to thank my coauthors at these organizations – Kustiyo, Arief Wijaya, Anna Tosiani, Muhammad Yazid, Inggit Sari, Tatik Kartika, Rizky Firmansyah, and Zuraidah Said. I learned so much from all of you, and I hope that the results presented here are worth the many very long days – including I don't remember how many weekends – we spent agonizing over pixels in windowless conference rooms. I would especially like to thank Pak Kustiyo and Pak Arief, without whose support this project would never have made it to this stage.

Most importantly, I would like to thank my family – my parents, John and Karen Parker, my brother Nathan Parker, and my husband, Aaron Myers. I would need to write another dissertation to describe the ways they have supported me, and I am so grateful to be surrounded by so many wonderful and inspiring people in my life. Aaron in particular has gotten me through this PhD, and I am so happy to be able to share my life with you.

Table of Contents

List of Figures

List of Abbreviations

National Institute of Aeronautics and Space of Indonesia (LAPAN)
Indonesian Ministry of Environment and Forestry (KLHK)
World Resources Institute (WRI)
Global Land Analysis and Discovery (GLAD)
International Union for Conservation of Nature (IUCN)
Brazilian Legal Amazon (BLA)
Conference of Parties (COP)
Reducing Emissions from Deforestation and Forest Degradation (REDD+)
Roundtable on Sustainable Palm Oil (RSPO)
"No Deforestation, No Peat, No Exploitation" (NDPE)
National Institute for Space Research (INPE)
Program to Calculate Deforestation in the Amazon (PRODES)
Real Time Deforestation Detection System (DETER)
Moderate Resolution Imaging Spectroradiometer (MODIS)
Synthetic Aperture Radar (SAR)
Badan Restorasi Gambut (Peatland Restoration Agency, BRG)
Bogor Agricultural University (IPB)
Normalized Burn Ratio (NBR)
Normalized Difference Vegetation Index (NDVI)
Near Infrared (NIR)
Shortwave Infrared (SWIR)
European Union (EU)
World Trade Organization (WTO)
Daichi-Advanced Land Observing Satellite (ALOS)
Phased Array type L-band Synthetic Aperture Radar (PALSAR)

Chapter 1: Introduction

1.1 Background and research importance

1.1.1. The importance of tropical forests and threats they face

Land, and arable land in particular, has been one of our most valuable natural resources since the development of agriculture and continues to hold immense economic importance today. It is also largely finite. Although high-cost cities such as New York or Hong Kong may carry out land reclamation projects to increase their footprints, agricultural expansion takes place primarily as it has for millennia – at the expense of natural landscapes. For the past several decades, most agricultural expansion has occurred in the tropics, where it is the dominant driver of deforestation[1,2].

This is happening while humanity faces two critical challenges – biodiversity loss and climate change – that are inextricably linked to tropical forests. Tropical forests are incredibly biodiverse. They are estimated to contain at least two-thirds of the world's terrestrial biodiversity, making them by far the most diverse terrestrial ecosystems on the planet[3–5]. Many of the species found in old-growth tropical forests cannot survive when those areas are degraded or cleared.[4,6]. Given the density of species and high levels of specialization and endemism, the potential for biodiversity loss when tropical forests are cleared is huge. The loss of plant and animal species in the tropics hurts us both culturally and scientifically. Tropical forest species include all seven non-human great apes, our closest living animal relatives. All are listed as either endangered or critically endangered on the International Union for

Conservation of Nature (IUCN)'s red list due to habitat loss, and the Tapanuli orangutan (*Pongo tapanuliensis*), which was first declared a unique species in 2017, contains less than 800 individuals[7]. Indigenous communities and other forest dependent peoples also rely on tropical forests as a source of food and traditional medicine. As these habitats are destroyed, centuries of traditional knowledge about the species within those ecosystems and their uses may also be lost. For indigenous communities living in or near tropical forests, their own cultural practices and religious beliefs can also be closely linked to the local environment. Many of these groups have been sustainably managing local natural resources for generations, and when they are given the power to control their traditional forests, indigenous communities can be highly effective at preventing encroachment even in very threatened areas[8].

Tropical forest species also contain chemicals that can be used in the development of new medicines, and the loss of tropical forests could prevent future discoveries. This nearly occurred in 1987, when a team of researchers in Sarawak, Malaysia collected samples from a variety of rainforest plants, one of which contained a compound that showed promise as a potential HIV treatment. When researchers returned to the site in 1991, the tree from which they had taken the sample had been cut down, and they were not able to find another tree of the same species in the area[9,10]. In this particular case, researchers were able to find a living specimen in the Singapore Botanic Gardens, however the near miss underscores the potential risks to science associated with primary forest conversion.

Beyond their importance for biodiversity, tropical forests also store carbon. This carbon is released into the atmosphere when forests are degraded or cleared, contributing to climate change. Because they contain more above-ground biomass compared to temperate and boreal forests, clearing humid tropical forests can have a proportionally larger impact on carbon emissions[11], just as it has a proportionally larger impact on biodiversity loss.

Humid tropical forests are typically not fire-adapted[12], meaning fire is not a naturally occurring phenomenon in these landscapes and forest species do not depend on periodic fire to regenerate, as is the case in some temperate and boreal forest landscapes. However, as tropical forests are increasingly degraded, they also become increasingly vulnerable to fire, particularly along forest edges and in peatland areas that have been drained[12–14]. These fires are themselves a source of carbon emissions, and repeated burning or particularly strong fires can lead to complete or near-complete tree mortality. The carbon released from cleared or burned forests, along with greenhouse gases from other sources such as the burning of fossil fuels, has already begun changing our climate. One consequence of this has been stronger and more frequent droughts, which in turn puts forests at further risk of fires – one of many feedback loops that could accelerate climate change. In the Amazon, researchers predict that deforestation and climate change is rapidly pushing the world's most iconic tropical rainforest towards a tipping point, where rainfall patterns will have been so disrupted that the Amazon will no longer be able to sustain itself[15].

At a local level, tropical forests provide other invaluable ecosystem services, including as watersheds and buffers against natural disasters. Many tropical forest countries also have relatively high levels of poverty and relatively high proportions of their populations who rely on agriculture for their livelihoods. Access to clean water and protection against natural disasters are important to all communities. However, lower income communities have fewer safety nets, meaning disruptions in the ecosystem services tropical forests provide could have even more devastating impacts.

Given the obvious benefits associated with protecting tropical forests, there have been increasing efforts in recent years to protect and restore these valuable ecosystems. In some cases, these efforts have been successful. In the mid-1990s, Costa Rica, which has been heralded as the first tropical country to reverse deforestation[16], was able to use innovative environmental protection policies, including a program that provided payments for environmental services, to largely halt the rapid deforestation that took place in the 1960s and 1970s and later experienced an increase in overall forest cover as forests regrew in abandoned pastures[17]. Brazil experienced a similarly dramatic reversal in forest loss trends in the mid-2000s. Although Brazil did not halt or reverse deforestation, the country was able to slow forest loss within the Brazilian Legal Amazon (BLA) in the mid- and late 2000s. From 2005-2009, deforestation inside the BLA dropped to just 36% of historic levels, following the implementation of policies designed to protect tropical forests[18].

As global awareness increases about the urgent need to control carbon emissions in order to avoid catastrophic climate change, the importance of protecting and rehabilitating forests has also become an international priority. At the 2021 Conference of Parties (COP), dubbed in the media as “the forest COP” or “the nature

COP," countries around the world, including many tropical forest countries, made an unprecedented pledge to end deforestation by 2030[19]. However, despite decades of concern over the environmental impacts of deforestation, and aggressive recent commitments to reverse forest loss and turn forests into a global carbon sink, rather than a source of emissions, deforestation continues, with particularly high rates of primary forest conversion occurring in the ecosystems with that are richest both in terms of carbon and biodiversity – the humid tropics[11,20–22]. The pressures on primary forests in the tropics are so intense that even countries that have succeeded in slowing deforestation in the past can see trends reverse as political priorities change[23].

1.1.2 Importance of Indonesian primary forests

Indonesian forests are particularly valuable, and understanding the deforestation dynamics in Indonesia particularly important, for several reasons. First, many Indonesian forests occur in peatlands – areas that contain much higher levels of below-ground biomass compared to forests on dry soils[12]. When peatlands are drained and degraded, fires can occur. These fires pose a serious public health risk, are a major source of carbon emissions, and can smolder for weeks or months at a time[24–26]. As an island nation, Indonesia is also extremely vulnerable to natural disasters and sea level rise. This makes the local ecosystem services forests provide extremely important and also means that carbon emissions from deforestation in Indonesia will have a direct and potentially devastating impact its citizens, many of whom live in coastal areas.

Monitoring deforestation in Indonesia is also important from a policy perspective. Indonesia has set aggressive targets to reduce its carbon emissions, including even higher targets that the country has said it can reach with foreign assistance. In 2011, Indonesia entered into a $1 billion partnership with Norway under the international Reducing Emissions from Deforestation and Forest Degradation (REDD+) framework to reduce greenhouse gas emissions from forest clearing. Indonesia has since implemented various forest protection policies, including a moratorium on the issuing of new concessions in primary forests and peatlands that was created as a direct result of the Norway partnership. In 2021, however, Indonesia backed out of the agreement, claiming that Norway had failed to deliver promised payments[27]. In the context of the Norway partnership, other REDD+ initiatives, and Indonesia's voluntary commitments to reduce greenhouse gas emissions from land cover change, accurate estimates of current deforestation rates and past deforestation trends are critically important to monitor progress towards emissions reduction goals.

Indonesia is also important as a test case for recent private-sector initiatives to end deforestation and reduce carbon emissions associated with commodity production. Indonesia's palm oil and pulp-and-paper industries have long been targets by environmental groups for deforestation as well as labor and human rights violations. Eventually, this led to reforms, including the creation of the Roundtable on Sustainable Palm Oil (RSPO) in 2004, a membership organization that certifies plantations meeting certain sustainability standards. Companies have also begun adopting voluntary "zero deforestation" or "No Deforestation, No Peat, No Exploitation" (NDPE) commitments[28–32]. Many of these commitments were adopted by international corporations and apply to global supply chains – not just to plantations in Indonesia. However, Indonesia is a major player in these industries, and in the case of palm oil, it is the world's largest producer. Understanding deforestation trends in Indonesia before and after these policies were adopted is critical to evaluating their success.

1.2 Remote sensing as a forest protection tool

Satellite data is a unique and extremely valuable tool for monitoring and protecting tropical forests. Brazil, the country with the world's largest tropical forest area and highest rate of deforestation, has been monitoring its forests using satellite imagery since the 1970s[33]. In the early 2000s, Brazil's National Institute for Space Research (INPE) made the data from its Program to Calculate Deforestation in the Amazon (PRODES) available to the public for the first time[34]. Shortly after, INPE launched its Real Time Deforestation Detection System (DETER), a product created using data from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite, designed to rapidly detect deforestation as it occurred.

DETER's implementation in 2004 corresponded with a steep drop in deforestation within the Legal Amazon that lasted until 2009[18,33,35]. While satellite monitoring and satellite data transparency was just one of many steps the Brazilian government took to protect the Amazon during that time period, the PRODES and DETER data undoubtably played a critical role both in increasing public awareness and facilitating enforcement of forest protection laws. The fact that forest clearing patterns in Brazil changed after these programs were implemented in ways that made it easier for deforesters to avoid detection by satellites underscores the importance of these programs – and the importance of continued development of new satellite monitoring tools[36,37].

Indonesia also has a long history of forest monitoring using satellite data. However, unlike in Brazil, these products are not made freely available to the public, although the Ministry of Environment and Forestry (KLHK) does publish annual forest loss statistics. Instead, researchers have filled the gap with regional and national-scale studies quantifying the area of forests and other important land covers in Indonesia. The Hansen et al. global tree cover loss product published in 2013 and the Margono et al. primary forest map released one year later in 2014 were some of the earliest and most important national-scale studies made available[21,38]. Much like Brazil's PRODES product, these studies provided annual estimates of tree cover loss in and outside primary forests over a long time period and at a high spatial resolution (30-meter and 60-meter resolution, respectively). Since then, a pan-tropical 30-m resolution primary forest map and a two pan-tropical near-real-time alert systems have been published[22,39,40]. These products, when combined with the Hansen et al. global tree cover loss product, enable primary forest loss in Indonesia to be quantified on an annual basis and compared to trends observed in other tropical forest countries. The various alert products also allow conservation practitioners to identify and quickly respond to deforestation on the ground shortly after it occurs. Together, these academic products can fill a similar role to that of Brazil's PRODES and DETER systems, with the advantage of being globally or pan-tropically consistent, which is useful for comparing forest dynamics between countries and regions.

Beyond forest and tree cover monitoring, major advances have also been made in mapping deforestation drivers in Indonesia, however, some challenges still remain. Palm oil and acacia plantations are two of the largest industrial drivers of deforestation in Indonesia. Several methods can be used to map large-scale plantations, which have distinct spatial patterns – specifically characteristic block patterns (for plantations located in lowland and peatland areas) and terracing (for plantations located in areas with steeper slopes). The type of plantation can be determined by comparing the location to available concession maps, although this poses some problems related to data quality, as concession maps are not made officially available by either local or national governments on a consistent basis. Plantation type can also be determined by the temporal clearing and regrowth patterns (acacia) and radar backscatter signatures (oil palm).

Several regional and national-scale plantation maps are currently available[41–49]. These studies rely primarily on two different methods and data sources – either visual interpretation by experts of plantation boundaries using multispectral data from the NASA/USGS Landsat archive or classification of radar data from Synthetic Aperture Radar (SAR) sensors. SAR data is useful for mapping mature oil palms, as closed canopy plantations have a radar backscatter signature that is distinct from most other land covers found in these areas[50–52]. Younger oil palms are less reliably mapped with SAR data, however, so this method is not appropriate for detecting plantations soon after they are established. For this, visual interpretation of Landsat data may be more appropriate, as the plantation infrastructure – specifically roads and canal networks – is what allows researchers to identify the class of interest, rather than the specific spectral signature of the plants themselves. Using this method, plantations can be identified even before oil palms have been planted. However, this method is not appropriate for smallholder plantation mapping, as these have more heterogenous spatial patterns that cannot be easily differentiated from other smallholder land uses. These visually interpreted maps can also overestimate the industrial oil palm area in cases where there is a delay between the establishment of plantation blocks and the actual planting, or where oil palms were damaged.

Fire is another important dynamic in Indonesia. Fires both in and outside forested areas are a source of carbon emissions and harmful air pollution. Fires within primary forests can also cause forest degradation and in some cases can lead to forest loss. The fire hotspot product derived from MODIS data is used both to combat fires as they occur, identify industries or individual land managers who may be contributing to fires, and to compare changes in fire patterns over time[53,54]. Researchers also use multispectral data to map burns scars directly, allowing them to see which landscapes are impacted by fires each year[55,56]. Burn scar maps and hotspot data can be compared to primary forest maps to see whether fires are occurring in areas that were previously forested. Deforestation from fire can also be mapped directly using multispectral data, and a recent study by Tyukavina et al.[57] provides both maps and sample-based estimates of forest loss from fire globally.

1.2.1 Importance of sample-derived land area estimates

Much of the research discussed above focuses on mapping land cover or land cover change directly. Maps created from remote sensing data are extremely valuable, particularly in cases where it is important to know exactly where land change is occurring. If your research aim is to create a product that can be used by practitioners to quickly identify deforestation as it occurs so that they can intervene on the ground, a map is the most useful product you can create. Even a map that underestimates the total area cleared can be useful for on-the-ground stakeholders, and in cases where resources to protect forests are scarce may be preferable compared to an overly sensitive product that contains a large number of commission, or false-positive, errors. However, if your aim is to compare deforestation rates over time or to quantify deforestation within a certain region, map errors can lead to over- or under-estimations. All maps contain bias, so to avoid this issue and to quantify the uncertainty of the statistics derived from your study, using a statistical sample to estimate land areas rather than map pixel counting is considered scientific good practice[58]. By using a statistical sample of the best available reference data, researchers can avoid the bias inherent in mapping and estimate the area of both the land cover class itself and the associated uncertainty. Some, but not all, of the studies mentioned above report areas based on statistical samples, and over time this has increasingly become the norm. However, since sample-derived areas are not universally provided in land cover studies in Indonesia, gaps still exist, making it difficult to compare the change in deforestation patterns over time.

1.3 Study goals and dissertation structure

This dissertation sets out to answer three main questions: 1) how much primary forest has been degraded and lost in Indonesia; 2) what land uses have replaced forest; and 3) to what extent have palm oil plantations, Indonesia's most significant industrial driver of deforestation, expanded in forested and non-forest areas. To answer these questions, I worked with my advisor and colleagues from the GLAD group, and with coauthors from Indonesia's National Agency for Aeronautics and Space (LAPAN), Indonesia's Ministry of Environment and Forestry (KLHK), and World Resources Institute (WRI) Indonesia, to generate sample-derived annual area estimates of forest cover, forest degradation, forest loss, and post-forest land uses over a 30-year period, from 1991 to 2020. I also estimated the area of both intact and degraded primary forest in 1990 and the area used for oil palm cultivation in 2020. I provide annual sample-derived estimates over a longer time period and for more land cover classes than existing studies, which allowed me to compare changes in deforestation rates over time in ways not previously possible. These changes in forest cover over time are explored in Chapter 2. In Chapter 3, I explore land uses after deforestation and quantify post-clearing land use classes not only immediately after forests are cleared by at various post-clearing time-steps. This detailed analysis of how land use continues to change after forests are cleared sheds new light on what drives forest loss in Indonesia. In Chapter 4, I provide a sample-derived estimate of the land area used for palm oil cultivation in Indonesia in 2020 and annual sample-derived estimates of palm oil expansion in previously forested areas over a 30-year period. Lastly, in Chapter 5, I discuss how these findings shed light on the potential impact of government and private-sector led forest protection policies in Indonesia and what further research may be needed to determine the extent to which policies are succeeding.

Chapter 2: Indonesian forest loss trends over time

2.1 Abstract

Indonesia contains the world's third largest area of primary tropical forest. It has also experienced rapid deforestation in primary forest areas for much of the last several decades, although in recent years deforestation declined dramatically. Here, I estimate Indonesia's primary forest area in 1990 and annual primary forest loss from 1991-2020. Indonesia lost roughly one quarter of its 1990 primary forest over a 30-year period – a total deforested area of 28.4 (standard error of +/-0.7) million hectares. One fifth (19.7% +/-1) of this deforestation occurred during a single two-year period, 1997 to 1998, when a severe El Niño event caused widespread fires throughout the country. More recently, primary forest loss rates have declined, and from 2017 to 2020 Indonesia experienced the lowest annual deforestation observed over the course of the study.

2.2 Introduction

In February 2021 at the Conference of Parties (COP) 26 climate talks, countries from around the world made an ambitious pledge to halt and reverse forest loss and land degradation by 2030 in an effort to curb greenhouse gas emissions from land use change. The declaration was endorsed by some of the world's top carbon emitters, including the United States and China, and the three countries with the largest tropical forest areas – Brazil, the Democratic Republic of Congo, and Indonesia[19]. Of these three, Indonesia has the least remaining primary forest and, until recently, was experiencing the highest rate of clearing proportional to its total forest area[22,59]. That changed in 2017, when the country experienced a sharp and sustained decline in primary forest loss, in what appears to be a rare success story in tropical forest conservation[60,61].

In the years leading up to its deforestation rate decline, Indonesia implemented a number of forest protection policies. These include a moratorium on new concessions inside primary forests and peatlands, which began in 2011 and was made permanent in 2019[62], expanded peatland protections enacted in 2016[63], and a temporary ban on all new palm oil concessions, which was imposed in 2018 and allowed to expire in 2021[64]. Indonesia's palm oil and pulp and paper industries, the primary industries responsible for large-scale deforestation in the country[65,66], had also, after years of attacks by environmental groups, adopted more forest-friendly policies, including commitments by many of these industries' largest actors to eliminate deforestation from their supply chains[31,32,67].

These policy changes may be responsible for Indonesia's recent reduction in primary forest loss. However, determining the extent to which policies contributed to the decline is difficult, since external forces such as economic or environmental conditions may have also played a role.

One factor that makes it difficult to determine how policies contribute to changing deforestation rates in Indonesia is the role that fire plays in forest conversion. Fire is both a driver of forest loss in Indonesia and a tool used to clear debris after tree felling[57,68–70]. During El Niño events or other drought periods, fires can be particularly severe[13,71], and a strong El Niño in 2015 corresponded to a spike in deforestation in Indonesia. The potential impact of drought-associated fires on deforestation rates in Indonesia makes it difficult to untangle the relative impacts of climate, government policies, and economic factors on deforestation trends. El Niño events may also become more frequent and severe with climate change[72–74], so understanding how drought and drought-induced fire affect Indonesian forests can help in designing future forest protection policies and predicting which areas are most at risk.

Most deforestation estimates also fail to adequately capture degradation dynamics. Degradation is itself a substantial source of carbon emissions and biodiversity loss[6,75,76]. In Indonesia, forest degradation may also predict future deforestation, since most forests are degraded before they are cleared[38]. Throughout the tropics, fragmented forests are at higher risk of conversion.[77] Road construction makes forests more accessible, which in turn increases the likelihood that they will be deforested. Degraded forests are also more vulnerable to fire, and in areas where fires occur frequently, repeated burning year after year may eventually lead to complete tree mortality[69,78]. In Indonesia, degradation may also provide a potential legal pathway for forest conversion, as intact primary forest areas located within the national forest estate are not legally eligible for rezoning for non-forest land uses such as palm oil[79].

Providing more detailed information about historic deforestation patterns in Indonesia can shed light on how the 2017-2020 period differed from past years. Here, I worked with coauthors to create sample-based primary forest loss estimates over a 30-year period, from 1991-2020. I also tracked degradation events within primary forests prior to clearing, enabling a better understanding of the relationship between forest disturbance and conversion. Lastly, I disaggregated forest fire clearing from other types of primary forest loss, shedding light on the impact weather patterns and drought have on annual loss rates in Indonesia.

2.2.1 Definitions

Primary forest area in 1990 and annual primary forest loss from 1991-2020 were quantified using a probability sample of remotely sensed reference data. This is consistent with good practice recommendations for estimating land change areas as it allowed me to generate uncertainties (I report uncertainty as +/-1 standard error of an estimate) and avoids the bias inherent in area estimates derived from map pixel counting[80]. I also tracked forest degradation events and classified forest clearing into two clearing types – forest fire clearing and active human clearing.

I defined primary forest as natural, old-growth woody vegetation at least 5m in height and with at least 30% tree cover at a 30-m spatial resolution. This included intact primary forest, with no observable evidence of human disturbance at a 30-m resolution or within a 120-m radius, and degraded primary forest, which shows evidence of human disturbance but maintains at least half of its original natural canopy. Forest degradation included any disturbance at a 30-m resolution or within a 120-m radius that resulted in less than 50% natural canopy loss. Examples of intact and degraded primary forests are provided in Figures 2-S1, 2-S2, and 2-S3. Degradation event examples can be seen in Figures 2-S4 and 2-S5.

I defined deforestation as the loss of at least 50% of the natural canopy at a 30-m spatial resolution, regardless of post-clearing land use. Deforestation was identified based on changes in the spectral signature of the sampled pixels, including a temporary or permanent increase in bare ground within the pixel or a persistent change in the vegetation signature indicating a substantial canopy disturbance. Loss events and the percent canopy loss (>=50% for deforestation, <50% for degradation) were confirmed with very high resolution data where available.

Deforestation events were classified into two categories based on the clearing mechanism – forest fire clearing and active clearing. Forest fire clearing was defined as the loss of at least 50% of the natural canopy from fire in a standing forest on land that was not planted or converted to another human land use for at least 12 months after the clearing event. Active clearing was defined as the rapid conversion (within 12 months) of a natural forest to a human land use or the removal of at least 50% of the natural canopy by human activity (manual, mechanical, or chemical clearing). Forests that were actively cleared and then subsequently burned were included in the active clearing category. A forest was classified as having been converted to a human land use if it was planted with crops or replaced with another land cover associated with human activity, such as built-up land, mining pits, or fish ponds. Examples of forest fire clearing and active clearing are provided in Figures 2-S6, 2-S7, and 2-S8.

2.3 Results

From 1991-2020, Indonesia lost an estimated 28.4 (standard error of +/-0.7) Mha of primary forest, equivalent to losing an area the size of Yellowstone National Park each year for 30 years (Fig 2-1). This represents a loss of 24.6% (+/-0.5) of the total primary forest area in 1990 of 115.4 (+/-0.8) Mha. An additional estimated 25.1 (+/-0.6) Mha of intact primary forest was degraded but not cleared. The majority of deforested areas (68.2% +/-1.2) were logged or otherwise degraded at least five years before being cleared (or were already degraded in 1990) and 77.4% (+/-1.1) were degraded at least one year before clearing. Degraded primary forests were also cleared more rapidly; of the estimated 26.4 (+/-0.6) Mha of forest already degraded in 1990, 49.7% (+/-1.3) was cleared by 2020, compared to just 17.1% (+/-0.5) of forests that were intact at the start of the study (Fig. 2-2). Forests that were still intact in 1990 but later degraded also had higher rates of forest loss. An estimated 29.4% (+/-1) of primary forests degraded after 1990 were cleared by 2020, compared to just 9% (+/-0.5) of intact forests that were never degraded. Within the 10.5 (+/-0.4) Mha of intact primary forest that was degraded and cleared during the study period, the median time between degradation and clearing was 7 years (Fig 2-S4).

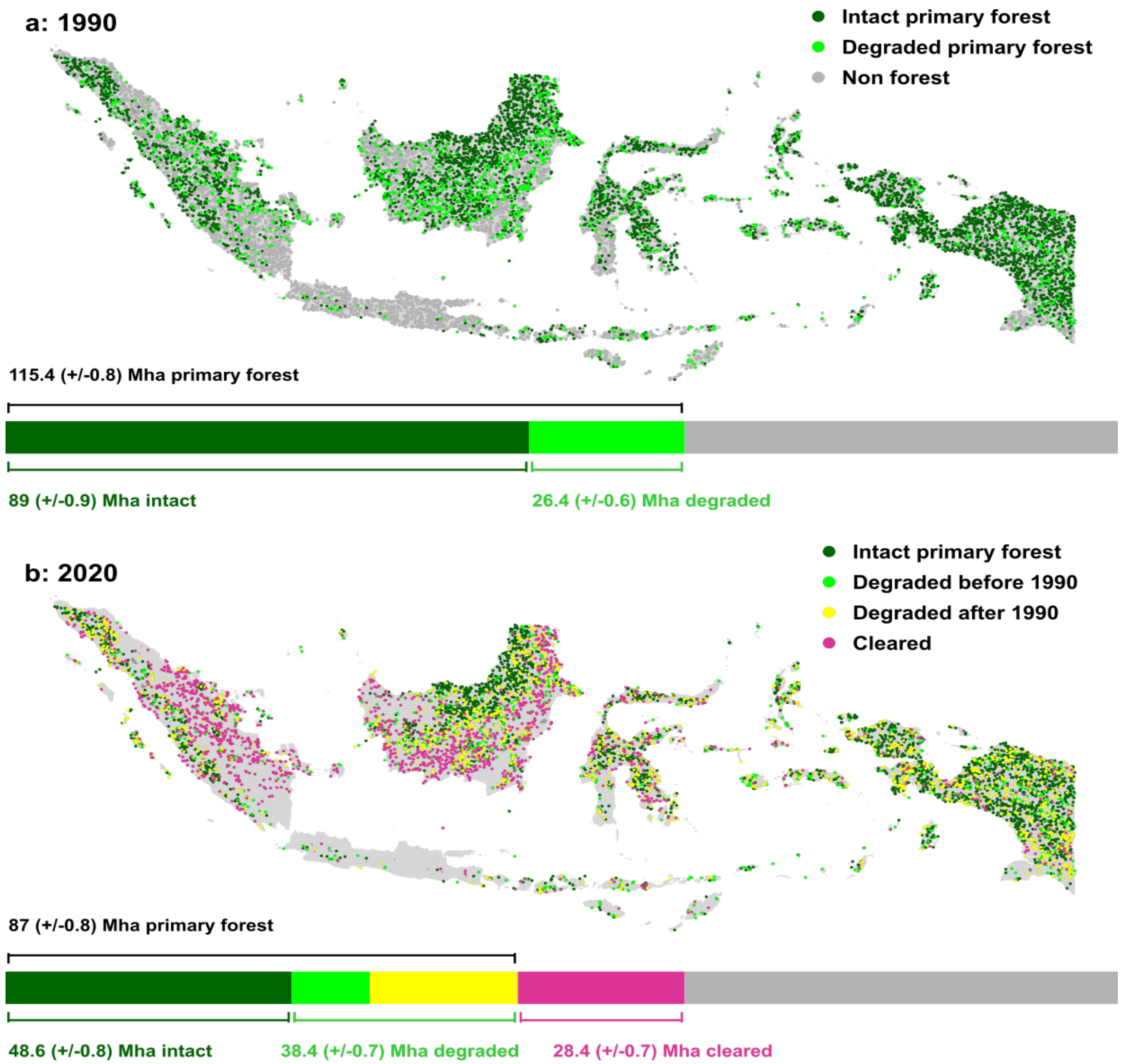


Figure 2-1: Sampled pixel locations and land cover estimates. *(a) 1990 and (b) 2020 classifications with derived intact, degraded, and cleared forest estimates. Standard errors are included in parenthesis.*

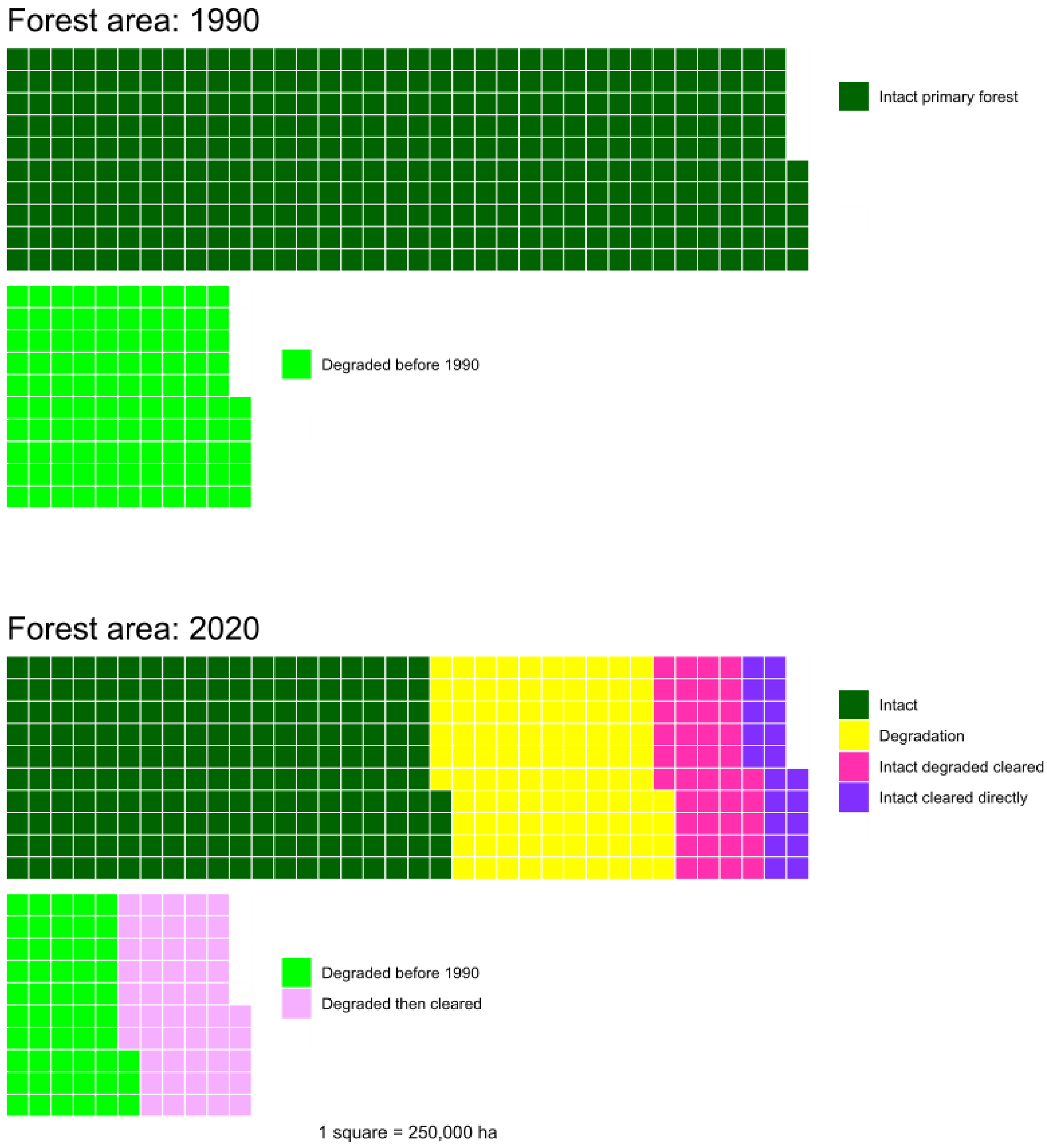


Figure 2-2: Intact and degraded forest trajectories. *Estimated intact and degraded primary forest areas in 1990 and the status of those areas in 2020. By 2020, Indonesia had lost roughly half (49.7% +/-1.3) of its primary forests that were already degraded in 1990, compared to a loss rate of 17.1% (+/-0.5) within forests that were intact in 1990.*

2.3.1 Temporal trends

For most of the study period, annual primary forest loss ranged from roughly 600,000 to 1.2 million hectares per year, with slightly higher average loss rates occurring in the 1990s compared to the 2000s and 2010s (Figure 2-3, Table 2-S1). However, there are two notable exceptions to this pattern – 1997/98 and 2017-2020.

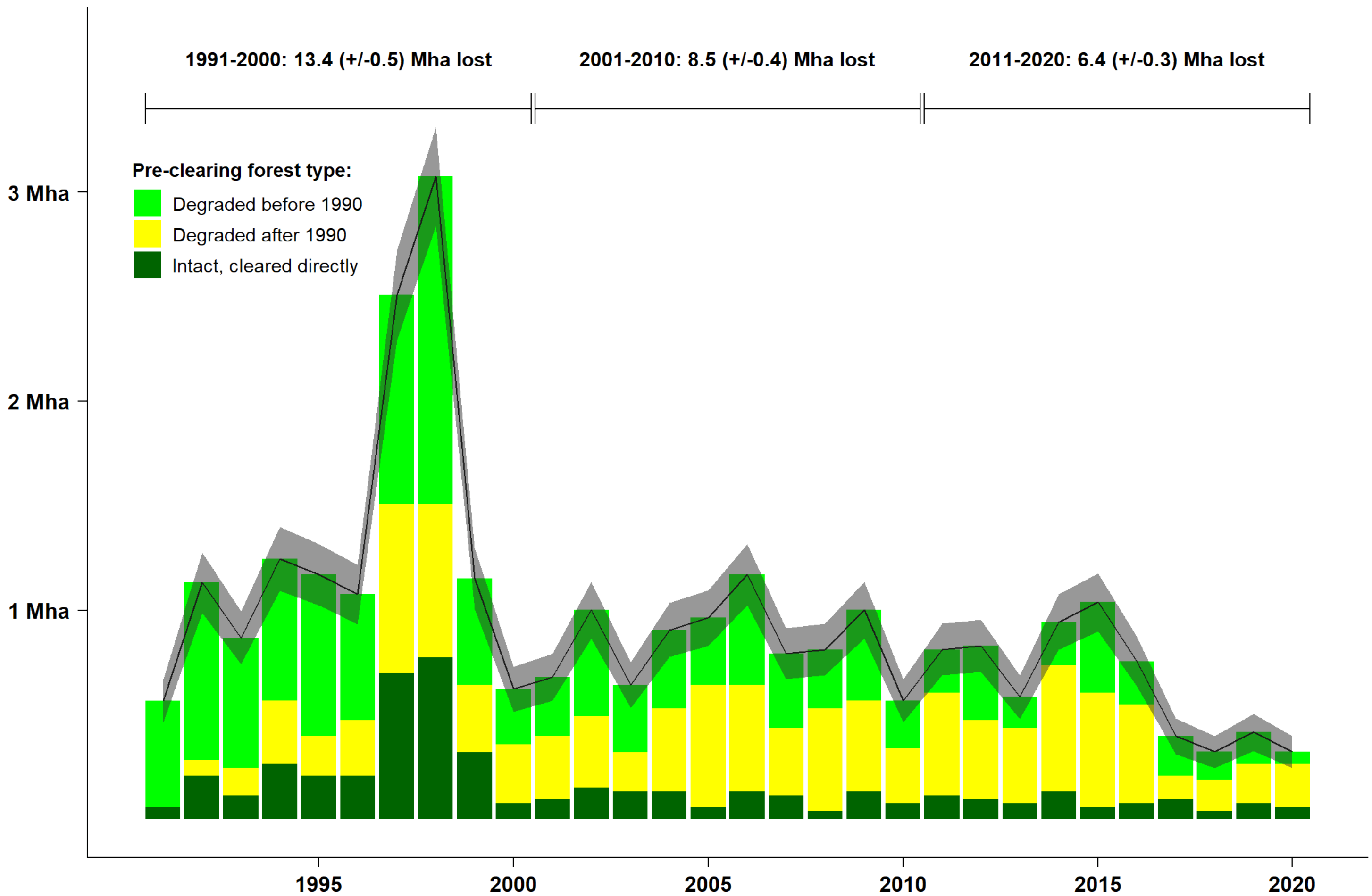


Figure 2-3: Annual primary forest loss. *Bars display estimated loss disaggregated by the type of primary forest cleared; ribbon represents one standard error above and below the annual loss estimates. Estimated annual loss areas and corresponding standard errors for each type of forest cleared are provided in Table 2-S1.*

Indonesia experienced a rapid increase in deforestation in 1997, when the country lost an estimated 2.5 (+/-0.2) Mha, more than double the amount of forest loss observed in the previous year. Another 3.1 (+/-0.2) Mha was lost in 1998, the year with the highest estimated primary forest loss of the study period, before deforestation rates returned to more normal levels in 1999. This spike corresponded to a particularly severe El Niño event, which caused widespread forest and land fires throughout the country[13]. When disaggregating by clearing mechanism, I found that forest fire clearing accounted for 64.7% (+/-4.1) and 59.5% (+/-3.8) of all primary forest loss in 1997 and 1998, respectively – the only two years in the study when forest fires were responsible for the majority of forest loss (Figure 2-4, Table 2-S1).

The other anomalous period was 2017-2020, when Indonesia experienced the lowest rates of annual primary forest loss observed during the study period (Table 2-S1). This confirms trends found in map-derived estimates[22,59,81], and could indicate that forest protection policies are succeeding. Annual degradation also declined during this period, from a nearly 20-year high observed in 2016 (Figure 2-5). However, this drop did not represent historically low levels – degradation had also declined throughout the 2000s, before reaching the study-period low in 2011.

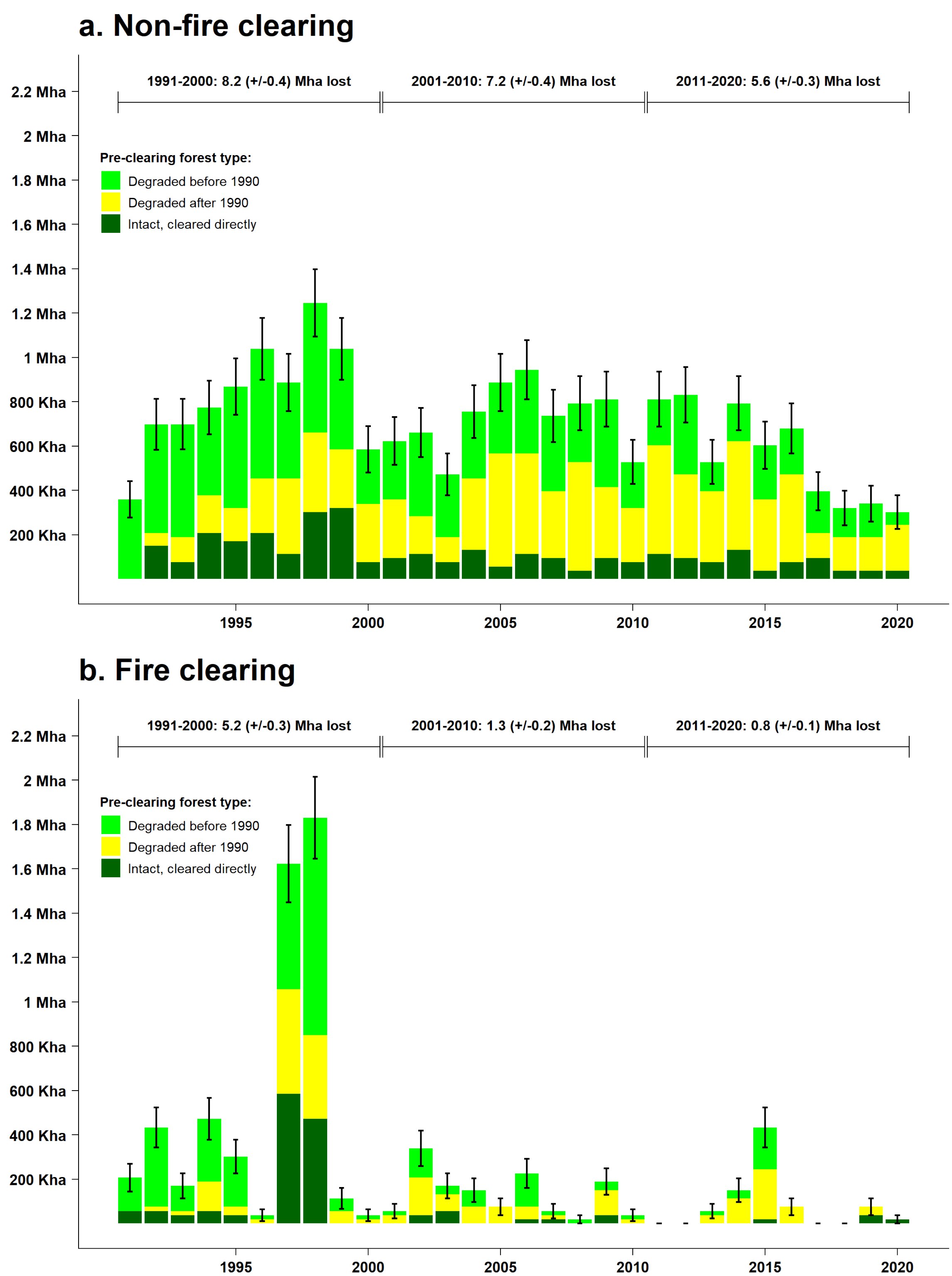


Figure 2-4: Annual (a) active clearing and (b) forest fire clearing. *Indonesia experienced a sharp increase in forest fire clearing in 1997 and 1998, during a severe El Niño event.*

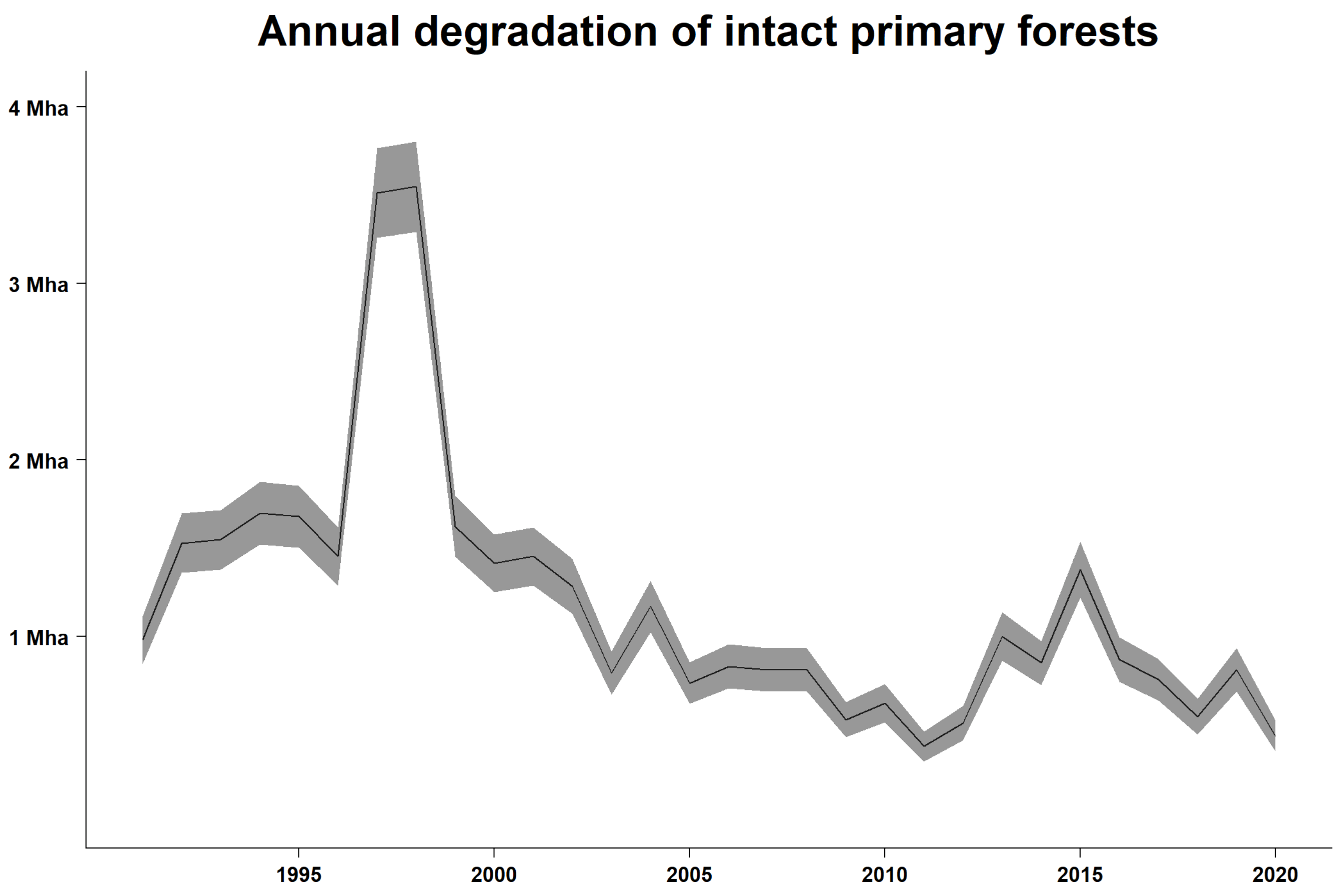


Figure 2-5. Annual degradation. *Estimated annual degradation within forests that were intact in 1990. Ribbons represent one standard error above and below the estimate.*

2.3.2 Forest fires and active clearing

Forest fire clearing accounted for an estimated 25.9% (+/-1.1) of all primary forest loss observed during the study period. Fire clearing occurred almost exclusively during El Niño events (Figure 2-6), and nearly half of all fire clearing 46.9% (+/-2.5) occurred during the 1997/98 El Niño alone. During the more recent 2015/16 El Niño, approximately half a million hectares of primary forest was cleared by fire, accounting for an estimated 6.9% (+/-1.3) of all fire clearing and 28.4% (+/-4.6) of all primary forest clearing over those two years. Averaged over the entire study period, forest fires accounted for an estimated 33.9% (+/-1.4) of clearing that occurred during El Niño events and just 6.3% (+/-1.2) of non-El Niño year clearing.

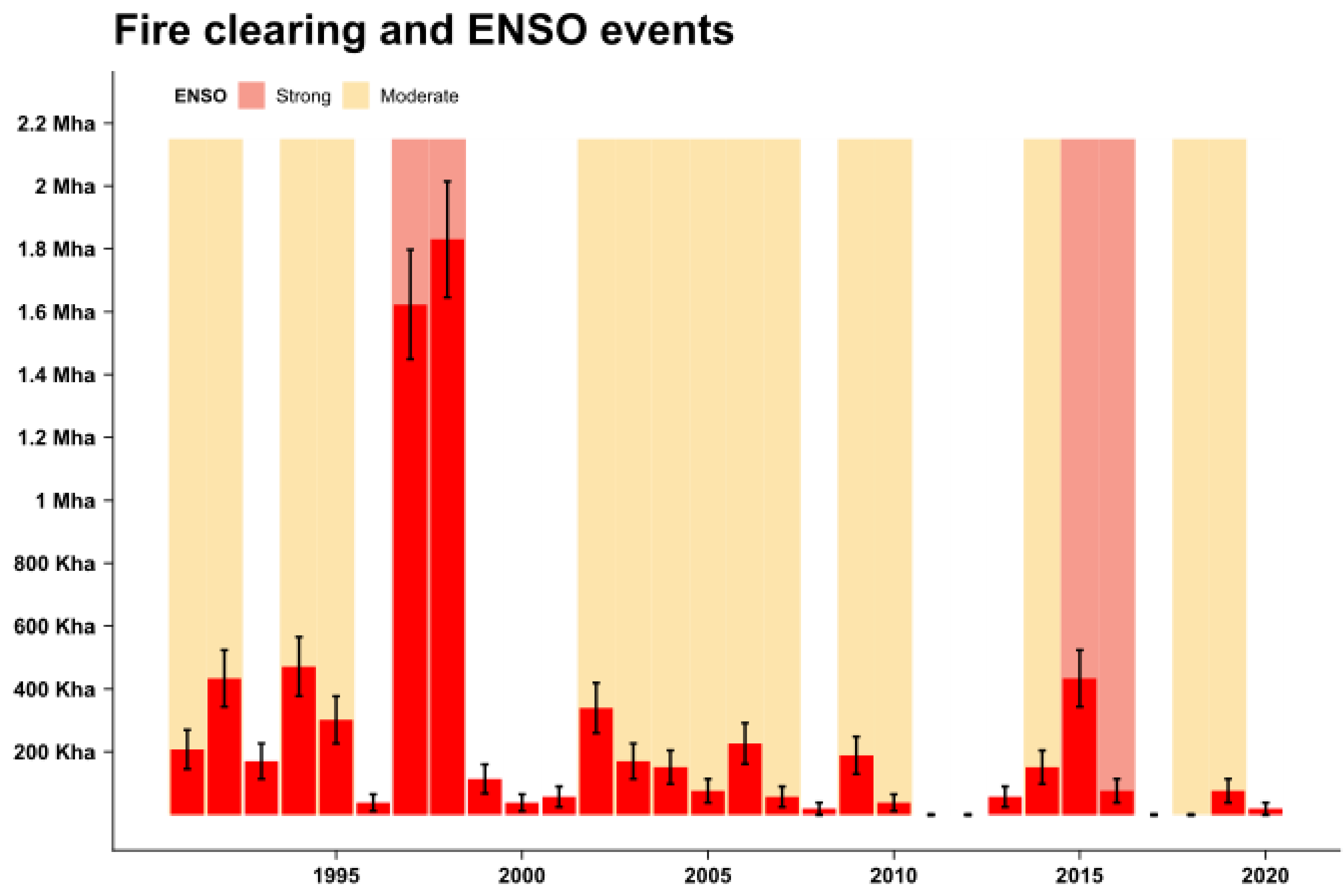


Figure 2-6: Annual forest fire clearing in El Niño and non- El Niño years. *Most forest fire clearing (93.1% +/-1.3) occurred during El Niño events. The two strongest El Niño events of the study period – 1997/98 and 2015/16, accounted for an estimated 46.9% (+/-2.5) and 6.9% (+/-1.3) of forest fire clearing, respectively.*

While fire clearing appears to be closely linked to El Niño events, active clearing demonstrated a different temporal pattern. Figures 2-4 and 2-7 show estimated active and forest fire clearing over the course of the study period, calculated annually (Figure 2-4) and as a three-year rolling average (Figure 2-7). Annual active clearing increased steadily throughout the 1990s before dropping in the early 2000s. This could be related to the political changes that were taking place around that time. The 1990s marked the end of a 32-year dictatorship led by Suharto, Indonesia's second president who took power soon after the country gained independence from the Dutch. This was also a period of rapid government-sanctioned expansion of

Indonesia's pulp and paper industry[82,83]. Growth of Indonesia's pulp production capacity in the 1990s occurred much more rapidly than tree plantation development, and the clearcutting of natural forests made up for this deficit[82].

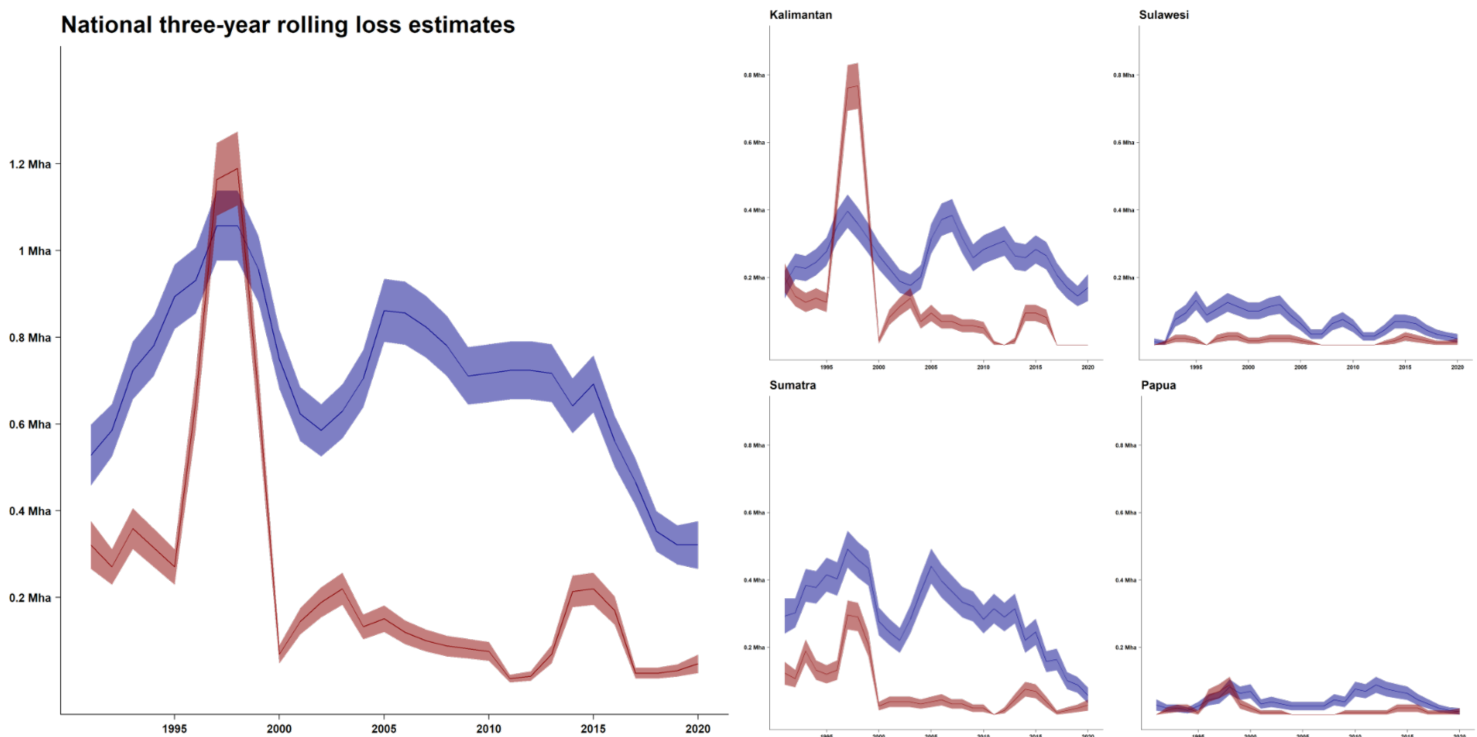


Figure 2-7: Three-year rolling averages for forest fire and active clearing. *Active clearing plus one standard error above and below the estimate is presented in blue for the entire country and for the four islands with the largest primary forest areas. Forest fire three-year rolling estimates and associated standard errors are presented in red.*

The 1998 fall of the Suharto government closely followed, and was in part triggered by, the 1997 Asian financial crisis, and the tumultuous economic and political atmosphere may have impacted deforestation. Active forest clearing peaked in 1998, the year Suharto resigned, remained high in 1999, then fell in 2000. In the early 2000s, active clearing remained low compared to the highs of the late 1990s, but began to increase in the mid-2000s until it reached another peak in 2006. This took place during Indonesia's democratic transition and a period of decentralization. Under

Suharto, natural resources including forests were tightly controlled by the central government. Much of this power was shifted to local governments during the post-Suharto *Reformasi* (Reform) period[84], which in turn led to a shift in the utilization, and, in some cases, abuse, of forest resources. As forest resources were decentralized, local government officials used concessions in forested areas to raise government revenue. Some corrupt public officials also used concessions to reward supporters who helped finance election campaigns and to personally enrich themselves and their friends and families[84–86]. Research comparing deforestation trends with local election schedules has found that deforestation, in particular illegal deforestation, accelerated just ahead of regional elections, and that forest loss increased as new political districts were created[84,85]. During the early *Reformasi* era, local elections took place on a staggered basis, as Suharto-appointed local leaders were allowed to finish their 5-year terms. The upward trend in active forest loss from 2000 to 2006 would have overlapped with this period.

From 2007 to 2016, annual deforestation rates varied from year to year, but the three-year rolling averages exhibit a downward trend during this period (Figures 2-4 and 2-7). Published map- and sample-based estimates of overall primary forest loss have shown an increase in primary deforestation in Indonesia over these years[22,38]. However, when the impact of forest fire clearing is taken into account, the map-derived trends more closely resemble this study's sample-based estimate[57,87]. Interestingly, palm oil prices, which previous studies have found to correlate with deforestation in Indonesia, were relatively high for much of this period, though palm oil prices did begin to fall around 2010[88]. Both active and forest fire clearing dropped precipitously after 2016, a trend also observed in the map products referenced above.

2.3.3 Regional trends

Most deforestation occurred on the islands of Kalimantan and Sumatra, which were responsible for an estimated 42.7% (+/-1.1) and 39.4% (+/-1.1) of total forest loss, respectively. These regions also had the highest relative rates of deforestation observed during the study period. By 2020, Sumatra had lost nearly half of its initial 1990 primary forest area (48.9% +/-1.4), and Kalimantan had lost roughly one-third (32.2% +/-1). Most regions – including the four islands with the largest areas of primary forest at the start of the study period – experienced a decline in annual active forest clearing in the last few years of the study (Figure 2-7). This decline was most dramatic in Sumatra, where deforestation rates have been falling since the mid-2000s. In 2005, Sumatra lost roughly half a million hectares of primary forest (528,000 +/-99,000), compared to just 75,000 (+/-38,000) hectares in 2020.

Deforestation in Kalimantan has also slowed since the mid-2000s, particularly in the last few years of the study. In Papua, the island with the largest area of primary forest remaining, deforestation peaked in 2011 when 113,000 (+/-46,000) hectares of primary forest was cleared, and by 2020 had slowed to levels below those detectable by this study's methodology. The decline in deforestation in Papua is important since the island still contains such a large area of primary forest, making the drop less likely, compared to a region like Sumatra, to be driven by a scarcity of forested land appropriate for conversion to palm oil or another agricultural use (Figure 2-8).

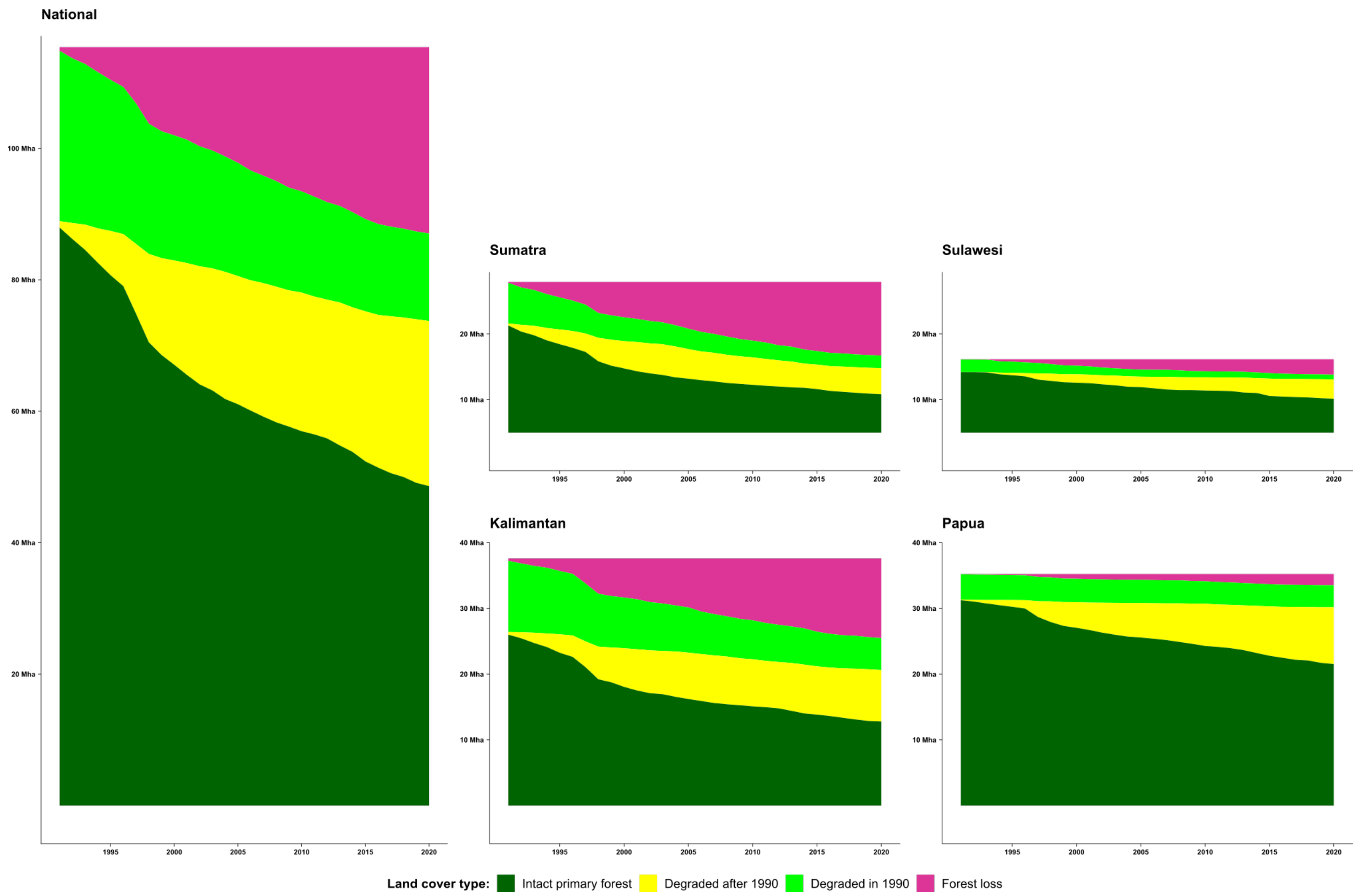


Figure 2-8: Primary forest area over time. *The intact, degraded in 1990, degraded after 1990, and cleared forest area are displayed for the entire country as well as the islands of Sumatra, Kalimantan, Sulawesi, and Papua. Sumatra experienced the highest relative clearing observed during the study period, losing 48.9% +/-1.4 of its 1990 primary forest by 2020.*

2.3.4 Regional fire patterns and potential impact of the Mega Rice Project

Fire and active clearing patterns varied by region (Figure 2-S9). Kalimantan experienced the highest proportion of clearing caused by forest fires, with fires responsible for 34.7% (+/-1.9) of all deforestation on the island. Much of this fire clearing was concentrated in Central Kalimantan province. Over half (53.4% +/-3.3) of Kalimantan's deforestation from fire occurred in Central Kalimantan, despite the province containing just 31.9% (+/-1) of the island's primary forest area in 1990.

Central Kalimantan has large areas of peat forests. These wetland ecosystems contain huge amounts of below-ground biomass, accumulated over millennia in saturated soils that slow the decomposition of leaf litter and other organic matter[12]. When these ecosystems are drained, that organic matter dries and can act as a tinder box, causing smoldering fires that can be extremely difficult to extinguish and release large amounts of carbon into the atmosphere[13,14].

Central Kalimantan is also the location of the Mega Rice Project, a massive government project carried out at the tail end of the Suharto regime that aimed to replace Kalimantan peatland forests with one million hectares of irrigated rice. The project, which ran from 1996-1998, did not succeed in its vision to turn Central Kalimantan into a rice cultivation hub. It did, however, result in the construction of thousands of kilometers of drainage canals over several years, creating perfect conditions for the spread of both intentional and unintentional fires during the 1997 and 1998 droughts[89]. In total, Indonesia lost 5.6 (+/-0.3) Mha of primary forest during the 1997/98 El Niño event – one fifth (19.7% +/-1) of the primary forest area lost over the 30 years examined in this study. Of the 5.6 (+/-0.3) Mha lost in 1997 and 1998, 22% (+/-2.4) was in Central Kalimantan, a province that contained just 12 (+/-0.4) Mha of primary forest in 1990.

2.4 Discussion

These findings provide several important pieces of information about deforestation trends in Indonesia broadly, and about the 2017-2020 drop in deforestation rates. First, fire is a significant driver of deforestation in Indonesia, and a single drought event, such as the 1997/98 El Niño, can have a huge impact on forests. Given that climate change may cause El Niño events to become more frequent and severe, this means that even under the best policy scenarios, forests will remain somewhat at risk. However, although severe El Niño events corresponded with spikes in clearing by fire in multiple regions throughout the country, the impact was not consistent across different geographies. Kalimantan experienced the highest proportion of forest fire clearing relative to total deforestation and saw the highest increase in clearing in 1997/98 compared to previous years. Much of Kalimantan's forest fire clearing was located in or near Central Kalimantan province, a region with extensive peatlands and the location of the failed Mega Rice Project. This likely means that poor policy decisions, specifically the draining and intentional burning of peatlands, combined with drought conditions to create a perfect storm for the large-scale destruction of primary forests. The Mega Rice Project has long been viewed as a policy failure, one which continues to contribute to pollution from fires as these areas re-burn year after year. The consequences of the Mega Rice Project have not, however, steered Indonesia away from planning large-scale agricultural projects, including in wetland areas[90]. These projects should be carefully examined, and detailed environmental impact assessments carried out to ensure they will not leave peatland areas vulnerable to burning.

Extreme drought events will likely always leave Indonesian forests at risk, and the 2015/16 El Niño also led to an increase in fire clearing compared to previous years. However, it did not cause the level of devastation that the country experienced in 1997/98. The 2015 fires also brought peatland management to the forefront of the public's attention, and in 2016 the Indonesian government created the *Badan*

Restorasi Gambut (Peatland Restoration Agency, or BRG) and tightened restrictions on development within peat areas beyond those already in place from the 2011 moratorium[91]. Based on historic trends, policies to protect and restore peatlands could have a particularly significant impact on future deforestation linked to drought.

I also found that both clearing from fires and active forest clearing dropped after 2016. The pattern of slowing deforestation was repeated on islands with both high and low levels of remaining primary forest, although Kalimantan did experience a small uptick in deforestation in 2020 compared to 2019. Annual forest degradation also dropped during this period. These declines began several years after Indonesia adopted its 2011 forest moratorium as part of a US$1 billion partnership with Norway to reduce carbon emissions from forest loss and degradation. While this is not the only policy that may have impacted forest loss rates in the last few years of the study, it is arguably the most wide-reaching. Under the moratorium, which was initially designed to last three years, but was eventually made permanent, no new concessions could be issued inside areas classified as either intact primary forest or peatlands. Existing concessions, including those that contained peatlands or intact forests, could continue to operate as usual, and new concession could be issued in old-growth forests that had already been degraded[92,93]. These loopholes were criticized by some environmental activists, and there was no immediate drop in primary forest loss after the policy was implemented. However, the moratorium may have contributed to the sharp declines observed after 2016, and the exemptions for existing concessions and degraded primary forests may have made a lagged impact more likely. Several other important policies were also adopted that coincided more closely with the decline in forest loss, including expanded peatland protections implemented in late 2016 and a temporary moratorium on new palm oil concessions from 2018-2021[94–96].

This study's findings alone do not prove that forest protection policies are working; there may still be other external factors, such as global palm oil prices, influencing deforestation rates in Indonesia. However, the drop in active clearing is a hopeful sign for the future of Indonesian forests.

2.5 Methods

A probability sample of remotely sensed reference data was used to estimate the area of primary intact and primary degraded forest in 1990 and the annual rates of intact forest degradation and primary forest loss. This method is consistent with good practice recommendations for estimating land cover areas,[80] and a similar method has been employed in prior studies quantifying forest loss and attributing forest disturbance drivers in the Brazilian Amazon and Congo Basin[35,97]. For this study, a simple random sample was selected from each of seven regional strata – Sumatra, Kalimantan, Java, Sulawesi, Nusa Tenggara, Maluku, and Papua. A total of 10,000 sample units, roughly 30x30 meters in size and corresponding to Landsat pixels, were selected, with the sample size per region proportional to the region's area. Strata were defined by region, rather than using wall-to-wall forest change products, because, at the time the study was designed, no maps of annual forest disturbance had been published covering the full spatial and temporal scope of the study (nation-wide, 1990-2016 period, with data later added to include 2017-2020, 30m resolution). The sampled pixel locations for each stratum are provided in Figure. 2-S10.

I interpreted satellite-derived reference data for each sampled pixel, together with analysts from Indonesia's Ministry of Environment and Forestry (KLHK), Indonesia's National Institute of Aeronautics and Space (LAPAN), and World Resources Institute (WRI) Indonesia. We recorded the 1990 land cover class (intact primary forest, degraded primary forest, or non-forest) and any subsequent forest degradation events. For sampled pixels that experienced forest loss during the study period, the year and type of forest conversion was also recorded. Sampled pixels were initially interpreted for the 1990-2016 period at a workshop in 2017 by participants from KLHK, LAPAN, and BGR, together with non-governmental researchers from WRI Indonesia and the Bogor Agricultural University (IPB). I joined these workshops as a facilitator and trainer on behalf of the University of Maryland's Global Land Analysis and Discovery (GLAD) group. These interpretations were later reviewed by a smaller quality control team that included two interpreters each from LAPAN (Inggit Sari and Tatik Kartika), KLHK (Anna Tosiani and Muhammad Yazid), and WRI-Indonesia (Rizky Firmansyah and Zuraidah Said), and myself. This second review was conducted in order to ensure that land cover definitions were used consistently. The interpreters from this smaller team are coauthors on this study, as well as the studies discussed in Chapters 3 and 4. Each member of the small interpretation team had participated in the original workshop either as an interpreter or, in my case, as a trainer/facilitator. The review by the quality control team took place during a second series of workshops, with all team members working in a room together so that difficult-to-interpret samples could be discussed. During this review, quality control team analysts reviewed each sampled pixel's original interpretation, comparing the results to the satellite-derived reference data and editing any aspects they found to be inconsistent with the reference data or the land cover definitions used in this study. Sampled pixels were assigned so that each interpreter reviewed a different subset of pixels than they saw in the original workshop, meaning each pixel was reviewed by two interpreters.

Following this update, I compared the interpretation results of all pixels to existing wall-to-wall map products: a forest/non-forest 1990 land cover map produced by KLHK and the Turubanova et al. 2001 primary forest map[1]. For pixels whose 1990 or 2001 land cover classes were inconsistent with classifications in the corresponding year's map product, the quality control team conducted an additional review. During this screening, quality control team analysts reviewed interpretation results, reference data, and the 1990 and 2001 map classifications, revising interpretations as needed. The resulting dataset was again compared to existing map products, including KLHK forest/non-forest maps (1990, 2000, 2012); Margono et al. and Turubanova et al. primary forest maps (2000 and 2012)[38,98]; tree cover maps created by LAPAN as part of the INCAS project (2000 and 2012)[99]; and Hansen et al. percent tree canopy cover (2000) and tree cover loss (2001-2016) products[21]. I conducted a third review of all pixels whose interpretations were inconsistent with the above map products, pixels marked as low confidence in one or more confidence categories, and all pixels experiencing primary forest clearing during the study period.

I defined map product inconsistencies as follows:

- Pixels classified as forest (an aggregation of the *hutan primer* and *hutan sekunder* land cover classes) in one or more KLHK product, but classified as non-primary forest in this study in the corresponding year; or pixels classified as non-forest by KLHK but classified as primary forest in this study;

- Pixels classified as primary forest by Margono et al[46]. in 2000 or Turubanova et al[1]. in 2001, but classified as non-forest in the corresponding year in this study; or pixels classified as non-primary forest in the above-mentioned products but classified as primary forest in this study;

- Pixels classified as non-forest in the INCAS[47] 2000 or 2012 products, but classified as primary forest in the corresponding year in this study (the INCAS forest definition included non-primary forest tree-covered landscapes, so pixels classified as forest by INCAS but non-primary forest in this study were not deemed inconsistent);

- Pixels identified as having <80% tree canopy cover in the Hansen et al[48]. global tree canopy cover product (2000), but classified as primary forest in this study in that year;

- Pixels for which the year of first clearing in this study occurred after 2000, if the year of clearing was more than three years before or after tree cover loss was identified in the Hansen et al[48]. tree cover loss product or if no loss event was identified in the Hansen et al. product;

- Primary forest pixels for which no loss events were identified in this study, but which were identified as loss in the UMD global tree cover loss product.

During this third review, I did not revise existing interpretations, but assigned pixels to one of three categories: agree with all aspects of the interpretation, unsure about one or more aspect of the interpretation, or recommend the interpretation be changed. Groups of two or more quality control team analysts (excluding myself) then reviewed all pixels assigned to the “unsure” or “recommend change” categories. Revisions were made based on the consensus reached by these analysts; groups were not required to revise pixels assigned to either “unsure” or “recommend change” categories.

The reference data used for this first series of interpretations included annual cloud-free Landsat composites from 1985-2016, high resolution SPOT 6/7 composites, and very high resolution Google Earth imagery where available. The University of Maryland Global Land Analysis and Discovery (GLAD) group provided Landsat composites for the years 1985-2014, created using the processing methods described in Potapov et al[100]. Each composite covered a 41x41-pixel area with the sampled pixel in the center. Indonesia’s National Institute of Aeronautics and Space (LAPAN) provided Landsat composites for the years 2015-2016, as well as a high-resolution true color composite for each pixel and the surrounding area using SPOT 6/7 data collected between 2013 and 2016. Additional reference data included graphs of minimum and maximum NDVI values based on cloud-screened Landsat observations and links to open KML files of the footprint of each sampled pixel in Google Earth. Links to Indonesia’s Ministry of Environment and Forestry (KLHK) land cover classification codes for each pixel in their 1990, 1996, 2000, 2003, 2006, 2009, and 2011-2014 land cover map products were also provided.

After analyzing these initial results, I found that a large area of primary forest in Indonesia was not replaced with an observable land use after clearing. In these cases, interpreters had instead noted the clearing mechanism – either clearing by forest fire, or actively cleared land not replaced with an observable land use. However, this proved challenging with the initial reference data, particularly in the 1990s, a period for which there is less available Landsat data. Data gaps in the annual cloud-free composites meant that for some study years, there was no composite image. Forest fire clearing was identified in part based on the presence or absence of an ash signature following clearing. When forest clearing occurred during data gap years, this signature would not be visible. Additionally, since fire is often used to clear debris after tree felling, the presence or absence of an ash signature in an annual composite was not always sufficient to determine whether forest fire was the driver.

To address this issue, I updated the reference data to include annual composite images from 2017-2020, as well as bimonthly and 16-day Landsat composites and a 16-day graph of NDVI, SWIR-1, and SWIR-2 band values for each sampled pixel for the years 1989-2020, derived from the Potapov et al.'s Analysis Ready Data[101]. Annual, bimonthly, and 16-day composites were created using the red, NIR, and SWIR-1 bands. To improve my ability to detect fires and burn scars specifically, I also created NIR-SWIR-1-SWIR-2 bimonthly composites for each pixel and added a graph showing the dates and confidence levels of MODIS hotspots detected within a 0.5-km and 2.5-km radius around the pixel, for the years for which MODIS hotspot data was available. Lastly, I added an annual composite created using the minimum normalized burn ratio (NBR – an index similar to NDVI but calculated using the NIR and SWIR) value, which covered a 5km by 5km area, allowing us to identify the shape of clearings larger than the 41x41 pixel annual composites. Clearing shape is useful for fire detection, and burn scars were often larger than the areas displayed in the annual composites. SPOT 6/7 composites for the years 2017, 2018, 2019, and 2020 were also provided by LAPAN.

I conducted a final review of all 10,000 sampled pixels to confirm the 1990 land cover, and, for all pixels that were primary forest in 1990, reviewed the bimonthly composite data for each year of the study (6 images per year from 1989-2020 for each of the two bimonthly composite types). I updated the interpretation results to include every degradation and land cover change event visible in the bimonthly composites, and recorded either the post-clearing land use or, in cases where no land use could be detected, the clearing mechanism, for each land cover change event. If the clearing mechanism was not clear from the bimonthly images alone, I referred to the 16-day composites.

Examples of the reference data and the land cover classes I used in this study are provided in Figures 2-S1 to 2-S8.

2.6 Definitions and interpretation methods for land cover and change event types

2.6.1 Primary forest

Definition: Natural, old-growth woody vegetation at least 5m in height and with at least 30% tree canopy cover at a 30-m resolution, including both intact and degraded forest types.

Identification methods: Spectral signatures indicating woody vegetation meeting the above height and canopy cover thresholds and consistent with natural (not cultivated) tree species; the absence of landscape cues indicating cultivated forests (such as the block patterns common to large-scale oil palm plantations) or forest regrowth (such as forest patches of varying canopy heights, indicating rotational agricultural systems).

Limitations: Monoculture rubber plantations can typically be identified in Landsat imagery by their spectral signature, however, some rubber plantations in Indonesia date back to the Dutch colonial period and have since been abandoned. Compared to well-maintained plantations, these older rubber groves have spectral signatures and canopy textures that more closely resemble natural forests and could therefore be mistaken for primary forest. Likewise, while older fallows within shifting cultivation areas can typically be distinguished from primary forests based on landscape-scale patterns of regrowth, larger areas of historical clearing that have been allowed to regrow for several decades could be indistinguishable in Landsat imagery from old-growth forests and could be mistakenly included in the primary forest category. In areas with lower canopy densities, such as seasonal dry forests, seasonal wetlands, or high elevation forests, it can be difficult to determine whether landscapes meet canopy cover or vegetation height thresholds.

2.6.2 Intact primary forest

Definition: Primary forests never disturbed by human activity or disturbed in the past but indistinguishable in the earliest available Landsat composite from undisturbed forest. Includes all samples meeting the primary forest definition and with no observable evidence of human disturbance inside the pixel or within a 120-m radius.

Identification methods: Spectral signatures consistent with this study's primary forest definition; landscape-specific cues indicating that the pixel had not been disturbed by human activity, for instance very dense (>90%) canopy cover in humid tropical forest areas, and no visible evidence of roads, drainage canals, or other forest clearing within the 120-m buffer; forests with less dense canopies, but otherwise appearing to be part of an intact landscape, such as seasonal dry forests, seasonal wetlands, and high-elevation forests, would be included in this category as long as vegetation within the pixel met 5m vegetation height and 30% canopy cover thresholds.

Limitations: Due to the relatively rapid vegetation regrowth found in humid tropical forest areas, the intact forest category could include areas that had experienced selective logging in the 1960's or 1970's, but which had been allowed to regrow to the point that evidence of logging was no longer visible in Landsat imagery at the start of the study. Certain types of low-density agro-forestry could also potentially be included in this category, such as areas where cultivated durian or rubber trees had been planted amongst natural vegetation before the start of the study period and located more than 120m away from roads, settlements, or other evidence of human activity. Degradation occurring below the canopy would also not be visible in Landsat reference data and would therefore not be captured in this study.

2.6.3 Degraded primary forest

Definition: Primary forests with tree canopies composed of at least 50% natural old-growth woody vegetation, but with evidence of human activity either inside the pixel or within a 120m buffer. This includes forests that had been selectively logged, natural forests located near shifting cultivation areas, human settlements, or mining activities, and agroforestry areas containing at least 50% natural canopy cover.

Identification methods: Spectral signatures consistent with the primary forest criteria together with evidence of human disturbance, for instance the presence of clearing or forest regrowth within a 120-m radius around the pixel such as logging roads, human settlements, or agricultural clearings; pixels with spectral signatures that differed from nearby undisturbed forests, for instance due to fire disturbance or hydrological changes from peatland draining, were also included in this category.

Limitations: Forests in Indonesia are often subject to multiple degradation events, for example repeated logging or repeated degradation by fire. In these cases, determining when the forest lost more than 50% of its natural canopy could be difficult for analysts. Mixed agroforestry areas containing greater than 50% cultivated tree species could also have been included in this category, if cultivated trees were mature and not spectrally distinct from natural vegetation.

2.6.4 Non primary forest

Definition: Pixels containing less than 30% natural tree canopy cover, defined as woody vegetation meeting a 5m threshold, or pixels for which greater than 50% of the natural vegetation showed evidence of having been cleared in recent history. This includes monoculture rubber, oil palm, or timber plantations planted before 1990, as well as older shifting cultivation fallows that had reached heights of greater than 5m. Mixed agroforestry areas containing greater than 50% cultivated tree species were also included in this category, to the extent that cultivated species could be distinguished from natural forest. Secondary forests, such as mangrove forests replanted after clearing for fishponds or fire-affected areas that had been allowed to regrow or were otherwise rehabilitated were also included in the non-primary forest category.

Identification methods: Spectral signatures consistent with bare ground, seasonal crops, grasslands, shrubs, or other vegetation not meeting canopy cover and height thresholds; spectral signatures consistent with monoculture tree crops; landscape patterns consistent with monoculture tree crops or intensive (greater than 50% cultivated species) agroforestry; landscape patterns and spectral signatures indicating forest regrowth; clearing events evident in pre-1990 reference imagery (1985-1989).

Limitations: Certain types of forest regrowth, for instance mangrove forest regrowth or regrowth in humid tropical forest areas, can be indistinguishable from old-growth forest after a relatively short time period. Pixels located in these areas may have been classified as primary forests if clearing events are not visible in historical imagery (for instance if clearing took place before 1985) and regrowth patterns did not indicate rotational agriculture. Cultivated tree species were also sometimes difficult to distinguish from natural forests, particularly in agroforestry areas or in older rubber plantations.

2.6.5 Forest degradation

Definition and identification methods: Canopy disturbances at a 30-m resolution or within a 120-m radius, but resulting in less than 50% natural canopy loss within the pixel of interest. Includes degradation due to logging, nearby clearing, or other human activities, or from forest fires. Identified based on spectral signatures indicating canopy removal within a 120-m radius (for example, bare ground signatures associated with logging roads), or changes in the spectral signatures of the sampled pixel itself indicating damage to the canopy or selective tree removal.

2.6.6 Forest fire clearing

Definition and identification methods: Fire event resulting in ≥ 50% canopy removal, identified by a spectral signature consistent with burning or ash and/or a clearing pattern consistent with fire (for instance clearing without sharp geometric boundaries), and no immediate conversion to a productive land use. Land burned after being manually cleared (slashed and burned) was not classified as fire clearing; these areas could typically be distinguished from fire clearing by the clearing and regrowth patterns and were less likely to have spectral signatures consistent with ash in annual composites. A bare ground signature followed by an ash signature would often be visible in these cases in the bimonthly or 16-day composites, depending on the data availability at the time of clearing and the amount of time debris was left to dry. These cleared-then-burned areas were classified based on the post-clearing land use, or, if no land use was evident, as actively cleared unplanted land.

2.6.7 Active clearing

Definition and identification methods: Forests that were cleared and replaced by an observable land use within 12 months of clearing, regardless of clearing mechanism, or land left unplanted for one or more years following deforestation using manual, mechanical, or chemical methods; identified by a spectral signature consistent with vegetation removal and not indicating fire clearing (e.g. no ash signature or a delayed ash signature, a sharp boundary between the cleared area and remaining forest, and the absence of remnant trees).

2.6 Supplementary materials

2.6.1 Supplementary figures

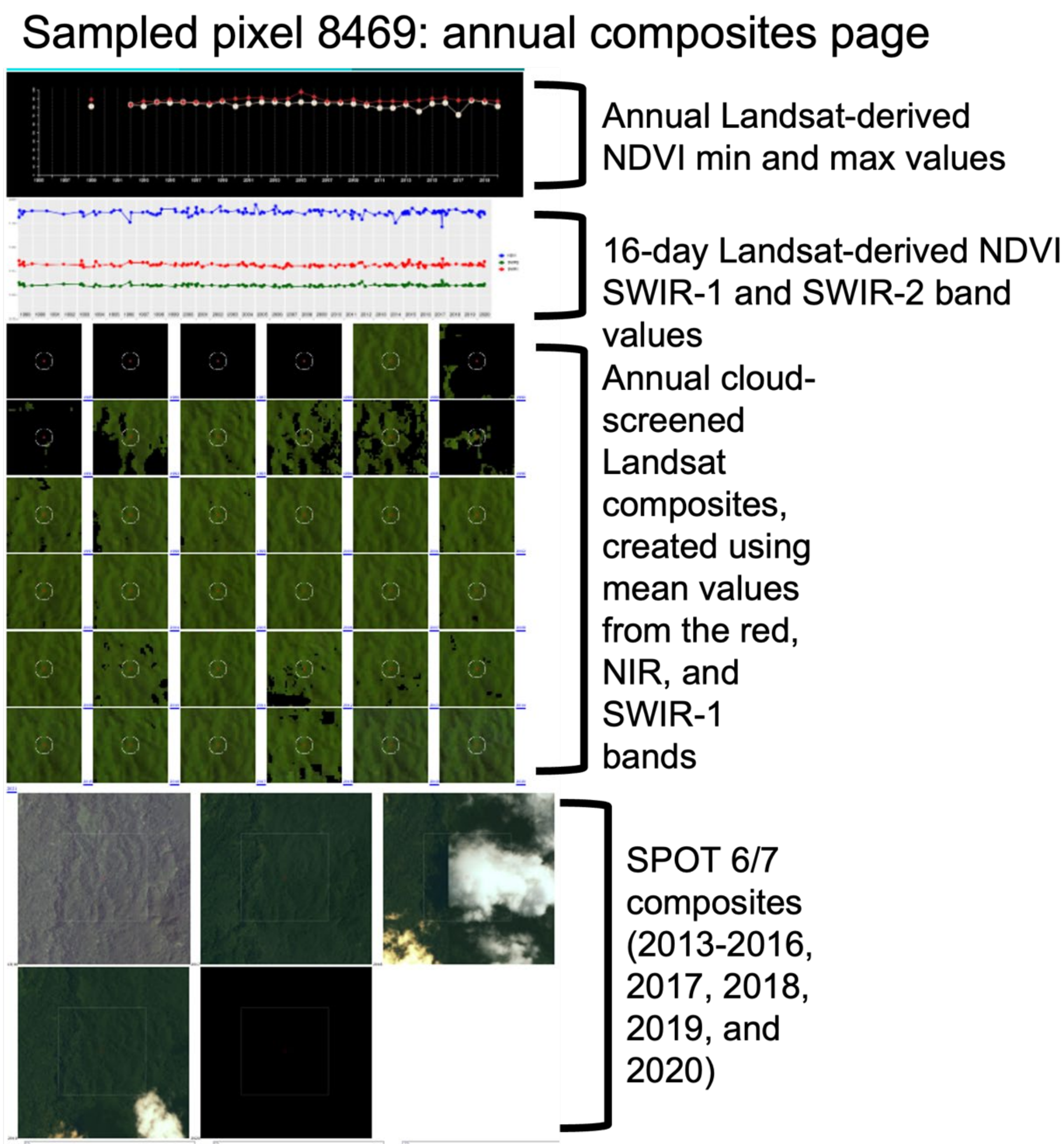


Figure 2-S1: Annual composites and other reference data for an intact primary forest pixel. *This sampled pixel located in Sumatra did not experience any degradation or clearing events during the study period.*

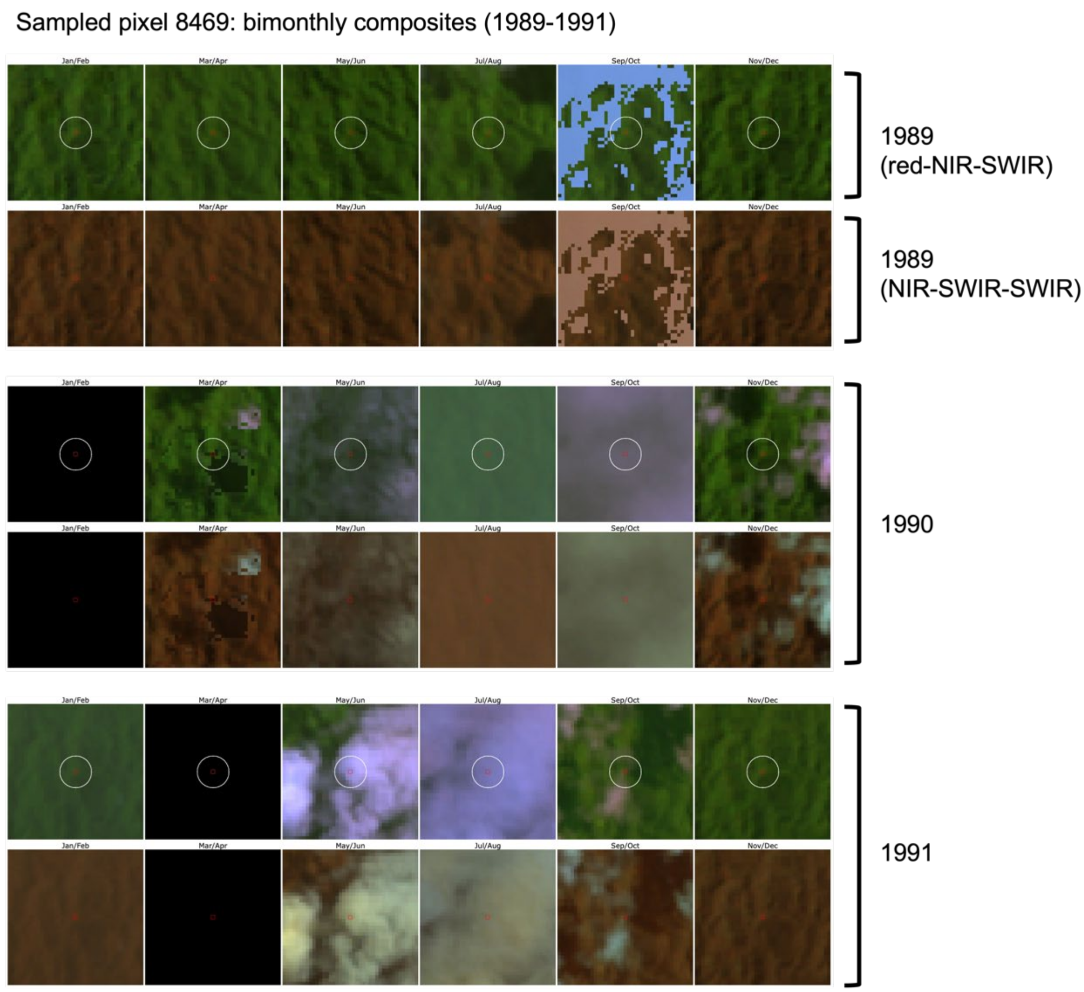


Figure 2-S2: Bimonthly composite reference data for an intact primary forest pixel. *Bimonthly composites for each year from 1989 to 2020 were reviewed for all sampled pixels classified as primary forest in 1990. For this pixel, poor data quality in 1990 meant that in the annual cloud-screened composites, no image was available for that year (Figure 2-S1), so bimonthly images were used to confirm the land cover in 1990.*

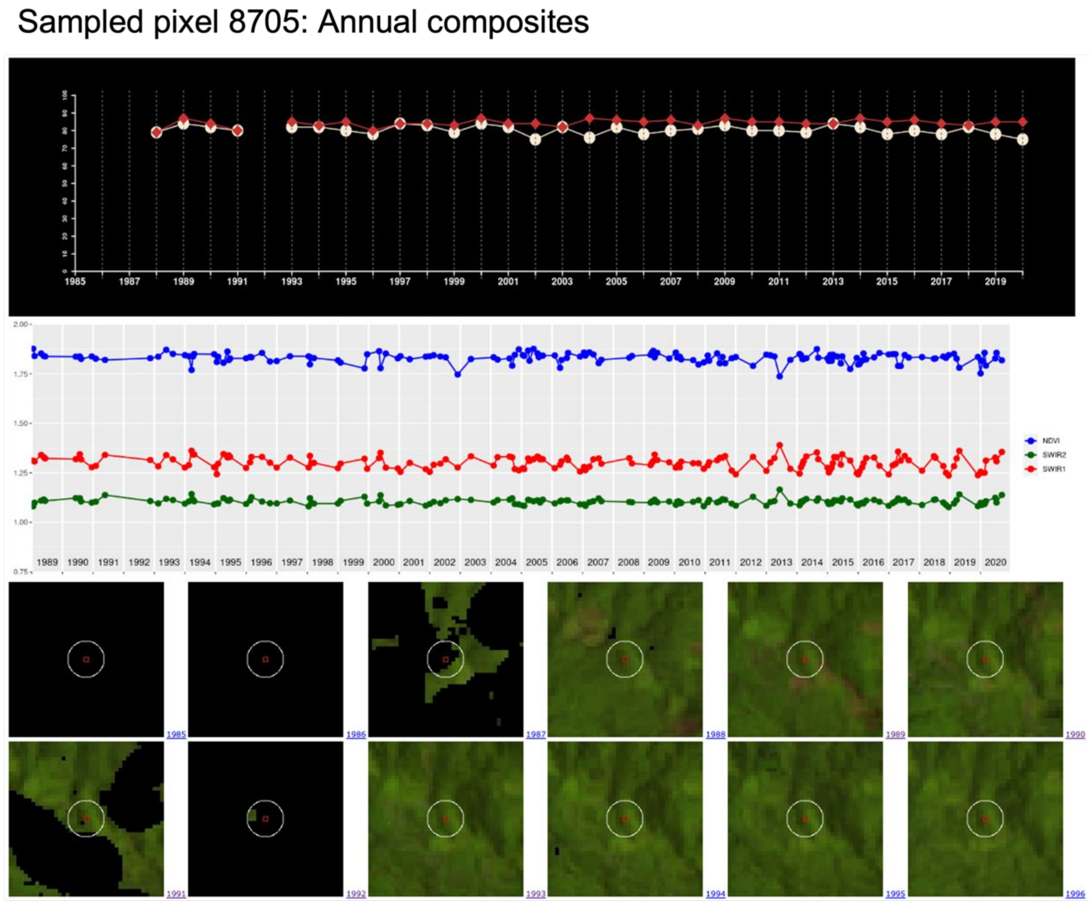


Figure 2-S3: Reference data for a sampled pixel classified as degraded primary forest in 1990. *Forest has been cleared within a 120-m radius around the pixel (indicated by the white circle), but the pixel itself retains at least 50% of its natural canopy.*

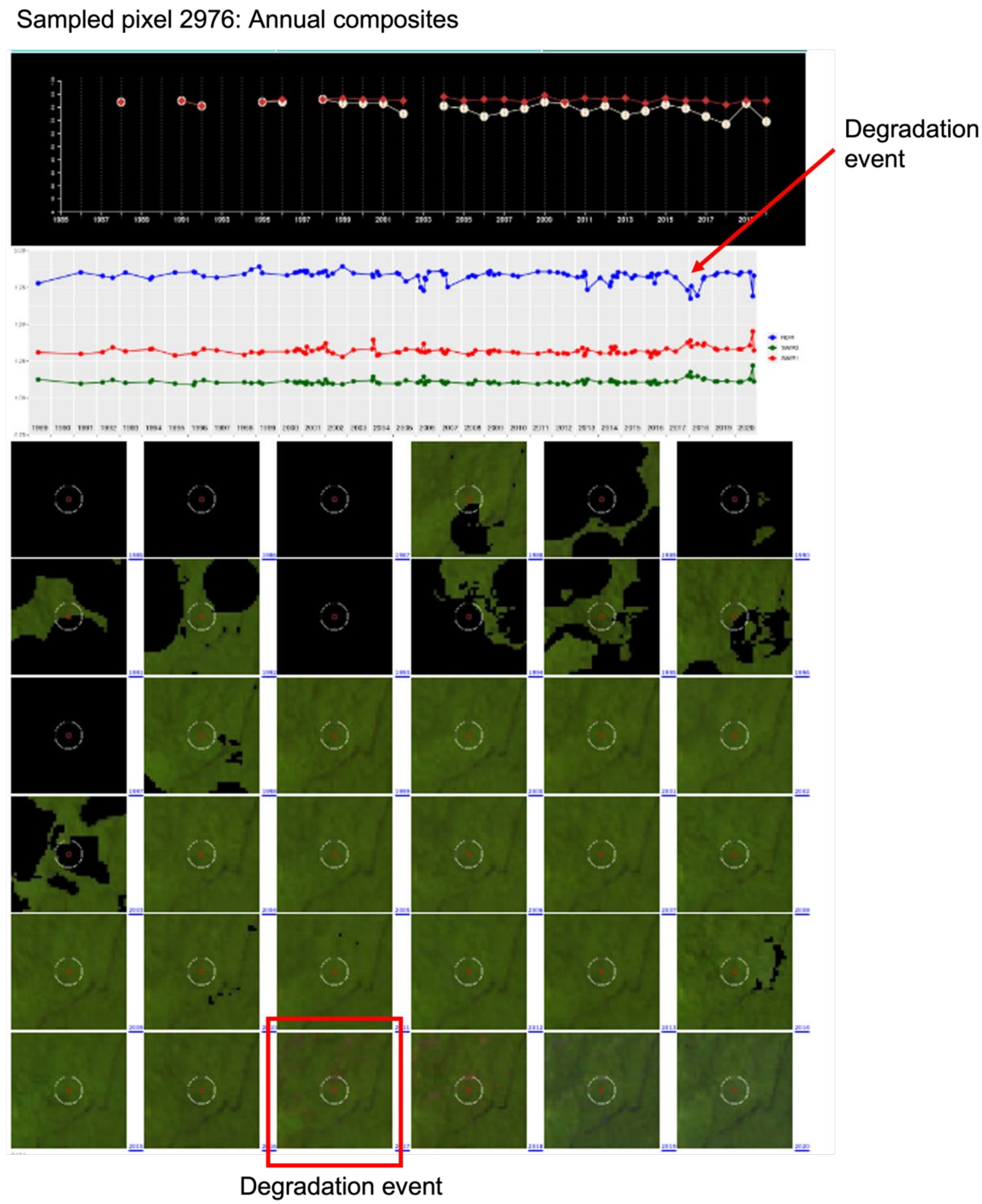


Figure 2-S4: Annual composite reference data for an intact primary forest pixel that was degraded in 2017. *The selective logging event can be seen in the 2017 annual composite and the 16-day NDVI, SWIR1, and SWIR2 plot.*

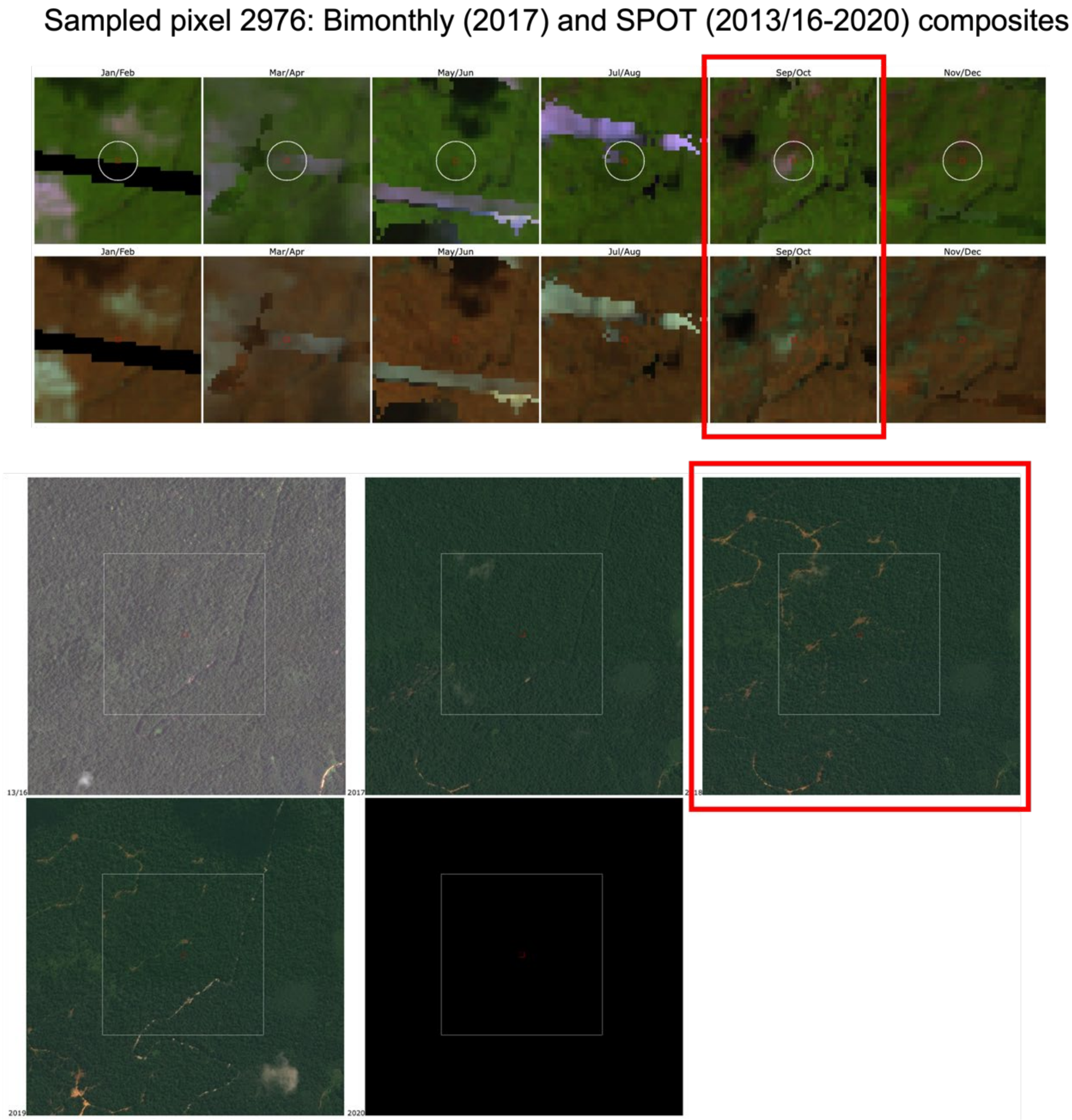


Figure 2-S5: Bimonthly and SPOT reference data for an intact primary forest sampled pixel degraded in 2017. *The degradation event was first visible in the Sept/Oct bimonthly image. Logging roads can be seen in the SPOT composite.*

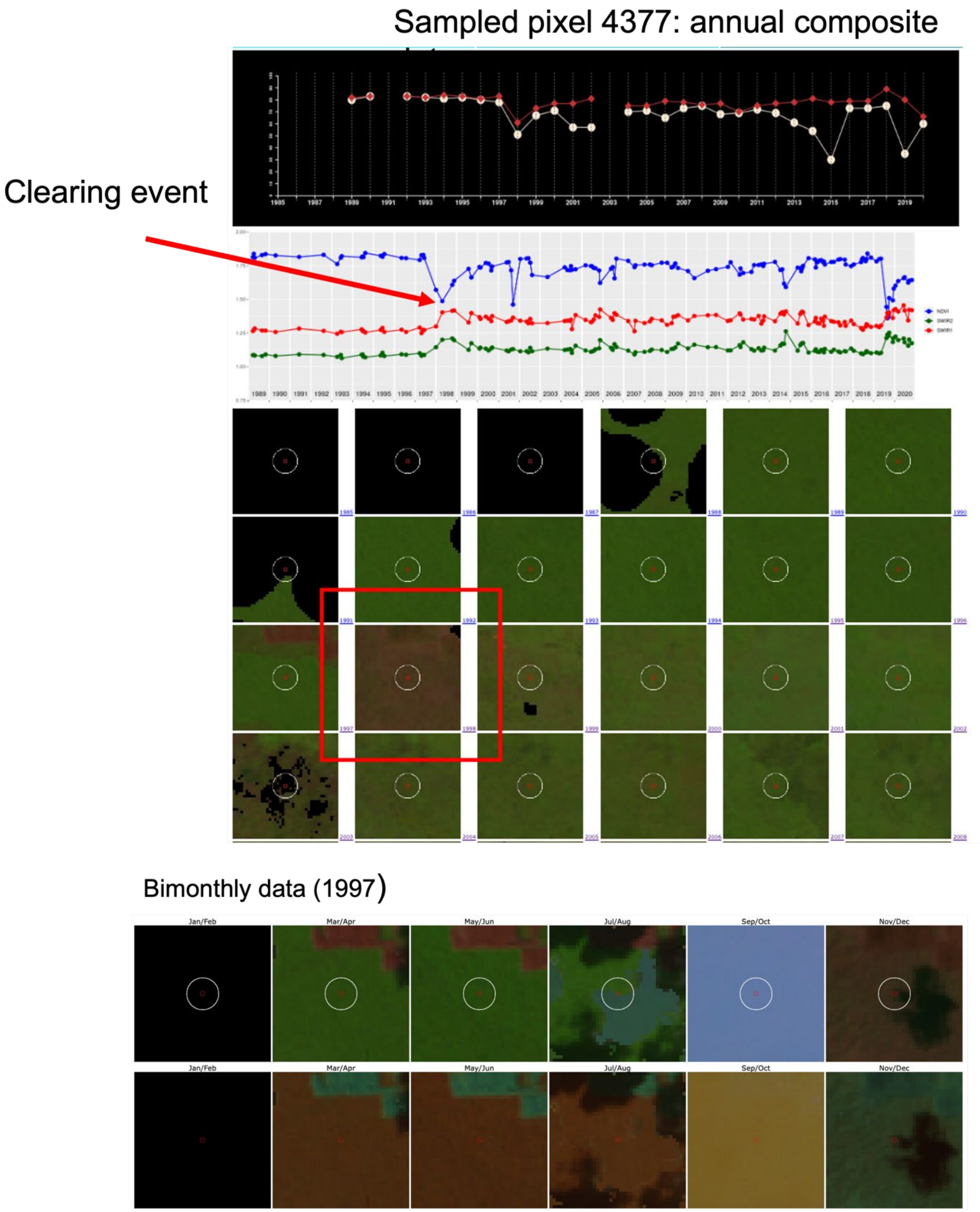


__Figure 2-S6: Reference data for a primary forest pixel experiencing a forest fire clearing event.__ The clearing event is visible in both the 1998 annual composite and the 16-day NDVI, SWIR-1 and SWIR-2 plots. Using the bimonthly composites, the clearing date can be more precisely identified - between Jul/Aug and Nov/Dec, 1997.

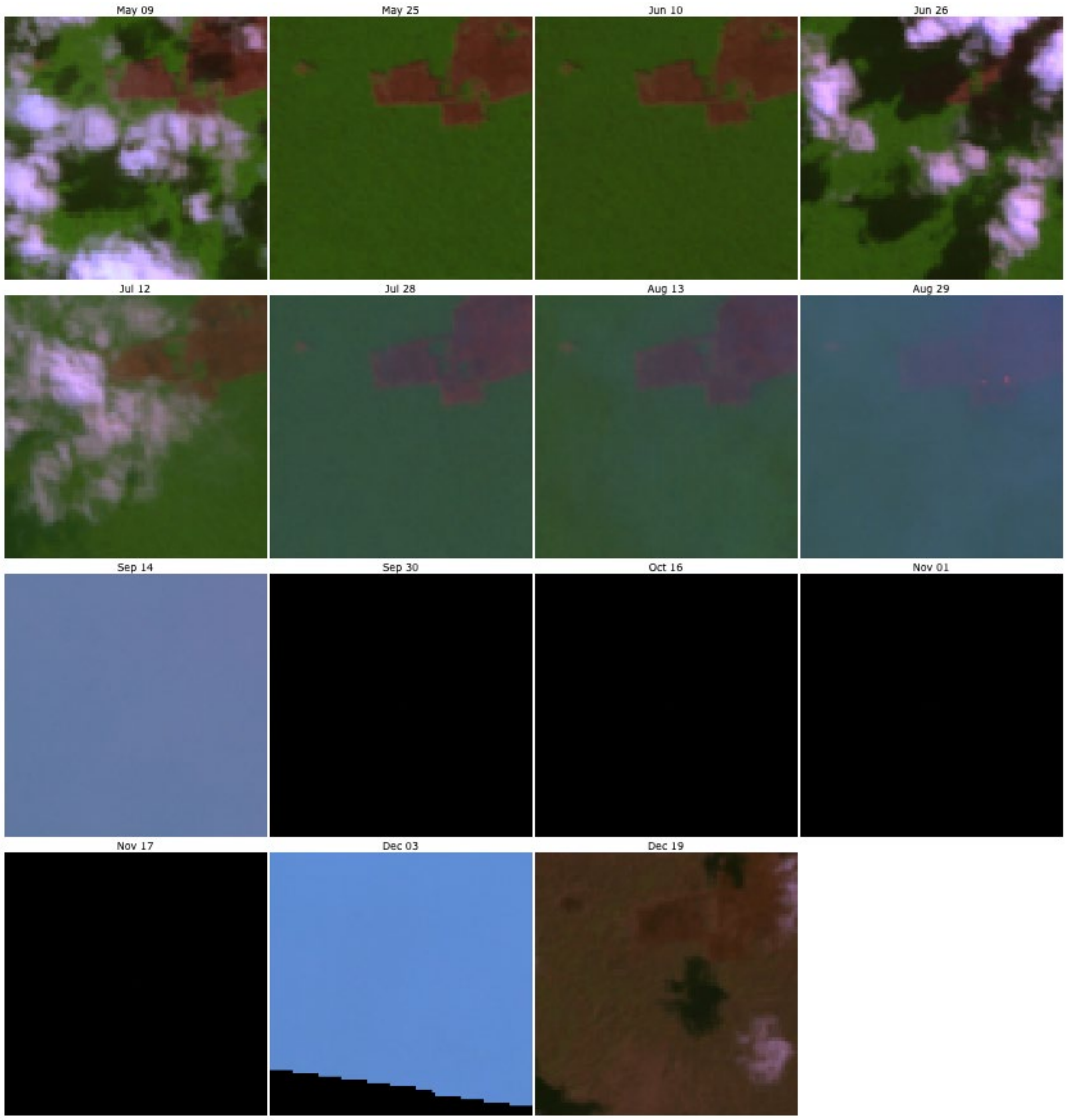


Figure 2-S7: 16-day composites for a fire cleared pixel. *In these 16-day composites from May-December, 1997, for sampled pixel 4377, a nearby cleared area is visible. This intentionally cleared area was burned after it was cleared, and the active fire is visible in the August 29th image. The fire later escapes and burns a larger area, deforesting the pixel. This pixel is located in Central Kalimantan, near the capital city of Palangkaraya and two Mega Rice project blocks.*

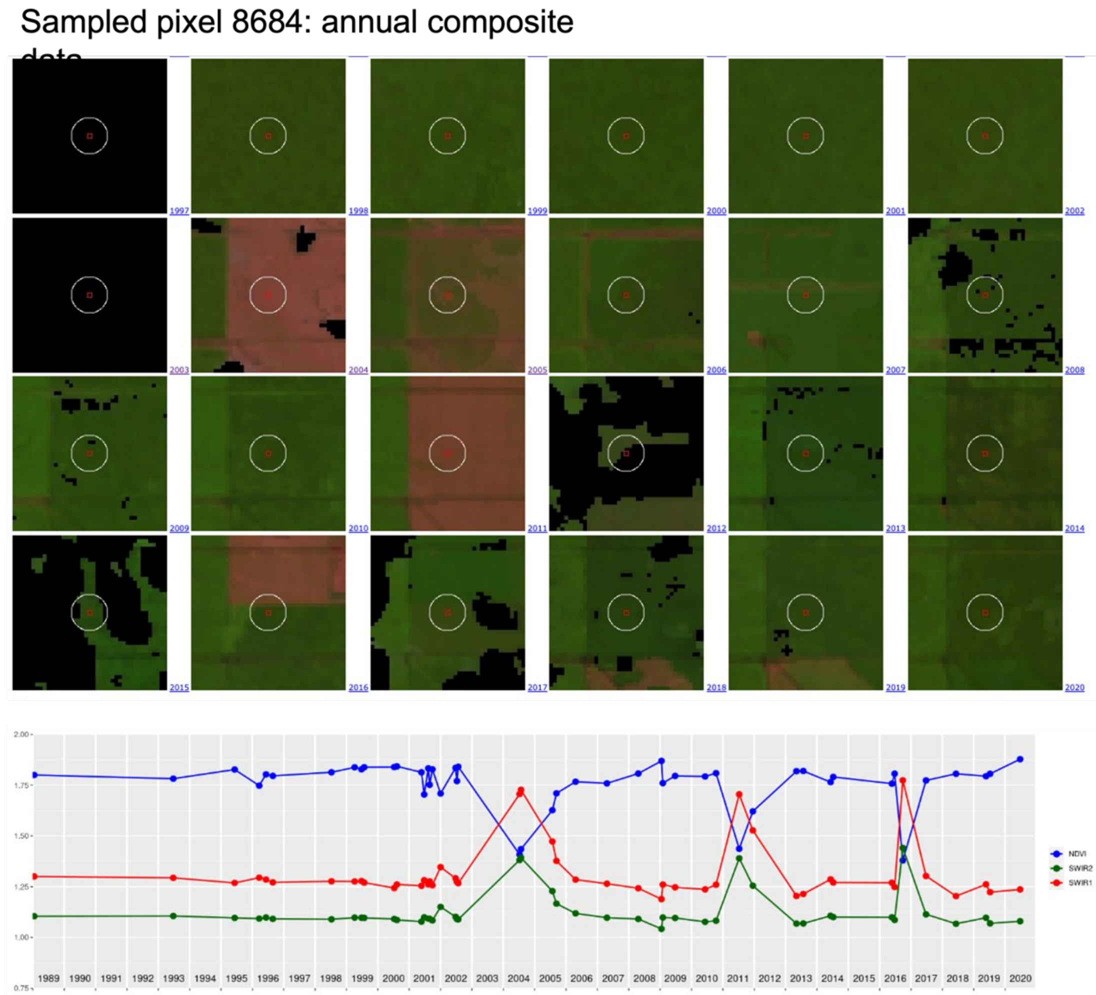


Figure 2-S8: Annual composite reference data for an actively cleared sampled pixel*. This pixel was actively cleared and converted to a tree plantation in 2004. The clearing is geometric, there is no evidence of an ash signature, and the regrowth pattern, visible in both the annual composites and NDVI-SWIR1-SWIR2 plot, is consistent with fast-growing acacia.*

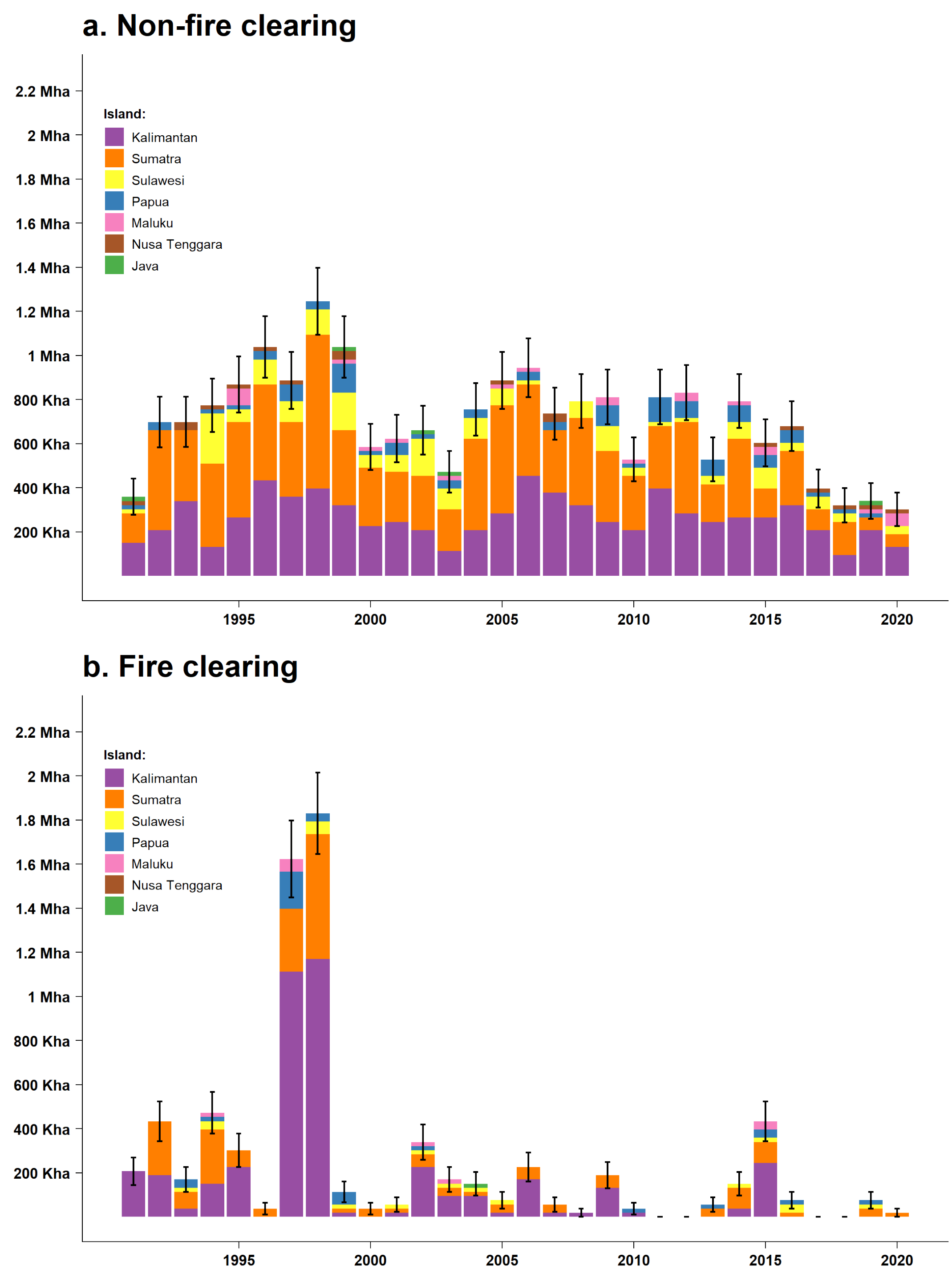


Figure 2-S9: Annual active and forest fire clearing, disaggregated by island. *Kalimantan experienced a higher proportion of forest fire clearing compared to other regions.*

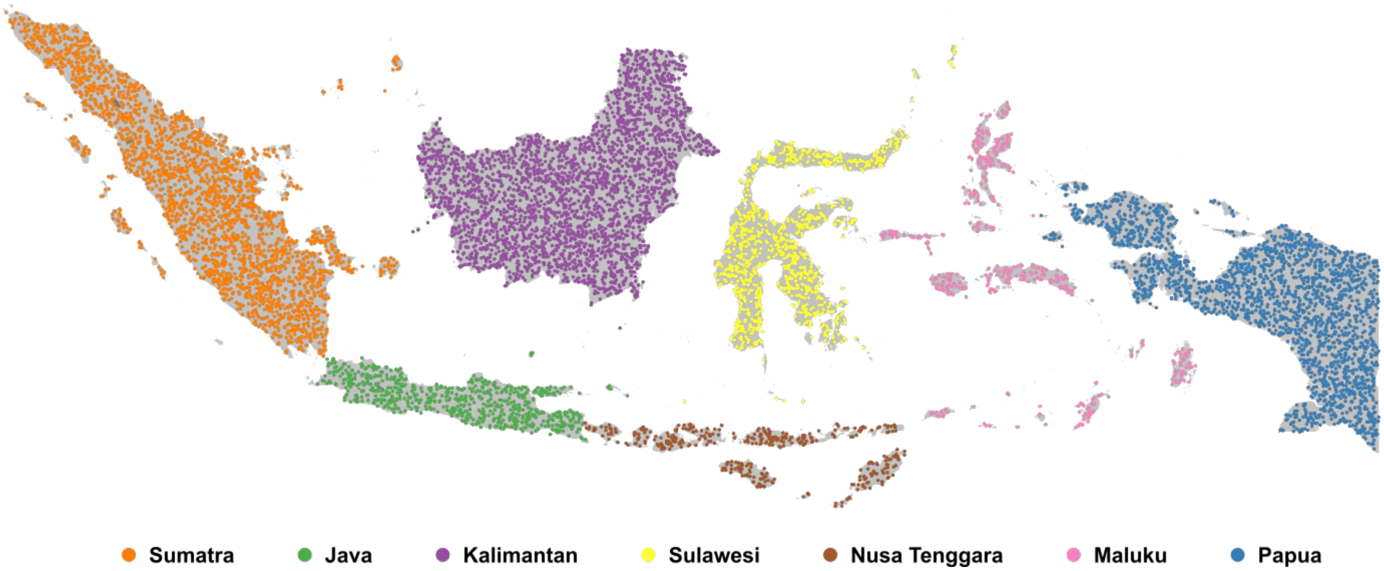


Figure 2-S10: Sampled pixel locations by strata. *Sampled pixels were selected from seven regional strata.*

2.6.2 Supplementary tables

Table 2-S1: Annual primary forest loss

Year	Total loss	Fire clearing	Non-fire clearing
1991	0.57 (+/-0.1) Mha	0.21 (+/-0.06) Mha	0.36 (+/-0.08) Mha
1992	1.13 (+/-0.15) Mha	0.43 (+/-0.09) Mha	0.7 (+/-0.11) Mha
1993	0.87 (+/-0.13) Mha	0.17 (+/-0.06) Mha	0.7 (+/-0.11) Mha
1994	1.25 (+/-0.15) Mha	0.47 (+/-0.09) Mha	0.77 (+/-0.12) Mha
1995	1.17 (+/-0.15) Mha	0.3 (+/-0.08) Mha	0.87 (+/-0.13) Mha
1996	1.08 (+/-0.14) Mha	0.04 (+/-0.03) Mha	1.04 (+/-0.14) Mha
1997	2.51 (+/-0.22) Mha	1.62 (+/-0.17) Mha	0.89 (+/-0.13) Mha
1998	3.08 (+/-0.24) Mha	1.83 (+/-0.18) Mha	1.25 (+/-0.15) Mha
1999	1.15 (+/-0.15) Mha	0.11 (+/-0.05) Mha	1.04 (+/-0.14) Mha
2000	0.62 (+/-0.11) Mha	0.04 (+/-0.03) Mha	0.59 (+/-0.1) Mha
1991-2000	**13.42 (+/-0.48) Mha**	**5.23 (+/-0.31) Mha**	**8.19 (+/-0.38) Mha**
2001	0.68 (+/-0.11) Mha	0.06 (+/-0.03) Mha	0.62 (+/-0.11) Mha
2002	1 (+/-0.14) Mha	0.34 (+/-0.08) Mha	0.66 (+/-0.11) Mha
2003	0.64 (+/-0.11) Mha	0.17 (+/-0.06) Mha	0.47 (+/-0.09) Mha
2004	0.91 (+/-0.13) Mha	0.15 (+/-0.05) Mha	0.75 (+/-0.12) Mha
2005	0.96 (+/-0.13) Mha	0.08 (+/-0.04) Mha	0.89 (+/-0.13) Mha
2006	1.17 (+/-0.15) Mha	0.23 (+/-0.07) Mha	0.94 (+/-0.13) Mha
2007	0.79 (+/-0.12) Mha	0.06 (+/-0.03) Mha	0.74 (+/-0.12) Mha
2008	0.81 (+/-0.12) Mha	0.02 (+/-0.02) Mha	0.79 (+/-0.12) Mha
2009	1 (+/-0.14) Mha	0.19 (+/-0.06) Mha	0.81 (+/-0.12) Mha
2010	0.57 (+/-0.1) Mha	0.04 (+/-0.03) Mha	0.53 (+/-0.1) Mha
2001-2010	**8.53 (+/-0.39) Mha**	**1.32 (+/-0.16) Mha**	**7.21 (+/-0.36) Mha**
2011	0.81 (+/-0.12) Mha	-	0.81 (+/-0.12) Mha
2012	0.83 (+/-0.12) Mha	-	0.83 (+/-0.12) Mha
2013	0.59 (+/-0.1) Mha	0.06 (+/-0.03) Mha	0.53 (+/-0.1) Mha
2014	0.94 (+/-0.13) Mha	0.15 (+/-0.05) Mha	0.79 (+/-0.12) Mha
2015	1.04 (+/-0.14) Mha	0.43 (+/-0.09) Mha	0.6 (+/-0.11) Mha
2016	0.76 (+/-0.12) Mha	0.08 (+/-0.04) Mha	0.68 (+/-0.11) Mha
2017	0.4 (+/-0.09) Mha	-	0.4 (+/-0.09) Mha
2018	0.32 (+/-0.08) Mha	-	0.32 (+/-0.08) Mha
2019	0.42 (+/-0.09) Mha	0.08 (+/-0.04) Mha	0.34 (+/-0.08) Mha
2020	0.32 (+/-0.08) Mha	0.02 (+/-0.02) Mha	0.3 (+/-0.08) Mha
2011-2020	**6.42 (+/-0.34) Mha**	**0.81 (+/-0.12) Mha**	**5.61 (+/-0.32) Mha**
1991-2020	**28.4 (+/-0.7) Mha**	**7.36 (+/-0.36) Mha**	**21.01 (+/-0.58) Mha**

Chapter 3: Land in Limbo

3.1 Abstract

Indonesia has experienced rapid primary forest loss in recent decades, although over the last several years deforestation has slowed. I examined the fates of deforested areas, immediately after clearing and over time, to quantify deforestation drivers in Indonesia. Using time-series satellite data, I tracked degradation and clearing events in intact and degraded natural forests from 1991-2020, as well as land use trajectories after forest loss. While an estimated 7.8 Mha (SE=0.4) of forest cleared during this period was planted with oil palms by 2020, an even larger area remained unused, including 4.8 (+/-0.3) Mha of land cleared by forest fires and another 4 (+/-0.3) Mha of land that was actively cleared but left idle for at least one year after forest clearing. Of the 28.4 Mha (SE=0.7) deforested, half was initially left idle and over half of these idle areas were cleared deliberately (not by escaped fires), indicating that speculation and land banking substantially contribute to forest loss. Some idle lands, particularly in areas that were cleared actively, were eventually utilized, typically for palm oil production.

3.2 Introduction

Understanding what drives deforestation can make it easier to prevent. The strategies for preventing accidental deforestation, for example from escaped or accidentally set fires, differ from the strategies needed to address deforestation carried out intentionally to convert land for agriculture or extract timber resources. Improving the capacity of law enforcement agencies or adopting stricter legal penalties for illegal forest clearing may help prevent illegal deforestation, but would not impact deforestation that was legally sanctioned. Slowing legal forest conversion, such as deforestation within government issued concessions, might require advocacy campaigns by civil society groups or pressure from foreign governments, directed either at the government issuing the concessions or the companies that produce or use deforestation-linked products. Economic development programs that provide alternative incomes through tourism or non-timber forest products may be effective at curbing deforestation being carried out by local communities to meet basic economic needs, but may not be effective at preventing deforestation carried out by non-local actors. At the international scale, initiatives such as the United Nation's Reducing Emissions from Deforestation and Forest Degradation (REDD+) program, which aims to provide payments to developing countries for reducing carbon emissions due to land use change[102], have the potential to help offset some of the economic incentives to convert forests. However, if the land uses driving forest loss provide more significant economic benefits compared to the payments being offered, these types of programs are less likely to succeed.

As we improve our understanding of these dynamics, both at the local, national, and international scale, those aiming to prevent the carbon emissions, biodiversity loss, and loss of ecosystem services associated with deforestation can develop and implement policies that target the unique circumstances of a particular area and are therefore more likely to succeed. However, given the complexities of the global economy, it is often difficult to pin down the true drivers of forest loss, which in turn makes it difficult to design and enforce effective policies to protect forests.

Within the academic literature, deforestation drivers have been classified into two primary categories: proximate drivers, or the local human activities that are directly responsible for forest clearing, such as agricultural expansion or timber extraction, and underlying causes, such as population growth or increasing demand for commodities[103]. Satellite data can provide important insights into both the proximate and underlying causes of forest loss. To characterize the proximate causes, researchers have mapped land use after forest conversion or used statistical samples of satellite reference data to estimate land use in previously forested area[2,35,97,104]. Using satellite data to characterize the spatial and temporal patterns of deforestation itself can also provide insight into the underlying causes of forest conversion. In the Democratic Republic of Congo, where forests are often replaced with shifting cultivation agricultural plots and where little food is imported, deforestation over time has been closely correlated with population growth[97]. In Indonesia, corruption has been identified as one of the underlying causes of deforestation, with bribes serving as incentives for politicians to issue concessions or to ignore illegal forest conversion.[84] Studies comparing satellite-derived annual deforestation estimates to local election cycles have found that deforestation – particularly illegal deforestation in areas that have not been zoned for forest clearing – increases in the run-up to local elections. Researchers believe this is linked to election financing, with local politicians turning a blind eye to illegal activities in exchange for financial support during their campaigns[84,85]. In areas zoned for legal forest conversion, deforestation increased immediately following elections, which could be the result of politicians rewarding those who provided financial support during the election with legal concessions[85].

In the tropics, agricultural expansion has been identified as the primary proximate driver of deforestation[1,2,105,106]. The types of agricultural land expanding in primary forest areas include small-scale subsistence farming, large-scale production of export crops such as soy or palm oil, and pasture, with the specific agricultural drivers varying across regions[2,106]. In Indonesia, environmental advocacy groups have identified the palm oil industry as a primary driver of forest conversion, and researchers have found that palm oil plantations have expanded in areas previously covered by natural forests[41–43,45,46,49,65,107–109]. However, estimates over the extent to which oil palm plantations caused deforestation vary between studies. This is caused, in part, by the transitional nature of land use change in Indonesia. Palm oil plantations are often developed in areas that had previously held natural forests, and some plantations are established soon after forest clearing[45,107]. However, not all plantations are established immediately after land is deforested. In cases where plantations are established after a delay, is palm oil the deforestation driver, or are plantations simply making use of underutilized non-forested land? Studies characterizing palm oil conversion within previously forested areas often provide a simple threshold for "rapid" conversion, though these thresholds are typically chosen somewhat arbitrarily without any robust scientific justification for the decision[45,65,109,110]. Private sector sustainability initiatives, such as corporate No Deforestation, No Peat, No Exploitation (NPDE) commitments or Roundtable on Sustainable Palm Oil (RSPO) certification requirements often select a cut-off year – plantations can be established on land deforested before a certain date, but not after. In the case of the RSPO, plantations established on primary forest land cleared after 2005 are not eligible for certification. Individual NPDE's vary, but many contain commitments to eliminate deforestation from their supply chains by no later than 2020[67]. The European Union (EU) applied an even more conservation approach when it adopted a policy stating that by 2030, palm-oil based biofuels would no longer be subsidized as a renewable fuel due to deforestation concerns, whether or not the palm oil used to create those fuels came from supply chains claiming to be deforestation free[111]. Officials from Indonesia and Malaysia, the world's two largest palm oil producers, have criticized the policy, claiming it amounts to discrimination against developing economies, and both countries have since challenged the EU's policy with the World Trade Organization (WTO)[112,113].

Indonesia contains extensive non-forest areas that have not been planted with commodity crops, sometimes referred to as degraded lands[45,65,108,114]. Academic researchers and environmental advocates have suggested that palm oil expansion in these degraded landscapes, rather than in primary forests, could help improve sustainability in the industry[43,45,108,114–116]. Some critics of the EU palm oil ban argue that by calling all palm-oil biofuels unsustainable, the policy unfairly penalizes plantations that were established in these low-carbon, degraded areas.

Many currently degraded areas were previously forested, however research investigating the origins of this land cover class has been limited. As discussed in Chapter 2, large areas of Indonesian primary forest have been cleared by forest fires, including 3.5 (+/-0.3) Mha cleared during the 1997/98 El Niño event alone. Researchers have suggested that forest fires associated with El Niño events are primarily responsible for deforestation resulting in unused grassland landscapes[65,106]. This assumption, however, is typically based on the lack of a land use after clearing, rather than by identifying the initial clearing mechanism directly.

In this study, I examined the fates of deforested areas, immediately after clearing and over time, to quantify deforestation drivers over a 30-year period (1991-2020). To determine the extent to which various drivers contributed to forest conversion, I tracked the expansion of economically productive land covers, such as oil palms or tree plantations, in previously forested areas. I also estimated the area of forest cleared without any visible land use, often referred to as "degraded land[114]." Within these seemingly unused areas, I classified deforested land based on the method of clearing: clearing of standing forests by fire and active clearing. This approach allowed me to quantify the extent to which unproductive areas were created by fire—consistent with the dominant narrative surrounding degraded land in Indonesia[65,106]—and the extent to which these areas were purposefully cleared by human actors. I also tracked degradation events prior to forest clearing, providing a comprehensive picture of forest change trajectories in Indonesia.

3.2.1 Definitions

To quantify the fate of deforested land, I used a probability sample of remotely sensed reference data to estimate primary forest area in 1990, annual primary forest loss from 1991-2020, and annual post-clearing land cover change. This is consistent with good practice recommendations for estimating land areas and allowed me to calculate the uncertainty of the area estimates (I report uncertainty as +/-1 standard error of an estimate) [80]. I defined primary forest as I did in Chapter 2: natural, old-growth woody vegetation at least 5m in height and with at least 30% tree cover at a 30-m spatial resolution; including intact primary forest, with no evidence of human disturbance at a 30-m resolution or within a 120-m radius, and degraded primary forest, which shows evidence of disturbance within a 120-m radius, but maintains at least half of its original natural canopy at the 30-m resolution.

This study builds upon the results of Chapter 2 by tracking land use trajectories after forest clearing. Using the same probability sample, I tracked all land cover and land use change events from 1991-2020 in areas that contained primary forest in 1990. Using a probability sample avoids the bias associated with map-derived area estimates[80]. It also allowed me to capture a wide range of land uses, some of which would have been difficult to map.

For the purpose of this study, I defined the deforestation driver by the land use following forest clearing. In the absence of a post-clearing land use, I classified deforestation based on the clearing mechanism – forest fire clearing or active conversion of forests for unplanted land. To capture the transitional nature of land use in Indonesia, I evaluated drivers at three different post-clearing time steps – immediately after clearing (within 12 months), five years after clearing, and at the end of the study period. The land cover/land use categories included large and small-scale palm oil plantations, smallholder agriculture (including both shifting cultivation and permanent agriculture, and excluding small-scale palm oil plantations), tree plantations, other land uses—an aggregated category including fishponds, mining, and rubber—and built-up land. Areas not planted or built up within 12 months of clearing were classified based on the initial forest clearing mechanism, either forest fires or active clearing.

Forest fires lead to varying degrees of tree cover loss in Indonesia, from mild degradation to near complete tree mortality[68,69]. I defined clearing by fire as I did in Chapter 2 – as the loss of at least 50% of the natural canopy from accidental or intentional fire in a standing forest. Fire is also widely used in Indonesia to remove felled trees and other debris after clearing and to prevent forest regrowth. Both fires in standing forests and land maintenance fires can cause burn scars that are visible in the satellite imagery. I differentiated fire clearing from actively cleared unplanted land based on the clearing pattern (active clearing is more likely to have a geometric clearing pattern, often with sharp boundaries between burned and untouched areas) and spectral characteristics (either no burn scar or a lag between the initial bare ground signature and the ash signature).

Fire can also be used to clear debris after tree felling in shifting cultivation agricultural landscapes. This type of clearing has a distinct spatial and temporal pattern and was assigned to the small-scale agriculture land cover class. Examples of active clearing with debris burning, fire clearing, and small-scale agricultural clearing are provided in Figures 3-S1 to 3-S5. Complete land cover definitions and a description of the methods used to distinguish between change types are provided in the methods.

3.3 Results

I found that more than half of all deforestation in Indonesia – 56% (+/-1.3) – was not immediately replaced with an observable land use after clearing. Of this area, an estimated 8.5 (+/-0.4) Mha was actively cleared using either manual, mechanical, or chemical (herbicide) clearing techniques, then left unplanted for at least 12 months. Another 7.4 (+/-0.4) Mha of land was cleared due to fires in standing forests. For the purposes of this study, I will refer to these areas as "unproductive," since they were not planted with crops or replaced with any other land covers associated with human land use. I recognize that although these areas were not replaced with a visible land use, they may be used in more abstract ways, such as contributing to a company's land bank or as a source of income through land sales. For this study, the term "unproductive" is meant to distinguish these idle areas from land that has been converted to visibly productive land uses, such as large- or small-scale agriculture.

Fires in standing forests were responsible for an estimated 25.9% (+/-1.1) of all primary forest loss observed during the study period, and just under half (46.3% +/-1.7) of all unproductive clearing. These could have been unintentional fires, such as fires that escaped areas where debris was being burned, or fires set intentionally in forests where trees were left standing prior to burning. In these cases, forests may have been prepared to make them more susceptible to burning, such as by building drainage canals in peat forests. For the purposes of this study, I did not differentiate between intentionally and unintentionally set fires. Areas where trees were actively cut down, the debris left to dry, then burned as part of the debris clearing process, were not classified as forest fire clearing. An example of this debris-clearing burning is provided in Figure 3-S1 and 3-S2.

As discussed in Chapter 2, forest fire clearing occurred almost exclusively during El Niño events, with an estimated 3.5 (+/-0.3) Mha of primary forest cleared by fire during the 1997/98 El Niño alone. Fire-cleared areas were often left idle for long periods of time. An estimated 92.1% (+/-1.4) of all forests cleared by fire had not been converted to a productive use five years after the initial clearing event, and 4.8 (+/-0.3) Mha of idle, fire-cleared land existed in Indonesia in 2022.

While forest fires did create a large area of degraded, deforested land, fire was not the primary mechanism by which unproductive lands were created. I estimate that over half of all unproductive deforested land (53.7% +/-1.7) was actively cleared. Compared to unproductive lands cleared by fire, these actively cleared unplanted lands were more rapidly converted to other land uses, although a large area of actively cleared unplanted land remained at the end of the study. Five years after clearing (or, for areas cleared after 2015, by the end of the study period), 25.7% (+/-2.1) of actively cleared unplanted land had been converted to a productive land use. Actively cleared areas that were eventually converted to a productive use experienced a median idle period of 6 years, compared to 12 years in productive areas initially cleared by fire.

These findings contradict the common assumption that most unused shrub and grassland landscapes were created by fire[65]. Fire did play an important role, but only accounted for about half of all degraded landscapes; the remainder were created deliberately. Additionally, the different trajectories in the years immediately following forest conversion indicate that plantation companies and others expanding into so-called degraded areas are not primarily utilizing landscapes cleared accidentally. Instead, the more rapid conversion of actively cleared unplanted land to productive uses compared to fire cleared areas suggests that this idle period may simply be part of the forest conversion process.

Of the drivers associated with economically productive clearing, smallholder land use and forest conversion for palm oil were the two largest contributors, accounting for an estimated 5.2 (+/-0.3) Mha and 2.6 (+/-0.2) Mha, respectively. While palm oil covered only half the area used by smallholders immediately after clearing, by the end of the study period, a much larger area of previously forested land was used for oil palm cultivation. In 2020, an estimated 7.8 (+/-0.4) Mha of primary forests had been replaced with palm oil plantations, compared to 5.1 (+/-0.3) Mha used for smallholder agriculture. These trajectories are visualized in Figure 3-1. Immediately after clearing, both unplanted actively cleared and fire cleared land replaced a larger area of primary forest than any other productive driver. Smallholder land use also took up a relatively large area, while palm oil, tree plantations, built-up land, and other clearing types all took up much smaller footprints. For an estimated 0.3 (+/-0.1) Mha area, the clearing driver could not be distinguished. In these cases, no high-resolution imagery was available to confirm whether crops had been planted and the use could not be determined by the spatial or temporal clearing patterns alone.

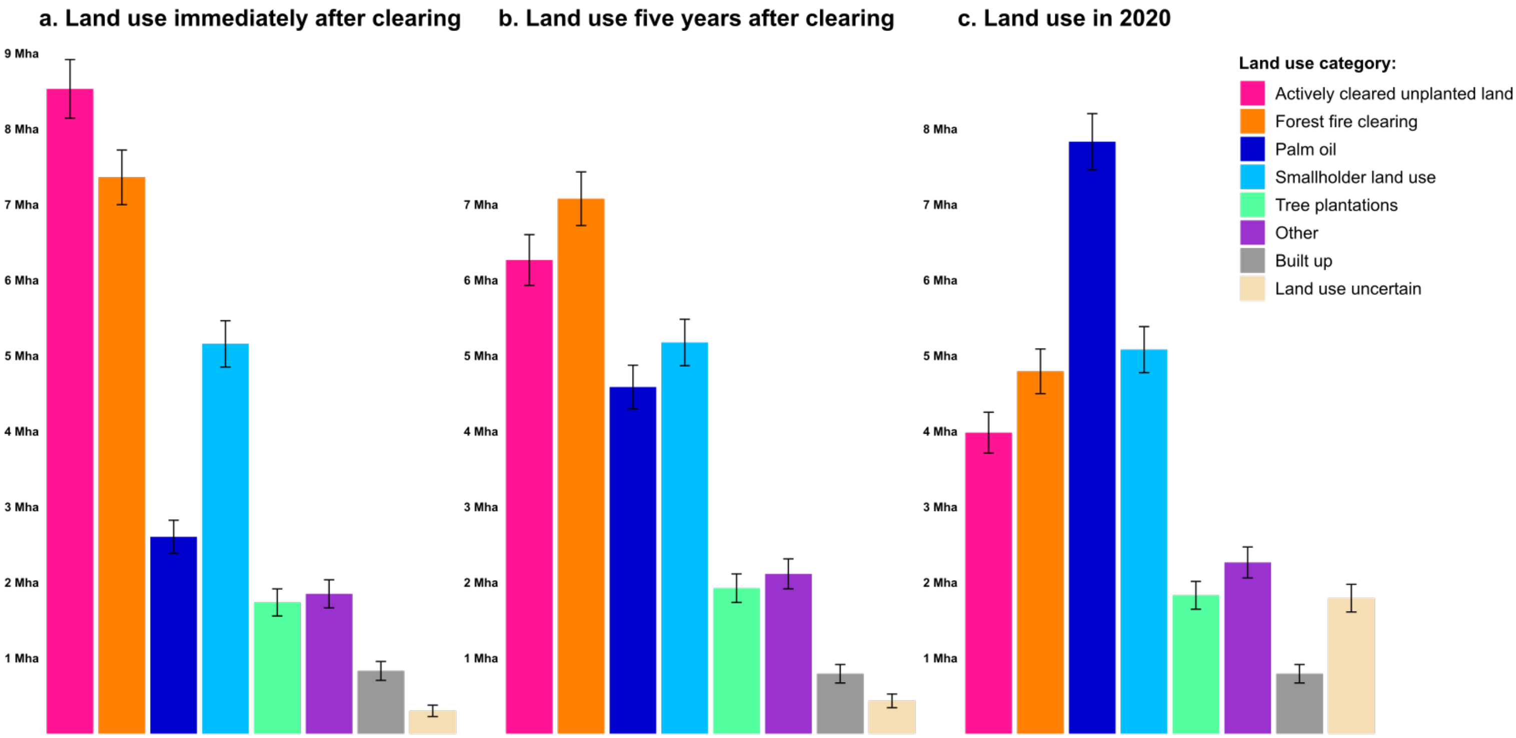


Figure 3-1: Land use after forest clearing. *The land use immediately after forest clearing (a.), five years after forest clearing (b.), and in 2020 (c.), including both unproductive (active cleared unplanted land and fire clearing) and productive classes.*

Five years after clearing, the areas converted for most of the productive classes (smallholder, tree plantations, other clearing types, and built-up land) had increased or decreased slightly, but had not changed dramatically. The area for which the land use could not be distinguished had increased to 0.43 (+/-0.09) Mha. These newly indistinguishable areas would have experienced at least one additional land cover change during the 5-year period, after which the land use could not be determined from either high resolution imagery or clearing patterns. The most dramatic changes five years after clearing occurred in the area used for palm oil plantations – which increased by roughly 2 Mha – and the actively cleared unplanted area, which decreased from 8.5 (+/-0.4) Mha immediately after forest loss to 6.3 (+/-0.3) Mha after five years. By the end of the study period, only 4 (+/-0.3) Mha of unplanted land remained. The area cleared by fire had also decreased, to 4.8 (+/-0.3) Mha, while palm oil now covered 7.8 (+/-0.4) Mha, more than one quarter of the total primary forest area cleared during the 30-year study.

3.3.1 Temporal patterns

While fire clearing occurred primarily during El Niño events, active clearing of forests for unplanted land occurred more consistently over the study period, though unplanted land production began to slow after 2012. Figure 3-2 shows the annual increases (positive y-axis) and decreases (negative y-axis) of both the fire clearing and unplanted land classes. Colors for bars on the positive y-axis indicate the land cover type before the area was burned or unplanted land was created. Along the negative y-axis, the colors represent the productive land cover type the area was converted to. Most idle land was created by the direct conversion of forests, although during the 2015 El Niño event some productively-used land was burned.

Palm oil was the primary productive land use to replace unproductive idle areas, particularly areas that were actively cleared. Palm oil also expanded into fire cleared areas, although fire clearings were replaced with a higher proportion of tree plantations compared to unplanted land. In unplanted land, the area converted annually to palm oil peaked in 2013, then began to decrease slightly, with a substantial drop-off occurring in 2019 and 2020. In those years, a relatively large area of unplanted land was cleared and the use could not be distinguished. Those areas may have remained unplanted after clearing, or could have been converted for palm oil or another productive land use.

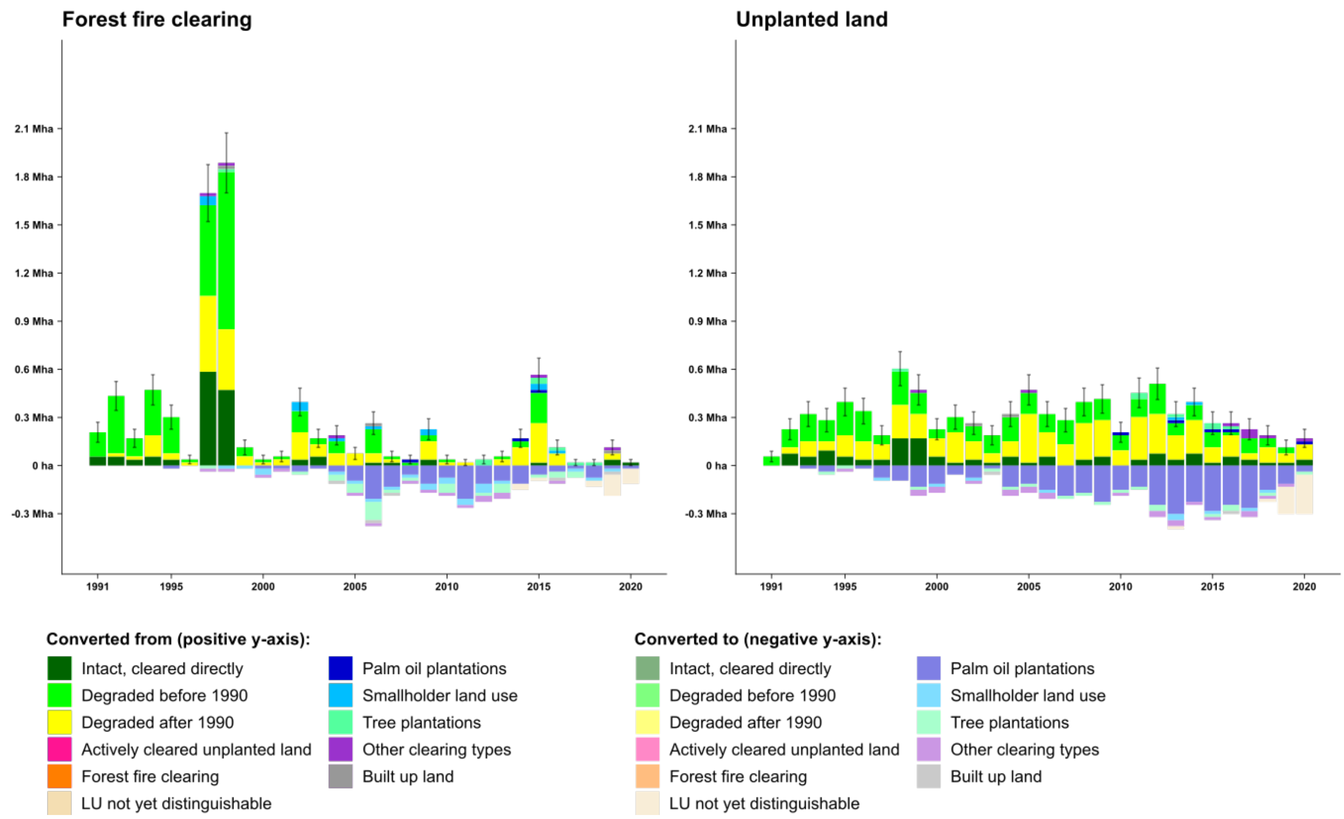


Figure 3-2: Annual loss and gain of unplanted land areas. *The gain of fire (a.) cleared land and actively cleared unplanted (b.) land are displayed on the positive y-axis, with bar chart colors representing the land cover classes these areas were converted from. The negative y-axis show the areas and land cover classes fire and unplanted land was converted to each year.*

Figure 3-4 shows the annual increases and decreases of both unplanted and fire-cleared land, as well as three productive classes – palm oil, smallholder land use, and tree plantations, for the last two decades of the study. Smallholder land use expansion typically occurred inside degraded forests, while tree plantations were developed in both degraded and intact forest areas as well as in fire cleared areas and, to a lesser extent, unplanted land.

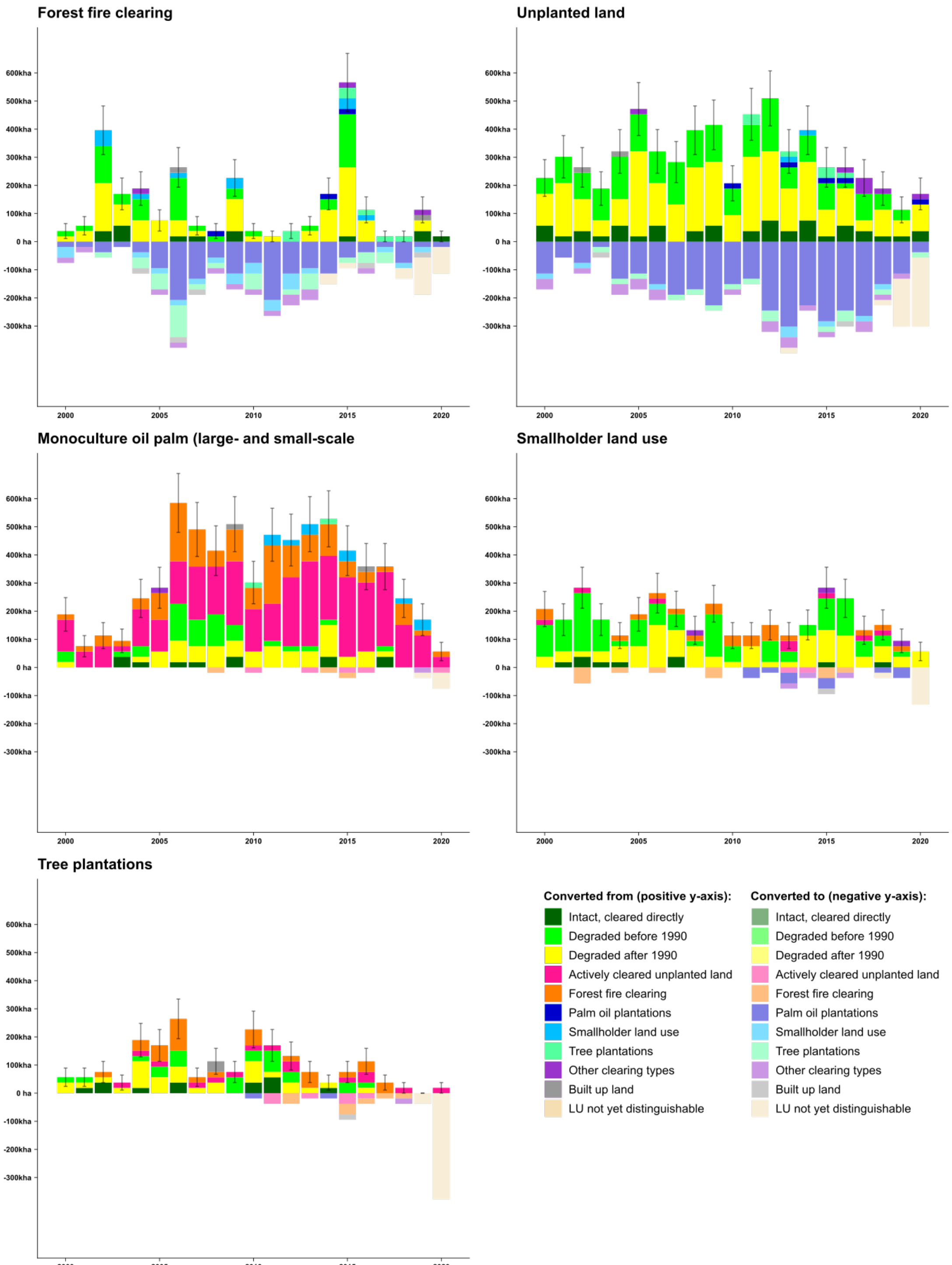


__Figure 3-3: Annual loss and gain of unproductive and productive land uses__. Positive y-axes show the areas converted to each class each year, and negative y-axes show the annual areas converted from each class into other land cover categories.

Palm oil expansion in previously forested areas occurred most rapidly from 2006 to 2014. After 2014, annual palm oil expansion began to steadily decline. During this period, palm oil replaced both intact and degraded primary forests, and expanded in both actively cleared unplanted land and fire-cleared areas, though the proportion being developed in fire-cleared areas began to decrease in the early 2010s. After 2015, palm oil expanded primarily into unplanted areas, and by 2017 the palm oil area directly replacing primary forests was too small to be detected by this study's methodology. Tree plantation expansion also declined and the direct conversion of tree plantations inside primary forest areas became increasingly rare in the last five years of the study. In 2020, a large area of existing tree plantations were converted to indistinguishable land. These areas were likely cleared as part of the regular harvesting and replanting cycle; however, this could not be confirmed using the available reference data.

3.3.2 Limitations based on data availability

For many of the productive land use classes, high resolution data was needed to confirm the land cover. This was particularly important in differentiating between unplanted land and young palm oil plantations. Much of the actively cleared unplanted land occurred in palm oil landscapes, including in areas where large plantation blocks characteristic of palm oil development were created, but then left idle. The spectral signatures and regrowth patterns of young oil palms can be similar to that of natural vegetation regrowth, meaning Landsat imagery alone is typically not sufficient to determine whether oil palms have been planted.

This limitation was particularly relevant in the last two years of the study, as Figure 3-4 shows. The area of indistinguishable land increased dramatically in 2019 and 2020, when less high-resolution data was available. In cases where land had been previously used for productive purposes, these clearing events may have been part of replanting cycles, meaning these areas will continue to be used for their original purpose. This is especially likely for areas that were originally used for palm oil or tree plantations, as those land uses are rarely converted to other productive classes (Figure 3-3). However, the same assumptions cannot be made for indistinguishable land clearing in unproductive or forested areas.

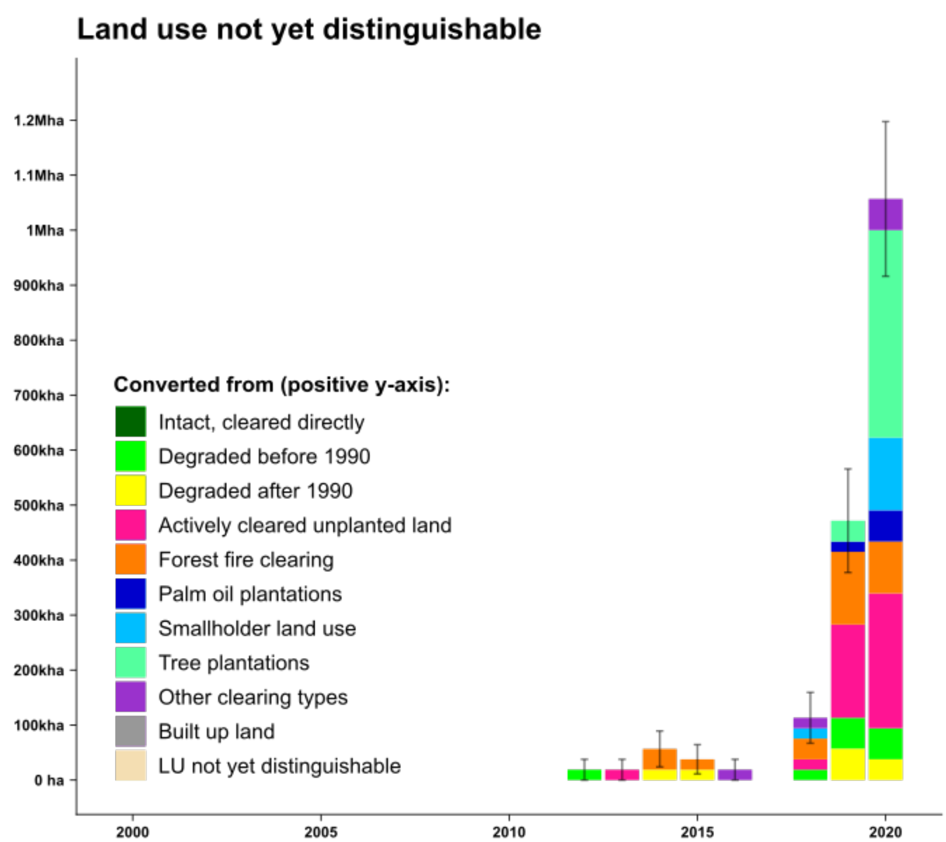


Figure 3-4: ***Annual gain of indistinguishable land.*** *Limited availability of high resolution data to confirm the land cover after a change event meant that the land use could not be identified for a substantial area (1.8 +/-0.2 Mha of previously forested land in 2020).*

3.4 Discussion

The extent to which primary forest in Indonesia is being actively cleared then left idle has not been well documented at a national scale. This study shows that many "degraded" lands (economically unproductive non-forest areas) created after 1990 were not caused by escaped fires but were the result of deliberate clearing. Furthermore, even as previously unproductive areas were converted to palm oil and other productive uses, new unplanted land clearings were continuously created (Figure 3-2).

This pattern of continuous expansion of unplanted land into primary forest areas, followed by the later conversion of unplanted areas to productive uses, suggests a transitional frontier dynamic similar to that seen in the Brazilian Amazon, where forest clearing for pasture is often followed by conversion of pasture to soy[104,117]. Qualitative research exploring land change dynamics in Indonesia further supports this comparison. Land banking and land speculation are common in Indonesia[116,118]. Palm oil plantation companies hold extensive land banks in the form of unutilized areas within their concessions set aside for future development, and palm oil license holders have been observed clearing primary forests then leaving the land idle for years[116]. In some of these cases, the extraction and sale of timber may have been the primary motivation for clearing, particularly in the 1990s, when demand for lower-grade timber for pulp and paper production outstripped tree plantation establishment[82]. Concession trading is also common in the palm oil industry, with concessions frequently issued to companies lacking the capacity or intention to develop a plantation. Instead, these companies profit by selling the licenses to other parties[86,118].

Land trading and speculation also occur at smaller scales. In Kalimantan, forest land cleared by local community members was commonly sold to non-local buyers, particularly land along roadsides, near urban areas, and in areas likely to be targeted for future palm oil development[116]. The buyers in these cases do not intend to develop the land, but instead plan to resell as land prices rise. In Sumatra, ready-to-plant land that had been slashed and burned was purchased at a higher price from buyers looking to establish palm oil plantations compared to the price of uncleared land or land that had been cleared but not fertilized through burning[119,120]. In regions where government-issued tenure certificates are rare and difficult to obtain, clearing land is also a method to assert informal ownership, allowing local community members to benefit from land sales to license holders should a concession be issued in the area[121].

This study confirms that palm oil expansion was a major contributor to forest loss in Indonesia from 1990-2020. Moreover, the real extent to which palm oil drives deforestation is likely much greater than the area directly converted, as the majority of unproductively cleared land that was eventually converted to a productive use was used for palm oil. More research is needed to understand why such extensive areas of forest are being cleared and left unplanted, including the extent to which unplanted land expansion is driven by planned future palm oil development. However, it is clear that efforts to protect primary forests in Indonesia should include measures designed to address speculation and land banking. Legal frameworks for prohibiting such speculation exist, including regulations requiring permits be developed within three years and preventing land sales to absentee owners[115,118]. If enforced, these offer a potential remedy for reducing primary forest loss in Indonesia.

The fact that both palm oil and unplanted land expansion declined in the latter years of the study also offers hope that existing forest protection policies are working. This corresponded in part to a period of declining palm oil prices, which could have impacted conversion rates for both classes. However, it also corresponded with a period of reform in the palm oil industry, when more and more companies began adopting NDPE commitments. These declines also began after Indonesia adopted its 2011 moratorium on new concessions inside primary forest areas, and the lowest deforestation years observed in the study overlapped with a temporary ban on all new palm oil licenses that was adopted in 2018 and then allowed to expire in 2021[122,123]. These correlations alone cannot prove causality or explain the relative extents to which economic or policy factors may have influenced deforestation rates. However, it does provide more detail about how land use in cleared forest areas has changed as overall deforestation rates in Indonesia declined. The annual forest loss and post-clearing forest trajectory estimates reported here could be the basis for future studies that investigate questions of causality more directly.

3.5 Methods

As with Chapter 2, this research was conducted as part of a collaboration with the Global Land Analysis and Discovery (GLAD) group at the University of Maryland and Indonesia's National Institute of Aeronautics and Space (LAPAN), Ministry of Environment and Forestry (KLHK), and the World Resources Institute

(WRI) in Indonesia. We used the same iterative sample interpretation process outlined in Chapter 2. An initial interpretation was conducted by myself along with coauthors from the organizations above for the 1990-2016 period, with that interpretation going through several iterations before being finalized. Following this, I updated the reference data in order to better differentiate between actively cleared unplanted and fire-cleared land, and to extended the study period through 2020. Definitions of the productive and unproductive land cover classes used in this study are included below in Section 3.6.

3.6 Definitions and interpretation methods for land cover and change event types

3.6.1 Forest clearing/land cover change

Definition: The removal of at least 50% of natural tree canopy cover (forest clearing) or other vegetation (post-clearing land cover change) at a 30-m resolution.

3.6.2 Economically unproductive clearing

Definition and identification methods: Forest clearing or land cover change in which land is not used for any observable economic purpose after the change event, and, for pixels eventually converted to a productive use, the land is re-cleared before the productive conversion.

3.6.3 Actively cleared unplanted land

Definition and identification methods: Land left unplanted for one or more years following mechanized, manual, or chemical (herbicide) vegetation removal; identified by a spectral signature consistent with vegetation removal and not indicating fire clearing (e.g. no ash signature or a delayed ash signature, a sharp boundary between the cleared area and remaining forest, and the absence of remnant trees), followed by regrowth signatures consistent with grass or shrubs; for pixels left unplanted at the close of the study period, the absence of productive crops was confirmed using SPOT and/or Google Earth imagery. Clearing patch size and landscape patterns were also used to distinguish unplanted land from rotational agriculture, which has a similar spectral profile but can be identified by distinct landscape-scale clearing patterns.

3.6.4 Forest fire clearing

Definition and identification methods: Fire event resulting in ≥ 50% canopy removal, identified by a spectral signature consistent with burning or ash and/or a clearing pattern consistent with fire (for instance clearing without sharp geometric boundaries), and no immediate conversion to a productive land use. Land burned after being manually cleared (slashed and burned) was not classified as fire clearing; these areas were less likely to have spectral signatures consistent with ash in annual composites and in bimonthly or 16-day composites often showed a bare ground signature followed after several weeks or months by an ash signature. These debris burning areas were assigned either to an economically productive class or classified as unplanted land.

3.6.5 Economically productive clearing

Definition and identification methods: Forest clearing or land cover change in which land was converted to an identifiable productive use within one year of clearing, or, in the case of slow-growing crops such as oil palm, in which spectral signatures following clearing are consistent with gradual vegetation regrowth and no subsequent clearing events occur before the presence of the crop can be identified. Productive use types can be identified by spectral & temporal regrowth patterns (such as for tree plantations) and/or by landscape-scale clearing patterns (such as for smallholder land use).

3.6.6 Palm oil

Definition and identification methods: Forest clearing or land cover change followed by planting of oil palms within the pixel of interest and not mixed with other crops; indicated by spectral changes consistent with vegetation removal (bare ground or young vegetation signatures), after which oil palm growth can be observed; no distinction was made between large- and small-scale oil palm development, though oil palms mixed with other crops were assigned to the "smallholder land use" or "other land use" category, depending on the scale; to distinguish this class from abandoned land or other classes with similar spectral signatures, the presence of oil palms was confirmed in SPOT and/or Google Earth imagery.

3.6.7 Smallholder land use

Definition and identification methods: Forest clearing or land cover change occurring in patterns consistent with smallholder land use; includes small-scale rotational agriculture, indicated by the clearing of small, roughly circular patches that are then left dormant while other nearby patches are cleared, as well as small-scale permanent agriculture, where patches are consistently replanted (for seasonal crops) or planted with permanent tree crops, excluding monoculture oil palm and monoculture rubber.

3.6.8 Tree plantations

Definition and identification methods: Forest clearing or land cover change followed by the planting of trees for timber or wood pulp; identified by spectral changes consistent with vegetation removal followed by the planting of monoculture, typically fast-growing tree species; often followed by another clearing event and replanted after trees reached maturity.

3.6.9 Other clearing types

Definition and identification methods: All land uses not falling into one of the above categories, including clearing for monoculture rubber plantations, fish ponds, mining, large-scale agriculture of crops not listed above, such as coconuts or cloves, or large-scale mixed agriculture. Canopy removal by natural disasters, river meandering, or the erosion of coastlines also falls into this category. Identified by spectral signatures following clearing, vegetation regrowth patterns, clearing patterns, and landscape cues.

3.6.10 Built up land

Definition and identification methods: Forest clearing or land cover change occurring along a straight or curved line and resulting in more than 50% vegetation removal within the pixel; the pixel would continue to have a bare-ground spectral signature in subsequent images in the case of permanent roads, or vegetation regrowth in the case of temporary logging-roads. This category also includes forest clearing for settlements, typically characterized by a bare ground signature visible in subsequent images and with patterns consistent with human settlements.

7.6 Supplementary materials

Sampled pixel 8100: bimonthly composites and MODIS hotspot data (2004)

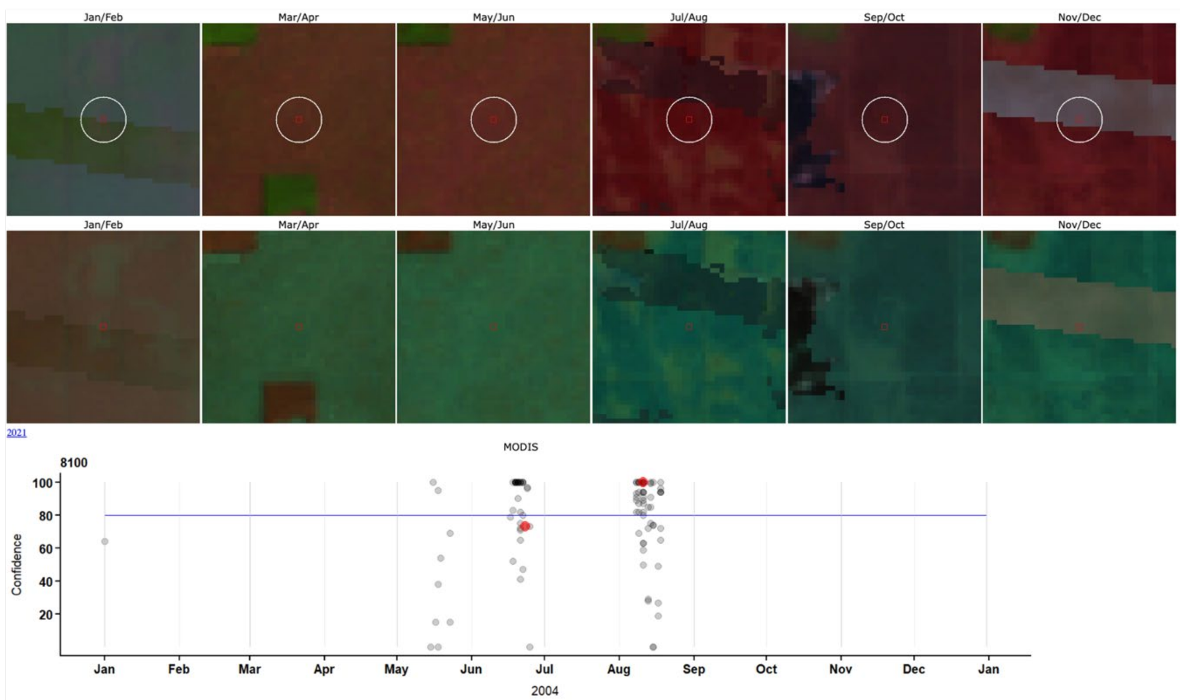


Figure 3-S1: Active clearing followed by debris burning. *A geometric cleared area without an ash signature can be seen in the Mar/Apr composite. An ash signature (dark purple in the red-NIR-SWIR1 composites, and dark blue in the NIR-SWIR-SWIR composites), is later visible starting in the Jul/Aug composite. MODIS hotspot data show two clusters of high confidence fire events located 1km (displayed in red) or 5km (displayed in gray) from the sampled pixel from May-August, several months after the pixel was initially cleared and corresponding to timing of the ash signature.*

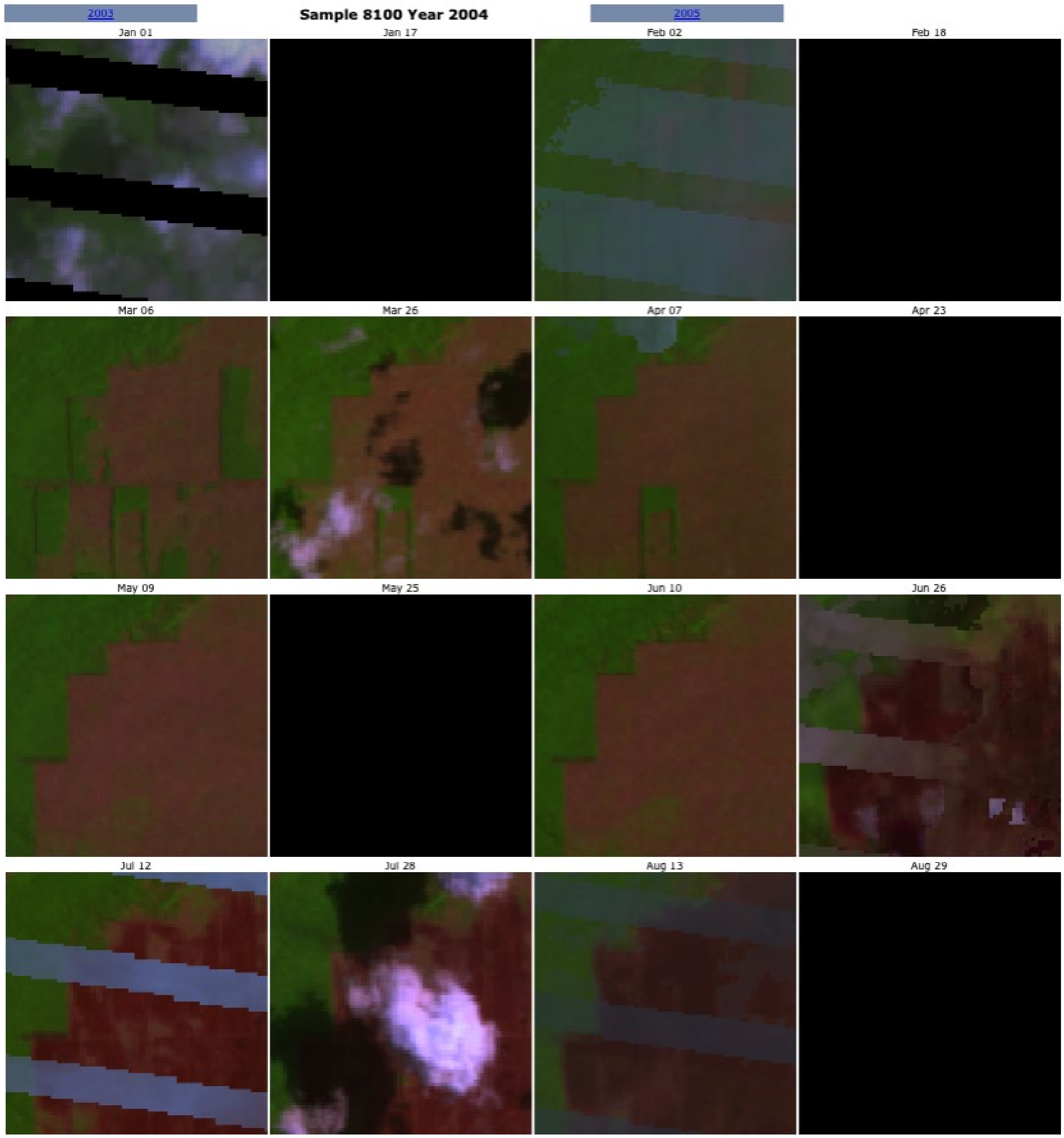


Figure 3-S2: Active clearing followed by debris burning. *16-day composites are displayed here for sampled pixel 8100. The pixel was burned between June 10th and June 26th, several months after the initial clearing event.*

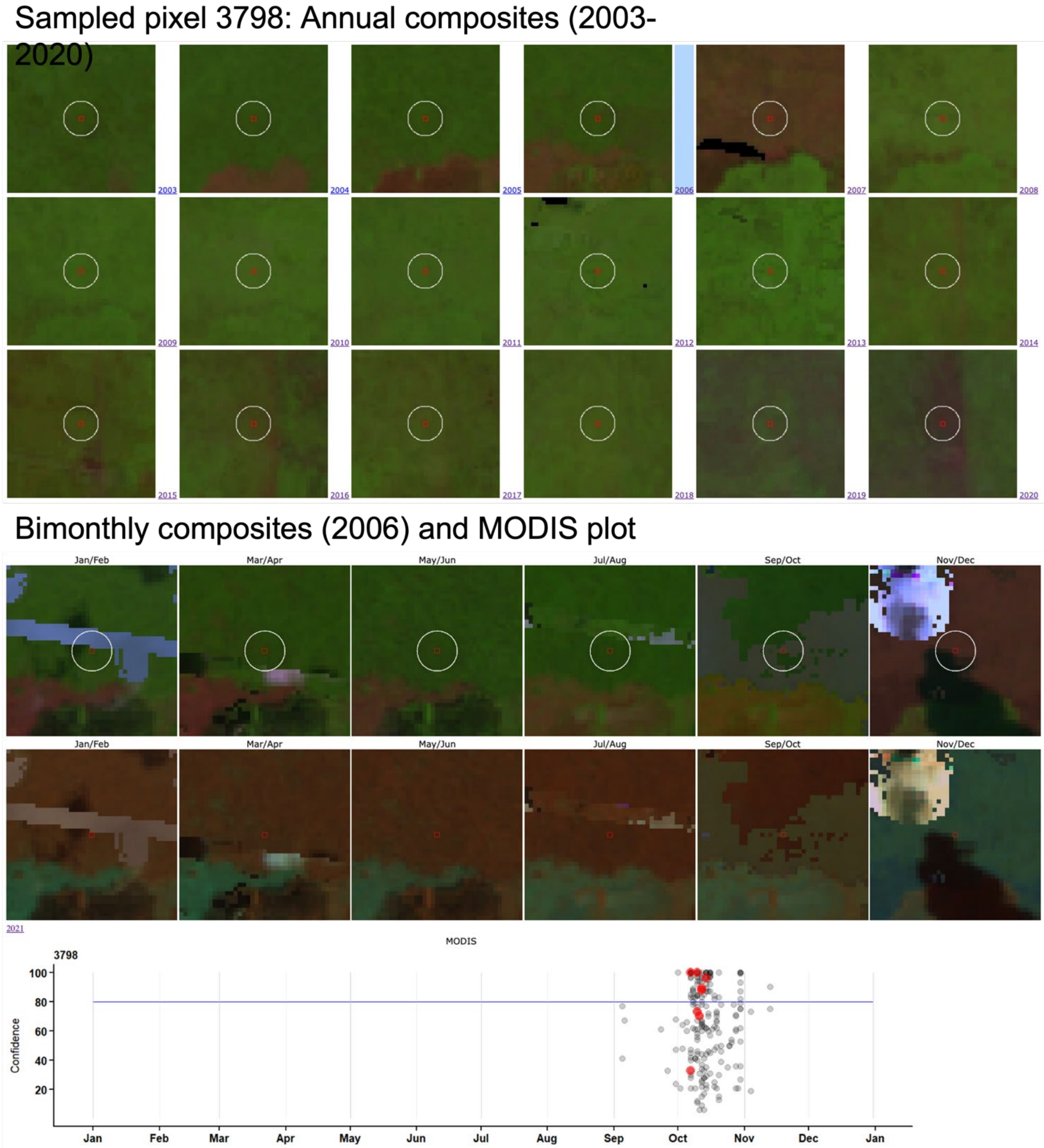


Figure 3-S3: Forest fire clearing. *An ash signature is visible immediately after clearing in the Nov/Dec. image. The clearing date also corresponds with a cluster of high-confidence MODIS hotspots detected in the vicinity of the pixel.*

Sampled pixel 3798:16-day composites (2006)

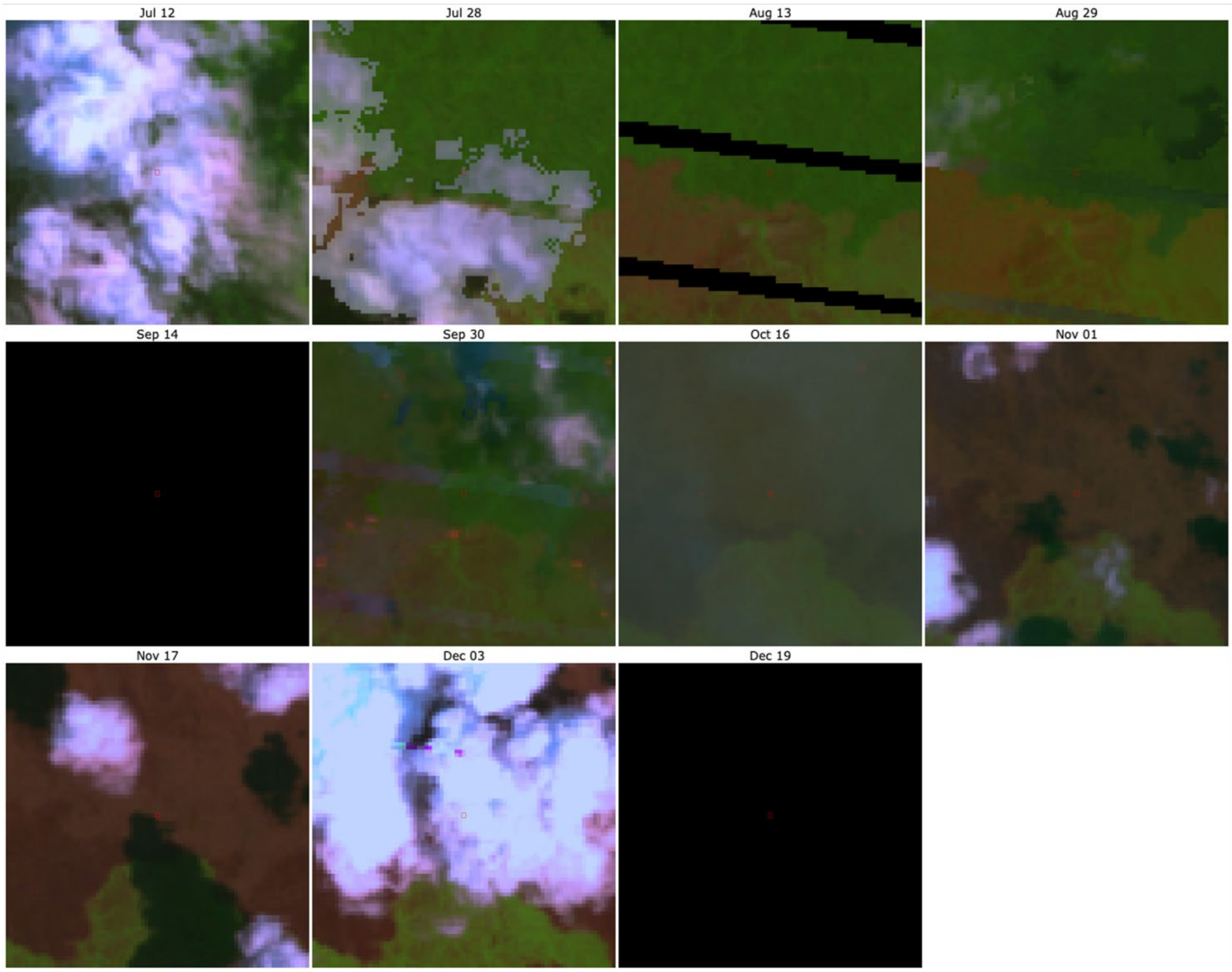


Figure 3-S4: Forest fire clearing. *In the 16-day composites for this image, active fires can be seen near the pixel in the Sept. 30th image and an ash signature is visible in the first clear image after the pixel was cleared. The date of clearing also corresponds to the dates of MODIS hotspots from Figure 3-S3.*

Sampled pixel 8369: Annual composites

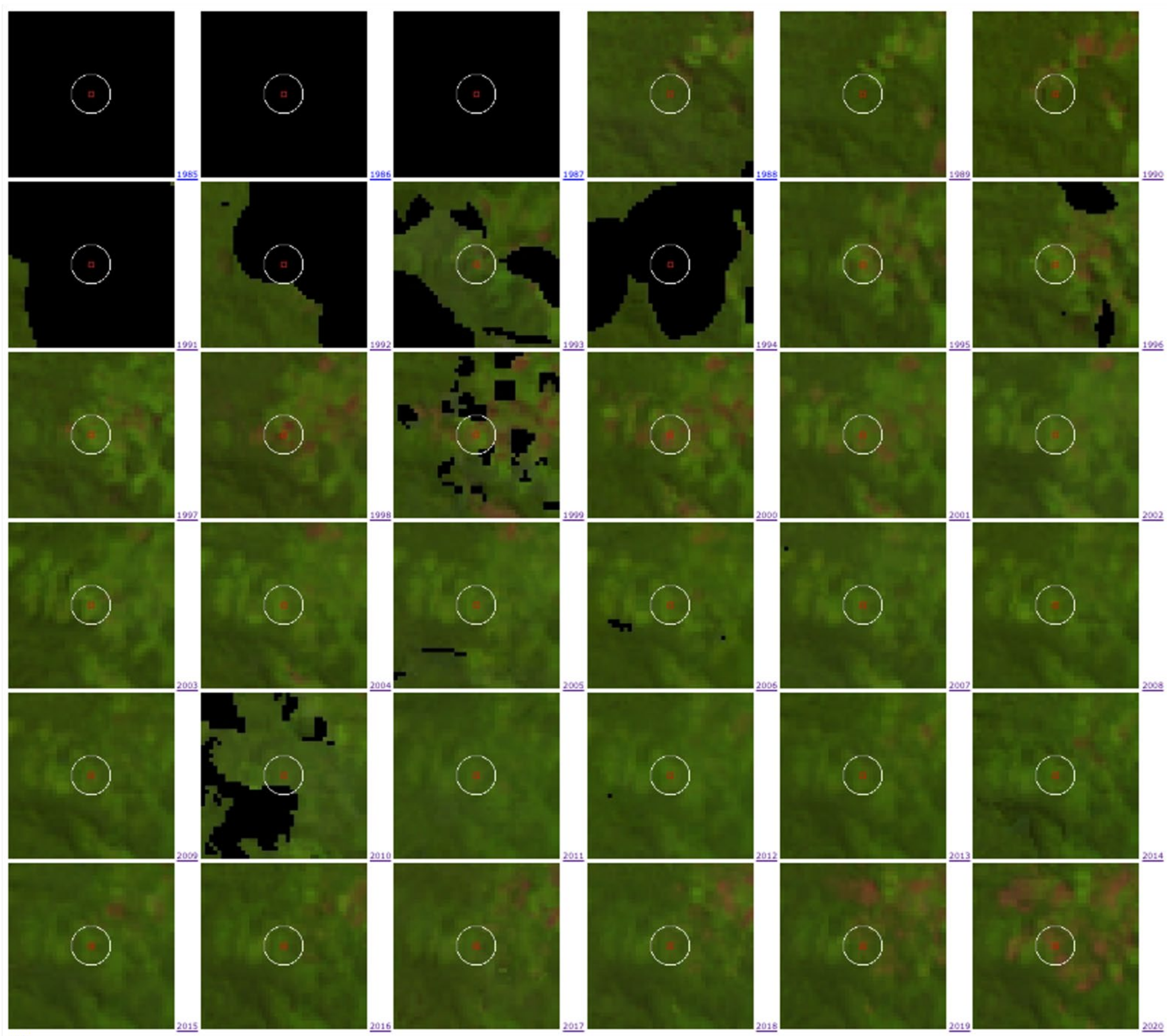


Figure 3-S5: Smallholder clearing. *Smallholder land use is associated with distinct spatial and temporal patterns, in this case, a patchwork of small fields that periodically display bare-ground signatures when they are planted or harvested.*

Chapter 4: Palm oil extent in 2020

4,1 Abstract

Palm oil is the world's most productive oil crop, and it is used around the world as a cooking oil, an additive to processed foods and cosmetics, and as a biofuel. Palm oil is particularly important for Indonesia, the world's largest producer, both as an export commodity and a staple food domestically. Palm oil grows best in the humid tropics, and the palm oil industry has been linked to tropical deforestation, resulting in a decision by the European Union to exclude palm oil-based biofuels as a sustainable energy source. In this study, I estimated the land area in Indonesia used for oil palm cultivation in 2020, and found that, of the 16 (+/-0.5) Mha of land planted with oil palms, roughly half had replaced primary forests, including 2.6 (+/-0.2) Mha developed immediately after forest conversion. I also found that palm oil expansion in areas that previously contained forests has slowed, a trend that corresponds with a period of low palm oil prices and an overall drop in deforestation rates in Indonesia.

4.1 Introduction

The African Oil Palm (*Elaeis guineensis*) is one of the world's most important and most productive oil producing crops, producing more oil per hectare than any of the other major cultivated oil-producing species[124]. Palm oil and palm kernel oil, produced from the fruits and seeds of the oil palm plant, are used in products ranging from cooking oil to cosmetics to biodiesel. Over the long term, global demand for vegetable oils will likely increase, driven by population growth, improvements in livelihoods, and by extension diets, in many parts of the world, and demand for biofuel as a renewable fuel source[125]. Palm oil's small land footprint compared to the amount of oil that can be produced makes it extremely valuable in this context. However, palm oil grows best in relatively wet areas near the equator – the same areas where the world's remaining humid tropical forests are located[124,125]. Because of this, palm oil expansion has often occurred at the expense of tropical forests[41,42,65,107–109], which has in turn prompted advocacy campaigns by environmental groups targeting the palm oil industry.

Concerns over palm oil's links to deforestation have led to laws mandating labels on palm-oil containing products and, in 2018, led the European Union to vote to end the use of palm oil as a sustainable energy source[111,113,126,127]. While this move was often referred to a as "ban" in the media, it did not mean palm oil or palm oil biofuels could not be imported or used in the EU. Instead, the policy would mean that biofuels derived from palm oil or crops with high deforestation risks would not count towards emissions reductions targets or be eligible for associated subsidies[111]. Indonesia and Malaysia, the world's two largest producers of palm oil, responded to the policy by filing challenges with the World Trade Organization (WTO), claiming the move was protectionist and violates international trade agreements[111–113].

While some stakeholders within the palm oil industry have denied any links to deforestation (claims that are not backed up by the scientific literature), criticism of the industry has also led to reforms. The Roundtable on Sustainable Palm Oil (RSPO) was established in 2004 as a membership organization that certified plantations meeting certain sustainability requirements. Individual companies later began adopting even stricter "zero deforestation" or "No Deforestation, No Peat, No

Exploitation" (NDPE) commitments, in part in response to criticisms that the RSPO's policies initially allowed plantations to be developed in some high carbon areas, such as degraded primary forests, and that RSPO guidelines were not always strictly enforced. As more industry actors began adopting NDPE policies, the RSPO also tightened its certification requirements. Currently, most large-scale actors in Indonesia's palm oil industry have made commitments to eliminate deforestation from their supply chain, including many palm oil processors, traders, and buyers, meaning smallholders selling to these actors are also by extension governed by these policies[67].

Given the high economic stakes, research showing where palm oil plantations are located and the deforestation histories of those areas is of great importance. Studies mapping palm oil areas have typically used one of two methods. Mature, closed canopy plantations produce a distinct radar backscatter signature, enabling researchers to create maps of mature plantations using Daichi-Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) or Sentinel-1 data[41,42,47]. These maps are valuable because they can detect plantations regardless of size or shape, provided that oil palms are sufficiently mature and well managed to result in a closed canopy. This means that radar-based maps can capture both large- and small-scale plantations. However they are less useful for detecting recently planted areas, and gaps in the historical radar record can make it difficult to determine the year plantations were established[41].

Another method is to create visually interpreted maps using multispectral (typically Landsat) data, based on landscape patterns[43,48]. Large-scale palm oil plantations share characteristic block patterns when developed on peatlands or in low-slope dryland areas, while plantations in steeper areas share distinct terrace patterns. These studies are not mapping planted oil palm trees directly, but instead rely on roads, canals, and the shape of clearings to map the plantations themselves. This method can capture plantations early in their development, when trees are too young to be identifiable with radar data. It can also capture plantations that have not yet been planted or where trees have been damaged. However, since smallholder plantations have more varied landscape patterns, these areas are missed.

Other studies have relied on high-resolution imagery, either though sampling or visual interpretation and delineation of plantation boundaries from high resolution data[65,128]. This allows even young oil palms to be identified directly, however data availability and cost pose additional challenges. Some published studies have used a combination of these approaches, minimizing the weaknesses of some of the individual methods[42,109].

In this study, I estimated the area under oil palm cultivation in Indonesia in 2020 using a sample-based approach. I also estimated the year of deforestation and year of oil palm conversion from 1991-2020 in areas that were covered by primary forest in 1990. I used high-resolution imagery from Google Earth and SPOT 6/7 to detect the presence or absence of oil palm in 2020 and 16-day analysis ready Landsat data to determine the dates of forest clearing and oil palm planting[101]. I also estimated the area for which the presence or absence of oil palm could not be determined, an important measure of uncertainty for this study and others that rely on similar high-resolution data sources.

4.3 Results

In 2020, Indonesia contained an estimated 16 (+/-0.5) Mha of land planted with oil palms. Roughly half of this area (49.1% +/-1.7) expanded in land that had contained primary forest in 1990, including 4.5 (+/-0.3) Mha that had been intact primary forest in 1990, and 3.3 (+/-0.2) Mha of forest that was degraded at the start of the study period. The status of another 4.1 Mha (+/-0.3) of land was unclear, meaning reference data was not sufficient to confirm the presence or absence of oil palms.

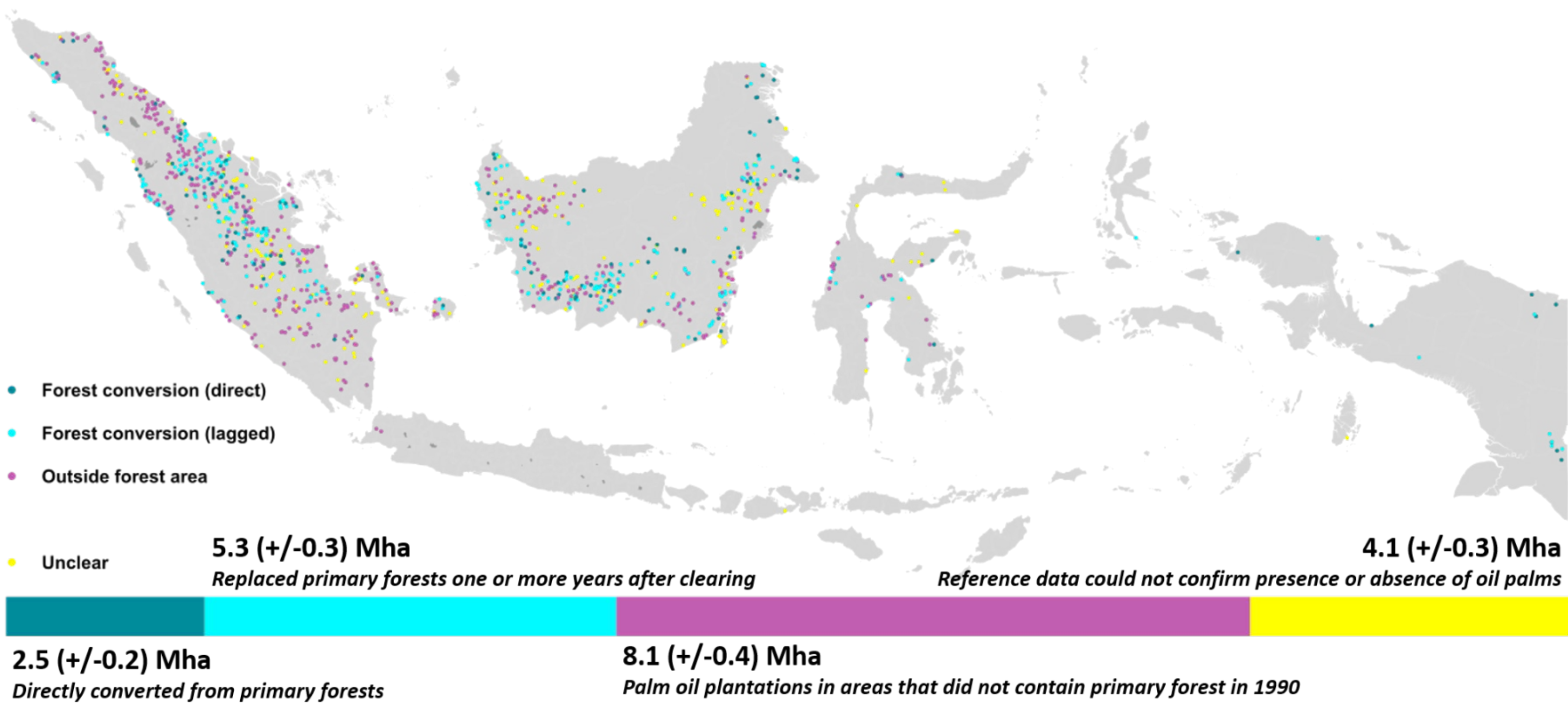


Figure 4-1: Palm oil area in 2020 and sampled pixel classifications. *Estimated areas of oil palm that replaced primary forests and in non-forested areas, and the location of sampled pixels and their classifications. The locations of pixels for which the presence or absence of oil palms could not be determined are also presented, along with corresponding area estimate.*

Approximately one third (32.5% +/-2.3) of the palm oil area that replaced primary forests was rapidly converted (within 12 months) after primary forest clearing (Figure 4-1). Another 43.6% (+/-2.4) was planted in areas that were actively cleared but left idle for one or more years after clearing, and 19.5% (+/-1.9) was planted in areas initially cleared by forest fire. The lag time between forest clearing and oil palm planting was typically shorter in areas that were actively cleared compared to areas cleared by fire. In cases of delayed palm conversion, actively cleared areas had a median gap between forest clearing and planting of 5 years, compared to 11 years in areas cleared by forest fire.

4.3.1 Regional patterns and temporal patterns

Most oil palms are located on the islands of Sumatra (59.1% +/-1.6) and Kalimantan (35% +/-1.5) (Figure 4-1). Of these two regions, Kalimantan had the highest proportion of oil palms that replaced forests. An estimated 61.1% (+/-2.8) of the Kalimantan's 5.6 (+/-0.3) Mha under oil palm cultivation in 2020 had been established in areas that had been primary forest in 1990. Sumatra had a larger oil palm area in 2020 (9.4 +/- 0.4 Mha), of which 40.8% (+/-2.2) occurred in previously forested areas.

The area of primary forest converted directly to palm oil plantations from forests was roughly equal on the two islands – 1.2 (+/-0.1) Mha in each region. The remaining oil palm areas that replaced forests on each of these two islands – 2.3 (+/-0.2) Mha in Kalimantan and 2.7 (+/- 0.2 Mha) in Sumatra – did so at least one year after forests were cleared. In Sumatra, this typically occurred in areas that had been actively cleared then left idle (77.5% +/-3.5 of all lagged palm oil conversion in Sumatra occurred in actively cleared unplanted areas). In Kalimantan, a relatively higher proportion of oil palm expanded into areas cleared by fire (45% +/-4.5, compared to 47.5% +/- 4.6 in actively cleared unplanted areas). A much smaller proportion on both islands expanded into areas that had been used for another productive purpose after forest clearing.

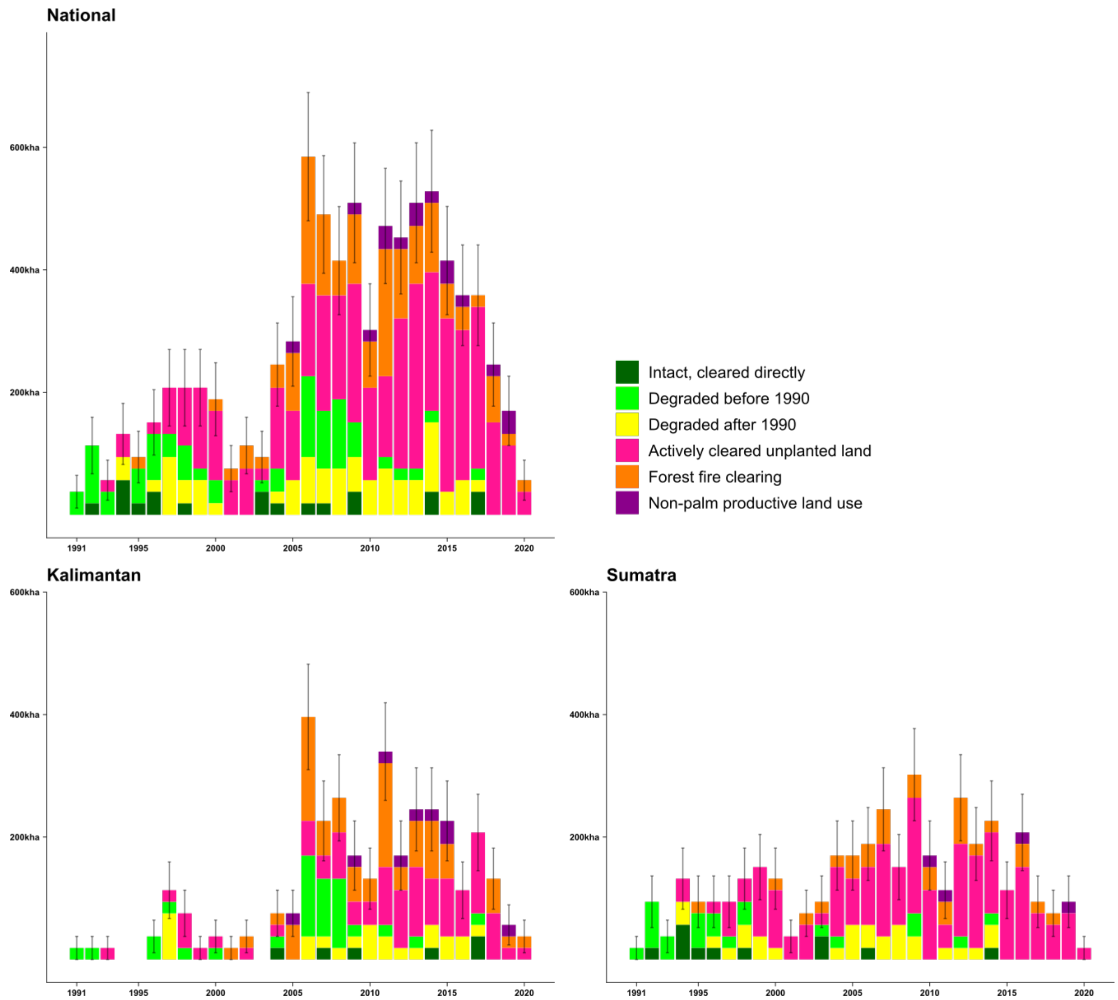
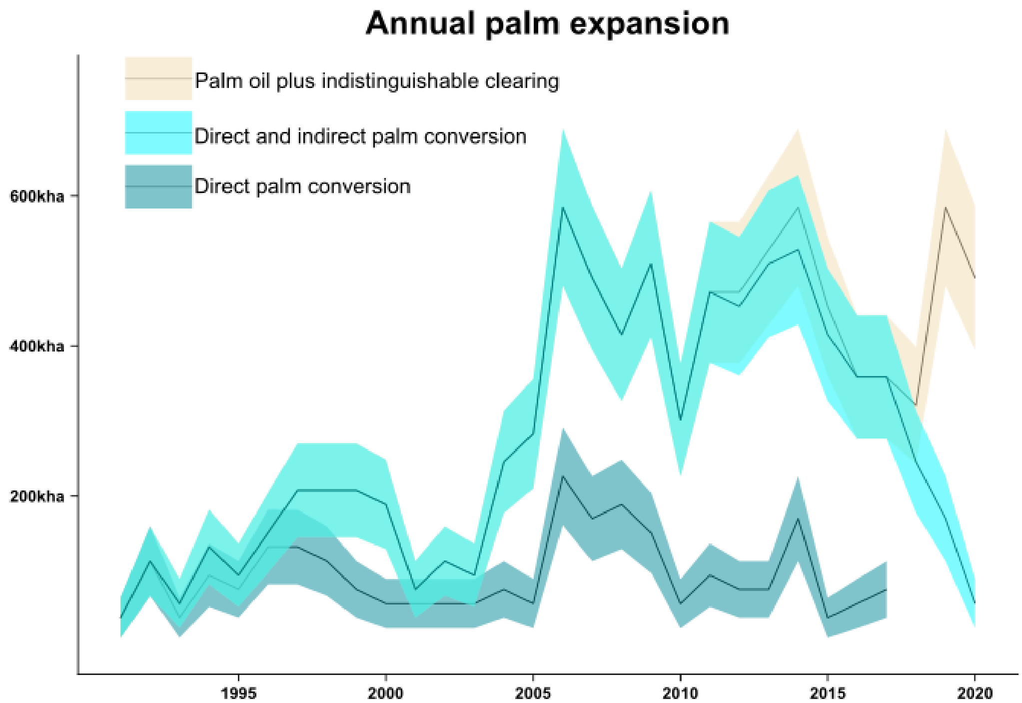


*Figure 4-2. **Annual expansion of palm oil in previously forested areas.** National estimates and regional estimates for Kalimantan and Sumatra of the annual oil palm areas that replaced forests either directly or indirectly.*

In both islands, and nationally, oil palm expansion in areas that had been forested in 1990 occurred most rapidly from 2005-2015, and expansion declined during the last five years of the study period (Figure 4-2). The direct, rather than lagged, conversion of primary forests for oil palm also slowed towards the end of the study period, and by 2017 the direct conversion of primary forest for oil palm had dropped to levels low enough as to be undetectable in this sample.

During the 2005-2015 period when palm oil expansion occurred most rapidly, global palm oil prices were also high (Figure 4-3). In the last few years of the study, the area directly converted to palm oil from primary forests dropped to levels too low to be detected with this sampling design, and lagged conversion also slowed. However, a relative lack of high resolution imagery to confirm the presence of absence of oil palms in the last two years of the study compared to earlier years means this study may be underestimating the area of previously forested land directly converted to oil palms. In Figure 4-3, I separately plot the direct palm conversion area (the area converted immediately after forest clearing), the direct and indirect palm conversion area, and the direct and indirect areas plus the indistinguishable land converted from either primary forests or unproductive land uses. Since most oil palm expansion in previously forested areas occurs either directly or in areas that were initially unproductive, indistinguishable clearing is more likely to be oil palm in these areas. Therefore, the true estimate of oil palm expansion in 2019 and 2020 is likely to somewhere between the plots presented in Figure 4-3. The combined annual expansion of direct, indirect, and indistinguishable areas are also compared with the mean annual palm oil prices in Figure 4-4.



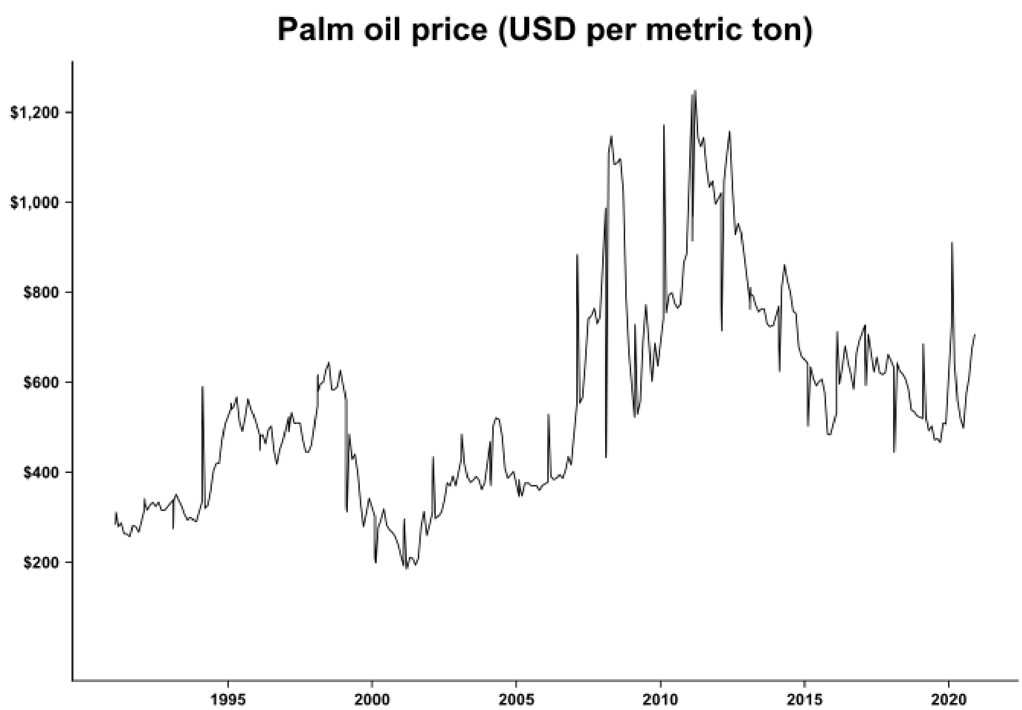


Figure 4-3. Annual oil palm expansion into previously forested areas and palm oil prices over time. *The area of direct palm oil conversion, indirect palm oil conversion, and indistinguishable land converted from forests or unproductive land uses is also presented. Palm oil conversion estimates are likely underestimated in the last two years of the study due to high resolution data availability, so the true number is likely somewhere between the confirmed and unclear areas.*

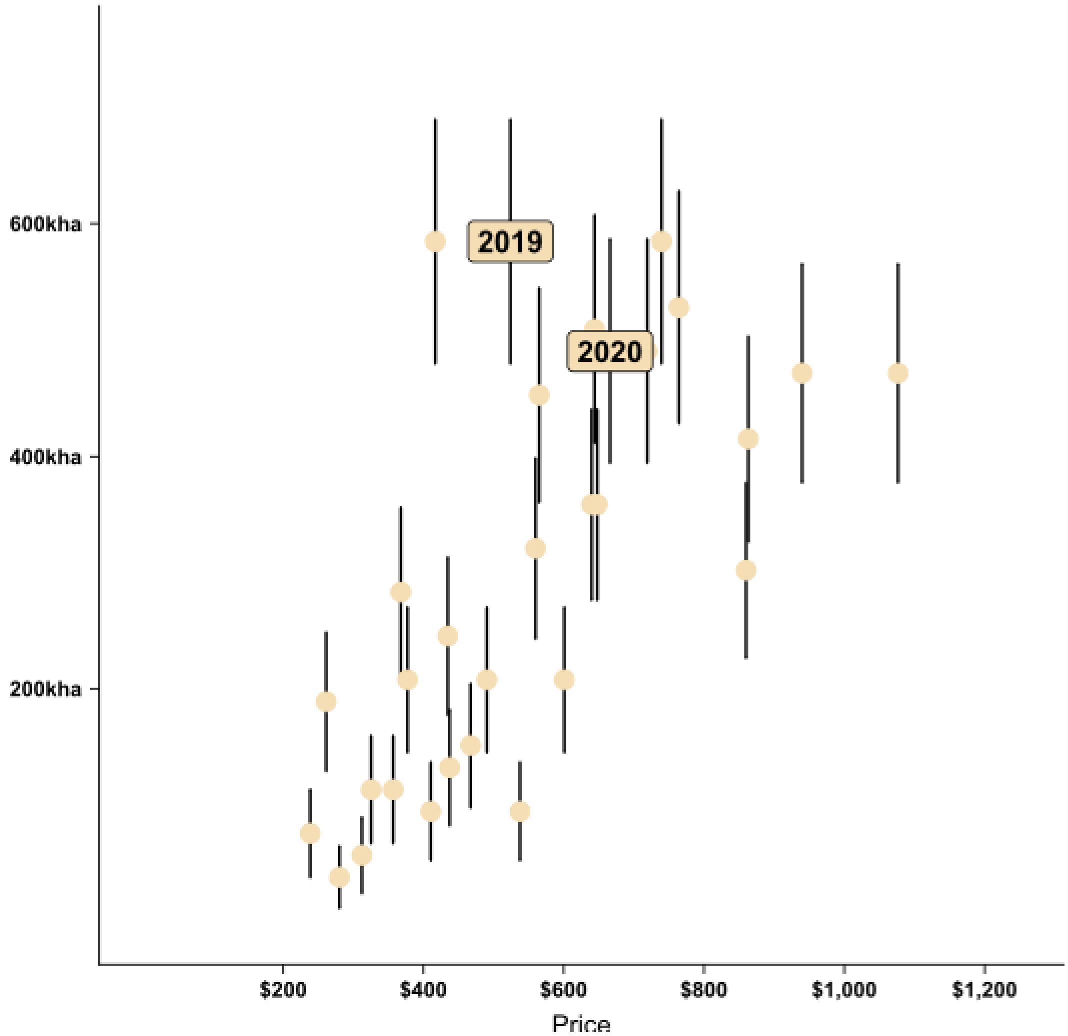


Figure 4-4. The combined annual expansion areas of direct palm oil conversion, indirect palm oil conversion, and indistinguishable land converted from forests or unproductive land uses in areas that were forested in 1990 (plotted on the y-axis) compared with annual mean palm oil prices (plotted on the x-axis). *The years 2019 and 2020, the years with the highest proportion of indistinguishable land, are labeled.*

4.4 Discussion

I found that roughly half of Indonesia's palm oil area in 2020 occurred in areas that had been previously forested, and that the period with the most rapid expansion into these areas, including both lagged and direct conversion to oil palm from primary forests, corresponded to a period of high palm oil prices. Other recent studies have measured the extent to which deforestation in Indonesia correlates with palm oil prices and found that a palm oil price increase does impact deforestation. From 2017 to 2020, when deforestation levels in Indonesia reached record lows, palm oil prices were also relatively low compared to the highs seen in the early 2010s. However, evaluating palm oil expansion trends in the last few years of the study period are more difficult given the large area of land (4.1 Mha +/-0.3 hectares in total, and 1.8 +/- 0.2 Mha in previously forested areas) for which the land use cannot be reliably identified.

4.5 Methods

This study used the same sample and reference data from which I derived the results of Chapters 2 and 3, and was also a collaboration between the GLAD group at the University of Maryland and LAPAN, KLHK, and WRI Indonesia. Sampled pixels classified as primary forest in 1990 were reviewed by an interpretation team composed of myself and collaborators from the above-mentioned organizations, and for forested pixels that experienced one or more land cover change over the course of the study, each subsequent land use was noted. Reference data were later updated and I reviewed all sampled pixels with the added reference data including bimonthly and 16-day composites and 16-day plots of NDVI, SWIR-1 and SWIR-2 values. SPOT 6/7 composites from 2017, 2018, 2019, and 2020 were also contributed by LAPAN, and were used along with Google Earth imagery to verify the oil palm status in 2020.

The presence or absence of oil palms could not be confirmed in 2% of sampled pixels, representing an estimated 4.1 (+/-0.3) Mha hectares, including 1.8 +/- 0.2 Mha hectares of land that was forested in 1990. This number may seem small, however most of these sampled pixels had undergone a land cover change in the last 1-2 years of the study (Figure 3-4) and many were located in palm oil landscapes. This is a significant limitation to this study, and a general problem that would impact all studies relying on Google Earth to conduct accuracy assessments of palm oil maps.

In cases where there was a delay between forest clearing and palm oil planting, the NDVI, SWIR-1 and SWIR-2 plots were used, together with annual, bimonthly, 16-day composites, and high resolution imagery, when available, to identify the data of palm oil planting. Examples of reference data for direct and indirect forest conversion for palm oil are provided in Figures 4-S1 and 4-S2.

4.6 Supplementary materials

Figure 4-S1: Direct conversion of forests to oil palm. *This pixel was cleared in 2004. Oil palms are visible in the 2013/16, 2017, and 2018 SPOT images, and, based on the growth patterns seen in the NIR-SWIR1-SWIR2 charts and consistently greener signatures in the annual composites, the pixel was likely planted soon after clearing.*

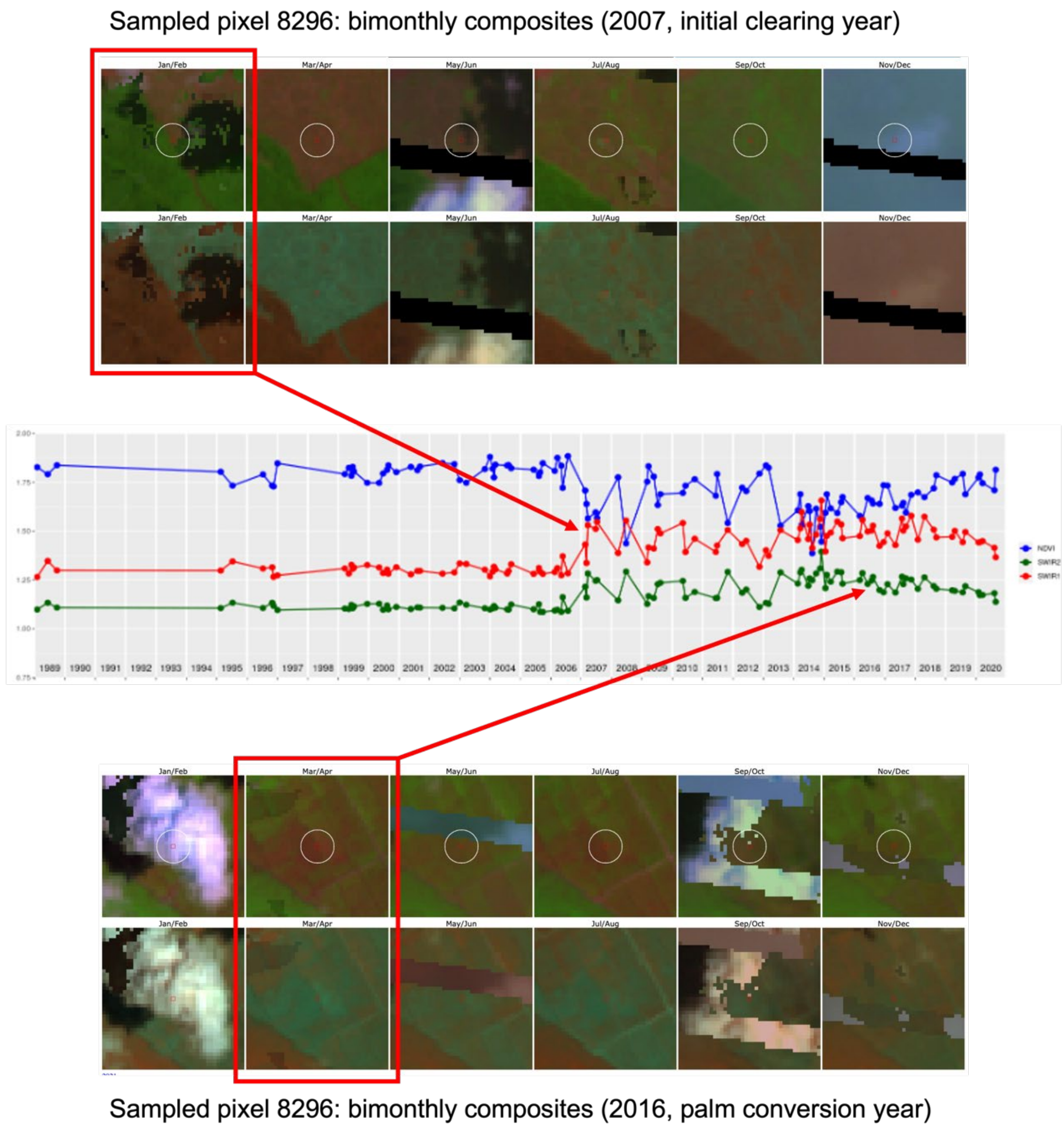


Figure 4-S2: Delayed conversion of forests to oil palm. *This forest was initially cleared in 2007, then planted with oil palms between 2014 and 2017 (see high resolution imagery in Figure 4-S3 below). The most likely clearing date based on the NDVI, SWIR1, and SWIR2 temporal patterns and the clearing and regrowth visible in the bimonthly composites, is early 2016.*

Figure 4-S3: Delayed conversion of forests to oil palm. *In the case of this pixel, the patterns seen in the Landsat-derived reference data can be confirmed using high resolution imagery. In this Google Earth image from 2014, seven years after the pixel was initial cleared, the land is still unplanted. Oil palms are also not visible in the first SPOT composite, created using imagery captured between 2013 and 2016. By 2017, however, young oil palms can be seen growing in the pixel.*

Chapter 5: Discussion

5.1 Summary of research contributions and study limitations

This research provides the most detailed sample-based assessment of primary forest loss and post-forest clearing land use currently available. In Chapter 2, I provided annual forest loss and intact forest degradation estimates and associated standard errors over a 30-year period. I also disaggregated primary forest clearing by the clearing mechanism and found that 25.9% (+/-1.1) of primary forest cleared from 1991-2020 was cleared by forest fire, including 3.5 (+/-0.3) Mha cleared during the severe Niño event in 1997 and 1998. Those two years were responsible for one fifth (19.7% +/-1) of the total deforestation that occurred during the study, underscoring the devastating impact that poor policy decisions, such as the draining of Central Kalimantan peatlands for the Mega Rice Project, can have when combined with extreme weather events. I also found that the majority (77.4% +/-1.1) of primary forests were degraded before they were cleared, confirming findings of previous studies showing that deforestation is typically preceded by degradation in Indonesia[38].

In Chapter 3, I followed land use trajectories after forest clearing, and found that more than half of all deforested land in Indonesia is left idle immediately after clearing. The majority (53.7% +/-1.7) of this unproductive land was not cleared by fires in standing forests but was actively cleared – a finding that contradicts assumptions in the existing academic literature that most degraded lands in Indonesia were created by fires[65]. When actively cleared unplanted areas were converted to productive land uses, they were most often planted with oil palms. This has important policy implications, both in terms of understanding the sustainability of Indonesia's palm oil industry, and for developing and implementing effective forest protection strategies. Given the frequent lags between forest conversion and oil palm planting, and the fact that this delayed oil palm conversion typically did not replace other productive land uses but deforested land left idle, the true extent to which palm oil drives deforestation is likely larger than the extent to which palm oil plantations directly replace forests. That said, although this research makes it clear that there is a relationship between palm oil and unplanted land in Indonesia, we don't know the extent to which palm oil or other factors drives the creation of these areas. That is one of the major limitations of this study. The most straightforward way to use remote sensing data to understand deforestation drivers is to look at the land covers, and associated land uses, that replace forests. When these areas are left idle, we cannot infer the land use from the remote sensing data alone. More research, particularly in situ social science research in unplanted land areas, is needed to understand why these areas being created and how they are used. Research into the dynamics of unplanted land within large-scale plantation landscapes is particularly lacking.

This study also found that deforestation overall, unplanted land creation, and the expansion of palm oil plantations in previously forested areas have all declined in recent years. The decline in palm oil plantations directly replacing primary forests is particularly hopeful, as it could indicate that government and private-sector initiatives to reform Indonesia's palm oil industry are working. However, as reported in Chapter 4, these declines have taken place during a period where palm oil prices were relatively low. Since 2020, palm oil prices have risen, driven by food and fuel shortages associated with the Covid-19 pandemic and the war in Ukraine. Previous research has found that increases in deforestation and palm oil expansion typically follow increases in palm oil prices. If this happens again, it could indicate that economic factors, rather than commitments to reduce carbon emissions, were driving the historically low deforestation rates observed over the past several years. However, if deforestation rates remain low as palm oil prices rise, it would provide even stronger evidence that policies are working.

My estimates of the declining rates of palm oil expansion and unplanted land creation are somewhat limited, however, by data availability, in particularly the availability of high resolution imagery to verify whether oil palms or other crops have been planted. In 2020, the land use could not be verified for 1.8 (+/-0.2) Mha of deforested land, and the presence or absence of palm oil could not be verified for 4.1 Mha (+/-0.3) of land located both in and outside of previously forested areas. This has important implications not just forthis study but for other studies reporting palm oil area in Indonesia. Within land that has been deforested, most indistinguishable clearing took place in the last two years of the study – 2019 and 2020 – meaning land use classes are most likely to be underestimated in those years. This data availability issue does not, however, impact my ability to report the area deforested in 2019 and 2020, as deforestation can be detected with Landsat imagery and does not typically need to be verified using high resolution data.

5.2 Opportunities for future research

Given the dramatic decline in deforestation that Indonesia has experienced in the last several years, the question I would most like to answer with this research is this: have Indonesia’s forest protection policies worked? Unfortunately, this research alone cannot fully answer that question. Measuring the impact of national-scale forest protection policies is difficult. The most robust way to establish causality would be to implement a policy using an experimental design, where specific regions would be randomly assigned to treatment and control groups[129]. When policies are implemented at a national or even regional scale, a true experimental design is typically not possible. It would be difficult if not impossible to randomly assign forest protection programs to countries, since their willingness to adopt or enforce an externally imposed program would be highly dependent on the local political will to protect forests generally, leading to selection bias. In Indonesia's case, policies were not randomly assigned but were designed to fit local political and economic contexts and implemented on a broad scale. In this context, observing an up or downward trend in deforestation after policies are implemented is not enough to establish causality. Instead, statistical tools such as matching analysis or cross-sectional regressions attempt to mimic experimental conditions. This technique, known as quasi-experimental design, has limitations, since it is difficult to control for all variables that may impact environmental outcomes. However, this type of analysis can provide stronger evidence of causality than evaluating trends alone[129].

A logical next step for this research would be to take the detailed data provided here on regional and temporal trends in Indonesia and apply quasi-experimental methods to attempt to draw more robust conclusions about the impact of policies relative to other factors affecting forest loss. Some existing studies have already done this using map-derived estimates of forest loss in Indonesia, including a recent study looking at the progress Indonesia has made in reducing carbon emissions under its agreement with Norway. Groom et al. found that while Indonesia fell short of its carbon reduction goals, the price Norway paid for the emissions Indonesia did avoid was still well under the amount they had agreed[93].

The Groom et al. study used data through 2018, so it did not fully capture the trend of the last few years, with deforestation rates remaining at record lows. Additionally, since the forest loss estimates used were derived from map pixel counting (based on the Hansen et al. tree cover loss product), the uncertainty in these estimates has not been quantified and we do not know how map bias may have impacted the results. Conducting a similar study evaluating avoided carbon emissions in Indonesia using my sample-derived estimates through the 2020 period is one possible avenue for future research.

Research into Brazil's a dramatic drop in deforestation in the mid-2000s is another way to see how data from this study might be used to evaluate policy impacts in Indonesia. The decline in Brazil has been widely attributed to the implementation and enforcement of government and private-sector policies designed to reduce deforestation within the Brazilian Amazon, in part due to research using quasi-experimental methods. This includes the decoupling of deforestation rates from soybean prices[130], lower rates of forest loss within protected areas, such as indigenous reserves, compared to similarly accessible forests outside protected areas[8], and changing patterns of illegal logging that suggest loggers are attempting to evade satellite monitoring. Brazil's more recent increases in annual primary forest loss under President Jair Bolsonaro, who is vocally opposed to forest protection and whose administration has worked to weaken agencies responsible for forest protection and monitoring, may also indicate that national-scale policies do have a real impact on deforestation rates, though I am not yet aware of any studies using the quasi-experimental methods to evaluate the impact Bolsonaro's administration has had on forests.

Palm oil is arguably Indonesia's most important commodity crop and a major driver of primary forest loss in the country, and previous studies have found that deforestation is correlated with palm oil prices[44,45,65,66,107]. This study found that Indonesia experienced high rates of palm oil expansion into previously forested areas during periods when palm oil prices were also high. More recently, palm oil expansion has slowed, although data limitations related to the availability of high resolution data mean these estimates are less reliable for the last few years of the study. Given the volatility of palm oil prices over the last two years, continued monitoring of palm oil expansion and deforestation trends, and econometric analyses to determine the extent to which these trends continue to be impacted by palm oil prices, is another interesting area for future research.

Bibliography

1. Gibbs, H. K. *et al.* Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. *Proc. Natl. Acad. Sci.* **107**, 16732–16737 (2010).
2. Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A. & Hansen, M. C. Classifying drivers of global forest loss. *Science* **361**, 1108 (2018).
3. Gardner, T. A. *et al.* Prospects for tropical forest biodiversity in a human-modified world. *Ecol. Lett.* **12**, 561–582 (2009).
4. Giam, X. Global biodiversity loss from tropical deforestation. *Proc. Natl. Acad. Sci.* **114**, 5775–5777 (2017).
5. Raven, P. H. Our Diminishing Tropical Forests. in *Biodiversity* (1999).
6. Gibson, L. *et al.* Primary forests are irreplaceable for sustaining tropical biodiversity. *Nature* **478**, 378–381 (2011).
7. Meijaard, E. *et al.* The historical range and drivers of decline of the Tapanuli orangutan. *PLOS ONE* **16**, e0238087 (2021).
8. Nolte, C., Agrawal, A., Silvius, K. M. & Soares-Filho, B. S. Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proc. Natl. Acad. Sci.* **110**, 4956–4961 (2013).
9. Nahar, L. *et al.* Naturally Occurring Calanolides: Occurrence, Biosynthesis, and Pharmacological Properties Including Therapeutic Potential. *Molecules* **25**, 4983 (2020).
10. Anti-HIV and anti-cancer drugs derived from Borneo rainforest progressing to final development stages. *Mongabay Environmental News*

https://news.mongabay.com/2009/06/anti-hiv-and-anti-cancer-drugs-derived-from-borneo-rainforest-progressing-to-final-development-stages/ (2009).

11. Harris, N. L. *et al.* Global maps of twenty-first century forest carbon fluxes. *Nat. Clim. Change* **11**, 234–240 (2021).
12. Kurnianto, S. *et al.* Carbon accumulation of tropical peatlands over millennia: a modeling approach. *Glob. Change Biol.* **21**, 431–444 (2015).
13. Page, S. E. *et al.* The amount of carbon released from peat and forest fires in Indonesia during 1997. *Nature* **420**, 61–65 (2002).
14. Hooijer, A. *et al.* Current and future CO₂ emissions from drained peatlands in Southeast Asia. *Biogeosciences* **7**, 1505–1514 (2010).
15. Boulton, C. A., Lenton, T. M. & Boers, N. Pronounced loss of Amazon rainforest resilience since the early 2000s. *Nat. Clim. Change* **12**, 271–278 (2022).
16. CNN, N. L. This country regrew its lost forest. Can the world learn from it? *CNN* https://www.cnn.com/2020/07/27/americas/reforestation-costa-rica-c2e-spc/index.html.
17. Sánchez-Azofeifa, G. A., Pfaff, A., Robalino, J. A. & Boomhower, J. P. Costa Rica's Payment for Environmental Services Program: Intention, Implementation, and Impact. *Conserv. Biol.* **21**, 1165–1173 (2007).
18. Nepstad, D. *et al.* The End of Deforestation in the Brazilian Amazon. *Science* **326**, 1350–1351 (2009).
19. COP26. Glasgow Leaders' Declaration on Forests and Land Use. *UN Climate Change Conference (COP26) at the SEC – Glasgow 2021* https://ukcop26.org/glasgow-leaders-declaration-on-forests-and-land-use/ (2021).

20. Song, X.-P. *et al.* Global land change from 1982 to 2016. *Nature* **560**, 639–643 (2018).

21. Hansen, M. C. *et al.* High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* **342**, 850 (2013).

22. Turubanova, S., Potapov, P. V., Tyukavina, A. & Hansen, M. C. Ongoing primary forest loss in Brazil, Democratic Republic of the Congo, and Indonesia. *Environ. Res. Lett.* **13**, 074028 (2018).

23. Amazon Rainforest: Highest deforestation rate in six years. *BBC News* (2022).

24. PAGE, S. E., RIELEY, J. O. & BANKS, C. J. Global and regional importance of the tropical peatland carbon pool. *Glob. Change Biol.* **17**, 798–818 (2011).

25. Van der Werf, G. R. *et al.* CO2 emissions from forest loss. *Nat. Geosci.* **2**, 737–738 (2009).

26. Shannon N Koplitz and Loretta J Mickley and Miriam E Marlier and Jonathan J Buonocore and Patrick S Kim and Tianjia Liu and Melissa P Sulprizio and Ruth S DeFries and Daniel J Jacob and Joel Schwartz and Montira Pongsiri and Samuel S Myers. Public health impacts of the severe haze in Equatorial Asia in September–October 2015: demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure. *Environ. Res. Lett.* **11**, 094023 (2016).

27. Indonesia terminates agreement with Norway on $1b REDD+ scheme. *Mongabay Environmental News* https://news.mongabay.com/2021/09/indonesia-terminates-agreement-with-norway-on-1b-redd-scheme/ (2021).

28. After GAR expands policy, over 50% of world's palm oil bound by zero deforestation commitments. *Mongabay Environmental News* https://news.mongabay.com/2014/03/after-gar-expands-policy-over-50-of-worlds-palm-oil-bound-by-zero-deforestation-commitments/ (2014).
29. After GAR expands policy, over 50% of world's palm oil bound by zero deforestation commitments. *Mongabay* http://news.mongabay.com/2014/0303-gar-palm-oil.html.
30. Greenpeace: APP making 'encouraging' progress on zero deforestation commitment. *Mongabay Environmental News* https://news.mongabay.com/2013/10/greenpeace-app-making-encouraging-progress-on-zero-deforestation-commitment/ (2013).
31. Carlson, K. M. *et al.* Effect of oil palm sustainability certification on deforestation and fire in Indonesia. *Proc. Natl. Acad. Sci.* 201704728 (2017).
32. Lambin, E. F. *et al.* The role of supply-chain initiatives in reducing deforestation. *Nat. Clim. Change* **8**, 109–116 (2018).
33. *Global forest monitoring from earth observation*. (CRC Press, 2013).
34. Official Deforestation Data for the Brazilian Amazon Now Available on Global Forest Watch | Global Forest Watch Blog. *Global Forest Watch Content* https://www.globalforestwatch.org/blog/data-and-research/official-deforestation-data-for-the-brazilian-amazon-now-available-on-global-forest-watch (2016).
35. Tyukavina, A. *et al.* Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. *Sci. Adv.* **3**, e1601047 (2017).

36. Richards, P., Arima, E., VanWey, L., Cohn, A. & Bhattarai, N. Are Brazil's Deforesters Avoiding Detection? *Conserv. Lett.* **10**, 470–476 (2017).

37. Morita, E. Y., Hiroaki Okonogi, and Takahiro. Protecting forests: Are early warning systems effective? *Brookings* https://www.brookings.edu/blog/future-development/2021/07/02/protecting-forests-are-early-warning-systems-effective/ (2021).

38. Margono, B. A., Potapov, P. V., Turubanova, S., Stolle, F. & Hansen, M. C. Primary forest cover loss in Indonesia over 2000–2012. *Nat. Clim. Change* **4**, 730–735 (2014).

39. Hansen, M. C. *et al.* Humid tropical forest disturbance alerts using Landsat data. *Environ. Res. Lett.* **11**, 034008 (2016).

40. Reiche, J. *et al.* Forest disturbance alerts for the Congo Basin using Sentinel-1. *Environ. Res. Lett.* **16**, 024005 (2021).

41. Xu, Y. *et al.* Annual oil palm plantation maps in Malaysia and Indonesia from 2001 to 2016. 21 (2020).

42. Descals, A. *et al.* High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth Syst. Sci. Data* **13**, 1211–1231 (2021).

43. Gaveau, D. L. A. *et al.* Rise and fall of forest loss and industrial plantations in Borneo (2000-2017). *Conserv. Lett.* e12622 (2018) doi:10.1111/conl.12622.

44. Gaveau, D. L. A. *et al.* Slowing deforestation in Indonesia follows declining oil palm expansion and lower oil prices. *PLOS ONE* **17**, e0266178 (2022).

45. Gaveau, D. L. A. *et al.* Rapid conversions and avoided deforestation: examining four decades of industrial plantation expansion in Borneo. *Sci. Rep.* **6**, (2016).

46. Gaveau, D. L. A. *et al.* Forest loss in Indonesian New Guinea (2001–2019): Trends, drivers and outlook. *Biol. Conserv.* **261**, 109225 (2021).

47. Miettinen, J., Shi, C., Tan, W. J. & Liew, S. C. 2010 land cover map of insular Southeast Asia in 250-m spatial resolution. *Remote Sens. Lett.* **3**, 11–20 (2012).

48. Harris, N., Goldman, E. D. & Gibbes, S. SPATIAL DATABASE OF PLANTED TREES (SDPT VERSION 1.0). 36.

49. Carlson, K. M. *et al.* Carbon emissions from forest conversion by Kalimantan oil palm plantations. *Nat. Clim. Change* **3**, 283–287 (2012).

50. Oon, A. *et al.* Assessment of ALOS-2 PALSAR-2L-band and Sentinel-1 C-band SAR backscatter for discriminating between large-scale oil palm plantations and smallholdings on tropical peatlands. *Remote Sens. Appl. Soc. Environ.* **13**, 183–190 (2019).

51. Miettinen, J. & Liew, S. C. Separability of insular Southeast Asian woody plantation species in the 50 m resolution ALOS PALSAR mosaic product. *Remote Sens. Lett.* **2**, 299–307 (2011).

52. Descals, A. *et al.* Oil Palm (Elaeis guineensis) Mapping with Details: Smallholder versus Industrial Plantations and their Extent in Riau, Sumatra. *Remote Sens.* **11**, 2590 (2019).

53. Adrianto, Spracklen, & Arnold. Relationship Between Fire and Forest Cover Loss in Riau Province, Indonesia Between 2001 and 2012. *Forests* **10**, 889 (2019).

54. Marlier, M. E. *et al.* Future fire emissions associated with projected land use change in Sumatra. *Glob. Change Biol.* **21**, 345–362 (2015).

55. Gaveau, D. L. A., Descals, A., Salim, M. A., Sheil, D. & Sloan, S. Refined burned-area mapping protocol using Sentinel-2 data increases estimate of 2019 Indonesian burning. *Earth Syst. Sci. Data* **13**, 5353–5368 (2021).
56. Gaveau, D. L. A. *et al.* Major atmospheric emissions from peat fires in Southeast Asia during non-drought years: evidence from the 2013 Sumatran fires. *Sci. Rep.* **4**, 6112 (2014).
57. Tyukavina, A. *et al.* Global Trends of Forest Loss Due to Fire From 2001 to 2019. *Front. Remote Sens.* **3**, 825190 (2022).
58. Olofsson, P. *et al.* Good practices for estimating area and assessing accuracy of land change. *Remote Sens. Environ.* **148**, 42–57 (2014).
59. Hansen, M. C. *et al.* High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* **342**, 850–853 (2013).
60. Fountain, H. Deforestation Remains High, Despite International Pledges. *The New York Times* (2022).
61. Harvey, F. & correspondent, F. H. E. Destruction of world's forests increased sharply in 2020. *The Guardian* (2021).
62. Afifa, L. Jokowi Makes Moratorium on Forest Clearance Permanent. *Tempo* https://en.tempo.co/read/1233740/jokowi-makes-moratorium-on-forest-clearance-permanent (2019).
63. Harvey, C. Indonesia just made a huge move to protect the climate. *Washington Post* (2016).

64. 'Forests will disappear again,' activists warn as Indonesia ends plantation freeze. *Mongabay Environmental News* https://news.mongabay.com/2021/12/forests-will-disappear-again-activists-warn-as-indonesia-ends-plantation-freeze/ (2021).
65. Austin, K. G., Schwantes, A., Gu, Y. & Kasibhatla, P. S. What causes deforestation in Indonesia? *Environ. Res. Lett.* **14**, 024007 (2019).
66. Abood, S. A., Lee, J. S. H., Burivalova, Z., Garcia-Ulloa, J. & Koh, L. P. Relative Contributions of the Logging, Fiber, Oil Palm, and Mining Industries to Forest Loss in Indonesia. *Conserv. Lett.* **8**, 58–67 (2014).
67. NDPE Policies Cover 83% of Palm Oil Refineries; Implementation at 78%. *Chain Reaction Research* https://chainreactionresearch.com/report/ndpe-policies-cover-83-of-palm-oil-refineries-implementation-at-75/ (2020).
68. Hiratsuka, M., Toma, T., Diana, R., Hadriyanto, D. & Morikawa, Y. Biomass Recovery of Naturally Regenerated Vegetation after the 1998 Forest Fire in East Kalimantan, Indonesia. *Jpn. Agric. Res. Q. JARQ* **40**, 277–282 (2006).
69. Siegert, F., Ruecker, G., Hinrichs, A. & Hoffmann, A. A. Increased damage from ®res in logged forests during droughts caused by El NinÄ o. **414**, 4 (2001).
70. Simorangkir, D. Fire use: Is it really the cheaper land preparation method for large-scale plantations? *Mitig. Adapt. Strateg. Glob. Change* **12**, 147–164 (2006).
71. Adrianto, H. A., Spracklen, D. V., Arnold, S. R., Sitanggang, I. S. & Syaufina, L. Forest and Land Fires Are Mainly Associated with Deforestation in Riau Province, Indonesia. *Remote Sens.* **12**, 3 (2019).
72. Li, J. *et al.* El Niño modulations over the past seven centuries. *Nat. Clim. Change* **3**, 822–826 (2013).

73. Yeh, S.-W. *et al.* El Niño in a changing climate. *Nature* **461**, 511–514 (2009).
74. Wang, B. *et al.* Historical change of El Niño properties sheds light on future changes of extreme El Niño. *Proc. Natl. Acad. Sci.* **116**, 22512–22517 (2019).
75. Houghton, R. A. Carbon emissions and the drivers of deforestation and forest degradation in the tropics. *Curr. Opin. Environ. Sustain.* **4**, 597–603 (2012).
76. Barlow, J. *et al.* Quantifying the biodiversity value of tropical primary, secondary, and plantation forests. *Proc. Natl. Acad. Sci.* **104**, 18555–18560 (2007).
77. Hansen, M. C. *et al.* The fate of tropical forest fragments. *Sci. Adv.* **6**, eaax8574 (2020).
78. Esquivel-Muelbert *et al.* A Spatial and Temporal Risk Assessment of the Impacts of El Niño on the Tropical Forest Carbon Cycle: Theoretical Framework, Scenarios, and Implications. *Atmosphere* **10**, 588 (2019).
79. Setiawan, E. N., Maryudi, A., Purwanto, R. H. & Lele, G. Opposing interests in the legalization of non-procedural forest conversion to oil palm in Central Kalimantan, Indonesia. *Land Use Policy* **58**, 472–481 (2016).
80. Olofsson, P. *et al.* Good practices for estimating area and assessing accuracy of land change. *Remote Sens. Environ.* **148**, 42–57 (2014).
81. *The State of Indonesia's Forests 2020*. https://balaikliringkehati.menlhk.go.id/wp-content/uploads/The-State-of-Indonesias-Forest-2020.pdf (2020).
82. Pirard, R. & Irland, L. C. Missing links between timber scarcity and industrial overcapacity: Lessons from the Indonesian Pulp and Paper expansion. *For. Policy Econ.* **9**, 1056–1070 (2007).

83. Barr, C. Banking on sustainability: structural adjustment and forestry reform in post-Suharto Indonesia. 142.
84. Cisneros, E., Kis-Katos, K. & Nuryartono, N. Palm oil and the politics of deforestation in Indonesia. *J. Environ. Econ. Manag.* **108**, 102453 (2021).
85. Burgess, R., Hansen, M., Olken, B. A., Potapov, P. & Sieber, S. The Political Economy of Deforestation in the Tropics. *Q. J. Econ.* **127**, 1707–1754 (2012).
86. Project, G. The making of a palm oil fiefdom. *The Gecko Project* https://thegeckoproject.org/the-making-of-a-palm-oil-fiefdom-7e1014e8c342 (2017).
87. What Happened to Forests in 2021? | Global Forest Watch Blog. *Global Forest Watch Content* https://research.wri.org/gfr/latest-analysis-deforestation-trends (2022).
88. IMF. Global price of Palm Oil (PPOILUSDM).
89. Goldstein, J. Carbon Bomb: Indonesia's Failed Mega Rice Project. 6 (2019).
90. Indonesia pushes rice estate project despite environmental red flags. https://news.mongabay.com/2020/08/indonesia-mega-rice-estate-project-kalimantan-borneo-peat-wetland/.
91. Indonesia's fires are bad, but new measures prevented them from becoming worse. https://www.science.org/content/article/indonesias-fires-are-bad-new-measures-prevented-them-becoming-worse.
92. Busch, J. *et al.* Reductions in emissions from deforestation from Indonesia's moratorium on new oil palm, timber, and logging concessions. *Proc. Natl. Acad. Sci.* **112**, 1328–1333 (2015).

93. Groom, B., Palmer, C. & Sileci, L. Carbon emissions reductions from Indonesia's moratorium on forest concessions are cost-effective yet contribute little to Paris pledges. *Proc. Natl. Acad. Sci.* **119**, e2102613119 (2022).
94. Indonesia expands protection for peatlands. http://finance.yahoo.com/news/indonesia-expands-protection-peatlands-095331124.html.
95. Post, T. J. Jokowi imposes moratorium on palm oil plantations. *The Jakarta Post* http://www.thejakartapost.com/news/2018/09/20/jokowi-imposes-moratorium-on-palm-oil-plantations.html.
96. STATEMENT: Indonesia Expands Protection of Carbon-Rich Peatlands With Update to Government Regulation. (2016).
97. Tyukavina, A. *et al.* Congo Basin forest loss dominated by increasing smallholder clearing. *Sci. Adv.* 13 (2018).
98. Turubanova, S., Potapov, P. V., Tyukavina, A. & Hansen, M. Ongoing primary forest loss in Brazil, Democratic Republic of the Congo, and Indonesia. *Environ. Res. Lett.* (2018) doi:10.1088/1748-9326/aacd1c.
99. Kustiyo *et al.* Annual Forest Monitoring as Part of the Indonesia's National Carbon Accounting System. (2015).
100. Potapov, P. V. *et al.* Quantifying forest cover loss in Democratic Republic of the Congo, 2000–2010, with Landsat ETM+ data. *Remote Sens. Environ.* **122**, 106–116 (2012).
101. Potapov, P. *et al.* Landsat Analysis Ready Data for Global Land Cover and Land Cover Change Mapping. *Remote Sens.* **12**, 426 (2020).

102. REDD+ - Home. https://redd.unfccc.int/.

103. Geist, H. J. & Lambin, E. F. Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *BioScience* **52**, 143 (2002).

104. Zalles, V. *et al.* Near doubling of Brazil's intensive row crop area since 2000. *Proc. Natl. Acad. Sci.* **116**, 428–435 (2019).

105. Hosonuma, N. *et al.* An assessment of deforestation and forest degradation drivers in developing countries. *Environ. Res. Lett.* **7**, 044009 (2012).

106. Seymour, F. & Harris, N. L. Reducing tropical deforestation. *Science* **365**, 756–757 (2019).

107. Koh, L. P. & Wilcove, D. S. Is oil palm agriculture really destroying tropical biodiversity? *Conserv. Lett.* **1**, 60–64 (2008).

108. Austin, K. G. *et al.* Shifting patterns of oil palm driven deforestation in Indonesia and implications for zero-deforestation commitments. *Land Use Policy* **69**, 41–48 (2017).

109. Gaveau, D. *et al. Slowing deforestation in Indonesia follows declining oil palm expansion and lower oil prices*. https://www.researchsquare.com/article/rs-143515/v1 (2021) doi:10.21203/rs.3.rs-143515/v1.

110. Cazzolla Gatti, R. & Velichevskaya, A. Certified "sustainable" palm oil took the place of endangered Bornean and Sumatran large mammals habitat and tropical forests in the last 30 years. *Sci. Total Environ.* **742**, 140712 (2020).

111. Mayr, S., Hollaus, B. & Madner, V. Palm oil, the RED II and WTO law: EU sustainable biofuel policy tangled up in green? *Rev. Eur. Comp. Int. Environ. Law* **30**, 233–248 (2021).

112. Malaysia initiates WTO dispute complaint against EU palm oil measures. https://www.wto.org/english/news_e/news21_e/ds600rfc_19jan21_e.htm.

113. Europe, in bid to phase out palm biofuel, leaves fans and foes dismayed. *Mongabay Environmental News* https://news.mongabay.com/2019/03/europe-in-bid-to-phase-out-palm-biofuel-leaves-fans-and-foes-dismayed/ (2019).

114. Gingold, B. *et al.* How to Identify Degraded Land for Sustainable Palm Oil in Indonesia. 24.

115. Goh, C. S. *et al.* Exploring under-utilised low carbon land resources from multiple perspectives: Case studies on regencies in Kalimantan. *Land Use Policy* **60**, 150–168 (2017).

116. Goh, C. S., Junginger, M., Potter, L., Faaij, A. & Wicke, B. Identifying key factors for mobilising under-utilised low carbon land resources: A case study on Kalimantan. *Land Use Policy* **70**, 198–211 (2018).

117. Brazil's key deforestation drivers: Pasture, cropland, land speculation. *Mongabay Environmental News* https://news.mongabay.com/2019/03/brazils-key-deforestation-drivers-pasture-cropland-land-speculation/ (2019).

118. McCarthy, J. F., Vel, J. A. C. & Afiff, S. Trajectories of land acquisition and enclosure: development schemes, virtual land grabs, and green acquisitions in Indonesia's Outer Islands. *J. Peasant Stud.* **39**, 521–549 (2012).

119. Purnomo, H. *et al.* Fire economy and actor network of forest and land fires in Indonesia. *For. Policy Econ.* **78**, 21–31 (2017).

120. Purnomo, H. *et al.* Reducing forest and land fires through good palm oil value chain governance. *For. Policy Econ.* **91**, 94–106 (2018).

121. Medrilzam, M., Dargusch, P., Herbohn, J. & Smith, C. The socio-ecological drivers of forest degradation in part of the tropical peatlands of Central Kalimantan, Indonesia. *For. Int. J. For. Res.* **87**, 335–345 (2014).

122. Indonesian president signs 3-year freeze on new oil palm licenses. *Mongabay Environmental News* https://news.mongabay.com/2018/09/indonesian-president-signs-3-year-freeze-on-new-oil-palm-licenses/ (2018).

123. Indonesia is clearing less forest for palm oil, but it's still not sustainable, activists say. *Mongabay Environmental News* https://news.mongabay.com/2022/01/indonesia-is-clearing-less-forest-for-palm-oil-but-its-still-not-sustainable/ (2022).

124. Meijaard, E. *et al.* The environmental impacts of palm oil in context. *Nat. Plants* **6**, 1418–1426 (2020).

125. Pirker, J., Mosnier, A., Kraxner, F., Havlík, P. & Obersteiner, M. What are the limits to oil palm expansion? *Glob. Environ. Change* **40**, 73–81 (2016).

126. Smedley, T. EU labelling changes force industry action on palm oil. *The Guardian* (2014).

127. EU response to palm oil is opportunity, not threat (commentary). *Mongabay Environmental News* https://news.mongabay.com/2022/03/eu-response-to-palm-oil-is-opportunity-not-threat-commentary/ (2022).

128. OIl palm cover in Indonesia: An Analysis of Satellite Imagery from 2014-2016. (2019).

129. Ferraro, P. J. Counterfactual thinking and impact evaluation in environmental policy. *New Dir. Eval.* **2009**, 75–84 (2009).

130. Macedo, M. N. *et al.* Decoupling of deforestation and soy production in the southern Amazon during the late 2000s. *Proc. Natl. Acad. Sci.* **109**, 1341–1346 (2012).