Assessing the effectiveness of zero-deforestation commitments

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ASSESSING THE EFFECTIVENESS OF ZERO-DEFORESTATION COMMITMENTS

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Floris Casper Leijten

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"It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of light, it was the season of darkness, it was the spring of hope, it was the winter of despair."

Charles Dickens, 1859, A Tale of Two Cities

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Summary

Summary

Forests are indispensable assets for mitigating climate change, protecting biodiversity and reducing poverty. While this has been widely recognized, vast swathes of forests are cleared each year, predominantly to make space for agricultural land. Since the 1980s, agricultural expansion into forest areas has been increasingly linked to international supply chains, especially of agricultural commodities such as beef, palm oil, soy, and timber. In response to the ongoing rates of forest loss, a large number of companies involved in the production, processing or distribution of deforestation-risk commodities publicly pledged to eliminate deforestation from their supply chains in the early 2010s.

Although these so-called Zero-Deforestation Commitments (ZDCs) have received ample scholarly attention, there are still large uncertainties as to how effective they have been up until now and how effective they could be if their uptake was increased. This is partly due to methodological challenges for assessing their effectiveness given the wide variation in specificity and adoption rates across industries, regions, and timescales. Moreover, it is conceivable that their implementation will trigger a range of unintended or unanticipated spillover effects, such as increased nature loss in areas that fall beyond the scope of ZDCs. Given such complexities, a variety of methodological approaches is needed to assess their effectiveness across space and time.

The overarching objective of this thesis is to investigate what insights can be gained from applying different approaches to assess the effectiveness of ZDCs and the degree of complementarity between these different approaches. In doing so, special attention will be paid to three distinct methodological approaches that hold great promise for advancing assessments of ZDC effectiveness: geospatial analysis, quasi-experimental designs for causal inference, and simulation modelling. While none of the three approaches is by itself sufficiently flexible to be applied in all types of ZDC assessments, they may – when combined – act in synergistic ways, thereby uncovering non-trivial insights on ZDCs effectiveness that cannot be derived from one of these approaches in isolation. By applying these three different methodological approaches across the thesis with each chapter predominantly relying on a single approach, the following four sub-questions will be addressed:

- How can geospatial analysis be leveraged to advance assessments (ex-post or ex-ante) of ZDCs?
- How do the insights from quasi-experimental assessments of the effectiveness of ZDCs differ from ex-ante simulation modelling assessments?
- What is the degree of complementarity between the different approaches?
- What do the different approaches tell us about the (potential) effectiveness of ZDCs?

Chapter 2 takes stock of the different definitions and criteria articulated in ZDCs and maps the potential coverage of ZDCs through geospatial analysis. Many ZDCs state that the protection of High Conservation Value Forests (HCVFs) and High Carbon Stock Forests (HCSFs) needs to be prioritized. However, the methodologies for identifying such forests were developed for local, case-by-case application as they require extensive field assessments and access to high-resolution remotely sensed datasets. In the absence of a clear methodology for delineating HCVFs and HCSFs at the global scale, Chapter 2 tries to fill this gap by putting forward a methodology for mapping the likely spatial distribution of both forests across the globe, thereby drawing on the official criteria articulated in the official HCVF and HCSF guidelines. In addition, it examines the risk that protecting HCVFs and HCSFs may displace deforestation to forests outside the scope of ZDCs. Overall, the chapter demonstrates the importance of geospatial analysis in any type of empirical research on ZDCs.

Chapter 3 builds on Chapter 2 by zeroing in on the local spillover effects (positive or negative) that may have occurred in the wake of a specific anti-deforestation policy: the Indonesian forest moratorium, enacted in 2011. To estimate how much deforestation may have been displaced or avoided near the official moratorium areas, one needs to construct a counterfactual scenario of what would have happened in the absence of the moratorium. Capitalizing on recent methodological developments in quasi-experimental research, the chapter provides a first-of-its-kind analysis and finds strong evidence that the enactment of the moratorium caused an uptick in deforestation near the official moratorium boundaries. In doing so, the chapter highlights the importance of accounting for spillover effects when assessing land-based anti-deforestation policies and the power of quasi-experimental techniques for uncovering causal relationships in the face of myriad confounding factors.

Chapter 4 takes a deep dive into the role that sourcing patterns of individual traders in Brazil's soy supply chain may play in the adoption and implementation of ZDCs. Similar to Chapter 3, state-of-the-art quasi-experimental methods are employed to infer a potential causal relationship, in this case between the degree of sourcing persistence in individual supply chains (i.e., stickiness) and the probability of adopting a ZDCs. Furthermore, the chapter examines whether stickier traders with ZDCs are more likely to successfully implement a ZDC compared to less sticky traders. The results show that although stickier traders are more likely to adopt ZDCs, they also appear to have less effective ZDCs than other traders (as indicated by the level of soy and territorial deforestation in their sourcing regions). While this does not necessarily mean that supply chain stickiness inevitably undermines the implementation of ZDCs, the chapter provides a first step towards a better understanding of how supply chain relationships may influence deforestation outcomes.

Chapter 5 builds on the previous chapters by providing an ex-ante hypothetical modelling experiment on how the worldwide implementation ZDCs could potentially affect the expansion of oil palm and other crops up until 2030, thereby accounting for potential spillover effects. In doing so, it leverages the maps presented in Chapter 2 showing the potential spatial coverage of ZDCs. The results suggest that under a scenario where ZDCs are strictly enforced across industries and regions, they are likely to bring about significant land sparing effects and reduce deforestation rates by a significant degree, even in areas that fall beyond the scope of ZDCs. This is because a reduction in the supply of land available for agricultural expansion is expected to boost land rental rates, thus incentivizing producers to intensify production on existing lands. In addition, higher land rental rates will translate into higher commodity prices and are expected to substantially reduce consumption of palm oil and other deforestation-risk commodities. Such insights are hard to gain from geospatial analysis or quasi-experimental assessments alone and highlight the importance of ex-ante simulation methods for exploring potential, future outcomes of ZDCs. While it is unlikely that the adoption and implementation rate of ZDCs across industries and regions will be anywhere near 100 percent in the coming decade, the chapter provides strong quantitative evidence that ZDCs hold potential for safeguarding the world's remaining forests if they are to be adopted at scale.

Taken together, the chapters show that none of the methodological approaches applied in the thesis – geospatial analysis, quasi-experimental designs for causal inference, and simulation modelling – are by themselves sufficiently flexible to assess all aspects of ZDCs effectiveness. While quasi-experimental methods are invaluable tools for exploring causal relationships over historic time periods, such relationships are often context-dependent and only apply to certain periods of time. Simulation models incorporate systems thinking and are therefore well-placed to explore future scenarios, but are only as reliable as the assumptions upon which they are based, which need to be evaluated through quasi-experimental evidence. Finally, both quasi-experimental and ex-ante simulation assessments would benefit from a deeper integration of geospatial analysis, as it provides the necessary level of spatial granularity to explore ZDC effectiveness. The three different methodological approaches applied in this thesis are thus highly complementary. When combined, they constitute a rigorous portfolio of approaches that enables researchers to assess both the actual and potential effectiveness of ZDCs under a wide range of conditions. It is hoped that this will help policy makers, companies, and civil society to make more informed decisions as to how targets regarding deforestation and other societal targets can be reconciled, thereby paving the way towards a more sustainable future.

1

Introduction

1.1. Background

Over the past 10,000 years, the world has lost one-third of its forests, an area twice the size of the United States of America (Dargavel and Williams 2004, Ellis *et al* 2020b). An estimated 420 million ha or 7% of the world's original forest area has been cleared since 1990, of which over 90% occurred within the tropical zone (FAO 2020). The increasing loss of forests poses significant challenges for climate change mitigation, biodiversity protection and poverty reduction (Seymour and Busch 2016, Johnson *et al* 2020). As an example, it is estimated that net emissions from tropical deforestation (after accounting for carbon sequestration from growing forests) account for 8% of annual anthropogenic emissions (Wolosin and Harris 2018). However, given their potential for sequestering carbon from the atmosphere, the potential of forests to mitigate global warming is much larger. It is estimated that reductions in both tropical deforestation and conversion of mangroves and wetlands could deliver up to 23% of the mitigation needed by 2030 to limit global warming to 2°C (Griscom *et al* 2017).

The last few decades have witnessed a major shift in the dominant drivers of deforestation. Up until the 1980s, deforestation was primarily driven by small-scale, state-supported farmers producing for local markets (Rudel *et al* 2009). Since then, there has been a gradual shift toward large-scale, enterprise-driven deforestation, spurred by augmented consumer demand in international markets (Austin *et al* 2017, Hosonuma *et al* 2012). While most deforestation is still driven by domestic demand for agricultural commodities, it is estimated that 26% of all deforestation in the period 2005 – 2013 was driven by exports (Pendrill *et al* 2019). It is expected that the global trade of all major agricultural commodities will continue to grow over the next decade, despite a temporary setback caused by the effects of the COVID-19 pandemic crisis (Wunder *et al* 2021).

Concerns about the ongoing rates of forest loss have given rise to a proliferation of initiatives to reduce deforestation across public and private sectors. Broadly speaking, three different types of such initiatives can be distinguished: 1) domestic public policies, often concerned with the establishment of legally protected areas; 2) intergovernmental initiatives such as the Reducing Emissions from Deforestation and forest Degradation (REDD+) program; and 3) voluntary sustainable supply chain initiatives within the private sector. The REDD+ program was launched in the late 2000s to improve on domestic public policies by enabling developing countries to receive payments from industrialized countries for verified emission reductions from deforestation and forest degradation. Although there have been a few cases where REDD+ has been credited for curbing deforestation to a significant extent (e.g., Roopsind *et al.*, 2019), the effectiveness of the program has been undermined by the international community's failure to generate financing of sufficient scale to reward action to reduce deforestation (Angelsen *et al* 2017, Seymour and Busch 2016) and overstated crediting deforestation baselines (West *et al* 2020).

In response to the growing recognition of the alarming deforestation rates and the challenges underpinning the REDD+ program, a large number of companies involved in the production, processing or distribution of deforestation-risk commodities have undertaken voluntary sustainable supply chain initiatives to reduce deforestation (Lambin *et al* 2018). In addition to the wide-scale endorsement of certification programmes such as the Roundtable of Sustainable Palm Oil (RSPO) or the adoption of collective aspirations to end deforestation, such as under the 2014 New York Declaration on Forests, this included individual pledges by companies to eliminate or reduce deforestation from their supply chains, often referred to as Zero-Deforestation Commitments (ZDCs). Given the growing recognition of the role of international supply chains in meeting deforestation targets (Thorlakson *et al* 2018), the zero-deforestation movement gained a lot of traction in the 2010s. Between 2012 and 2017, the number of companies with ZDCs increased by 250%, resulting in a total of 336 companies (Haupt *et al* 2018).

Although ample scholarly attention has been paid to the challenges and opportunities of designing and implementing ZDCs (Grabs *et al* 2021, Garrett *et al* 2019, Austin *et al* 2021), there are still large uncertainties as to how effective they have been up until now and how effective they could be if their uptake was increased. This is partly due to methodological challenges for assessing their effectiveness; ZDCs tend to be heterogeneous in terms of their specificity and their adoption varies across industries, regions, and timescales (Pirard *et al* 2015). Moreover, it is conceivable that their implementation will trigger a range of unintended or unanticipated spillover effects, such as increased nature loss in areas that fall beyond the scope of ZDCs (often referred to as leakage or displacement effects; Aukland *et al.*, 2003). Given such complexities, a variety of methodological approaches is needed to assess their effectiveness across space and time.

1.2. Approaches for assessing ZDCs

In what follows, three promising methodological approaches will be discussed that could be leveraged to advance assessments of ZDCs. These approaches include geospatial analysis, quasi-experimental analysis, and simulation modelling. While this is by no means an exhaustive list of the methodological approaches that could be undertaken to assess ZDCs, these have been repeatedly applied in the literature to assess the effectiveness of a number of related policies and therefore hold great promise for improving future assessments of ZDCs.

1.2.1. Geospatial analysis

Geospatial analysis refers to all transformations, manipulations and methods that can be applied to data referencing a specific geographical area or location (Longley *et al* 2020).

It is key to account for the role of spatial heterogeneity and the linkages between local and global phenomena (Hertel *et al* 2019). Applied sustainability research has for a long time been constrained by the limited availability of geospatial data, but such data have become increasingly accessible for the scientific community, stemming from advances in remote sensing (Vancutsem *et al* 2021), promotion of supply chain transparency (Tayleur and Phalan 2018), and the ubiquitous increases in computing and processing power (Huang and Wang 2020).

The increasing wealth of geospatial data has facilitated a surge in the geospatial assessments of anti-deforestation policies. High resolution spatiotemporal data sets such as the annual tree cover loss dataset from (Hansen *et al* 2013) enable fine-scale monitoring of deforestation and have been repeatedly leveraged to identify deforestation hotspots (Harris *et al* 2017). In addition, the increasing availability of fine-scale socio-economic and agronomic data enable detailed spatial assessments of how anti-deforestation policies could affect land use and a wide range of environmental outcomes (Srinivasan *et al* 2021, Pirker *et al* 2016). The opportunities of assessing such policies have been further enhanced through the Spatially Explicit Information on Production to Consumption Systems (SEI-PCS) approach, which traces company-specific exports of commodities back to subnational jurisdictions, resulting in the TRASE dataset (Trase 2020b, Godar *et al* 2016).

Although geospatial analysis has been increasingly integrated into ZDC assessments – for example through quantifying deforestation risk associated with individual supply chains (zu Ermgassen *et al* 2020), the potential of geospatial analysis remains largely untapped. For example, there are large uncertainties regarding the spatial coverage of ZDCs, which constitutes a major hurdle for increasing their effectiveness (Haupt *et al* 2018). In addition, ex-ante simulations of ZDC effectiveness are hampered by large uncertainties in the future availability of land as previous estimates of cropland availability have to failed to account for spatially heterogeneous cropping systems (Eitelberg *et al* 2015). This underlines the importance of geospatial analysis for advancing assessments of ZDC effectiveness.

1.2.2. Quasi-experimental methods

Causal inference is indispensable for monitoring progress against ZDCs. Randomized controlled trials (RCTs) – trials in which subjects are randomly assigned to treatment and control groups – are typically considered the 'gold standard' for inferring a causal relationship (Rubin 2008). Random assignment solves the problem of selection bias when covariates are unequally distributed across the sample of interest. Whilst RCTs have been increasingly used in social science (Bouguen *et al* 2019) and even in conservation science (e.g., Jayachandran *et al.*, 2017), their application remains limited due to ethical, financial, and practical concerns (Baldassarri and Abascal 2017). This is especially true for large-scale anti-deforestation policies, which by virtue of their high stakes are unlikely to be randomly assigned across companies or geographies. Quasi-experimental methods have been developed to identify the causal impact of a particular intervention or policy measure when randomization is not possible. They aim to mimic randomized trials by comparing treatment and control groups after controlling for confounding variables. This provides an indication as to what may have happened in the absence of the treatment (i.e., the counterfactual scenario), which can be used to estimate the direction and magnitude of the hypothesized causal effect.

However, a challenge underpinning quasi-experimental methods is that they can never exclude the possibility of endogeneity. Endogeneity occurs when the analysis suffers from omitted variables bias, reverse causality or measurement error. It results in biased parameter estimates and potential misguided estimates of the causal effect. Nevertheless, quasi-experimental methods are considered the second-best alternative for estimating causal treatment effects (Angrist and Pischke 2008). Moreover, they have become increasingly sophisticated in recent years, spurred by advancements in econometric theory as well as increases in computing power (Abadie and Cattaneo 2018), which is why they are increasingly adopted for causal inference.

Quasi-experimental methods have been widely used for ex post evaluations of various anti-deforestation initiatives. In particular, there have been many such evaluations of the effectiveness of protected areas (e.g., Eklund *et al.*, 2016; Ferraro *et al.*, 2013; Jones and Lewis, 2015), REDD+ initiatives (e.g., Ellis *et al.*, 2020; Roopsind *et al.*, 2019; West *et al.*, 2020) and sustainability certification schemes (e.g., Blackman *et al.*, 2018; Carlson *et al.*, 2018) These studies typically exploit large panel (longitudinal) datasets and employ a difference-in-difference (DID) design with fixed effects regression models. In addition, statistical matching techniques and synthetic controls have become popular ways to evaluate conservation programs, partly because these do not rely on the strong assumptions that underpin regression analysis (Schleicher *et al* 2020).

Despite the wealth of literature adopting quasi-experimental methods to assess anti-deforestation policies, there have been relatively few attempts to empirically assess the effectiveness of ZDCs, most likely because subnational data on individual supply chains were unavailable until recently. Most studies have focused on collective ZDCs such as the Amazon Soy Moratorium or the G4 Cattle Agreement in Brazil (e.g., Alix-Garcia and Gibbs, 2017; Heilmayr *et al.*, 2020b), which do not require data on individual supply chains. To the best of the author's knowledge, zu Ermgassen *et al* (2020) is the only empirical assessment of ZDCs employing data on individual supply chains. However, no quasi-experimental methods were employed and hence, the study does not attempt to evaluate the causal effect of ZDCs on deforestation, but rather the deforestation risk associated with individual supply chains. Hence, to effectively evaluate the causal effect of ZDCs, quasi-experimental methods should be incorporated into future assessments.

1.2.3. Simulation modelling

Simulation modelling is broadly concerned with the application of parameterized computer models to predict potential states of a pre-specified system (Freebairn *et al* 2016). In contrast to quasi-experimental methods, they heavily draw on systems thinking and assumptions as to how systems respond in the face of external shocks. Notable examples of often-applied simulation models in the land system science literature include computable general equilibrium (CGE) models, partial equilibrium models, agent-based models, or spatial dynamic models. One of their unique features is their ability to explicitly account for iterative feedback loops, which is particularly useful when simulating processes that are non-stationary (i.e., changing over time). As a result, they have been widely adopted to explore the outcomes of a wide range of land use policies. For example, such models have been repeatedly employed to project the possible implications of biofuel mandates (e.g., Golub and Hertel, 2012; Searchinger *et al.*, 2008; Taheripour and Tyner, 2020), conservation programs (Wolff *et al* 2018, Suwarno *et al* 2018), or REDD+ programs (Kuik 2014, West *et al* 2018).

Although there have been a few studies simulating the ex-ante effectiveness of ZDCs, they all tend to focus on a single sector within a single country (Soterroni *et al* 2019, Mosnier *et al* 2017). This could give rise to misleading conclusions if deforestation is displaced to other economic sectors or countries (Bastos Lima *et al* 2019). To the best of the author's knowledge, Villoria (2021) is the only study that takes an economy-wide approach to assess the implications of ZDC, focusing on the soy sector in South America. However, as their results are aggregated at the country-level, they provide little insights into how local landscapes will be affected. Economy-wide projections at the pixel level would thus be a major step forwards towards improving ex-ante simulations of ZDC effectiveness.

1.3. Research gaps and objectives

The foregoing has highlighted the untapped potential of three approaches that could be leveraged to advance assessments of ZDCs. While each of these holds great potential for analysing ZDCs, none offers a comprehensive mode of analysis to measure and explain all aspects of ZDC effectiveness. For example, geospatial analysis can be leveraged to provide more spatial granularity to ZDC assessments and account for local spatiotemporal dynamics but does not directly inform on the actual or potential effectiveness of ZDCs. While quasi-experimental methods are invaluable tools for inferring historic causal relationships, there are poorly equipped to anticipate future impacts and implications of ZDCs in the face of non-stationarity. By virtue of their ability to explicitly account for feedback loops, ex-ante simulation methods are arguably better placed to assess the future impacts of ZDCs. However, the outcomes of simulation models are only as reliable as the assumptions upon which they are based, which is why geospatial analysis and quasi-experimental assessments are needed to assess how well these models perform against historic periods in geographic areas of interest.

Thus, while none of the three approaches is by itself sufficiently flexible to be applied in all types of ZDC assessments, they may – when combined – act in synergistic ways, thus uncovering non-trivial insights on ZDCs effectiveness that cannot be derived from one of these approaches in isolation. Although there are many more methodological approaches that could complement ZDC assessments other than the ones that have been described above, a deeper integration of these three approaches into ZDC assessments would help build a more holistic understanding of ZDC effectiveness.

For that reason, *the overarching objective of this thesis is to investigate what insights can be gained from applying different approaches for assessing the effectiveness of ZDCs and the degree of complementarity between these different approaches*. In doing so, the following four sub-questions will be addressed:

1. How can geospatial analysis be leveraged to advance assessments (ex-post or ex-ante) of ZDCs?
2. How do the insights from quasi-experimental assessments of the effectiveness of ZDCs differ from ex-ante simulation modelling assessments?
3. What is the degree of complementarity between the different approaches?
4. What do the different approaches tell us about the (potential) effectiveness of ZDCs?

1.4. Thesis outline

This thesis contains 6 chapters in total. In Chapters 2 – 5, the three complementary methodological approaches discussed above are repeatedly applied to assess the effectiveness of ZDCs. The degree to which each of the three methodological approaches is applied varies across the 4 chapters, with each chapter predominantly relying on a single approach (see Figure 1).

Chapter 2 provides a spatial overview of the global forests that may be protected by ZDCs under a scenario of full implementation and enforcement across industries and regions. The second part of the chapter assesses the conversion risk within forests that are likely to fall beyond the scope of ZDCs, thus providing an indication of the potential displacement effects that may be induced by ZDCs.

Chapter 3 examines the evidence of local spillover effects by homing in on a specific anti-deforestation policy – the Indonesian Forest Moratorium – that was enacted by the Indonesian government in 2011. The chapter draws on state-of-the-art quasi-experimental methods to estimate the direction and magnitude of local spillover effects (positive or negative) that may have been induced by the moratorium.

Chapter 4 also employs quasi-experimental methods to examine how certain sourcing strategies from deforestation-risk regions by individual companies could influence the adoption and effectiveness of corporate ZDCs in Brazil's soy industry.

Chapter 5 draws on the data and findings of Chapter 2 by exploring how ZDCs could play out in terms of land use change if they were to be fully adopted and enforced across all industries and regions using ex-ante simulation modelling techniques. It examines the influence of ZDCs on the expansion of oil palm, a crop that has been strongly associated with deforestation in recent decades.

Finally, Chapter 6 synthesizes the thesis's main findings by revisiting the sub-questions listed above and discussing the broader implications of the research.

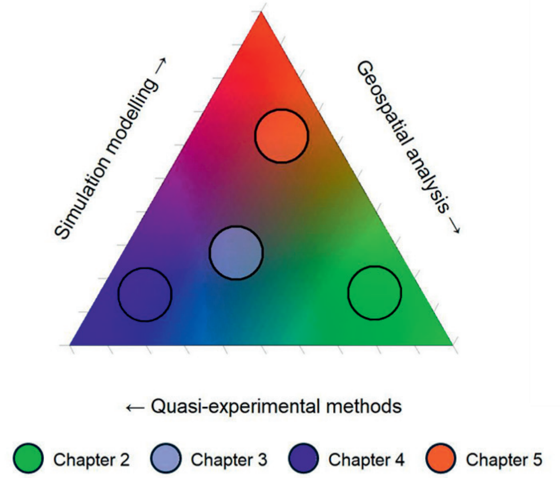

Figure 1 – Ternary plot showing the degree to which each methodology approach is adopted across the thesis chapters.

2

Which forests could be protected by corporate zero deforestation commitments? A spatial assessment

The production of palm oil, soy, beef and timber are key drivers of global forest loss. For this reason, over 480 companies involved in the production, processing or distribution of these commodities have issued commitments to eliminate or reduce deforestation from their supply chains. However, the effectiveness of these commitments is uncertain since there is considerable variation in ambition and scope and there are no globally agreed definitions of what constitutes a forest. Many commitments identify High Conservation Value Forests (HCVFs), High Carbon Stock Forests (HCSFs) and forests on tropical peatland as priority areas for conservation. This allows for mapping of the global extent of forest areas classified as such, to achieve an assessment of the area that may be at reduced risk of development if companies comply with their zero deforestation commitments. Depending on the criteria used, the results indicate that between 34 and 74% of global forests qualify as either HCVF, HCSF or forests on tropical peatland. However, we found that the total extent of these forest areas varies widely depending on the choice of forest map. Within forests which were not designated as HCVF, HCSF or forests on tropical peatland, there is substantial overlap with areas that are highly suitable for agricultural development. Since these areas are unlikely to be protected by zero-deforestation commitments , they may be subject to increased pressure resulting from leakage of areas designated as HCVF, HCSF and tropical peatland forests. Considerable uncertainties around future outcomes remain, since only a proportion of the global market is currently covered by corporate commitments. Further work is needed to map the synergies between corporate commitments and government policies on land use. In addition, standardized criteria for delineating forests covered by the commitments are recommended.

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2.1. Introduction

Commodity-driven deforestation is a major driver of global forest loss accounting for approximately 27% of global forest loss (Curtis *et al* 2018). Recognizing this, many multinationals sourcing deforestation-risk commodities have adopted goals to eliminate or reduce deforestation from their supply chains (Lambin *et al* 2018). These Zero-Deforestation Commitments (ZDCs) typically focus on the four agricultural commodities most strongly associated with tropical deforestation: beef, palm oil, soy, paper and pulp (Newton and Benzeev 2018, Henders *et al* 2015). In recent years, the number of companies adopting ZDCs has grown rapidly to at least 484, representing an unknown market share (Donofrio *et al* 2019).

However, the effectiveness of ZDCs is uncertain since there is considerable variation in ambition and scope (Taylor and Streck 2018, Jopke and Schoneveld 2018). In addition, there are no globally agreed definitions of what constitutes a forest; variations arise from consideration of tree density, tree height, ecological properties etc. (Chazdon *et al* 2016). The choice of forest definition influences estimates of forest areas globally and therefore deforestation estimates. As an example, Romijn *et al* (2013) demonstrated the total area estimated to have been deforested between 2000 and 2009 in Indonesia increased by 27% when using Indonesia's national forest definition instead of the Food Agricultural Organization (FAO) definition.

Many companies identify High Conservation Value Forests (HCVFs) (Brown *et al* 2013) and High Carbon Stock Forests (HCSFs) (Rosoman *et al* 2017) as priority areas for conservation within their ZDCs. HCVFs are defined as forests of outstanding biological, ecological, social or cultural significance and divided into 6 categories: four focus on biodiversity, habitat and ecosystem conservation, and a further two on community needs and cultural values (Brown *et al* 2013). HCSFs are defined by a practical, field-tested methodology – the High Carbon Stock Approach (HCSA) – that prioritizes forests for conservation based on their above-ground biomass (AGB) carbon, while respecting communities rights' to their lands and typically integrating the findings of an HCV assessment (Rosoman *et al* 2017). In addition, many companies have also committed to the protection of forest on tropical peatlands (Newton and Benzeev 2018). The adoption of these so-called "No Deforestation, No Peat and No Exploitation" (NDPE) commitments has been limited to the oil palm sector in Southeast Asia where 74% of the palm oil refining capacity is now covered by such commitments (Steinweg *et al* 2017). Recently, the Roundtable on Sustainable Palm Oil (RSPO) integrated the HCSA into its Principles and Criteria (RSPO 2018). Discussions are ongoing as to whether the HCS approach should also be included by other standard bodies, including the Roundtable on Responsible Soy (RTRS), the Forest Stewardship Council (FSC) and the United Nations Reducing Emissions from Deforestation and forest Degradation (REDD+) Programme (Cheyns *et al* 2019).

Although commitments to protect HCVF and HCSFs have been recognized as potentially effective approaches for implementing a ZDC (Garrett *et al* 2019), the spatial extent of HCVFs and HCSFs is unknown (Carlson *et al* 2018, Pirker *et al* 2016). Both approaches were developed for local, case-by-case application requiring on-the-ground field visits and stakeholder consultation. As a result, mapping has been conducted mainly at the local scale, leaving unclear what the global coverage of the ZDCs is. In addition, concerns around deforestation extend to the development of new production areas on forests and other biomes which fall outside of the HCVF and HCSF classifications – a phenomenon often referred to as activity leakage (Bastos Lima *et al* 2019, Meyfroidt *et al* 2018). Therefore, the primary objective of this chapter is to make an estimate of the global land area that could be classified as HCVF, HCSF or forest on tropical peatland, and hence at reduced risk of development if companies comply with their ZDCs. A secondary objective is to identify the remaining forest areas that are at risk of conversion due to agricultural development or forestry.

2.2. Methodology

A stepwise approach was adopted to estimate the global forested land area that can be classified as HCVF, HCSF or forest on tropical peatlands. First, a forest reference map for the current situation was created (section 2.1.1). Then, HCVFs (section 2.1.2), HCSFs (section 2.1.3) and tropical peatland forests (section 2.1.3) were identified separately by matching a variety of data sources to the official definitions and descriptions listed in the HCV guidelines and HCSA toolkit.

The forested areas that were not classified as HCVF, HCSF or tropical peatland forest were intersected with several maps displaying agricultural suitability for the 4 main deforestation-risk commodities, market accessibility, future land use change projections and areas where commodity-driven deforestation and forestry are considered the main driver of forest loss (sections 2.2.1, 2.2.2 and 2.2.3).

2.2.1. Estimating the global extent of HCVF, HCSF and forests on tropical peatland in 2017

2.2.1.1. Mapping forest areas

To create a forest reference map for the current situation, the binary forest map from Schulze *et al* (2019) was used. This 1 km^2 resolution map is based on a hybrid forest map created by Schepaschenko *et al* (2015) and represents the year 2000, calibrated with the most recent FAO statistics. We modified the forest extent to represent the year 2017 using 1 km^2 raster data on tree cover gain (2000 – 2012) and tree cover loss (2000 – 2017) from Hansen *et* *al* (2013, 2019), accessed through Google Earth Engine. Recognising that tree cover loss data from Hansen *et al* do not distinguish between temporary loss and permanent conversion (Curtis *et al* 2018) and that tree cover gain data include plantation forests and herbaceous crops (Tropek *et al* 2014), we tested the sensitivity of the mapped forest area using both the original and our updated Schulze map. In addition, we tested the sensitivity of mapped forest areas arising from the choice of forest map by using 9 alternative global forest maps (Table 1). Finally, all spatial data were converted to an equal-area Eckert IV projection as advocated in Šavrič *et al.* (2015).

2.2.1.2. Mapping HCV forests

We used the HCV guidelines (Brown *et al.* 2013) to identify and map HCVFs using 12 distinct indicators that together cover the full range of HCV categories, as shown in Table 1 (see also Table 1 of the supplementary material for an extended version of this list, including the official definition of each HCV category and the rationale for selecting each indicator). To harmonize the different datasets, all indicators were converted to a 1 km^2 resolution. We used three different thresholds to classify HCVFs, defined as forest areas containing at least 1, 2, or 3 HCV categories. The different levels of coverage were used to represent the uncertainty in the final HCVF classification and illustrate the sensitivity of the mapped spatial extent to the indicator selection. We assumed that areas with multiple overlapping categories are more likely to qualify as HCVF.

2.2.1.3. Mapping HCS forests

According to the HCS Toolkit Version 2.0 (Rosoman *et al* 2017), potential HCSF can be identified based on an above-ground biomass (AGB) threshold of 35 t C/ha. Although some potential HCSF may still be released for development, all tropical forests containing more than 75 t C/ha are generally designated as HCSF (Rosoman *et al* 2017). We used both thresholds to indicate the range of uncertainty in the classification of HCSF and its mapped spatial extent. Above ground biomass data from Santoro and Cartus (2019), representing the year 2017, were resampled from a resolution of 1 ha to a resolution of 1 km^2 using the majority resampling approach. For sensitivity analyses, two alternative AGB carbon maps were considered (see Table 1). Since the HCS approach is not applicable for forests outside the tropics (Rosoman *et al* 2017), these were not classified as HCS.

2.2.1.4. Mapping forests on tropical peatland

Tropical peatland forests were mapped using data on the pan-tropical extent of peatlands in 2011 from Gumbricht *et al* (2017).

Table 1 – List of indicators and data sources to identify HCSF, HCVF and forest on tropical peatlands

	Indicator		Thresholds	Data sources
Forest extent 2017	Hybrid forest map for the year 2000 that integrates 8 different forest products, validated with crowdsourced data, consistent with FAO statistics, updated to the year 2017 based on remotely sensed data of tree cover loss and gain between 2000 – 2017. As a sensitivity analysis, 9 different forest maps are considered. Percentage tree-cover maps from Hansen *et al* (2013, 2019) and Sexton *et al* (2013) were converted to binary forest maps (forest/no forests) by applying a 10% and 30% threshold, following the official forest definitions of the FAO (FAO 2012) and the United Nations Framework Convention on Climate Change (UNFCCC 2006), respectively.			Schulze *et al* (2019) & Hansen *et al* (2013, 2019) Sensitivity analysis: Bartholomé and Belward (2005) Bontemps *et al* 2016) Buchhorn *et al* (2019) Hansen *et al* (2013, 2019) (2 maps with 10 and 30% canopy cover threshold) Schaaf, C., Wang (2015) Sexton *et al* (2013) (2 maps with 10 and 30% canopy cover threshold) Shimada *et al* (2014, 2019)
High Conservation Value	HCV 1 Species diversity	Biodiversity Hotspots		Hoffman *et al* (2016)
		Key Biodiversity Areas		BirdLife International (2018)
		Nationally Designated Protected Areas		UNEP-WCMC and IUCN (2018)
	HCV 2 Landscape-level ecosystems and mosaics and Intact Forest Landscapes	Intact Forest Landscapes		Potapov *et al* (2017, 2008)
	HCV 3 Ecosystems and habitats	Areas of high forest biodiversity significance		Hill *et al* (2019)
	HCV 4 Ecosystem services	Areas of high overlap of nature's contributions and people's needs in terms of coastal risk reduction, crop pollination, erosion protection, reduction of flood risk, water quality and water supply.		Chaplin-Kramer *et al* (2019), Stehfest *et al* (2014) and CIESIN (2018)
	HCV 5 Community needs	Presence of Indigenous Community		Garnett *et al* (2018)
	HCV 6 Cultural values	UNESCO World Heritage Sites (part of Nationally Designated Protected Areas)		UNEP-WCMC and IUCN (2018)
High Carbon Stock	Above-ground biomass (t C/ha) within tropical forest areas.		75 (Low Density Forest) 35 (Young Regenerating Forest)	Santoro and Cartus (2019) Sensitivity analysis: Avitabile *et al* (2016) Baccini *et al* (2012)
Pan-tropical peatlands	Presence of peatland in the tropics.		Pan-tropical soils having at least 30 cm of decomposed, or semi decomposed organic material with at least 50% of organic matter.	Gumbricht *et al* (2017)

2.2.2. Evaluating forests at risk of agricultural development

We evaluated the deforestation risk of forest areas not designated as HCVF, HCSF or tropical peatland. Forests designated as HCV or HCS were for this analysis defined as forests with at least 2 overlapping HCVF categories or at least 75 t C/ha if located in the tropics (section 2.1). The risk of potential future conversion of forest was assessed using three alternative approaches to account for the uncertainty in future development: 1) by identifying and overlaying suitable and accessible expansion areas for the 4 main deforestation-risk commodities (2.2.1), 2) by using integrated assessment model predictions (2.2.2), and 3) by masking areas where commodity-driven deforestation and forestry are considered the main drivers of forest loss (2.2.3).

2.2.2.1. Overlap with suitable and accessible expansion areas for the 4 deforestation-risk commodities

Data on agro-ecological suitability for oil palm, soybean and pasture were sourced from the International Institute for Applied Systems Analysis / Food and Agriculture Organization (2012) and Van Velthuizen *et al* (2007) and resampled to a resolution of 1 km^2 using the majority resampling approach (a list of all data sources can be found in Table 2 of the supplementary material). These suitability maps include 8 different suitability classes for current agricultural or pastoral production areas as well as those which could be developed for future production. To identify suitable areas for forestry, a similar suitability map for potential production forests was made by classifying a continuous suitability map from Schulze *et al* (2019) into 8 suitability classes. For each commodity, potential areas for expansion were identified by excluding areas already under production. For oil palm, soybean and pasture, only the estimated fraction of any given grid cell currently under cultivation was known (International Food Policy Research Institute 2019, Ramankutty *et al* 2010). We therefore excluded grid cells where cropland or pastureland already extend over more than 50% of the area (a sensitivity analysis towards this assumption is provided in the supplementary material). Grid cells comprising urban land were also excluded, using data from Schneider *et al* (2003). Forest areas outside the HCV, HCS and tropical peatland areas overlapping with suitable expansion areas were assumed to be at risk of conversion.

As inaccessible lands may face lower risk of development (Busch and Ferretti-Gallon 2017), we refined the analysis by mapping the joint distribution of market accessibility and agricultural suitability for forests falling outside the HCV, HCS and tropical peatland areas. Data from Weiss *et al* (2018) on travel time to the closest port or the closest city with at least 50,000 inhabitants – resampled to a resolution of 1 km^2 using bilinear interpolation – were used as a proxy for market accessibility. To obtain an overall measure of agricultural suitability for the 4 commodities, a raster layer was created indicating, for each grid cell, the highest overall suitability class of the 4 suitability layers (a separate map for each of the 4 commodities is presented in the supplementary material).

2.2.2.2. *Overlap with land use projections*

An alternative estimate of the conversion risk placed on areas falling beyond the HCVF, HCSF and tropical peatland forests classifications was derived using spatially explicit land use projections of cropland and pastureland expansion at 5 arc minutes resolution from the Integrated Model to Assess the Global Environment (IMAGE) 3.0 model (Doelman *et al* 2018). These projections were made for the period 2020 – 2030 and based on the second Shared Socioeconomic Pathways (SSP2) scenario (a "middle-of-the-road" scenario for future climate mitigation action) (O'Neill *et al* 2014). Forest areas that were not classified as HCVF, HCSF or tropical peatland forest and were found to overlap areas of projected cropland or pastureland expansion were considered to be at additional risk of development.

2.2.2.3. *Overlap with areas where commodity-driven deforestation and forestry are dominant drivers of forest loss*

Finally, we assessed the overlap between forests not classified as HCS, HCV or tropical peatland and areas where forestry and commodity-driven deforestation are classed as the main drivers of forest loss. Data on the drivers of forest loss at 10 x 10 km resolution were sourced from Curtis *et al* (2018). This provides an indication of the forest areas that are at additional risk of development, assuming these forests will indeed be subject to forestry or commodity-driven deforestation.

2.3. Results

2.3.1. The estimated extent of HCVF, HCSF and forests on tropical peatland in 2017

Based on the updated Schulze *et al* map for the year 2017, the global forest area amounts to 39.4 million km^2 (this compares with an area of 40.3 million km^2 if the Schulze *et al* map is not updated). Figure 1 shows the variation in the spatial extent of HCVF and HCSF, depending on the stringency of the criteria. The total extent of HCVF and HCSF combined comprises between 34% and 74% of global forests, of which between 28% – 34% has already been designated as protected area (UNEP-WCMC 2017). The global extent of HCVF alone encompasses between 7% and 65% of global forests (Table 2), with Indigenous lands accounting for the largest part of potential HCVF (i.e. 43% of all potential HCVF, see Figure 1 of the supplementary material).

Since HCSFs are by definition limited to the tropical zone, the total extent is much smaller than the extent of HCVF and varies in the range of 31% to 43% of global forests, which equates to 66% – 91% of all tropical forests, depending on the choice of AGB map and whether an AGB threshold of 35 or 75 t C/ha is applied. Within the tropical zone, there is an overlap between HCVF and HCSF, with the percentage of total tropical forest for which

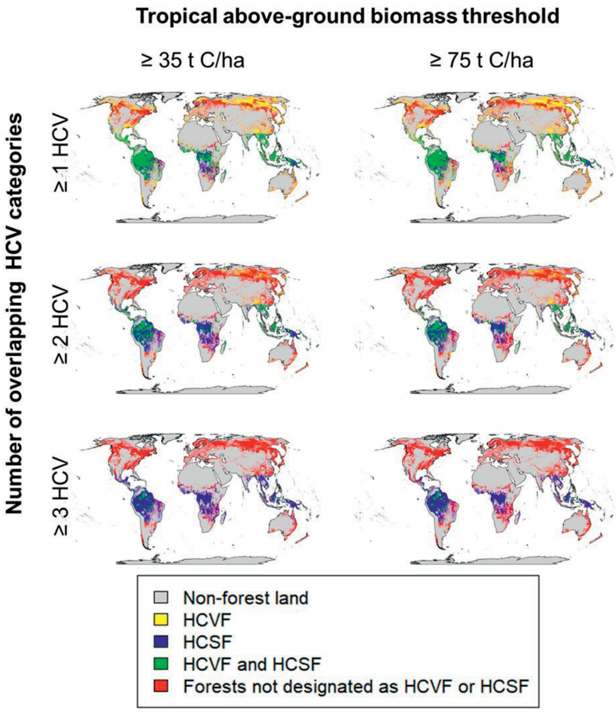

Figure 1 – Spatial overview of forests potentially at reduced risk of development due to the corporate zero-deforestation commitments, based on a range of criteria to delineate High Conservation Value Forest (HCVF) and High Carbon Stock Forest (HCSF).

Table 2 – Estimated total extent of High Conservation Value Forests, High Carbon Stock Forests and tropical peatland forests. High Carbon Stock estimates are based on Santoro and Cartus (2019), while the parentheses behind the High Carbon Stock estimates indicate the lower and upper range using 2 alternative above-ground biomass maps (i.e. Avitabile *et al* (2016) and Baccini *et al* (2012)).

Geographic scope	Type of forest	Million km²	% Total Forest Area
Global	High Conservation Value		
	≥ 1 Category	25.67	65%
	≥ 2 Categories	10.61	27%
	≥ 3 Categories	2.56	7%
Tropical	High Conservation Value		
	≥ 1 Category	13.59	73%
	≥ 2 Categories	7.09	38%
	≥ 3 Categories	2.17	12%
	High Carbon Stock		
	≥ 35 t C/ha	14.89 (13.53 – 17.00)	80% (73% – 91%)
	≥ 75 t C/ha	12.75 (12.30 – 15.26)	68% (66% – 82%)
	Peatland Forests	0.62	3%

the 2 classifications converge – measured by the Jaccard Similarity Index (Intersection over Union) – varying between 14% and 67%, depending on both the AGB threshold and minimum number of overlapping HCV categories. Tropical peatland forests comprise 3% of all tropical forests, of which between 82% and 98% overlap with HCVFs and HCSFs.

At a regional or country level, the large sensitivity of the extent of HCVF and HCSF to the choice of criteria can lead to dramatic differences (see Figure 2 and 3 of the supplementary material). For example, the total extent of HCVF, HCSF and tropical peatland forest in Sub-Saharan Africa varies in the range of 51 to 84% of all forests.

To test how sensitive the results are to the choice of forest map, Figure 2 shows the variation in the extent of HCVF, HCSF and tropical peatland forest when different forest maps are considered. Forests designated as HCVF or HCSF are here defined as forests containing at least 2 overlapping HCVF categories or exceeding the AGB threshold of 75 t C/ha. To account for the uncertainty in the extent of HCSF and HCVF, the error bars in Figure 2 denote the upper and lower range of the extent of HCSF, HCVF and tropical peatland forest using the full range of criteria shown in Figure 1 (see Table 3 of the supplementary material for a detailed comparison of the 10 forest maps based on the Jaccard Similarity index). The total extent of forests designated as HCVF, HCSF or tropical peatland depends to a large extent on the choice of forest map and varies in the range of 11 – 40 million km^2, notably because large areas considered forest by some maps are classified as closed shrublands or woody savannahs by others.

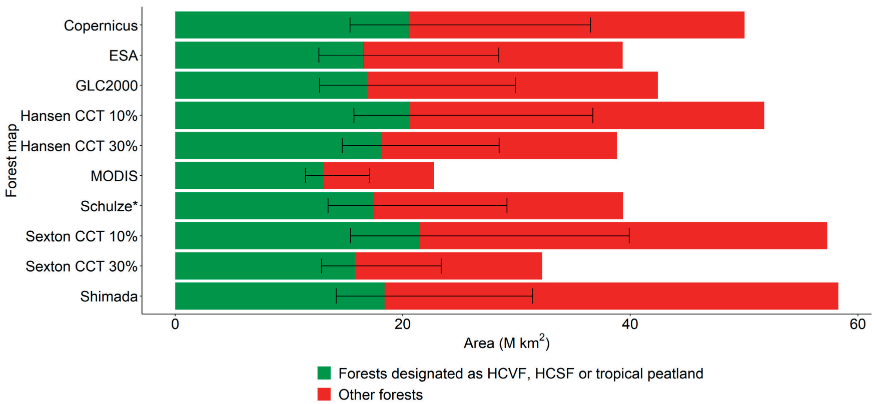

Figure 2 – Total extent of forests and forests designated as HCVF, HCSF or located on tropical peatland, based on 10 different forest maps. Forests designated as HCV or HCS are here defined as forests with at least 2 overlapping HCVF categories or at least 75 t C/ha if located in the tropics. Error bars denote the upper and lower range of the total extent of HCVF, HCSF and tropical peatland forest using the other criteria to delineate HCVF and HCSF shown in Figure 1. CCT denotes canopy cover threshold. *Note: the Schulze *et al* (2019) map is an updated version of the original Schulze *et al* map using data on tree cover loss between 2000 – 2017 and tree cover gain between 2000 – 2012 from Hansen *et al* (2013, 2019).

2.3.2. Forest at risk of agricultural development

Figure 3 shows the extent to which potential suitable expansion areas for the 4 deforestation-risk commodities overlap with forest areas and forest areas designated as HCVF, HCSF or tropical peatland, based on different land suitability thresholds. Depending on the suitability classes included, 39 to 92% of the areas suitable for forestry expansion and 57 to 80% of the areas suitable for the expansion of oil palm plantations overlap with forests designated as HCVF, HCSF or tropical peatland. The total forest area outside HCVFs, HCSFs and tropical peatland forests that is suitable for forestry ranges between 0.57 to 17.81 million km^2, while the area suitable for oil palm plantations ranges between 0.30 and 6.82 million km^2. Potential suitable expansion areas for pasturelands and soybean fields are much more abundant resulting in a lower percentage overlap with forests (36 to 52% and 6% to 36%, respectively). Still, given their overall larger extent, the total forest area not covered by HCVFs, HCSFs and peatland forests is as high as 19.73 million km^2 for pastureland and 10.61 million km^2 for soybean fields.

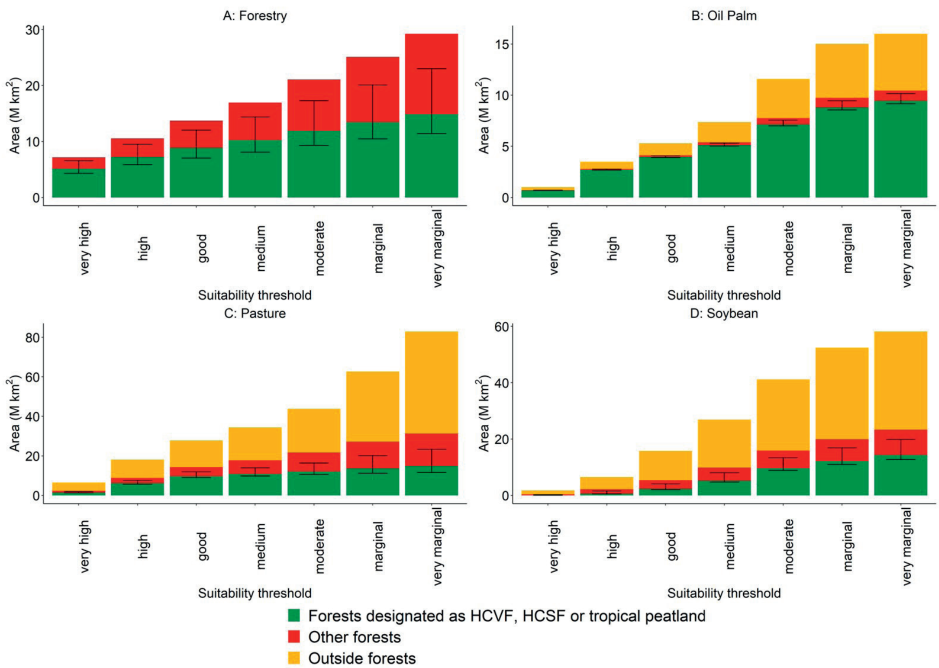

Figure 3 – Overlap of agro-ecological suitability for 4 main deforestation-risk commodities with forests designated as High Conservation Value Forest (HCVF), High Carbon Stock Forest (HCSF) and tropical peatland forest. The error bars denote the uncertainty in the total extent of HCVF, HCSF and tropical peatland forests. Suitable areas outside forests do not include urban areas or areas already under cultivation or used for production.

2

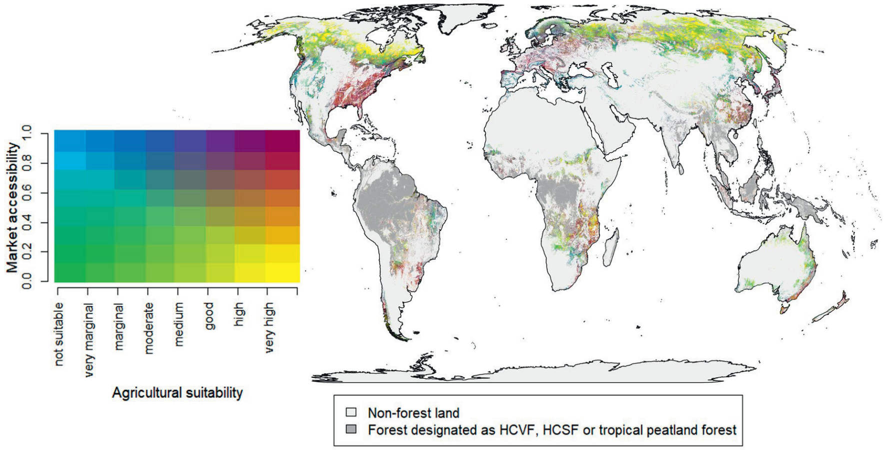

Figure 4 – Joint distribution of market accessibility and agricultural suitability across forests not designated as HCVF, HCSF or tropical peatland forest. Market accessibility is based on travel time to the nearest port or city with at least 50,000 inhabitants and classified into 8 octiles. Agricultural suitability is determined by taking the highest suitability class for each grid cell after overlaying 4 suitability layers for forestry, oil palm cultivation, soybean cultivation and pastureland – each comprising 8 suitability classes. A separate map for each commodity is presented in Figure 5 of the supplementary material.

To assess where pressures from forestry and agricultural expansion are especially high, Figure 4 displays the joint distribution of market accessibility – classified into 8 octiles – and agricultural suitability, based on the highest land suitability class for the 4 commodities (see Figure 5 of the supplementary material for 4 separate maps per commodity). Forests not designated as HCVF, HCSF or tropical peatland forest with high market accessibility and agricultural suitability tend to be clustered in the Eastern United States, Central Europe, East China, the Gran Chaco in Latin America and near the Swahili Coast in Sub-Saharan Africa (see Figure 6a – 6c of the supplementary material for three zoom maps of Latin America, Sub-Saharan Africa and Southeast Asia; the 3 main global deforestation regions (FAO 2018)). Around 36% of these forest areas with the highest market accessibility and agricultural suitability are estimated to be already used as production forests, based on data from Schulze *et al* (2019).

These results merely indicate risk based on agro-ecological suitability and accessibility and do not account for projected changes in land use linked to anticipated growth in demand, population density and market accessibility. Projections from the IMAGE 3.0 model for crop and pasture expansion between 2020 and 2030, reflect drivers of land use change. These projections indicate that 38% of the total forest area not designated as HCVF, HCSF or tropical peatland forest, may be subject to land use change for agricultural production. Assuming these predictions provide a reasonable indication of the location of future production for the 4 deforestation-risk commodities, the total forest area at risk of becoming converted to oil palm plantations, soybean fields or pastureland becomes much smaller – especially in the temperate zone – and decreases on average by 59% (see Figure 7 of the supplementary material). It is important to note though that these estimates do not account for potential leakage effects from protecting HCVFs, HCSFs and tropical peatland forests.

Alternatively, when including only areas where commodity-driven deforestation or forestry is considered the main driver of forest loss, the total forest area at risk amounts to 56% of the total forest area not classified as HCVF, HCSF or tropical peatland forest, of which 17% overlaps with areas where commodity-driven deforestation is considered the main driver of forest loss.

2.4. Discussion and conclusion

This study provides a first approximation of the global forest area that may be covered by corporate zero deforestation commitments (ZDCs), defined on the basis of three commonly used criteria: protection of High Conservation Value Forests (HCVF), High Carbon Stock Forests (HCSF) and tropical peatland forests. The results show that between 34 and 74% of all forests may classify as HCVF, HCSF or peatland forest. This large range indicates the level of uncertainty in the extent of forest that could be at reduced risk of development if these commitments were fully adopted. However, given that market coverage of the corporate commitments is less than 100%, the protected area will be much smaller in reality and deforestation can move to supply chains falling beyond the scope of the corporate commitments (Garrett *et al* 2019). Moreover, even in case of full uptake, legally protected forest accounts for only 28 to 34% of the forest area that we identified as meeting our ZDC criteria.

In comparison with individual site-based local assessments conducted by companies, our global assessment of the spatial coverage of HCVF and HCSF is likely to identify some different areas for conservation. First and foremost, this is because the methods used to identify HCVFs and HCSFs were developed for local assessments requiring extensive field work and free, prior and informed consent from local communities, meaning they are not easily applied at larger scales (i.e. the 1 km^2 resolution we use) (Pirker *et al* 2016, Lake *et al* 2016). In addition, many of the criteria documented in the HCV guidelines contain ambiguous and subjective terms that depend on individual assessors' discretion. This has led to an inconsistency between various local HCV assessments (Senior *et al* 2015), meaning that there is no consensus on what potential HCV indicators are most appropriate. There are also no spatial data sets available on areas already designated as HCVF and HCSF (Carlson *et al* 2018, HCSA Steering Group 2019) to enable validation. Finally, all indicators used to approximate the spatial extent of HCVF and HCSF had to be resampled to a resolution of 1 km^2, which inevitably leads to some loss of spatial detail (Zhu *et al* 2017). To reduce uncertainty in the spatial extent of forest protected under the corporate commitments, standardized criteria for delineating forests and defining areas of HCVF and HCSF at the global scale and across tropical and temperate forests are recommended. In addition, advances in remote sensing and biodiversity mapping should be exploited to produce more accurate and up-to-date indicators of HCVFs and HCSFs.

Despite these uncertainties, our results are relatively consistent with previous attempts to map HCV and HCS areas at larger scales. For example, Miranda *et al* (2003) estimated that 37% of all areas designated as forest according to our reference map are potentially HCVF, which compares with our estimate of 27% (for 2 overlapping HCVF categories), and Austin *et al* (2017) estimated the total extent of HCSF in Gabon to be between 80% – 87% of Gabon's land, which compares with our estimate of 83% (regardless of the choice of carbon threshold).

Our analysis has also shown that the extent of HCVF, HCSF and tropical peatland forests is contingent on the choice of forest map, resulting in a range from 11 to 40 million km^2 according to the criteria specified in Figure 2. This finding adds to a growing body of literature showing that the definition of forest significantly impacts estimates of forest cover and forest cover change (Mermoz *et al* 2018, Sexton *et al* 2016, Chazdon *et al* 2016). The lack of a well-agreed forest definition led 9 environmental and social NGOs to launch the Accountability Framework initiative in 2016; a framework that has been developed to provide companies with detailed guidance to implement their commitments and standardize definitions of forest, deforestation, and related terms (Weber and Partzsch 2018). Greater consensus on forest classification is needed to reduce the uncertainty in the area covered by the corporate commitments and facilitate more effective monitoring (Lyons-White and Knight 2018).

Even if the ZDCs are fully implemented across all commodity markets, some of the environmental and social benefits associated with the protection of HCVF, HCSF and tropical peatland forest may be undermined if agricultural expansion is displaced to forests that are not covered, hence resulting in activity leakage (Bastos Lima *et al* 2019, Meyfroidt *et al* 2018). Using data on land suitability for the 4 main deforestation-risk commodities, we have shown here that many forest areas not designated as HCVF, HCSF or tropical peatland forest are highly suitable for the production of these commodities, indicating an increased potential risk of development due to ZDCs. Hence, with a growing world demand for all 4 commodities (Johnston 2016, Thornton 2010, Corley 2009, Masuda and Goldsmith 2009), pressures on potential expansion areas will likely increase and could possibly come at the expense of forests or other natural biomes that are not designated as HCVF, HCSF or tropical peatland forest, in particular when market accessibility is high (Atmadja and Verchot 2012). In addition, pressures may be higher at local scales due to imperfect substitution between commodities originating from different sources (Hertel 2018). However, the total area at risk of development may be much smaller when accounting for future land use change scenarios or historic trends in commodity-driven deforestation or forestry.

It should be noted, though, that there are many factors that we have not been able to consider in our assessment of the areas at risk of future agricultural development. For example, there are a range of interacting socio-economic factors – including mobility of capital and labour, easy access to credit and differences in price and terms (Atmadja and Verchot 2012) – policy and governance factors (Fernandes *et al* 2015) as well as crop-to-crop cascade effects (Lambin and Meyfroidt 2011), which are all likely to affect future land use outcomes. Further work to map synergies between corporate commitments and government policies influencing land use outcomes is recommended. This will help to refine estimates of the potential effectivenes of national and supply chain governance levers for halting deforestation and for the identification of complementary strategies which may accelerate efforts towards zero deforestation.

3

Local deforestation spillovers induced by forest moratoria: evidence from Indonesia

Moratoria on commodities produced in deforestation-risk areas have been shown to be highly effective in reducing deforestation within targeted areas. Various studies have shown, however, that such policies are prone to large local spillover effects, i.e., non-trivial changes (reductions or increases) in the amount of deforestation in areas just outside the direct scope of the moratorium. Little is known about the direction and magnitude of local spillover effects that may have been induced by the Indonesian forest moratorium, an anti-deforestation policy enacted in 2011 that covers around a third of Indonesia's terrestrial area and that is of high importance in meeting international deforestation goals. Here, we empirically assess the evidence of spillover effects near the Indonesian moratorium boundaries, using several proximity metrics and a panel dataset spanning the years 2001 – 2018. Based on our negative binomial fixed effects regressions, we estimate that the moratorium induced 1,324 km^2 of deforestation in areas located within 10 km of the targeted areas in the period 2011 – 2018, most of which occurred near conservation and protection forests. Evidence of spillover effects is also strong within concession areas slated for development. This suggests that companies may have shifted their planned production activities from areas targeted by the moratorium to neighbouring concession areas, resulting in additional forest loss. To minimize or halt such spillover effects, the scope of the Indonesian moratorium could be expanded to high-deforestation risk areas, such as forest areas outside mountainous regions, with relatively high GDP per capita and high agro-ecological suitability for oil palm plantations. In addition, a higher uptake of certification schemes and increased international finance would complement the moratorium, helping to reduce incentives to deforest both within and outside the moratorium areas.

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3.1. Introduction

In recent years, efforts by governments, corporations and civil society to curb deforestation have steadily increased (Brown and Zarin, 2013; Geldmann *et al.*, 2019; Lambin *et al.*, 2018). Typical examples of anti-deforestation policies include protected areas (Bebber and Butt, 2017), agri-environmental certification schemes (van der Ven *et al.*, 2018) and moratoria on commodities produced in deforestation-risk areas (Nolte *et al.*, 2017; Sloan, 2014). The rise in these policies has been accompanied by an increase in studies employing quasi-experimental methods and counterfactual thinking to assess their effectiveness (Börner *et al.*, 2016). The central research question underlying these studies has been: "what would have happened in terms of deforestation in the absence of the policy intervention?". While these studies typically control for the influence of other variables to estimate the effect of the intervention (e.g. agricultural suitability and market accessibility), they are often limited to areas falling directly within the scope of the policy, thus overlooking potential spillover effects on neighbouring or more distant areas (see e.g. Carlson *et al.* 2018; Panlasigui *et al.* 2018). Failing to account for spillover effects may give rise to misleading conclusions and policy recommendations (Ewers and Rodrigues, 2008; Pfaff and Robalino, 2017).

There is a growing body of evidence suggesting that land development restrictions, such as commodity moratoria, may trigger deforestation spillovers (positive or negative) to areas falling beyond the direct scope of the policy (Dou *et al.*, 2018; Fuller *et al.*, 2019; Magliocca *et al.*, 2019; Meyfroidt and Lambin, 2009). As an example, Moffette and Gibbs (2019) provided empirical evidence that two highly effective anti-deforestation policies targeting the soy and cattle production sectors in the Brazilian Amazon displaced agricultural production to surrounding areas, thus causing further deforestation outside the targeted areas. Such displacement of agricultural production activities – often referred to as activity leakage (Meyfroidt *et al.*, 2018) – is more likely to occur if there is a lack of off-farm employment alternatives and if neighbouring areas can be substituted for the restricted areas (Atmadja and Verchot, 2012). However, other studies have also found that anti-deforestation policies may also give rise to boosting effects. In this case, less deforestation is observed in neighbouring areas than would have occurred in the absence of the intervention (Giudice *et al.*, 2019; Heilmayr *et al.*, 2020a; Herrera, 2015). This may occur if restrictions on land development slow down regional investments in roads and other types of infrastructure, thus reducing the risk of deforestation (Herrera, 2015).

One anti-deforestation policy that has not received much attention in the scientific literature is the Indonesian forest moratorium. Indonesia is one of the world's largest emitters of greenhouse gases and the forest moratorium was, at the time of its enactment, considered to be the single policy with the largest mitigation potential (Wijaya *et al.*, 2017). Implemented in 2011 as part of a 'REDD+ Readiness' programme in collaboration with Norway, the moratorium suspended the granting of new concession licenses for logging, oil palm and wood fibre concessions within designated areas with the aim of reducing deforestation and associated CO_2 emissions (Austin *et al.*, 2012; President of Indonesia, 2011; Sloan, 2014). Existing concession licenses were exempt. Although the moratorium was initially established for two years, it was extended three times before being made permanent in 2019 (Mongabay, 2019a). The extent of the moratorium has been subject to 15 revisions between 2011 – 2018 but varies in the range of 64 – 67 Mha or 34 – 35% of Indonesia's total terrestrial area, depending on which (revised) moratorium map is considered (Ministry of Environment and Forestry, 2021). The moratorium covers three different types of areas, namely conservation and protection forests, peatlands and primary forests, all designated by the Indonesian Ministry of Environment and Forestry (note that the designated peatlands and primary forests do not cover all Indonesian peatlands and primary forests). Conservation and protection forests include nature reserves and forests designated to safeguard certain hydrological services, both of which were already legally protected when the moratorium was enacted in 2011 (Murdiyarso *et al.*, 2011). Although this implies that the moratorium bestowed no additional legal protection on conservation and protection forests, the moratorium may have strengthened law enforcement within these areas, thus contributing to the declining deforestation rates in recent years (World Resources Institute, 2019). The remaining moratorium areas designated as either peatlands or primary forests are much smaller and comprise only 20% of the total moratorium extent according to the 8th revised moratorium map (Ministry of Environment and Forestry, 2021). However, these areas largely constitute additional protection (meaning they were largely unprotected before 2011), and hence, it is plausible that the moratorium induced positive or negative spillover effects around these areas.

Very few studies have attempted to assess the effectiveness of the moratorium in reducing deforestation in Indonesia. Busch *et al* (2015) estimated that if the moratorium had been in place from 2000 to 2010, the total deforested area would have been reduced by 1,160 – 3,050 km^2, which equates to 1.0 – 2.7% of the total estimated deforestation over that time. However, since their analysis was solely based on data on the decade preceding the moratorium, it did not provide an indication of the actual effectiveness following implementation. Conversely, both Suwarno *et al* (2018) and Chen *et al* (2019) explored potential post-implementation impacts of the moratorium, but did not consider possible displacement effects beyond the moratorium boundaries. Given that similar anti-deforestation policies enforced in other countries have triggered large spillovers to areas within 10 km of the targeted areas (Bruggeman *et al.*, 2018; Fuller *et al.*, 2019; Robalino *et al.*, 2017), it is conceivable that similar effects have occurred in Indonesia in the wake of the forest moratorium. Therefore, to effectively govern Indonesia's remaining forests, a better understanding of the effectiveness of the Indonesian moratorium is needed, considering the potential for local deforestation spillovers.

The objective of this chapter is to empirically assess the direction and magnitude of local spillovers in the direct neighbourhood of Indonesian forest moratorium areas. We define areas located in the direct neighbourhood of a moratorium border on the basis of several proximity metrics and employ an econometric model to assess whether there is a strong statistical relationship between deforestation and proximity to a moratorium border after the enactment of the moratorium. In addition, we show how the spillover effects have varied across space and over time; and employ matching methods to explore the robustness of our results.

3.2. Methodology

3.2.1. Study area and data processing

Our analysis sought to examine how proximity to the moratorium border affected deforestation outcomes in the post-moratorium period (i.e., from 2011 onwards). To account for both spatial and temporal variation in deforestation, we exploited a panel dataset spanning the years 2001 – 2018, with the annual deforested area as our dependent variable, using data on tree cover loss from Hansen *et al* (2013, 2019), aggregated to a resolution of 5 x 5 km. Deforestation was defined as any tree cover loss (in ha) within areas with at least 30% canopy cover, following the official forest definition of Indonesia (Ministry of Environment and Forestry, 2016). Tree cover gain was not considered as the Hansen *et al* data do not distinguish between plantation forests and natural forests (Tropek *et al.*, 2014). To explore the sensitivity of our results to the choice of forest definition, we report alternative results using 2 different forest definitions in Appendix C, based on canopy cover thresholds of 10% and 60%.

Proximity to the moratorium border was measured using the 8th revised moratorium map from Indonesia's Ministry of Environment and Forestry (2021, see Figure 1), published in May 2015 and digitized by Greenpeace (2021). As the year 2015 is near the middle of our study period, the 8^{th} revised moratorium map provides a more representative spatial overview of the moratorium extent than more recent maps. Nevertheless, to explore the sensitivity of our results depending on the choice of moratorium map, we also considered an alternative moratorium map based on the intersection of the initial moratorium map (published in July 2011) and the 15^{th} revised moratorium map (published in December 2018), shown in Figure 1 of Appendix D. There are no major spatial differences between both maps as the percentage of overlap (intersection over union) amounts to 93%. Both moratorium maps consist of a patchwork of many disjoint polygons spread out across thousands of islands that are designated as either primary forest, peatland or conservation and protection forest. These different types of moratorium areas are officially mutually exclusive, even though it

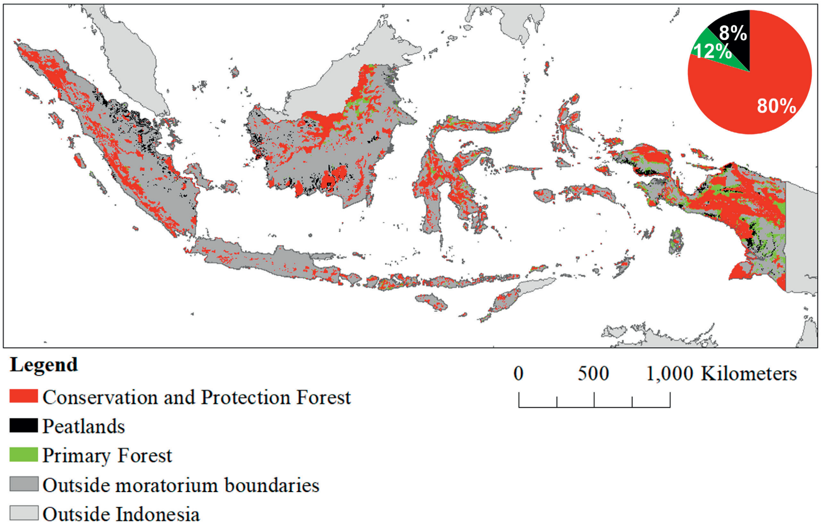

Figure 1 – Map of Indonesia showing the spatial extent of the three different types of areas covered by the moratorium, based on the 8th revised moratorium, first published in 2015 by the Indonesian Ministry of Environment and Forestry and digitized by Greenpeace (2021). The pie chart presented in the top right of the figure shows the percentage of the different types of area covered by the moratorium.

has been recognized that areas designated as peatland may contain primary forest and vice versa, according to different land cover maps (Murdiyarso *et al.*, 2011).

As the risk of spillover effects is arguably higher near areas that were not already protected before the enactment of the moratorium, we distinguished between moratorium areas that constituted additional protection and areas that were already protected before the enactment of the moratorium, in our analysis. Whilst areas designated as conservation and protection forests were already protected before the enactment of the moratorium, 89% of all areas designated as primary forest and 98% of all areas designated as peatlands were not, based on data from the Indonesian Ministry of Environment and Forestry (2010, see Figure 2 of Appendix D). Since spillovers to neighbouring areas are less likely to occur if the area targeted by the moratorium is relatively small (Sinclair *et al.*, 2012) or if the risk of deforestation was already low (Di Lallo *et al.*, 2017), we excluded moratorium polygons smaller than 50 km^2 and grid cells with less than 1% forest cover at the start of 2011, and limited our analysis to the 5 largest Indonesian islands (see Figure 3 of Appendix D for a map of these islands). Together, these islands capture 94% of all deforestation in the pre-moratorium period. Since a deforested grid cell does not add any meaningful variation to the sample, observations after 2011 within fully deforested grid cells were set to missing (this only applied to one grid cell in our sample). As mountainous areas are typically at minimal risk of development and hence unlikely to be affected by spillovers (Busch and Ferretti-Gallon, 2017; Edwards *et al.*, 2019), we also excluded grid cells with average elevation exceeding 3,000 m and average slopes exceeding 30°, based on data from Jarvis *et al.* (2008). For all remaining grid cells outside the moratorium boundaries (n = *27,849* in the case of the 8th revised moratorium map), we computed the Euclidean distance (in kilometres) from the grid cell's centroid to the nearest moratorium border, thereby distinguishing between the different types of areas covered by the moratorium.

3.2.2. Exploratory data analysis

To explore the general dynamics around the moratorium borders before and after the moratorium was enacted, we smoothed the relationship between deforestation and distance to the nearest moratorium border for both periods, using a Generalized Additive Model smoother (GAM). GAMs are statistical models that incorporate non-parametric regression techniques to summarize local (non-linear) statistical relationships that can often not be detected using a linear regression model (Keele, 2008). As the magnitude of deforestation spillovers is likely to vary with distance, detecting such local statistical relationships is key for exploring the general dynamics around moratorium areas. Since our dependent variable (annual deforested area in ha) is a nonnegative, overdispersed variable with many observations without any deforestation (27% of all observations outside moratorium areas), we used a negative binomial GAM instead of a Gaussian or Poisson GAM (see Appendix A for a more detailed discussion of overdispersion and the negative binomial model).

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3.2.3. Empirical strategy

Our empirical strategy relies on the assumption that areas in the vicinity of a moratorium area are more likely to be exposed to deforestation spillovers (positive or negative) than areas that are further away. By comparing deforestation outcomes in grid cells close to a moratorium border with outcomes in more distant grid cells in both the pre- and post-moratorium period, our analysis sought to measure the direction and magnitude of local spillovers. Following Moffette and Gibbs (2018), we created two different metrics to identify grid cells in the vicinity of a moratorium area. The first is a dummy variable (one that only takes the value 0 or 1) indicating whether grid cell i is within 10 km of a moratorium border, using the same distance threshold as Fuller *et al* (2019) and Robalino *et al* (2017). The second is a continuous variable ranging from 0 to 1 that equals 1 if grid cell i is closest to the moratorium border and 0 if it is the farthest away, based on the following formula:

$$Closeness_i = \frac{Dist_i}{MaxDist} - 1, \qquad (1)$$

where, $Dist_i$ denotes distance to the moratorium border and $MaxDist$ represents the maximum distance of all grid cells. In Appendix C, we explore the sensitivity of our results to alternative proximity metrics (using different distance thresholds, including quadratic terms etc).

A challenge when estimating the direction and magnitude of local spillovers is that the spatial coverage of the moratorium is not randomly distributed across Indonesia. Even after excluding areas with high altitude and slope (see section 2.1), areas within and around the moratorium boundaries tend to be located in more mountainous regions with less agro-ecological suitability for oil palm plantations and less access to palm oil mills, cities and ports in comparison with areas further away (see Appendix D Figures 4 – 8). This suggests that areas closer to a moratorium border may be at a lower risk of development than undeveloped areas further away. However, Figure 2 shows that before the moratorium was enacted, areas within 10 km of a moratorium border experienced a similar trend in deforestation to areas further away. A common trend in the pre-moratorium period indicates that areas further away may provide a valid comparison group for areas within 10 km of a border (Angrist and Pischke, 2008). The post-moratorium divergence in trends shown in Figure 2 could potentially be (partly) attributed to spillover effects.

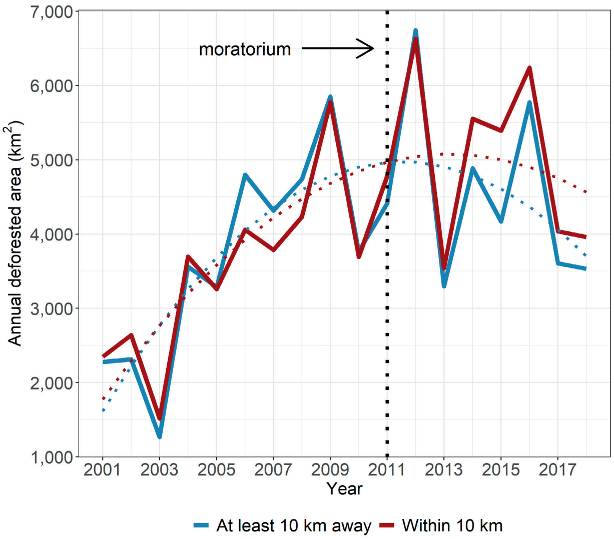

Figure 2 –Time series of annual deforestation between 2001 – 2018 within forest areas more than 10 km away from a moratorium border and within 10 km of a moratorium border. None of the time series include deforestation within the moratorium areas. Data on deforestation are sourced from Hansen *et al* (2013, 2019). Dotted lines represent quadratic trend lines.

To identify spillover effects as distinct from the effects of potential confounding variables such as commodity prices (Gaveau *et al.*, 2018), population dynamics (Darmawan *et al.*, 2015) or major El Niño events (Noojipady *et al.*, 2017), we sought to control for these variables using a multivariate negative binomial regression model, estimated with the fixest software package in R version 4.0.2 (Bergé, 2020, 2018; R Core Team, 2020, see Appendix A for further details). By including fixed effects, we can control for the influence of (unobserved) spatial differences that are constant over time (e.g., topography, soil type), as well as year trends that vary across pre-defined geographical units (e.g., population dynamics or economic development within administrative units). In addition, we controlled for the presence of concession areas since these are already designated for development and hence more likely to be deforested. Data on concession types (logging, oil palm and wood fibre concessions) were sourced from Global Forest Watch (2019a – c, see Figure 9 of Appendix D). Grid cells with less than 50% of their total area (i.e., 12.5 km^2) overlapping with one of the three concession types were assumed to be outside concession areas. As both the year of establishment and the actual year of development was unknown for most concession areas, we included year trends for each concession type in our model, thus controlling for the expansion of concession areas over time. We further refined the analysis by controlling for areas that became certified in a certain year by the Roundtable on Sustainable Palm Oil (RSPO) as certification tends to reduce the risk of deforestation (Carlson *et al*., 2018a; Cattau *et al*., 2016). Spatiotemporal data on RSPO-certified concessions were sourced from Carlson *et al* (2018b).

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Finally, we also controlled for the remaining forest area within each grid cell at the start of each year, as well as the total remaining forest area in neighbouring forests, using a spatial weight matrix. Accounting for the remaining forest in neighbouring areas is key, as the risk of deforestation varies with the degree of forest fragmentation (Taubert *et al*., 2018). The spatial weights were constructed using an inverse-distance algorithm and a distance threshold of 15 km. We also considered alternative distance thresholds of 10 and 20 km, as well as alternative spatial weight algorithms (weights based on queen and rook contiguity), but this resulted in a lower overall fit, as indicated by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

More formally, we estimated the following equation for our negative binomial model:

$$Def_{i,c,r,t} = exp(\beta(Post\_mora_t * Proximity_i + \delta log\ (For_{i,t-1}) + \eta(w'_i log(For_{i,t-1})) + \omega\ RSPO_{i,t} + \alpha_1 + \Phi_{c,t} + Y_{r,t}) \quad (2)$$

Here, $Def_{i,c,r,t}$ denotes the annual deforested area in ha within grid cell i, concession type c, regency r (i.e., second-level administrative units. Indonesian: *kabupaten*) and year t; $Post\_mora_t$ is a dummy variable indicating the period after which the moratorium was enforced; $Proximity_i$ represents one of the two proximity metrics described above; $log\ (For_{i,t-1})$ represents the natural logarithm of the remaining forest area (ha) in grid cell i in year t-1; w'_i denotes a vector of row-standardized weights placed on the natural logarithm of the remaining forest area in neighbouring grid cells, represented by the vector $log\ (For_{i,t-1})$; $RSPO_{i,t}$ is a variable indicating the proportion of the area of grid cell i that was RSPO-certified at time t, α_i, $\Phi_{c,t}$ and $Y_{p,t}$ denote fixed effects and β, δ, η and ω are parameters to be estimated. To account for temporal and spatial autocorrelation, we clustered our standard errors at the province level (Indonesian: *provinsi*). Alternative results with standards errors clustered at the island or regency level are shown in Appendix C.

We used the results of equation (2) to gauge how much deforestation may have been induced or avoided in areas within 10 km of a moratorium border by comparing the fitted values using the baseline covariate values with a counterfactual scenario in which no moratorium was enacted. The counterfactual scenario was constructed by predicting for each grid cell within 10 km of a border how much deforestation would have occurred in the post-moratorium period after setting β (the parameter capturing the effect of the moratorium) in equation (2) to zero. Thereafter, we summed the difference between the two scenarios in terms of the predicted amount of deforestation, thus arriving at an estimate of how much deforestation may have been induced or avoided by the moratorium within 10 km of its borders. Given the non-linear nature of the negative binomial model, we explore the sensitivity of this result to alternative parameter values by running a Monte-Carlo simulation in Appendix D, following Heilmayr *et al* (2020a;) and Carlson *et al* (2018).

3.2.4. Robustness checks

We explored the robustness of our results by a) re-estimating equation (1) for several subsets of the sample (2.4.1), b) testing how the estimated magnitude of spillover effects within 10 km of a moratorium border varies by year (2.4.2) and c) pre-processing the sample using a matching algorithm (2.4.3).

3.2.4.1. Subsamples

To assess how the direction and magnitude of spillovers vary across space, we estimated the model separately for each major Indonesian island, all remaining islands not included in the baseline model (Figure 3b and 3c – Appendix D) and for each of the different concession areas (note that this reduces the concession-specific year trend, $\Phi_{c,t}$ in equation (2) to a general year trend). Given the large variation in the size of moratorium areas (Figure 3a – Appendix D), we also sought to investigate whether forests near larger moratorium areas are more likely to be affected by spillovers than those near smaller ones, using alternative area thresholds of 0, 100, 500 and 1,000 km^2 (see section 2.1). Finally, we tested how the magnitude of estimated spillover effects changes when focussing on areas deemed at higher risk of development, based on a number of covariates known to influence deforestation outcomes (see Table 1 for the list of covariates; also see Busch and Ferretti-Gallon (2017) for a meta-analysis of the spatial drivers of deforestation). This means we explored the sensitivity of the results after excluding grid cells with covariate values below a certain threshold, using quartiles to define the cut-off values (see Table 1 of Appendix C).

3.2.4.2. Temporal effects

A potential concern of our estimation strategy is that areas within 10 km of a moratorium area are perhaps fundamentally different from areas further away (e.g., due to spatial variation in market accessibility) and that our fixed effects model does not eliminate the influence of all confounding variables, resulting in omitted variable bias. In that case, we may find statistically significant effects of proximity to a moratorium border on deforestation in the years before the moratorium was implemented. Assuming such statistically significant effects are not the result of sampling variation or deforestation agents anticipating the enactment of the moratorium (which is unlikely as the moratorium was not discussed within official circles until 2010, Murdiyarso *et al.*, 2011), this would indicate that the effect of proximity is conflated with another confounding variable for which we have not controlled. Alternatively, if our model does not suffer from omitted variable bias, we would expect to find no statistically significant parameter estimates before 2011. To test whether this is the case, we re-estimated equation (2) after replacing the term $Post\_mora_t * Proximity_i$ by 17 year-specific proximity effects (described below), using the year 2011 as our reference year. In addition to testing whether there is a relationship between proximity and deforestation in the period before the moratorium, this also gives an indication as to how the post-moratorium spillover effects have varied over time. This means we estimated the following equation:

(3)
$$Def_{i,c,r,t} = exp(\textstyle\sum_{\tau=1}^{7} \beta_{-\tau} * Proximity_{i,t-\tau} + \sum_{\tau=1}^{10} \beta_{+\tau} * Proximity_{i,t+\tau} +$$
$$\delta log\,(For_{i,t-1}) + \eta(w_i' log(For_{i,t-1})) + \theta\, RSPO_{i,t} + \alpha_1 + \Phi_{c,t} + Y_{r,t}),$$

where the first summation term $\sum_{\tau=1}^{7} \beta_{-\tau}$ captures 7 lags or post-treatment effects for each year from 2012 up to and including 2018 and the second summation term $\sum_{\tau=1}^{10} \beta_{+\tau}$ captures 10 anticipatory or pre-treatment effects for each year from 2001 up to and including 2010.

3.2.4.3. Matching

Many studies have found that pre-processing data by matching methods can improve the performance of the fixed effects models (Ferraro and Miranda, 2017; Ho *et al.*, 2007; Jones and Lewis, 2015). Pre-processing in this context means that regression analysis is done on a subset of the data where the treated and control groups are matched such that they have similar covariate distributions, with the aim of minimizing selection bias. To balance covariate distributions between grid cells within 10 km from a moratorium border and grid cells further away, we used genetic matching, an evolutionary search algorithm that iteratively checks

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and improves covariate balance (Diamond and Sekhon, 2013, see Appendix B for further details). To ensure that only observations were matched that are reasonably similar, we used a caliper width (a tolerance level indicating the maximum allowed dissimilarity between observations) of 0.2 times the standard deviation, as recommended by Austin (2011).

Matching was done with replacement on all variables listed in Table 1. For time-varying covariates (i.e., population density and GDP per capita), matching was done using the values from the year 2010. The reason we picked the year 2010 is that matching should not be done on observations that may have been affected by the moratorium (Stuart, 2010), and the moratorium was not announced until 2011. Balance was assessed by means of standardized mean differences, empirical quantile-quantile plots and Kolmogorov-Smirnov test statistics (see Figure 10 – Appendix D). After trimming the data to our matched sample, we re-estimated equation (2).

Table 1 – List of covariates used to match observations

Variable	**Source**	**Original Resolution**
Elevation (m)	Jarvis *et al* (2008)	90 m^2
Gross Domestic Product per Capita at Purchasing Power Parity in constant 2011 international US dollars (log)	Kummu *et al* (2018)	5-minute resolution (approximately 10x10km at the equator)
Market accessibility (hours)	• Travel time to the nearest city with at least 50,000 inhabitants: Weiss *et al* (2018) • Travel time to the nearest port (regardless of size): Weiss *et al* (2018)	• 30-arcsec resolution (approximately 1 x 1 km at the equator) • Idem
Oil palm suitability (0.01 - 100)	Suitability estimates sourced from Version 3 of the Global Agro Ecological Zones (GAEZ) (International Food Policy Research Institute/Food and Agriculture Organization, 2012). The data are based on the SRES H3A1 emission scenario for the 2020s and control for a CO2 fertilization effect.	5-minute resolution (approximately 10x10km at the equator)
Population density (log)	Stevens *et al.* (2015)	100 m^2
Remaining forest area in 2010 in ha (log)	Hansen *et al* (2013, 2019)	30 m^2
Slope (°)	Jarvis *et al* (2008)	90 m^2
Travel time to the nearest oil palm mill (hours)	• Friction surface enumerating land-based travel speed for all land pixels for the year 2015 from Weiss *et al* (2018) • Coordinates of Indonesian palm oil mills (Global Forest Watch, 2019d)	• 30-arcsec resolution (approximately 1 x 1 km at the equator) • N.A.

3.3. Results

3.3.1. Evidence of local deforestation spillovers

Figure 3 shows how deforestation trends varied across grid cells within 100 km of the different moratorium areas in the pre- and post-moratorium period. Deforestation levels near the border generally increased in the post-moratorium period, with the peak shifting from 30 to 25 km away from the border (Figure 3a). A similar pattern holds if only areas near conservation and protection forests are included. However, near peatland and primary forests, there is no evidence of a shift in deforestation intensity to areas closer to the border, with deforestation levels largely remaining flat in the case of peatland forests (Figure 3c) and increasing with distance in the case of primary forests (Figure 3d). These opposite trends in deforestation levels near moratorium areas suggest spatially heterogeneous spillover effects near the different types of area covered by the moratorium. However, they are likely to be (partly) driven by underlying trends such as the degree of forest fragmentation, the presence of concession areas and regional socio-economic developments.

To account for such confounding trends, Table 2 reports the regression estimates based on equation (2) for all moratorium areas (columns (1) – (2)) and the three types of area covered by the moratorium (columns (3) – columns (8)). Separate results focussing only on areas that constituted additional legal protection as of 2011 are presented in Table 3 of Appendix C. Note that the variable Closeness in columns (2), (4), (6) and (8) of Table 2

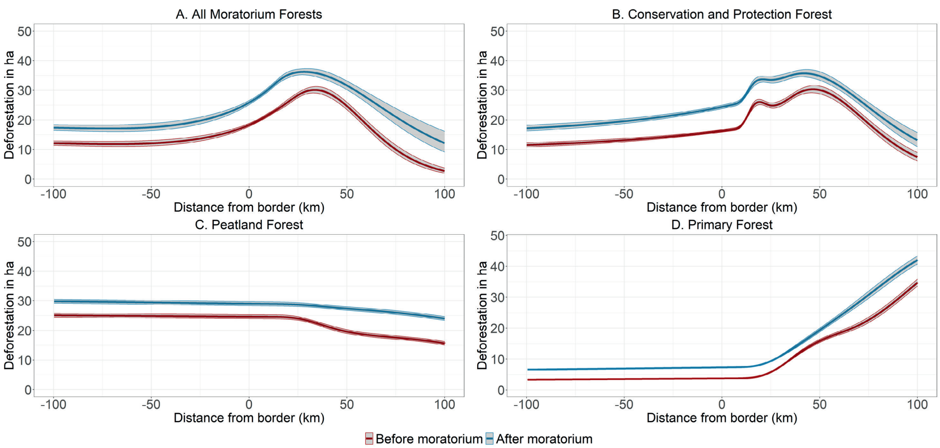

Figure 3 – Smoothed relationship between deforestation and distance from moratorium areas within 100 km in the pre- and post-moratorium period based on a) all moratorium areas, b) only moratorium areas designated as Conservation and Protection Forest, c) only moratorium areas designated as Peatland Forest and d) only moratorium areas designated as Primary Forest. Moratorium areas smaller than 50 km^2 were not considered. Smoothing was done with a negative binomial one dimensional penalized regression spline with smoothing parameters selected by generalized cross-validation. Deforestation levels and distance indicators are analyzed within a 5 x 5 km^2 grid. Negative distances indicate Euclidean distances within moratorium areas to the closest border. Shaded areas denote 95% confidence intervals.

Table 2 – Negative binomial regression estimates of deforestation. Positive (negative) parameter estimates indicate a positive (negative) association between the variable and deforestation, holding other factors constant. Unit of observation is the 5 x 5 km grid cell. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity that assumes values in the unit interval, as described by equation (1). AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC).

	Dependent variable: Deforestation (canopy cover threshold 30%)							
	All moratorium areas		Conservation Forests		Peatland Forests		Primary Forests	
Proximity to:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables:								
Within 10 km of border (0/1)	0.07**		0.07***		0.02		0.03	
	(0.03)		(0.03)		(0.07)		(0.06)	
Closeness		1.24***		1.61***		-1.04		-1.13**
		(0.40)		(0.38)		(1.14)		(0.54)
ln(forest (ha))	1.76***	1.76***	1.76***	1.76***	1.75***	1.75***	1.75***	1.75***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
ln(neighbouring forest (ha))	-0.23	-0.24	-0.23	-0.26	-0.20	-0.22	-0.20	-0.16
	(0.23)	(0.22)	(0.23)	(0.22)	(0.23)	(0.21)	(0.23)	(0.21)
RSPO-certification	-0.71	-0.71	-0.71	-0.69	-0.71	-0.70	-0.71	-0.72
	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)
Dispersion parameter	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Fixed effects:								
Grid cell	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Concession type x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regency x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	499,870	499,870	499,870	499,870	499,870	499,870	499,870	499,870
AIC	3,314,629	3,314,572	3,314,621	3,314,416	3,314,678	3,314,650	3,314,678	3,314,550
BIC	3,690,634	3,690,577	3,690,626	3,690,421	3,690,683	3,690,655	3,690,683	3,690,555
McFadden's adjusted Pseudo R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Table 3 – Negative binomial regression estimates of deforestation within different concession areas. Positive (negative) parameter estimates indicate a positive (negative) association between the variable and deforestation, holding other factors constant. Unit of observation is the 5 x 5 km grid cell. Grid cells were assumed to be located within a certain concession area (logging, oil palm or wood fibre) if at least 50% of their total area (i.e., 12.5 km^2) overlapped with one of the three concession types. As some grid cells dominated by either logging concessions or wood fibre concessions may also contain oil palm concessions, the variable 'RSPO-certification' is included in all models. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity that assumes values in the unit interval, as described by equation (1). AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC).

	Dependent variable: Deforestation (canopy cover threshold 30%)					
Concession area:	Logging concessions		Oil palm concessions		Wood fibre concessions	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables:						
Within 10 km of border (0/1)	0.17***		0.06		0.12**	
	(0.05)		(0.07)		(0.05)	
Closeness		2.91***		2.07*		1.38
		(0.78)		(1.14)		(0.96)
ln(forest (ha))	2.30***	2.31***	1.65***	1.65***	1.47***	1.47***
	(0.21)	(0.21)	(0.05)	(0.05)	(0.09)	(0.09)
ln(neighbouring forest (ha))	-2.12**	-2.20***	0.87***	0.83***	-0.14	-0.13
	(0.92)	(0.83)	(0.21)	(0.23)	(0.26)	(0.27)
RSPO-certification	-3.95***	-4.06***	-0.87	-0.87	-1.10	-1.10
	(0.32)	(0.28)	(0.57)	(0.57)	(0.83)	(0.85)
Dispersion parameter	0.56	0.56	0.87	0.87	0.75	0.75
Fixed effects:						
Grid cell	Yes	Yes	Yes	Yes	Yes	Yes
Regency x year	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110,691	110,691	59,956	59,956	56,196	56,196
AIC	543,246	543,209	534,965	534,928	469,470	469,477
BIC	618,307	618,270	582,789	582,752	514,493	514,500
McFadden's adjusted Pseudo R^2	0.16	0.16	0.08	0.08	0.10	0.10

refers to the continuous proximity metric that assumes values in the unit interval, as described by equation (1). Results from column (1) indicate that areas within 10 km of a moratorium border (first row) are typically associated with more deforestation in the post-moratorium period ($p < 0.05$), holding other factors constant. More specifically, we estimate that in the period 2011 – 2018, the Indonesian moratorium induced 1,324 km^2 of forest loss in areas within 10 km of a moratorium border, which equates to approximately 2 ha per 5 x 5 km grid cell (Figure 11 of Appendix D explores the uncertainty around this estimate using a Monte Carlo simulation). In addition, column (2) suggests that grid cells that were the closest to the moratorium border – as described by equation (1) – experienced 246% more deforestation ($\approx 100 * \exp(1.24) - 100$) in the post-moratorium period than the most distant areas ($p < 0.01$). Focussing only on conservation forests (column (3) – column (4)), similar results are obtained, even though these areas were already legally protected before the enactment of the moratorium. However, consistent with Figure 2, there is no evidence of leakage effects near peatland forests (column (5) – column (6)) as none of the parameters are statistically significant at conventional levels (i.e., $p < 0.1$). Column (8) implies that areas near primary forests may even have experienced boosting effects, as they are associated with less deforestation in the post-moratorium period than areas further away ($p < 0.05$).

These results remain robust when focussing only on peatland and primary with additional legal protection (see Table 3 of Appendix C) or when using an alternative moratorium map, based on the intersection of the initial moratorium map, published in 2011, and the 15th revision of the map, published in 2018 (see Table 4 of Appendix C). To further explore the sensitivity of our results, we also considered different forest definitions (canopy cover thresholds of 10 and 60%), different distance metrics (based on different distance thresholds and a quadratic term for closeness) and different levels at which to cluster our standard errors; these did not alter any of the qualitative conclusions either (see Tables 5 – 7 of Appendix C and Figure 12 of Appendix 10).

3.3.2. Subsamples

Table 3 reports the regression estimates for the three different concession types (oil palm, logging and wood fibre). Columns (1) and (5) reveal that there is strong evidence that the moratorium induced forest loss between 2011 and 2018 within logging and wood fibre concession areas located within 10 km of a moratorium border ($p < 0.05$), amounting to an estimated 480 and 578 km^2, respectively. This suggests that around 80% of all induced forest loss near moratorium areas (see section 3.1) occurred within these areas. Re-estimating the model for different islands, we find a strong variation in the direction and magnitude of spillover effects across islands. Whilst most of the parameter estimates are positive, there is strong evidence of negative spillover effects (boosting effects) near peatlands in West Papua and near primary forests in Sumatra (see Figure 13 of Appendix D). Differences in parameter estimates across concession types and islands can potentially be explained by spatial differences in economic development (proxied by GDP per capita), agro-ecological suitability for palm oil plantations and topography, as shown by Figure 14 of Appendix D. In general, spillover effects increase in magnitude with higher GDP per capita, higher oil palm agro-ecological suitability, lower elevation and less variation in slope.

Another potential reason that could partially explain these differences in parameter estimates is that the direction and magnitude of spillover effects depend on the size of the nearest moratorium area. Figure 15 of Appendix D indicates that forests within 10 km of peatlands exceeding 500 km^2 or primary forests exceeding 1,000 km^2 are associated with strong positive (more deforestation) spillover effects, whilst the evidence of spillover effects diminishes if smaller moratorium areas (< 500 km^2) are included. However, there is an opposite pattern near conservation and protection forests as the evidence of leakage effects disappears if only the largest moratorium areas are included. This suggests that there is no consistent relationship between the size of an area and deforestation across different types of areas covered by the moratorium.

3.3.3. Temporal effects

To assess the way in which the direction and magnitude of spillover effects varied over time, Figure 4a plots the temporal parameter estimates (or point estimates) of being within 10 km of a moratorium border for each individual year in both the pre- and post-moratorium period, including their 95% confidence intervals (note, the year 2011 is selected as a reference year). There are no statistically significant effects in the pre-treatment period, suggesting our model sufficiently eliminates the influence of confounding trends, at least in the pre-moratorium period. From 2014 onwards, all parameter estimates become statistically significant and increase in magnitude, indicating that spillover effects did not become prominent until 2014. Focussing only on areas near conservation forests, a similar pattern emerges. However, consistent with Table 2, there is no evidence of spillover effects near peatland and primary forests, with virtually no statistically significant effects in both the pre- and post-moratorium period.

3.3.4. Matching

The findings from section 3.1 remain robust after trimming the dataset to observations within a caliper width of 0.2 times the standard deviation, which discards around 26% of the original observations (see Table 8 of Appendix C). This lends further support to the conclusion that leakage effects were particularly strong near conservation and protection forests, even though these forests were already protected before the enactment of the moratorium. In addition, the results provide further evidence that areas near primary forests may have experienced boosting effects.

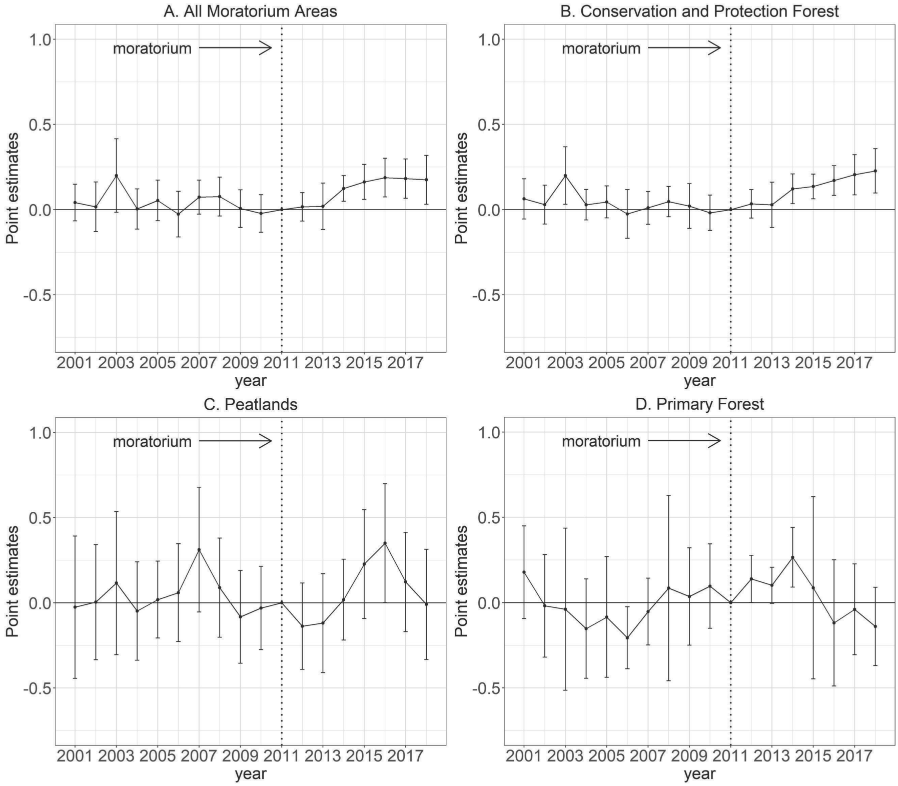

Figure 4 – Temporal point estimates of the effect of being within 10km of a moratorium border. The year 2011 is selected as a reference year. Error bars denote 95% confidence intervals. A point estimate is significantly different from 0 at the 0.05 level if the 95% confidence interval does not contain 0.

3.4. Discussion and conclusion

This is the first assessment of the direction and magnitude of local spillover effects that may have been induced by the Indonesian moratorium on new concession licenses. We have found strong evidence that the moratorium induced forest loss in areas within 10 km of the targeted areas, amounting to a total of 1,324 km^2 between 2011 and 2018. This equates to 166 km^2 per year or 60 – 157% of the annual deforestation that may have been avoided by the moratorium, according to the ex-ante simulation study by Busch *et al* (2015). These findings suggest that the effectiveness of the moratorium may have been substantially undermined due to activity leakage. Surprisingly, the evidence of leakage is particularly strong around conservation and protection forests, even though these areas were already legally protected before the moratorium was enforced in 2011. This could be a sign that law enforcement increased within these areas following the enactment of the moratorium, thus displacing some forest-risk activities to neighbouring areas. Although local government agencies may have had limited awareness of the moratorium in the first years after implementation (Austin *et al.*, 2014), this may have changed in recent years, given the strong evidence of spillover effects near conservation and protection forests from 2014 onwards. However, there is also evidence that the moratorium gave rise to boosting effects – i.e., less deforestation – near primary forests. A potential explanation for this is that the moratorium discouraged investments in infrastructure near these areas, thus inhibiting further land development.

In addition, the evidence suggests that leakage effects are predominantly occurring in logging or wood fibre concession areas. This could be a sign that companies or smallholders involved in the logging or wood fibre industry originally aiming to expand their activities within moratorium areas shifted their planned activities to concession areas just outside the moratorium boundaries, causing activity leakage. Companies or smallholders involved in the oil palm industry may have been more constrained to shift their activities to neighbouring areas as these areas have relatively low agro-ecological suitability. Indeed, our sensitivity analysis confirms that the evidence of activity leakage within 10 km of moratorium areas becomes much stronger after excluding areas with low agro-ecological suitability.

We have also shown that evidence of spillover effects generally increases in smoother terrains and in areas with higher GDP per capita, potentially because it increases demand for agricultural and tropical products and access to markets (Angelsen and Kaimowitz, 1999; Cuaresma and Heger, 2019). By contrast, there is an ambiguous relationship between the size of a moratorium area and its estimated spillover effects. This is consistent with Fuller *et al.* (2019), who found that socioeconomic factors are more important in predicting whether a national protected area shows signs of spillover effects than the size of a protected area.

However, our results should be interpreted with caution. Instead of displacing agricultural activities, the moratorium may have incentivized companies to intensify production within concession areas. Since the remotely-sensed dataset on tree cover loss from Hansen *et al* does not distinguish between natural forests and plantation forests (Tropek *et al.*, 2014), it is possible that the estimated spillover effects within logging and wood fibre concessions are a reflection of increased logging intensities within previously developed plantation forests instead of encroachment into natural forests designated for, but not yet developed as plantation forests. This may also be the reason why the estimated spillover effects are substantially larger within logging and wood fibre concessions than in oil palm concessions.

Moreover, our results may be biased if proximity to the moratorium border is correlated with other unobserved time-varying covariates that influence deforestation outcomes and that are unrelated to the enactment of the Indonesian moratorium. Although we have controlled for all unobserved year trends at the regency level, it is conceivable that our results are partly driven by unobserved time-varying heterogeneity within regencies. Examples of potential confounding variables within regencies include the number of political districts (i.e. the number of third-level administrative levels, Indonesian: *kecamatan*), election cycles within districts and inter-governmental fiscal transfers (Burgess *et al.*, 2012; Pailler, 2018; Tacconi and Muttaqin, 2019). Inaccuracies in the selected moratorium map (due to the high number of revisions between 2011 - 2018) may also have influenced our results.

Finally, our study does not consider spillover effects that manifest themselves further away from the moratorium boundaries, for example due to market feedback effects. Although increases in land rents due to the moratorium are more likely to occur in the vicinity of the official moratorium border (Miranda *et al.*, 2019), changes in commodity prices induced by the Indonesian moratorium could have driven cropland expansion much further away. Assessing such market-mediated effects is challenging as it requires information on the price-responsiveness and price-elasticities of affected commodities. Recent advances in Computable General Equilibrium (CGE) models, such as the GTAP-BIO model (Taheripour *et al.*, 2017), provide a well-developed framework to gauge their magnitude, but often lack the fine spatial detail needed to detect local spillovers. Linking global or continental macro-economic models with local, spatially explicit land use change models offers a promising way forward for holistic assessment of spillover effects from commodity moratoria (Johnson *et al.*, 2020; Verburg *et al.*, 2008). In addition, accounting for the role of local political economy factors in spatially explicit land use models is key, as land use change models solely based on commodity demand and land properties typically fail to capture deforestation dynamics (Nolte *et al.*, 2017).

Despite these limitations, our study highlights the importance of accounting for spatially heterogeneous spillover effects when assessing land zoning policies, thereby building on previous work that has attempted to quantify such effects (Bruggeman *et al.*, 2018; Moffette and Gibbs, 2019; Robalino *et al.*, 2017). Further work to assess the environmental consequences of such spillover effects is recommended. To minimize or halt deforestation due to leakage, the scope of the Indonesian moratorium could be expanded to high-deforestation risk areas, such as secondary forest areas outside mountainous regions with relatively high GDP per capita and high agro-ecological suitability for oil palm plantations, consistent with the recommendations of Sloan *et al* (2012) and Lim *et al* (2019). The recent ban on all new licenses for oil palm plantations imposed by the Indonesian government for a period of three years could be a step forwards (Mongabay, 2019b), especially when complemented with a similar ban on all licences for logging and wood fibre concessions. In addition, a larger uptake of commodity certification schemes such as RSPO-certified palm oil or Forest Stewardship Council (FSC) certified timber could reduce the risk that the protection of forest areas within moratorium areas comes at the expense of High Conservation Value Forests (HCVFs) and High Carbon Stock Forests (HCSFs) within certified areas. Finally, scaling up international climate finance for nationwide anti-deforestation programs such as the Indonesian moratorium could increase law enforcement and reduce incentives to deforest (Yusuf *et al.*, 2018), as exemplified by the recent Norway-Guyana REDD+ program (Roopsind *et al.*, 2019).

4

The influence of company sourcing patterns on the adoption and effectiveness of zero-deforestation commitments in Brazil's soy supply chain

Many companies sourcing agricultural commodities with high deforestation risk have committed to zero deforestation, meaning they intend to eliminate deforestation from their supply chains. While previous research has attempted to assess progress against such initiatives, little is known about how the characteristics of sourcing patterns may influence the adoption and potential effectiveness of zero-deforestation commitments. Supply chain stickiness – here defined as the geographic persistence in trade relationships between traders and sourcing regions over time – may reflect lock-in effects and the level of trust between the parties involved. Here, we use a metric of supply chain stickiness, calculated from temporal network analyses on the Brazilian soy export supply chain, as a proxy for these underlying dynamics to explore their effect on the adoption and effectiveness of zero deforestation commitments (ZDCs). Using data for 2004 – 2017, we find that although stickier traders are more likely to adopt ZDCs, they also appear to have less effective ZDCs than other traders (as indicated by the level of soy and territorial deforestation in their sourcing regions). This finding suggests that additional strategies are needed to increase the effectiveness of ZDCs.

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4.1. Introduction

The international trade and consumption of agricultural commodities are estimated to drive around 26% of forest loss in the tropics and sub-tropics (Pendrill *et al* 2019). As a result, multiple agricultural supply chain actors have committed to eliminate or reduce deforestation from their supply chains, either through multi-stakeholder coalitions, such as the Amazon Soy Moratorium (ASM) or through unilateral Zero-Deforestation Commitments (ZDCs) (Garrett *et al* 2019, Lambin *et al* 2018).

Recent advances in remote sensing (Curtis *et al* 2018) and supply chain mapping (Godar *et al* 2015, Trase 2020a) have facilitated empirical research on such initiatives' effectiveness. For example, zu Ermgassen *et al* (2020) used spatial data on individual supply chains to monitor progress against ZDCs in the Brazilian soy export sector. While these studies inform on the overall effectiveness of ZDCs, they provide scant evidence on how different sourcing strategies and patterns influence this effectiveness. Sourcing strategies are the main lever through which traders of deforestation-risk commodities influence activities further upstream in the supply chain (Lyons-White and Knight 2018). Therefore, a better understanding of how different sourcing strategies, as reflected in spatiotemporal sourcing patterns, could influence actions on the ground is needed to enhance the effectiveness of ZDCs.

A critical characteristic of supply chain sourcing patterns is the degree of geographic persistence in bilateral trade flows (Villoria and Hertel 2011). Such persistence may have a considerable influence on traders' capacity to source deforestation-risk commodities compliant with their ZDCs (Reis *et al* 2020, Garrett *et al* 2019).

Patterns of trade persistence may result from traders' strategies but also other factors beyond their direct control. For example, at the country-to-country trade level, geographic distance between trading countries affects the persistence of bilateral trade flows as more distant countries tend to have less persistent bilateral flows (Disdier and Head 2008). Additionally, larger economies tend to have more persistent linkages (Kepaptsoglou *et al* 2010), as do those with greater openness or exposure to trade (Melitz 2002), ethnic and post-colonial linkages and those with similar governance regimes (Yu 2010).

The above referenced studies have provided insights into why trade relationships persist at the country-to-country level. However, the factors determining the persistence of subnational trade relationships, *i.e.*, between companies, producers and subnational jurisdictions, are less well known. Persistent subnational trade relationships are driven by both financial (e.g., transportation costs) and non-financial factors (e.g., levels of trust) that are hard to quantify and disentangle from each other. Key gaps remain in our understanding of how such unobserved drivers of persistent subnational trade relationships may influence sustainability outcomes.

We apprehend persistence in trade patterns through the notion of "stickiness", which is defined as "*the maintenance and recovery, over time and through shocks, of supply chains' geographic network configurations, i.e., the network of trade linkages and flows between* *specific places of production and consumption, and specific actors including producers, traders, retailers, and consumers*" (Reis *et al* 2020).

At the subnational trade level, various non-financial factors may influence supply chain relationships' stickiness at the supply-side (between production places and traders), including the social structure of supply chains, and power dynamics, which can induce various forms of lock-in effects. The social structure of supply chains – *i.e.*, the networks of social relations embedded in economies that determine the market structure – is influenced by the level of trust among supply chain actors and may make trade relationships more or less persistent over time (Uzzi 1997, Krippner and Alvarez 2007, Henderson *et al* 2002, Bair 2008, Polanyi 1944, Granovetter 1985).

In some circumstances, these social and power dynamics, as well as other factors including actors' past decisions that constrain their supply chain relationships, can result in lock-in effects, i.e., situations where negative feedbacks reinforce existing supply chain relationships. These can be (i) infrastructural (Vanloqueren and Baret 2009, Payo *et al* 2016), when physical facilities bind together different supply chain actors; (ii) financial, *e.g.*, through the existence of credit mechanisms; (iii) technological, *e.g.,* when one actor dominates and patents key technologies upon which other actors are dependent (Fares *et al* 2012), (iv) institutional when governance systems and norms exist (*e.g.* the ASM); or (v) related to consumer preferences for a brand, product or ingredient transparency, origin or quality (Narasimhan *et al* 2009, Akkermans 2001).

The literature suggests that such non-financial factors are likely to influence the adoption (Gardner *et al* 2019, Dauvergne and Lister 2013, Thorlakson *et al* 2018) and effectiveness of sustainability commitments by companies (Garrett *et al* 2019, Lambin *et al* 2018). First, lock-in effects due to social dependence, technology and investments, bind farmers and companies together in long and stable relationships, potentially leading to imbalances in market power relations (Narasimhan *et al* 2009). In some markets, especially in buyer-driven supply chains (Gereffi 1994), traders strive for more power imbalances in their supply chains to exert more control over their suppliers (Dauvergne and Lister 2013). Committing to sustainability criteria that condition suppliers' practices can further increase buyer companies' supply chain power, lock-ins and market dominance (Bastos Lima and Persson 2020, Heron *et al* 2018). Reverse causality is also possible: companies that are more dominant may be more likely to commit to sustainability criteria because they have the means to do so or the agency to influence actors upstream in the supply chain. Finally, different levels of trust or distrust may promote or hinder more effective engagement between companies and producers to implement sustainability criteria (Ghosh and Fedorowicz 2008, Skandrani *et al* 2011, Heron *et al* 2018).

Given the above, it is plausible that such non-financial factors influence both the observed patterns of stickiness in supply chain relationships and the adoption and effectiveness of sustainability commitments. However, no datasets exist that measure these factors comprehensively over large supply chains in a way that would enable quantitative evaluation of their influence on the adoption and effectiveness of ZDCs. Here we use observed patterns of trade stickiness as a proxy for these different factors. We measure these stickiness patterns through temporal network analyses of traders' relationships with production locations to explore their combined effects on both ZDC adoption and effectiveness by traders in the Brazilian soy export supply chain.

We focus on the soy export sector in Brazil, given its importance in deforestation and the momentum of ZDCs in this sector. We use spatiotemporal data on supply chain stickiness from Reis *et al* (2020) covering the years 2003 – 2017. Two distinct econometric models are employed to assess (i) whether and to what extent supply chain stickiness tends to increase the probability of adopting a ZDC, and (ii) how supply chain stickiness may influence the overall effectiveness of ZDCs, measured through observed reductions of native vegetation loss in sourcing regions for companies with or without commitments. We highlight that our objective is not to assess the effectiveness of the ASMs or individual company's ZDCs according to their own definitions of forest and deforestation. As these definitions are heterogeneous, sometimes unclear or ambiguous, and temporally changing (zu Ermgassen *et al*. 2020, Leijten *et al*. 2020), this would essentially preclude any meaningful and statistically robust analysis. We rather build on a standardized and well-accepted definition of deforestation and native vegetation conversion in Brazil (see Trase 2020b). By doing so, our assessment of ZDC effectiveness encompasses not only the aspects of implementation but also the design of these policies.

Through our empirical analysis, we seek to test two hypotheses:

1. Supply chain stickiness tends to increase the probability of adopting a ZDC, as stickier companies are more likely to have lock-ins, trust and power over a market, suggesting they also have the capacity to commit to sustainability.
2. The stickiness of different traders influences their effectiveness in implementing their ZDCs, through their capacity to influence their upstream supply chain, thus potentially reducing overall deforestation.

4.2. Methodology

To explore how the level of stickiness may influence the adoption and effectiveness of ZDCs within the Brazilian soy export sector, we used a panel data set with observations for all 1,599 traders involved in the export of Brazilian soy during the years 2004 – 2017. These data control for mergers and acquisitions during the period 2004 – 2017. Below, we first describe how we compiled and processed these data (section 2.1). After that, we describe the methods used to estimate the effect of stickiness on the adoption (section 2.2) and effectiveness (2.3) of ZDCs.

4.2.1. Data

We obtained time-varying data on the level of stickiness for each of the 1,599 traders from Reis *et al* (2020). These data are based on the topological overlap metric used in network analysis. This metric captures the supply network configuration changes over time around a specific trader (given the municipalities from which they source in a certain year) and ranges from 0 to 100%. Stickiness levels of 0% would indicate a complete change in a specific trader's supply chain configuration in two consecutive years (the minimum time step needed to detect changes given available data). In contrast, stickiness levels of 100% would indicate complete persistence in the supply chain configuration. Figure 1 in the supplementary material plots the general trend in stickiness between 2004 – 2017 in the Brazilian soy supply chain.

To examine how different levels of stickiness may influence the effectiveness of ZDCs, we focus on two outcome variables believed to be directly related to the effectiveness of ZDCs: the level of soy deforestation risk and territorial deforestation allocated to individual traders (Trase 2020c). Soy deforestation risk refers to the annual area of soy expansion (in hectares) within areas that have been deforested in the previous five years. Risk refers to the way this deforestation is allocated to the actors (here traders) along the supply chain, which is in proportion to the volume of soy that they export from a given municipality, relative to the total production of soy (by all producers) in the same municipality (Trase 2020b, note that supply chain data at the submunicipal level are not available). Territorial deforestation differs from soy-deforestation in that it captures all deforestation from a municipality in the soy supply chain, regardless of whether it is linked to the direct expansion of soy or not (TRASE 2020c). Although this could mean that some territorial deforestation cannot be directly linked to the expansion of soy, it arguably provides a more accurate indication of the overall effectiveness of ZDCs, as it also partially accounts for indirect deforestation

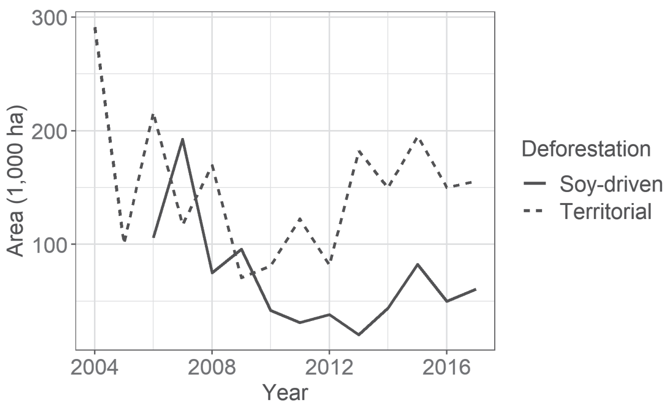

Figure 1 – Time series plot showing the total level of soy deforestation and territorial deforestation in Brazil's soy sourcing regions, after aggregating the data for all 1,599 traders. Soy deforestation levels are not available for the years 2004 and 2005.

(Gollnow *et al* 2018). We sourced data on both types of deforestation risks from Trase (2020b; 2020c) and zu Ermgassen *et al* (2020). Deforestation includes any conversion of native vegetation within the Amazon, Cerrado and Pantanal biomes. We provide a sensitivity analysis towards forest definition choice in the supplementary material. Figure 1 plots the aggregated annual level of both soy deforestation and territorial deforestation between 2004 – 2017.

As the empirical relationships between stickiness and the adoption and effectiveness of ZDCs may be confounded by other variables, we sought to control for these variables in our multivariate regression analysis (see sections 2.2 and 2.3). Table 1 lists all variables (i.e., both the variables of interest and control variables) used in the analysis, including their types and sources.

Table 1 – Variables used in the multivariate regression analysis. All variables are attributed to companies.

Variable	Type	Source
Variables of interest:		
Adoption of zero-deforestation commitment	Binary (0/1)	zu Ermgassen *et al* (2020)
Soy deforestation risk (in kha)	Continuous	Trase (2020c) and zu Ermgassen *et al* (2020)
Supply chain stickiness (unitless)	Continuous	Reis *et al* (2020)
Territorial deforestation risk (in kha)	Continuous	Trase (2020c) and zu Ermgassen *et al* (2020)
Control variables:		
Export share (company's export relative to total exports) (percentage)	Continuous	Trase (2020c)
Exports to Asian markets (company's export to Asian markets relative to company's total exports) (percentage)	Continuous	Trase (2020c)
Exports to European markets (company's export to European markets relative to company's total exports) (percentage)	Continuous	Trase (2020c)
Total unprotected area suitable for soy in sourcing region (ha)	Continuous	FUNAI (2020), ICMBio (2020), INCRA (2020), GeoLab - USP (2017)

4.2.2. The influence of stickiness on the adoption of ZDC

To explore how the probability of adopting a ZDC may depend on the company-specific level of stickiness, we estimated several logistic regression models using the variables listed in Table 1, with the adoption of a ZDC in a particular year as the dependent binary variable. As traders can only once commit to zero deforestation, we set traders' observations after the first year of the announcement to missing, as recommended by McGrath (2015). In all models, we controlled for each trader's export share within a given year and the share of exports going to the two most important export markets (Asia and Europe). As companies may be triggered to adopt ZDCs in response to increases in overall deforestation risk (Rueda *et al* 2017), we also controlled for the level of territorial deforestation risk in the previous year.

To account for time-invariant heterogeneity across traders (e.g., stemming from different attitudes toward environmental management practices; see Ho and Lin, 2012), we used a weighted demeaning approach that enabled us to explicitly estimate trader-specific fixed effects, implemented in the 'alpaca' package in R version 4.02 (R Core Team 2020, Stammann 2017). Although this approach could lead to biased estimates if the number of traders with commitments is large relative to the number of years – a statistical phenomenon known as the incidental parameters problem (Neyman and Scott 1948, Lancaster 2000) – this was not a concern in our case given that only 22 traders in our dataset have adopted ZDCs (which, when taken in aggregate, account for 78% of all soy exports between 2004 – 2017).

Formally, we estimated the following model:

$$ln \frac{P_{i,t}}{1-P_{i,t}} = \alpha_1 + \beta_1 \text{ stickiness}_{i,t} + \textstyle\sum_{k=1}^{K} \omega_k X_{k,i,t}, \quad (1)$$

where $P_{i,t}$ denotes the probability that trader *i* adopts a ZDC in year *t* (where ZDC can either refer to an individual ZDC or a ZDC adopted as part of the ASM), *stickiness*$_{i,t}$ denotes the level of stickiness, $X_{k,i,t}$ is a control variable (see Table 1), and α_i, β_1 and $\omega_1,...,\omega_k$ are parameters to be estimated. This equation resulted in 3 different regression models: one for all ZDCs, one for just the ASM and one for unilateral commitments.

Given the low number of traders with ZDCs, we did not account for year-specific fixed effects and the unprotected area suitable for soy as this would overfit the model (Hawkins 2004). As the number of traders with unilateral commitments (i.e., commitments that are not part of the ASM) is even lower (n = 5), we set the third model's positive convergence tolerance to 0.2, thus ensuring convergence (see McCullough 2009 for further details). To assess the overall effect of stickiness on the probability of adopting a ZDC, we used all three models' parameter estimates to compute the Average Marginal Effect (AME; Hilbe 2009) of stickiness. Although it is plausible that the adoption of a ZDC also affects levels of stickiness in consecutive years (i.e., reverse causality), we circumvented the issue by setting all consecutive observations to missing.

4.2.3. The moderating effect of stickiness on the effectiveness of ZDCs

Having assessed the effect of stickiness on the adoption of ZDCs, we examined how stickiness could moderate the effectiveness of soy ZDCs in reducing deforestation in Brazil.

We estimated several regression models specifying how stickiness may amplify or repress the effect of ZDCs on soy deforestation and territorial deforestation, holding other things constant. As both dependent variables follow a heavily skewed distribution with many observations equal to 0, we used a negative binomial regression model. As opposed to the linear regression model, the negative binomial regression model's underlying probability density function is more suited for modelling non-negative distributions clustered around 0 (Hilbe 2011). Although the Poisson regression model may also be used for modelling such zero-inflated variables, it imposes the restrictive assumption that the mean and variance of the dependent variable are equal, which does not hold for our data. In the absence of publicly available information on the intended time schedules of all individual zero-deforestation commitments (Garrett *et al* 2019), we arbitrarily assumed an implementation deadline of 2 years for all traders after the commitment was announced (after which a ZDC is expected to become effective). As a sensitivity test, we also consider an alternative implementation deadline of 5 years.

To explicitly estimate the trader-specific fixed effects in a computationally efficient way, we used the *fixest* package in R version 4.0.2 (Bergé 2020, R Core Team 2020). The underlying algorithm replicates the results of an unconditional negative binomial fixed effects model with no downward bias in the standard errors (Bergé 2018; Allison and Waterman 2002). This measure enabled us to estimate the following equation:

$$Def_{i,t} = exp\ (\alpha_i + \beta ZDC_{i,t} + \Phi\ stickiness_{i,t} + \delta ZDC_{i,t-2} * stickiness_{i,t}$$
$$\sum K\kappa{=}1 \omega_k X_{k,i,t} + Y_t) \qquad (2)$$

where $Def_{i,t}$ refers to either the annual level of soy risk or territorial deforestation for trader *i* in year *t*, $ZDC_{i,t-2}$ is a dummy (binary) variable denoting whether trader *i* has adopted a commitment in the 2 years preceding year *t*, $stickiness_{i,t}$ refers to the level of stickiness (rescaled to the unit interval to address overdispersion), $X_{k,i,t}$ is a control variable (see Table 1), and α_i, Φ, β, δ, Y_t and $\omega_1,...,\omega_k$ are parameters to be estimated. To explore the sensitivity of our results to the choice of forest definition, we re-estimated equation (1) after excluding sourcing areas outside the Amazon biome, as these may not be considered forest according to some definitions (Leijten *et al* 2020).

To gauge the moderating effect of stickiness on the effectiveness of ZDCs, we used the results of our regression estimates to predict, for each company that has adopted a commitment, what the effect of ZDCs would have been in the absence of an interaction effect. In other words, we compared the outcomes of a scenario that assumes no interaction between stickiness (i.e., δ = 0) and the effectiveness of ZDCs with a scenario that does account for interaction (i.e., δ - 0). To explore our estimates' uncertainty, we drew on the variance-covariance matrix of the parameter estimates and ran 1,000 Monte Carlo simulations, thereby following (Heilmayr *et al* 2020a).

4.3. Results

4.3.1. The influence of stickiness on the adoption of ZDCs

Table 2 reports the regression estimates of equation (1). The first column shows the results for all ZDCs, while the second and third columns show separate regression estimates for the ASM (column 2) and unilateral commitments (column 3). Due to the small number of companies with ZDCs (*n* = 22, which nevertheless account for 78 % of all soy exports), the sample size reduces to 104 observations in model 1. The results in column 1 indicate that stickiness has a positive and significant effect on the adoption of ZDCs ($P < 0.05$) in the consecutive year, other things being equal. More specifically, the results from column 1 suggest that a one percentage point increase in stickiness increases the odds of adopting a ZDC by 5% ($\exp(0.05) \approx 1.05$). We obtained the same result when focussing only on the Amazon Soy Moratorium (second column, first row; $P < 0.1$). However, stickiness appears to have a stronger effect on the adoption of unilateral commitments ($P < 0.001$): a one-percentage-point increase in stickiness increases the odds of adopting a unilateral ZDC by 14% ($\exp(0.13) \approx 1.14$).

Table 2 – Logistic regression estimates of the probability of adopting a ZDC. Heteroskedasticity robust (White-Huber) standard errors in parentheses. Asterisks indicate the level of statistical significance (· p < 0.10, *p < 0.05, **p <0.01, ***p <0.001). AIC denotes Akaike information criterion and BIC denotes Bayesian information criterion.

	All commitments	Amazon Soy Moratorium	Unilateral Commitments
Stickiness (%)	0.05 *	0.05 .	0.13 ***
	(0.03)	(0.03)	(0.03)
Territorial deforestation (1-year lag)	0.02	0.01	0.09 ***
	(0.02)	(0.02)	(0.02)
Export share (%)	0.04	0.05	-0.73 **
	(0.26)	(0.26)	(0.26)
Destination - Europe (%)	0.58 *	0.56 *	-0.04
	(0.29)	(0.28)	(0.03)
Destination - Asia (%)	0.60 *	0.58 *	0.04 **
	(0.29)	(0.27)	(0.01)
McFadden's Pseudo R^2	0.34	0.28	0.61
Observations	104	92	61
Trader fixed effects	Yes	Yes	Yes
Year fixed effects	No	No	No
AIC	125.35	123.15	33.55
BIC	196.75	188.71	124.54
Log Likelihood	-35.67	-35.57	-6.77

Figure 2 plots the Average Marginal Effect (AME) of stickiness on the probability of adopting a ZDC. The top row of Figure 2 indicates that on average, the probability of adopting a ZDC increases by 0.6% if stickiness increases by one percentage-point. Similar results are obtained when focussing only on the ASM (second row) or on unilateral commitments (third row).

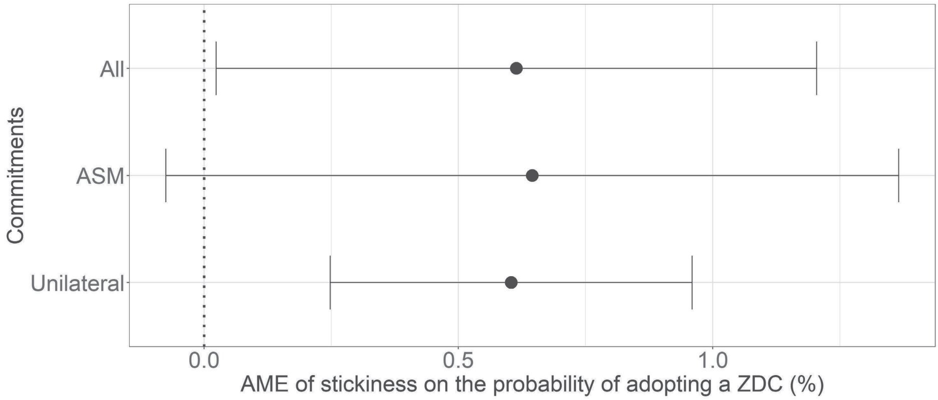

Figure 2 – Average Marginal Effect (AME) of stickiness on the probability of adopting a ZDC, thereby distinguishing between commitments made as part of the Amazon Soy Moratorium (ASM; second row) and unilateral commitments (third row). Error bars denote 95% confidence intervals. Confidence intervals that do not contain the number 0 (here indicated by the dotted vertical line) are statistically different from 0.

4.3.2. The moderating effect of stickiness on the effectiveness of ZDCs

We report the regression estimates of equation (2) in Table 3. The first two columns show a positive and statistically significant relationship between stickiness and soy deforestation (first row, $P < 0.01$). Conversely, there is no statistically significant relationship between stickiness and territorial deforestation, as shown in columns (3) and (4). In addition, there is no relationship between the adoption of ZDCs and soy deforestation or territorial deforestation, regardless of whether a 2-year (third row) or 5-year lag (fourth row) is assumed. However, the third and fourth columns indicate a positive interaction effect between stickiness and the adoption of ZDCs on territorial deforestation ($P < 0.05$, regardless of the choice of implementation deadline), suggesting that stickiness may hamper the effectiveness of ZDCs. These results remain robust when focussing only on deforestation in the Amazon biome (see Table 1 of the supplementary material).

To examine the magnitude of this interaction effect (in kha) as well as the underlying uncertainty, Figure 3 shows the results of the Monte-Carlo simulation. Each of the four notched boxplots compares the results of 1,000 simulations with and without an interaction effect on the total level of soy deforestation (top row) and territorial deforestation (bottom row). Given the uncertainty regarding the implementation deadline of ZDCs, boxplots in

Table 3 – Negative binomial regression estimates of the annual amount of soy deforestation risk and territorial deforestation. Columns (1) and (3) assume a ZDC implementation deadline of 2 years, while columns (2) and (4) assume an implementation deadline of 5 years. Heteroskedasticity robust (White-Huber) standard errors in parentheses. Asterisks indicate the level of statistical significance (· $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$). Soy and territorial deforestation are represented in kha.

	Soy deforestation risk	Soy deforestation risk	Territorial deforestation	Territorial deforestation
Stickiness (0 –1)	0.60 **	0.63 **	0.13	0.11
	(0.22)	(0.23)	(0.20)	(0.20)
Commitment (2-year lag)	0.06		0.69	
	(1.18)		(0.51)	
Stickiness x Commitment (2-year lag)	0.30		1.23 *	
	(1.32)		(0.61)	
Commitment (5-year lag)		0.79		-0.34
		(1.00)		(0.79)
Stickiness x Commitment (5-year lag)		-1.57		1.98 *
		(1.22)		(0.89)
Export share (%)	0.29 ***	0.24 *	0.16 *	0.20 **
	(0.09)	(0.10)	(0.06)	(0.07)
Destination - Europe (%)	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.01)	(0.01)	(0.00)	(0.00)
Destination - Asia (%)	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Unprotected suitable forest area	0.48 *	0.52 *	0.42 *	0.53 *
	(0.22)	(0.24)	(0.21)	(0.23)
Theta (overdispersion)	1.17 ***	1.20 ***	0.99 ***	0.96 ***
	(0.18)	(0.19)	(0.11)	(0.11)
McFadden's Pseudo R^2	0.61	0.61	0.60	0.60
Observations	4692	4692	7168	7168
Trader fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
AIC	1980.98	1978.99	2994.98	3003.94
BIC	4626.96	4624.97	6660.63	6669.59
Log Likelihood	-580.49	-579.49	-964.49	-968.97

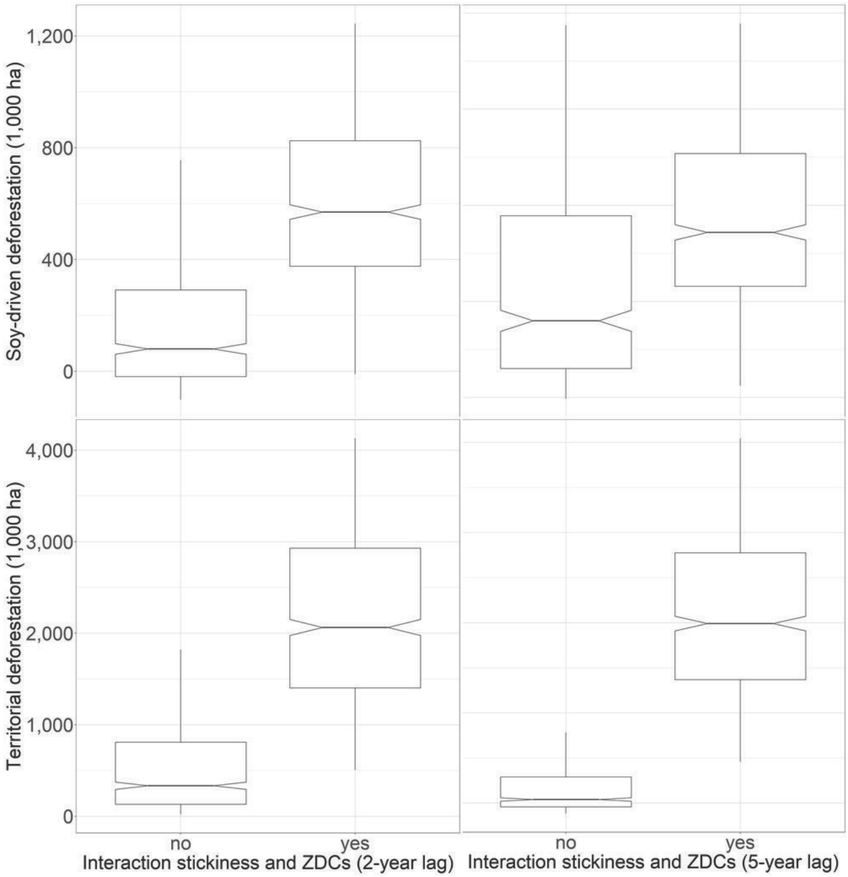

Figure 3 – Notched box plots showing the results of 1,000 Monte Carlo simulations of the effects of ZDCs – with and without an interaction effect with stickiness – on soy deforestation and territorial deforestation. Median estimates – including their confidence intervals - are indicated by the notches in each plot. Upper hinges represent 75% quantiles, and lower hinges represent 25% quantile. Upper (lower) whiskers represent the largest outcomes that are less than or equal to upper (lower) hinge * the interquartile range.

the left column account for an implementation period of 2 years, and boxplots on the right account for an implementation period of 5 years. The boxes display the interquartile range (25 to 75th percentile) of all 1,000 simulations' outcomes. The notches show the 95% confidence interval around the median (see McGill *et al* 1978 for a more detailed explanation of notched box plots). Most simulations confirm that the interaction effect of stickiness and ZDCs tends to result in more soy deforestation and territorial deforestation, with none of the notches overlapping. By way of example, the top-left plot shows that the median estimate of the effect of ZDCs on soy deforestation increases from 28 (6 – 49) to 738 (697 – 778) kha if there is an interaction effect between stickiness and ZDCs. These findings suggest that traders with higher stickiness are less likely to effectively implement their ZDCs than traders with lower stickiness. However, even in the absence of an interaction effect, most simulations still show a positive effect of ZDCs on soy deforestation and territorial deforestation, suggesting that notwithstanding the level of stickiness, additional efforts are needed to implement ZDCs.

4.4. Discussion and conclusion

We find that stickiness tends to increase the probability of adopting a ZDC in the consecutive year, supporting our first hypothesis that stickier companies are more likely to have lock-ins, trust, and bargaining power. A potential explanation for this is that stickier traders deliberately aim for stable trade relations with certain geographical regions and committing to zero-deforestation can be a strategy to reduce the risk of supply disruptions (Rueda *et al* 2017). Additionally, sticky traders may also be more vulnerable than volatile traders to reputational damage if their suppliers are brought into disrepute, which may incentivise sticky traders to adopt ZDCs (Tamayo-Torres *et al* 2019). This explanation is consistent with the green club theory, which describes how reputational risk aversion may trigger firms to participate in 'green clubs' (Barnett and Hoffman 2008, Potoski and Prakash 2013).

Despite the presumed positive influence of stickiness on the adoption of ZDCs, we also found strong evidence that stickiness tends to increase the risk of soy-deforestation, supporting our second hypothesis on the link between stickiness and effectiveness of commitments. Moreover, traders committed to zero-deforestation with higher levels of stickiness also show higher risks of territorial deforestation. Both findings suggest that stickiness may undermine the implementation and overall effectiveness of ZDCs at the traders' level. This explanation could be because sticky traders drive continued demand for soy from certain regions, which may send encouraging signals to actors on the ground to expand production (Richards *et al* 2012). Moreover, stickiness may also give rise to lock-in effects where traders become dependent on certain suppliers, thus hindering traders from switching to producers complying with ZDC-criteria (Schmitz *et al* 2016). Effectiveness of ZDCs could in some cases be further undermined if the adoption of ZDCs leads to a situation where producers continue to deforest to produce soy, whilst selling to intermediaries instead of through direct contracts(Meyfroidt *et al* 2018, Alix-Garcia and Gibbs 2017, Carvalho *et al* 2019).

Conversely, low-stickiness traders may more easily achieve a ZDC, but if only by switching to low-deforestation sourcing regions, this may not necessarily contribute to more effective deforestation reduction on the ground. We highlight that we did not find any evidence that the ZDCs reduce native vegetation loss, regardless of the level of stickiness. This finding is consistent with recent literature for individual ZDCs (zu Ermgassen *et al* 2020). In contrast, for the ASM as a collective ZDC, the literature shows it effectively reduces deforestation (Heilmayr *et al* 2020b). These two studies nuance the interpretation that stickiness is indeed thwarting the effectiveness of ZDCs, as it could also be that at the end of our study period (*i.e.,* the year 2017), no action had been taken yet to implement the individual commitments.

A limitation of our study is that, as explained in the introduction, our stickiness metric captures and reflects several underlying dynamics, including lock-in effects, trust, and certain power dynamics. Thus, the data do not allow us to identify which of these factors are more influential in the adoption and effectiveness of ZDCs. Whilst there are reasons to believe that stickiness is a useful proxy for these value chain dynamics, additional data are required to attribute the overall effect of stickiness to these underlying factors. These factors may influence ZDC adoption and effectiveness in different, contradictory ways. Furthermore, due to the small number of traders with ZDCs in our sample, our analysis may suffer from a lack of statistical power, potentially resulting in type II errors, *i.e.*, failing to identify certain statistical significance effects that are occurring. Moreover, given that the supply chain data are aggregated at the municipality level, it is conceivable that our conclusions do not hold at the property level (an example of the ecological inference problem; Freedman *et al* 1998). Yet, assessing ZDC at municipality level allows to account for local spillovers and thus measures ZDC's effectiveness at jurisdictional level beyond the specific sourcing farms (Leijten *et al* 2021, Godar *et al* 2016). Further research could explore the extent to which our qualitative conclusions hold in other supply chains or at more disaggregated levels, assuming future data availability.

Despite these limitations, our study contributes to a burgeoning empirical literature on the effectiveness of ZDCs (Bager and Lambin 2020, Moffette and Gibbs 2019, zu Ermgassen *et al* 2020). Our study builds on this work by highlighting the concept of stickiness as a potential proxy for unobserved value chain dynamics that may influence the adoption and effectiveness of ZDCs and other corporate sustainability initiatives. Whilst our findings suggest that stickiness incentivises traders operating in the Brazilian soy export sector to adopt ZDCs, they also show that, up until 2017, stickiness may have counteracted their effectiveness. This finding suggests that additional strategies, such as public-private partnerships (Furumo and Lambin 2020), moratoria (Soterroni *et al* 2019), certification schemes (van der Ven *et al* 2018) and enhanced representation of upstream actors in ZDCs (Virah-Sawmy *et al* 2019) may be needed to support the implementation of ZDCs and to eliminate deforestation.

5

Projecting global oil palm expansion under zero-deforestation commitments: direct and indirect land use change impacts

In the last three decades, global production of oil palm has boomed, which has partly come at the expense of tropical rainforests. Recognizing this, many companies operating in the palm oil industry have committed to eliminate deforestation from their operations, often referred to as Zero-Deforestation Commitments (ZDCs). However, even if such pledges are fully adopted and enforced, there are large uncertainties as to how they may affect land use and in particular, the area under oil palm across the globe. Here, we combine a multi-commodity, multiregional comparative static computable general equilibrium model with a dynamic land use model to assess the effect of ZDCs on oil palm and other land uses, as well as the degree to which conversion of natural areas may be avoided or displaced. We estimate that if ZDCs are fully adopted and enforced across all sectors and geographies, the global extent of oil palm plantations may be 11 Mha or 40% smaller in 2030 than in a Business-As-Usual (BAU) scenario that assumes no compliance with ZDCs. The total area devoted to other crops, forestry, and pastureland in oil palm-producing countries is also expected to decrease as a result of globally enforced ZDCs, although the percentage changes relative to the BAU scenario are smaller. As a result of such land-sparing effects, we estimate that 96 Mha of forests are saved from conversion, of which, 17% would otherwise have been converted (directly or indirectly) due to expanding oil palm plantations. Overall, these figures suggest that ZDCs have the potential to deliver major environmental benefits if they are fully implemented across all industries and regions. Given the goals of international agreements to eliminate deforestation by 2030, this should motivate the international community to increase the uptake, but also the enforcement of ZDCs.

This chapter is under review as:

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5.1. Introduction

In the last three decades, global production of oil palm (*Elaeis guineensis*) fresh fruit bunches (FFBs) has boomed, increasing by nearly 600% (FAOSTAT 2021). Oil palm provides two types of vegetable oil: palm oil and palm kernel oil. These oils are used in a variety of applications including foods, soaps, detergents, cosmetics, pharmaceuticals, and biofuels (Corley and Tinker 2015). Although the yields vary substantially depending on the age of the plantation (Woittiez *et al* 2017), the time-averaged yields of palm oil per hectare are by far the highest of all oil crops (Carrasco *et al* 2014). Over the last decades, palm oil has become the most consumed and traded vegetable oil in the world and demand will very likely continue to grow in the near future (Bentivoglio *et al* 2018, OECD and FAO 2020, Mosnier *et al* 2017).

However, in contrast to other major agricultural commodities such as rice or wheat, increased demand for oil palm has mostly been met by expanding the total area under production rather than intensification (i.e. increasing yields on existing production areas (Byerlee *et al* 2016). This has resulted in an increased area of oil palm plantations of more than 350% – from 6 to 28 M hectares (ha) – since 1990 (FAOSTAT, 2021, see Appendix A Figure 1). As oil palm only grows in the tropics, this expansion has partly come at the expense of tropical rainforests (Qaim *et al* 2020). This is especially true for Southeast Asia, which is the largest palm oil producing region of the world, accounting for 84% of production in 2018 (FAOSTAT). It is estimated that around 45% of all new oil palm plantations established in Southeast Asia since 1989 have replaced forests (Vijay *et al* 2016).

At the same time, there are large opportunities for the expansion of oil palm plantations outside tropical forests (Smit *et al* 2013, Pirker *et al* 2016) and recent evidence suggests that recent oil palm expansion in Latin America has been largely deforestation-free (Furumo and Aide 2017, Brandão *et al* 2021). In recent years, many companies involved in the palm oil industry have pledged to eliminate or reduce deforestation from their supply chains. These pledges are often referred to as Zero-Deforestation Commitments (ZDCs) (Lambin *et al* 2018). As of April 2020, 83% of the palm oil refining capacity in Indonesia and Malaysia (which, together, accounted for 84% of global production between 2010 – 2019; FAOSTAT, 2021) was covered by ZDCs (ten Kate *et al* 2020).

Whilst various studies have considered the past effectiveness of ZDCs (Leijten *et al* 2022, Heilmayr *et al* 2020b, zu Ermgassen *et al* 2020), less attention has been given to understanding how full implementation and enforcement of ZDCs could potentially play out in terms of future global land use and land use change. The difficulty in predicting the potential impacts of ZDCs arises from the necessity to construct a plausible counterfactual, i.e., a scenario of what would happen in the absence of ZDCs. Such an assessment should account for global market-mediated effects that may occur in response to the implementation of ZDCs as well as for local differences in land availability, land suitability and baseline changes in the economy. Mosnier *et al* (2017) provided an ex-ante assessment of the overall forest loss that may be avoided due to ZDCs in Indonesia but did not account for economy-wide effects and spillover effects in other countries. Such spillover effects have the potential to seriously undermine the effectiveness of ZDCs (see e.g., Meyfroidt and Lambin, 2009). Taheripour *et al* (2019) offered a comprehensive, global assessment of the amount of deforestation that may be avoided if certain economic policies are adopted by the Indonesian and Malaysian government, but they did not consider the role of ZDCs in curbing deforestation. Furthermore, both studies only assessed aggregate forest loss at the country level and did not consider spatialised deforestation outcomes within countries. As impacts depend on the spatial patterns of forest loss, more spatially explicit assessments are needed to anticipate the potential environmental benefits of the ZDCs (Lam *et al* 2019).

The objective of this chapter is to make a spatial assessment of how the worldwide implementation of zero-deforestation commitments across all agricultural commodities, economic sectors and geographies could alter the spatial configuration of oil palm and other land uses up until 2030 whilst accounting for expected baseline changes in the economy. The analysis will facilitate an evaluation of the extent to which fully executed ZDCs may moderate conversion of forests and other (semi) natural areas over this time period. We link the results from a computable general equilibrium model with a dynamic land use change model to project how land use may evolve under two scenarios: a business-as-usual (BAU) scenario assuming no implementation of ZDCs and a ZDC scenario assuming full implementation and enforcement of ZDCs across all economic sectors. The spatial distribution of oil palm and other land uses is modelled from 2014 (the most recent reference year for which global economy-wide data are available) up until 2030. The year 2030 coincides with the target year of the 2014 New York Declaration on Forests (Schulte *et al* 2019); a declaration signed by more than 200 companies, governments, non-governmental organizations and groups representing indigenous communities to end all global natural forest loss.

5.2. Methodology

5.2.1. Overall approach

We took a stepwise approach to project changes in oil palm area from 2014 up to 2030, as a result of fully implemented and enforced ZDCs. We first employed a multi-commodity, multiregional comparative static computable general equilibrium model to make baseline projections of economic activity up to 2030, assuming no compliance with ZDCs (see section 2.2). This model operates at a spatial resolution of 37 world regions, stratified by 18 global Agro-Ecological Zones (AEZs), resulting in 337 region-specific AEZs (see Appendix A Figures 2 & 3), and accounts for legally protected areas. To account for heterogeneity in the area available for cropland expansion across the different regions, we calibrated the model with new spatially explicit estimates of region-specific supply of available land, also referred to as land supply asymptotes (see section 2.3). We then constructed an alternative scenario that assumes full implementation of and compliance with ZDCs (section 2.4) but otherwise equal to the BAU scenario. This scenario implies a reduction in the supply of land available for expansion equal to the areas covered by ZDCs, and hence, simulates a potential change in both the supply and demand of oil palm, and other crops, relative to the baseline scenario. The outcomes of these two scenarios were then used to model the spatial distribution of oil palm plantations within each oil palm producing region up to 2030, using a spatially explicit and dynamic land use change model, operating at a spatial resolution of 10 x 10 km (section 2.5). This model accounts for competition between all land uses for space and can therefore simulate displacement of land uses. Comparison of the land use configurations resulting from these two scenarios provides an indication of the potential influence of ZDCs on oil palm and other land uses up to 2030. A stylized flowchart of the methodology is shown in Figure 1.

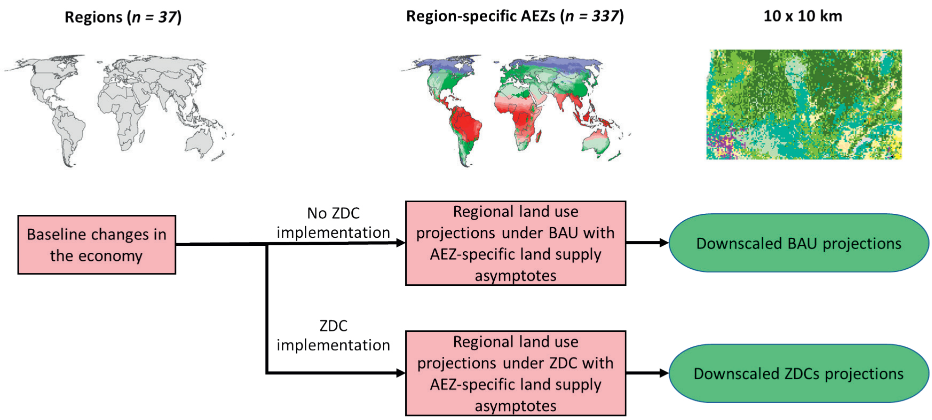

Figure 1 – Flowchart of the methodology. Maps above the flowchart indicate the spatial resolution of each step in the modelling process. Downscaled land use projections are only made for oil palm-producing regions. CGE denotes computable general equilibrium model. BAU denotes Business-As-Usual. ZDCs denotes zero-deforestation commitments.

5.2.2. Computable general equilibrium modelling

Computable general equilibrium (CGE) models are systems of mathematical equations that describe economies as a whole and the interaction among their parts (Burfisher 2011). They are based on the premise that market economies will tend towards market-clearing, which occurs when the aggregate supply of goods and services equals aggregate demand. Producers are assumed to choose levels of input and output that minimize costs and consumers are assumed to maximize their utility subject to budget constraints. Policy changes can be simulated by changing exogenous variables of the model, which leads to a reallocation of labour, capital and land across sectors and geographies, until the system reaches equilibrium again. Responsiveness of producers and consumers to changes in relative prices and income is simulated by empirically calibrated elasticities of supply and demand.

In order to model the global market-mediated effects of ZDCs from 2014 up to 2030, we employed the most recent version of the Global Trade Analysis Project with differentiated Ago-Ecological Zones (GTAP-AEZ) CGE model (Johnson *et al* 2021) using the most recent GTAP database (Aguiar *et al* 2019). The database describes the world economy in 2014, disaggregated into 65 different sectors and 37 different regions (see Appendix A Figure 2). Given that coverage of ZDCs across industries and regions was far from 100% in 2014, our model experiment is hypothetical as it does not inform on the actual effectiveness of ZDCs. Instead, the model experiment is designed to capture the potential effects that could be induced by ZDCs if they were fully implemented across industries and regions.

To account for likely macroeconomic trends between 2014 – 2030 that are unrelated to the adoption of ZDCs, we constructed a baseline or BAU scenario for the year 2030 that is largely consistent with the second Shared Socioeconomic Pathway (SSP), a scenario where socioeconomic trends broadly follow their historical patterns (van Vuuren *et al* 2017, O'Neill *et al* 2014). Following Johnson *et al* (2021), we used growth rates of real GDP, capital stock, population, unskilled and skilled labor from ECONMAP (v2.4) (Fouré *et al* 2013) which are calibrated based on the SSP2 scenario. Sector specific productivity growth for ruminants and non-ruminants are taken from Ludena *et al* (2007). Due to lack of estimates for forest sector productivity growth, agricultural productivity growth figures are also taken from Ludena. Following Chateau *et al* (2020), a 2% productivity growth gap between manufacture and service sectors is also imposed. Finally, to account for baseline growth rates in crop yields, we used data from FAOSTAT (2021) and extrapolated yields up until 2030 based on the observed linear growth rate between 1998 – 2014 (given the reference year of the GTAP database) for each agricultural commodity group within each region in the GTAP database. To remain consistent with official projections, we scaled these projections using the global yield projections from the OECD-FAO Agricultural Outlook (OECD-FAO, 2018; OECD/FAO, 2021).

A special feature of GTAP-AEZ is that, in contrast to the standard GTAP model (Hertel 1997, Corong *et al* 2017), each region is further disaggregated into spatially heterogeneous land endowments or AEZs. These AEZs are determined based on climatic zones (tropical, temporal and boreal) and the length of the growing period (6 x 60-day intervals, see Lee *et al.*, 2005), resulting in 18 different AEZs that may intersect multiple countries (see Appendix A Figure 3). Within each region-specific AEZ (337 in total), the supply of available land is modelled using an empirically calibrated asymptotic curve specifying the relationship between land supply and the real land rental rate (Woltjer and Kuiper 2014, Eickhout *et al* 2009). The land supply curves are predicated on the assumptions that expansion occurs within the most productive areas that are still available and that the land rental rate

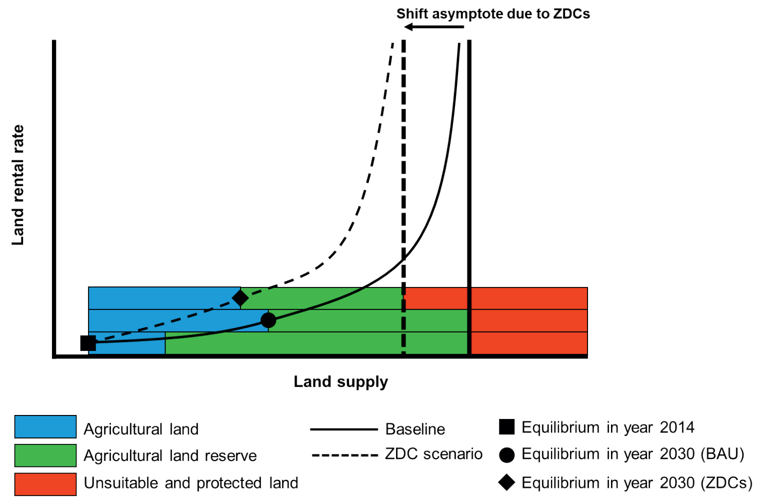

Figure 2 – Stylized graph – adapted from Overmars *et al* (2014) – showing the relationship between land rental rates and the supply of land under two scenarios: a baseline scenario assuming no compliance with Zero-Deforestation Commitments (ZDCs) and an alternative scenario assuming full implementation of ZDCs. Land availability is constrained by the land supply asymptote: all areas beyond the asymptote are assumed to be unavailable for agricultural production. Implementation of ZDCs implies a leftward shift of the land supply asymptote as it involves an increase in the area that is protected from agricultural encroachment.

monotonically increases whenever the supply of available land decreases (see Figure 2). The maximum area available for expansion within each region-specific AEZ is constrained by a prespecified land supply asymptote. As land supply is critical in our scenarios, spatial differences in land availability need to be accounted for in the most accurate way. Therefore, we updated GTAP-AEZ by including new estimates of the land supply asymptotes for each region-specific AEZ (see section 2.3), thereby better accounting for the constraints to land availability defined by earlier studies (Eitelberg *et al* 2015, Lambin *et al* 2013).

A challenge for our model experiment is that the most recent GTAP database aggregates all oil crops (including oil palm) into one sector. Hence, to distinguish between oil palm and other oil crops in our analysis of GTAP outcomes, we used data from FAOSTAT (2021) on the area and production volumes of oil palm and other oil crops over the period 1998 – 2019 and made region-specific projections with respect to the oil palm share up until 2030. We considered 4 alternative approaches to project the share of oil palm and used the period 2015 – 2019 to evaluate the accuracy of each approach within each region. Accuracy was measured through the Root Mean Square Error (RMSE) of the predictions. For each region, we identified the approach with the lowest RMSE during the period 2015 – 2019 and used it to make projections up until 2030, provided that the RMSE in the period 1998 – 2014 was not unreasonably high (i.e., more than 2 times the size of the approach with the lowest RMSE during the period 1998 - 2014). The 4 different approaches were based on linear and quadratic extrapolations of the observed share over the period 1998 – 2014, constant value extrapolations using the observed share in 2014, and constant value extrapolations using the observed average share in the period 2010 – 2014 (see Appendix A Figure 5 for an overview of the different approaches by region). To explore the sensitivity of our results to the choice of attribution method, we present alternative results using the observed share of oil palm in 2019 as a parameter to attribute changes in the oil crop sector to oil palm.

5.2.3. Land supply asymptotes

To estimate the extent of area that is potentially available for cropland expansion within each region-specific Agro-Ecological Zone (AEZ), we took three steps (see Appendix A Figure 6 for a flowchart of the methodology). We first identified areas where cropland could possibly expand given certain biophysical, socio-economic, and institutional constraints through a residual approach. This means, we computed the total area within each region-specific AEZ after excluding areas already under cultivation, areas biophysically unsuitable for cropland cultivation, legally protected areas, rough terrains, and urban areas (see Table 1 and Appendix C for further details). To harmonize the different input data, all data were resampled to a 1 km^2 grid.

Second, to account for tiny landscape features that inhibit cropland expansion but cannot be detected at a 1 km^2 resolution (e.g., roads, rocky outcrops, water infrastructure, hedgerows, buildings etc.) we multiplied the extent of the remaining area of each region-specific AEZ by 0.85. This parameter is based on Verburg *et al* (2009), who estimated that across different agriculturally dominated landscapes about 15% of the area is not used for crop cultivation. This approach for calculating available land may over- or underestimate the extent of the available area that can be harvested as it does not account for multiple cropping and fallow systems (Waha *et al* 2020, Siebert *et al* 2010). Therefore, for each AEZ, we further multiplied the extent of the total area available for expansion by the estimated region-specific multiple cropping intensity in 2014. This approach assumes that the multiple-cropping intensity within each region-specific AEZ remains constant between 2014 – 2030. To reduce the influence of outliers (areas with either extremely high or low cropping intensities, see Appendix A Figure 7), we constrained the cropping intensities to lie in the range 0.5 – 2.0. Formally, this means we computed the area available for cropland expansion within each region-specific AEZ as follows:

$$Available\ area_i = \begin{cases} (TA_i - UA_i) * 0.5 & if\ CI_j < 0.5 \\ (TA_i - UA_i) * CI_j & if\ 0.5 \le CI_j \le 2, \\ (TA_i - UA_i) * 2 & if CI_j > 2 \end{cases} \tag{1}$$

where *Available area$_i$* denotes the available area within region-specific AEZ *i* in hectares; *TA$_i$* denotes the total terrestrial area in hectares; *UA$_i$* denotes the total area unsuitable for

Table 1 – Criteria used to identify areas unsuitable for cropland expansion

Indicator	Source	Original resolution	Data processing	Classification rule
Agricultural suitability for the 16 most important food and energy crops based on climatic, soil and topographic conditions	Zabel *et al* (2014)	30 arc seconds (approximately 1 x 1km at the equator)	Resampled to a 1000 x 1000 m resolution using the nearest neighbour method	All grid cells classified as unsuitable by (Zabel *et al* 2014) were assumed to be available for expansion
Existing cropland	ESA-CCI – Defourny *et al* (2017); reference year: 2014	10 arc seconds (approximately 300 x 300 m at the equator)	Resampled to a 1000 x 1000 m resolution using the majority resampling method	All areas classified as "Cropland, rainfed", "Cropland, irrigated or post-flooding" were assumed to be unavailable for expansion. For the two mosaic classes, ("Mosaic cropland (>50%) / natural vegetation (< 50%)" and "Mosaic natural vegetation (>50%) / cropland (< 50%)"), a cropland fraction of 58 and 38% was assumed, respectively
Legally protected areas	UNEP-WCMC & IUCN, (2018)	N.A. (shapefile)	Rasterized to a 1000 x 1000 m grid	All protected areas were assumed to be unavailable for expansion
Rough terrains (steep slopes)	Lloyd (2016)	100 x 100 m	Resampled to a 1000 x 1000 m resolution using the majority resampling method	Region-specific slope threshold based on the top 5% slope values within existing cropland areas. A minimum threshold of 10 degrees was imposed.
Urban areas	ESA-CCI – Defourny *et al* (2017); reference year: 2014	10 arc seconds (approximately 300 x 300 m at the equator)	Resampled to a 1000 x 1000 m resolution using the majority resampling method	All areas classified as "Urban areas" were assumed to be unavailable for expansion

cropland expansion in hectares; and CI_i denotes the cropping intensity. Cropping intensities were estimated by computing for each region-specific AEZ the ratio of the harvested area of all crops in the GTAP database (Aguiar *et al* 2019) to the total extent of cultivated area, based on the 10 arc-seconds resolution ESA-CCI satellite-based land cover map for the year 2014 (Defourny *et al.*, 2017; see Table 1 for further information).

Finally, we summed the total harvestable area available for expansion and the total area harvested in 2014 to arrive at an estimate of the land supply asymptote for each region-specific AEZ (see Appendix A Figure 8a).

5.2.4. Implementation of zero-deforestation commitments

Implementing ZDCs involves reducing the (forest) area available for cropland expansion and hence, shifting the land supply asymptote to the left (see Figure 2). There are large uncertainties regarding the spatial coverage of ZDCs as the uptake and specificity of ZDCs varies across individual firms, commodities, and regions (Jopke and Schoneveld 2018). Nevertheless, common criteria outlined in many ZDCs are the protection of High Conservation Value Forests (HCVF) and High Carbon Stock Forests (HCSF). At least 78% of the palm oil refining capacity in Indonesia and Malaysia is covered by commitments which include these criteria (ten Kate *et al* 2020) and the uptake of similar commitments in other industries and regions is on the rise (Cheyns *et al* 2019, Areendran *et al* 2020). We used data from Leijten *et al* (2020) on the likely spatial distribution of HCVFs and HCSFs to delineate areas covered by ZDCs (see Appendix A Figure 8). We focussed on a middle-of-the-road estimate, which includes all tropical peatland forests and all forests with at least two overlapping HCVF categories or with at least 75 t C ha^{-1} if located in the tropics (see Leijten *et al* for further details). Updated estimates of the land supply asymptotes that account for the coverage of ZDCs are presented in Figure 8b of Appendix A. To explore the robustness of our results, we present alternative results using the top and bottom range estimates of the likely spatial extent of HCVFs and HCSFs. The low estimate (i.e. least protective) is based on three overlapping HCVF categories with a 75 t C ha^{-1} threshold while the upper estimate only requires one HCVF category with a 35 t C ha^{-1} threshold.

5.2.5. Spatial land use modelling

We used the GAEZ-AEZ output as input for a dynamic land use model to simulate the spatial dynamics of oil palm and other land systems within all oil palm producing regions.

5.2.5.1. CLUMondo

CLUMondo is a spatially explicit and recursive dynamic land change model that can be used to simulate the spatial dynamics of land systems (Schulze *et al* 2021, van Asselen and Verburg 2013). One of the unique features of the model is that it incorporates multifunctional land systems, i.e., land systems that provide multiple types of goods and services. To simulate future land use configurations, the model uses an iterative procedure where grid cells are allocated to the land system with the highest transition potential. Transition potentials are calculated for each individual land system though the following formula:

$$Ptrans_{i,t,LS} = Ploc_{i,t,LS} + Pres_{LS} + Pcomp_{t,LS} + Pneigh_{i,t,LS} \quad (2)$$

where $Ptrans_{i,t,LS}$ represents the overall transition potential to land system *LS* in grid cell *i* at time *t*, $Ploc_{i,t,LS}$ represents the local suitability of land system *LS* (see section 2.5.2), $Pres_{LS}$ represents the conversion resistance of land system *LS*, proxying conversion and investment costs as well as cultural attachments to the current land use (see section 2.5.3), $Pcomp_{t,LS}$ represents the relative competitive advantage of land system *LS*, determined by the demand for the different products/services delivered by the land system (section 2.5.4) and $Pneigh_{i,t,LS}$ denotes the neighbourhood influence, representing agglomeration processes, for example due to economies of scale (2.5.5). By iteratively updating $Pcomp_{t,LS}$, the model constructs a spatial configuration of land use such that meets the aggregate demand of goods and services within each region, here represented by the demand projections of the GTAP-AEZ model. Further details on the allocation procedure can be found in Van Asselen and Verburg (2013).

To simulate the likely future spatial distribution of oil palm (given the GTAP-AEZ projections), we first created a 10 x 10 km land use map for the year 2014, the reference year of the GTAP-AEZ database. The land use map was primarily based on the 2014 ESA-CCI land cover map (Defourny *et al.*, 2017), which we reclassified into 8 distinct land cover classes (see Table 1 of Appendix B). To distinguish oil palm producing systems from other systems, we overlaid the resulting land cover map with a remotely sensed oil palm map from (Descals *et al* 2021), aggregated to a 10 x 10 km resolution. We classified all grid cells with at least 50% oil palm cover as oil palm areas. Grid cells with 10 – 50% oil palm cover were classified as oil palm mosaics, which in addition to oil palm, produce a variety of other agricultural commodities (see below). GTAP regions with no oil palm areas or oil palm mosaic (according to the Descals map) were excluded from the analysis.

Demand for all other agricultural commodities is supplied by either cropland areas or cropland mosaics (which, like oil palm mosaics, represent a mixture of different land uses). As these two cropland categories vary in their agricultural intensity across space, we distinguished between high yielding systems, medium yielding systems, and low yielding (or extensive) systems. To classify cropland areas and cropland mosaics into these three different yielding systems, we overlaid the land use map with spatially explicit data (10 x 10 km) on the yields of all agricultural crops from the International Food Policy Research Institute (2019) and divided the data into quantiles. More specifically, we computed the sum of all yields within each pixel and selected the three top quintiles to differentiate between high yielding, medium yielding and low yielding systems, respectively.

Finally, to distinguish grasslands that are intensively grazed from other grasslands, we used spatially explicit data (10 x 10 km) on the distribution of cattle in 2010 from Gilbert *et al* (2018). Grasslands within the top octile (12.5%) of the cattle density distribution were assumed to be intensively grazed. Figure 3 shows the resulting land use map. Regions with no or barely any oil palm area were excluded from the analysis. This includes China and Madagascar, which both accounted for less than 0.23% of global oil palm area in 2014 (FAOSTAT, 2021).

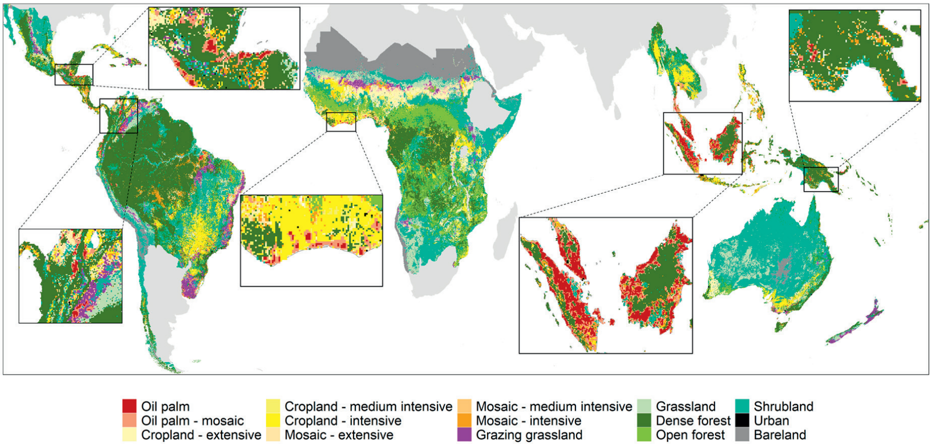

Figure 3 – Initial land use map used in the CLUMondo simulations. Zoom maps zero in on major oil palm-producing regions. Non- oil palm-producing regions are greyed out. Reference year is 2014.

5.2.5.2. Local suitability

Local suitability ($Ploc_{i,t,LS}$; see equation (2)) of the different land systems was assessed based on empirically quantified relations between land use patterns and several explanatory variables, using a logistic regression analysis for each land system within each oil palm producing region. Table 2 lists all 44 predictor variables used in the regression analysis (see Table 2 of Appendix B). Model selection was done through a backward model selection procedure based on Akaike's Information Criterion. To avoid multicollinearity, predictor variables with intercorrelations exceeding 0.8 were removed from the analysis.

To allow for dynamic changes in local suitability, we used spatiotemporal predictions of total and rural population density up to 2030 from CIESIN (2018). The data were linearly interpolated for years for which no predictions were available.

5.2.5.3. Conversion resistance

For each land system in each region, a parameter was specified that captures the degree to which it is resistant to any type of land system conversion ($Pres_{LS}$, in equation (2). Land systems that involve large capital investments are typically more resistant to change (Mellino *et al* 2015). Oil palm plantations typically require a large amount of capital investment, especially since they only start bearing fruit in the third or fourth year after establishment (Rist *et al* 2010). For that reason, we assumed that oil palm plantations tend to be relatively resistant to change, whereas land systems requiring little capital investment (e.g., extensive croplands) were assumed to be more reversible.

In addition to conversion resistance, the spatiotemporal dynamics of the simulation are also influenced by a prespecified land conversion matrix that stipulates the type of land system conversions that are allowed and how long it takes before such conversions may take place. Given the time lag between the establishment of an oil palm plantation and the yielding period, the land conversion matrix was specified such that oil palm plantations can only be established after three years with stable land use. Finally, we also assumed, based on the estimates of Liebsch *et al* (2008), that after a period of 30 years, open forest may mature into dense forest. In the absence of detailed information on the history of each land system, we assigned a random number to all pixels indicating the number of years that the land system is already in place. All other land conversion rules developed for this analysis can be found in Table 3 – 4 of Appendix B.

5.2.5.4. Relative competitive advantage

The relative competitive advantage ($Pcomp_{t,LS}$ in equation (2)) of a land system in a certain region is determined through an iterative procedure in which the provided goods and services are compared to the total demand for those goods and services in the same region. Drawing on the GTAP-AEZ projections, we distinguished between five different types of demand: forestry, oil palm, other agricultural commodities, pastureland and urban areas (see Table 3). As our GTAP-AEZ results only provide predictions for the year 2030, we interpolated the annual changes in demand between 2014 – 2030 based on the compounded growth rate of each type of demand.

To ensure consistency with the GTAP projections, both in terms of area allocated to crops as well as to production volumes, the allocation was constrained by both the hectarage and the production volume. Given these constraints, the land allocation procedure determines the area and distribution of production in terms of low, medium and high intensity land systems (see section 2.5.1).

Since GTAP-AEZ does not solve for the amount of urban land in a region, we used global projections of future urban land expansion for the years 2020 and 2030 that are consistent with the SSP2 scenario from Chen *et al* (2020a). Future expansion patterns of urban land were assumed to be independent of the implementation of ZDCs.

To determine the quantities of the different goods and services that each land system provides per unit area, we took two steps. First, we used the aggregate demand values for the year 2014 to compute the average yield per grid cell across all the yielding land systems. Second, to calibrate the relative yields of the different land systems, we used several spatially explicit datasets on yields or production area ratios from the International Food Policy Research Institute (2019) and computed the relative yields of the different systems. Spatially explicit data on production forests and grazing grasslands were sourced from Schulze *et al* (2019) and Gilbert *et al* (2018).

Finally, to attribute changes in land use to changes in oil palm demand, we compared the outcomes of our BAU and ZDC CLUMondo runs with two counterfactual scenarios (one for each scenario) that keep demand for oil palm constant until 2030 but are otherwise equal to the BAU scenario. This approach ensures that the oil palm-driven changes in land use can be distinguished from the other non-oil-palm driven changes in land use.

Table 3 – Specification of region-specific demand scenarios for the CLUMondo simulations. 'Other agricultural commodities' represents the residual of the output of all agricultural sectors in the GTAP database after subtracting oil palm output.

	Demand type				
	Forestry (ha)	**Oil palm (ha)**	**Other agricultural commodities (ha and metric tonnes)**	**Pastureland (ha)**	**Urban (ha)**
Cropland - extensive			x		
Cropland - intensive			x		
Cropland - medium intensive			x		
Dense forest	x				
Grassland				x	
Grazing grassland				x	
Mosaic - extensive	x		x		
Mosaic - intensive	x		x		
Mosaic - medium intensive	x		x		
Oil palm		x			
Oil palm - mosaic		x			
Open forest	x				
Shrubland and herbaceous					
Urban					x

5.2.5.5. Neighbourhood influence

Land use changes are often influenced by the spatial configuration of land use in neighbouring areas. For example, it has been found that the strongest determinant of oil palm expansion in Malaysia is accessibility to previously existing plantations (Shevade and Loboda 2019). This is especially important for oil palm as several plantations often deliver to one single mill, which has to be in close proximity. To account for such neighbourhood influences ($Pneigh_{i,t,LS}$, in equation (2)), we used a 3 x 3 kernel function to adjust the transition potential in each grid cell for each land system, depending on the land system configuration in neighbouring grid cells. The magnitude of the neighbourhood effect was determined by a set of weight factors (see Table 2 of Appendix B) and the fraction of the neighbourhood that is occupied by each land system. Given that some land systems produce multiple goods (e.g., oil palm mosaics produce both oil palm and other crops), we scaled the weight factors depending on the average area composition of each land system.

Finally, in light of the empirically supported theory that intensification is more likely to occur if land availability is scarce (Kyalo Willy *et al* 2019, Hadush *et al* 2019, Boserup 1965), we followed Van Asselen and Verburg (2013) by implementing a function that promotes cropland intensification under limited land availability and extensification under high land availability. Land availability within each 3 x 3 kernel was measured based on the land supply asymptotes specified in section 2.3.

5.3. Results

5.3.1. Effects on oil palm area and other types of land use

The results of the GTAP experiments show that the global oil palm area in 2030 under the ZDC scenario is nearly 3 Mha or 14% smaller relative to the area in 2014 (see Figure 10 of Appendix A). As the global area under oil palm is expected to expand by 42% under the BAU scenario during the same period, the worldwide implementation of ZDCs leads to a 39% smaller oil palm area relative to the BAU scenario up until 2030. The reduction in oil palm area due to ZDCs is largest in Indonesia (6.3 Mha), Malaya (2.4 Mha) and Nigeria (0.8 Mha; see Figure 4). These results are rather sensitive to how the share of oil palm in the aggregate oil crop sector of GTAP is calculated (see section 2.2). If it is assumed that the share of oil palm in 2030 equals the observed share within each GTAP region in 2019, the global oil palm area expands by 19% between 2014 – 2030 under the BAU scenario and reduces by 28% under the ZDC scenario over the same period.

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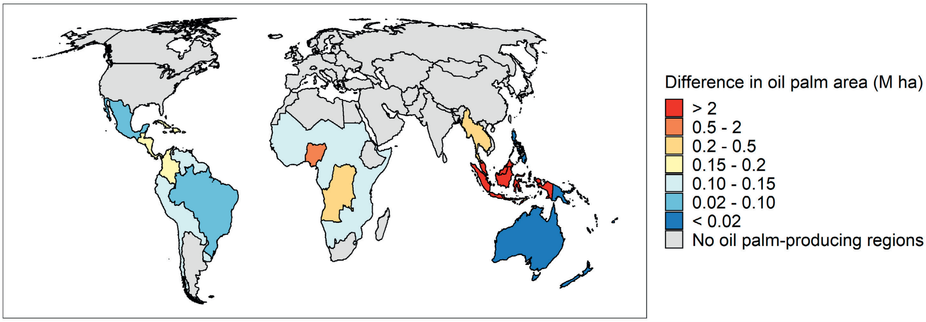

Figure 4 – Spatial overview of the ZDCs-induced difference in oil palm area relative to the BAU scenario in 2030. In all regions, the difference represents a reduction in oil palm area.

The large differences in oil palm area are partly a result of land scarcity-induced increases in oil palm yields, resulting in a 18% increase in oil palm yields. On average, oil palm yields go up by 2.7 M metric tonnes or 4.6 M metric tonnes if regions are weighted according to their production share in 2014. Increases in oil palm yields are estimated to be highest in Malaysia, Indonesia, and Colombia (see Figure 5).

In addition to boosting yields, the ZDC-induced increase in land rental rates will partially translate into an increase in global commodity prices (see Figure 11 of Appendix A) and hence a reduction in the demand for oil palm. Whereas oil palm production increases by 42% under the BAU scenario between 2014 – 2030, it only increases by 1% under the ZDC scenario. Thus, due to ZDCs, the global production of oil palm FFB relative to the BAU scenario is expected to decrease by 29% or 117 M metric tonnes.

The results also indicate that ZDCs will partially displace production to new areas and encourage inter crop substitutions. Production of oil crops is expected to increase by 7.4 M metric tonnes in non-oil palm producing countries (which equates to 0.9% of the global production in 2014). It is likely that some of the production of oil palm will also be displaced to other oil palm-producing regions with potentially more land availability. However, Figure 4 shows that none of these regions experience a net increase in oil palm due to ZDCs, which implies that any such effects are offset by the demand and yield effects.

In addition to a major difference in oil palm area, total area devoted to other crops, forestry, and pastureland is also expected to decrease relative to the BAU scenario, although the percentage changes are smaller (ranging from -10 to -20%). Apart from oil palm, major reductions are expected in the area devoted to fruit and vegetables, coarse grains, and rice (see Figure 12 of Appendix A).

These results remain largely robust if the alternative estimates of ZDC coverage are used (see section 2.4), with the projected reduction in oil palm area relative to BAU conditions varying from 38 – 42%. Results for the other land use types are similar too, with the percentage reductions in area varying in the range of 9 – 26%.

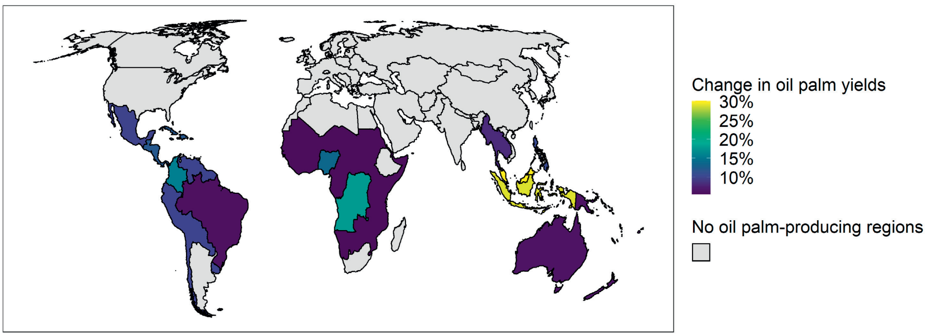

Figure 5 – Spatial overview of the impact of zero-deforestation commitments on oil palm yields in 2030 (relative to the BAU scenario).

5.3.2. Effects on natural areas

Due to the reduction in oil palm area and other land uses, ZDCs are estimated to avoid a lot of encroachment into (semi-) natural areas, which include dense forests, open forests, shrublands and grasslands. Based on our CLUMondo simulations, we estimate that 53 Mha of dense forests and 43 Mha of open forests are saved from conversion, of which 26% and 6%, respectively, would otherwise have been cleared due to expanding oil palm plantations (Figure 6; note that this includes both direct and indirect oil palm-driven conversions). However, as there are large forests outside the scope of ZDCs (see Figure 9 of Appendix A), their implementation triggers a chain of displacement effects in the simulations. Around 13 Mha of dense forests and 26 Mha of open forests are converted as a result of ZDCs, of which 11% and 33%, respectively, can be attributed to displaced oil palm plantations. Such effects are particularly large in Central Africa, Colombia and other parts of South America (see Figure 13 of Appendix A).

Results for shrublands are markedly different with a staggering 103 Mha of avoided conversion, of which only a small amount is displaced (2%). These effects are to a lesser extent driven by oil palm as shrublands tend to be less dominant in the main oil palm-producing regions (Figure 3). Most of the avoided conversion is in Oceania (notably Australia), where shrublands tend to be the dominant natural biome and where many of these areas are covered by ZDCs. By comparison, only a small area of grasslands is saved from conversion (3 Mha), while a much larger area is converted due to ZDCs (23 Mha, of

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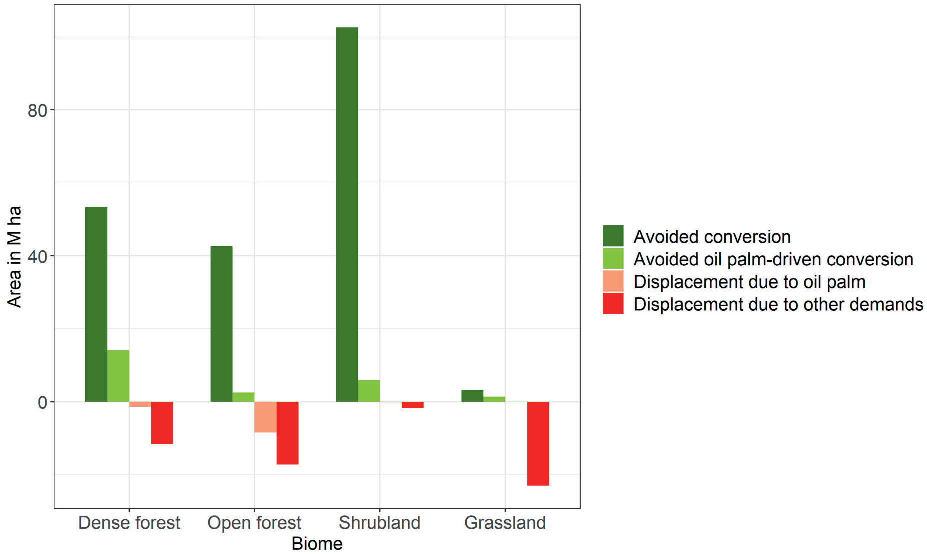

Figure 6 – Absolute area changes as a result of ZDCs within 4 (semi-) natural biomes: dense forests, open forests, shrublands and grasslands. Green coloured bars represent avoided conversions. Red coloured bars represent displacement effects. Light coloured bars indicate absolute area changes that can be directly attributed to changes in the demand for oil palm.

which less than 1% can be attributed to oil palm). The reason why displacement effects for grassland are larger than for other biomes is that most grasslands fall beyond the scope of ZDCs, which is why cropland expansion tends to be redirected to grasslands.

When taken in aggregate, the area of natural areas that is saved from conversion is 217% larger than the area converted due to ZDCs. This suggests that the ZDCs are likely to deliver substantial environmental benefits within the oil palm-producing world, although there is considerable heterogeneity across regions.

5.4. Discussion and conclusion

This is the first study to provide a modelling experiment of how the worldwide implementation of ZDCs could alter the spatial configuration of oil palm and other land uses up until 2030, assuming full adoption and enforcement across industries and regions from 2014 onwards. The results suggest that under these assumptions, ZDCs are likely to bring about significant land-sparing effects. Due to increases in yields and an overall decrease in demand for oil crops, ZDCs may induce a decrease in global oil palm area of 11 Mha or 39% relative to a BAU scenario that assumes no compliance with ZDCs. These results remain largely robust when using alternative estimates of the potential spatial coverage of ZDCs. A potential explanation for this is that the spatial differences between these different estimates are relatively minor after masking out areas unavailable for oil palm production, suggesting there is little additional impact when considering more ambitious forest protection scenarios.

Apart from oil palm, the total area devoted to other crops, forestry, and pastureland in the oil palm-producing world is expected to be smaller as well. Overall, ZDCs are estimated to prevent the conversion of around 96 Mha of forests, of which 17% would otherwise have been converted due to expanding oil palm plantations. Notwithstanding the large land-saving effects, potential environmental benefits associated with reductions in nature loss are likely partially offset by displacement effects to natural areas that fall beyond the scope of ZDCs. Not only does this include displacement effect within oil palm-producing regions, but also displacement effects to temperate regions. This suggests that temperate oil crops such as rapeseed, sunflower and soybean are expected to partially substitute for oil palm, which is particularly likely in the case of biofuels (Santeramo *et al* 2021). In addition, although yield increases help to free up crop areas for other uses, anticipated increases in the use of fertilizers, pesticides and heavy machinery (likely needed to achieve these yield increases) could lead to larger local and global environmental impacts from existing agricultural areas (Pellegrini and Fernández 2018). The degree to which ZDCs are to deliver environmental benefits thus partially hinges on the impact of displacement effects and the technology through which yield increases are achieved.

We also find that due to land scarcity and increasing commodity prices, ZDCs are expected to depress consumption of agricultural commodities. Future research should evaluate the welfare and nutritional implications of such effects and the extent to which these vary across space, thereby accounting for ecosystem services provided by forests and other natural areas (see e.g., Johnson *et al.*, 2021).

Our findings build on a burgeoning literature that has found that anti-deforestation policies, if implemented at large scales, could induce major environmental benefits outside targeted areas (Taheripour *et al* 2019, Overmars *et al* 2014). However, previous studies have also found that the risk of leakage effects is much higher if adoption and implementation varies widely across space (Busch *et al* 2022, Haddad *et al* 2019, Ingalls *et al* 2018). Our results should thus be interpreted carefully as they are projected on the assumption that all industries and regions will be fully covered by ZDCs. It is likely that the anticipated land-sparing effects will be considerably diminished if large consumer markets fall beyond the scope of ZDCs. Moreover, the results are rather sensitive to how the share of oil palm in the aggregate oil crop sector of GTAP is calculated, with much less oil palm expansion projected under the BAU scenario between 2014 – 2030 (19% instead of 42%) if the share of oil palm relative to other crops is assumed to remain constant rather than growing at historic rates. However, given that FAOSTAT data (2021) show a major increase in the share of oil palm over the period 2014 – 2019 for most oil palm-producing regions (see Appendix A Figure 5), this appears to be a less plausible assumption.

Our analysis is subject to some additional uncertainties that we cannot fully address. First and foremost, it is possible that the region-specific land supply curves underpinning our analysis imply land supply elasticities that are too high for some regions. As a result, we may have overestimated the magnitude of the overall market-mediated effects of ZDCs. The land supply elasticities may be too high because data on current land prices are only available for a limited number of regions in the world (Woltjer and Kuiper 2014). For regions with no data on land rents, it is assumed that the marginal land rents are inversely proportional to marginal yields. Whilst this assumption may be a reasonable approximation of the land rent trajectory in many developed countries (Eickhout *et al* 2009), it is less likely to hold true in developing countries with poorly functioning land markets and weakly enforced land tenure rights (Bah *et al* 2018).

A related point is that the analysis is based on a shift in the land supply asymptotes that are assumed to remain unaltered throughout the simulation period. In practice, it is more likely that such asymptotes are dynamic as they depend on annual weather fluctuations, changes in soil quality, the spatial dynamics of legally protected areas, land governance, and the degree of technological progress. A case in point is the Brazilian Cerrado, a savannah ecoregion that was largely considered unsuitable for agricultural production in the 1970s until advances in soil amendment technologies and crossbreeding transformed it into the world's "soy basket" (Byerlee *et al* 2016). It should be noted, though, that given the relatively short time period for our simulation (2014 – 2030), it is unlikely that such unforeseen dynamics will have a major impact on the amount of available land until 2030.

A final major source of uncertainty is that our estimates of the overall impact of ZDCs are dependent on the validity of our counterfactual projections which describe what might happen in the absence of ZDCs (i.e., the BAU scenario). Although the BAU scenario largely follows the SSP2 scenario, which is considered a benchmark for baseline projections (Crespo Cuaresma *et al* 2018), it is likely that there will be deviations between our projections and the actual changes in oil palm area. These deviations may occur due to political economy factors that are not well predicted by a CGE model (e.g., biofuel mandates, election cycles, imperfect law enforcement). In addition, we may have under- or overestimated future crop yields as they are currently assumed to grow at a linear rate. Although this assumption is largely consistent with historic crop yield trajectories (Grassini *et al* 2013), assumptions about future crop yields are known to constitute a major source of uncertainty (Plevin *et al* 2015) and future research should explore the sensitivity of our results to alternative yield assumptions. More accurate baseline scenarios are likely to be constructed when the GTAP database is updated to a more recent reference year.

Despite these uncertainties, our study provides a first estimate of how full implementation and enforcement of ZDCs globally may moderate the expansion of oil palm and its encroachment into forest areas. It provides a benchmark against which future estimates can be compared, for example assessments of ZDC implementation with incomplete coverage across sectors and geographies. Although it is unlikely that the coverage of ZDCs will be anywhere near 100 percent in the coming decade, our study provides strong quantitative evidence of the major reduction in deforestation and agricultural expansion they could deliver if they are adopted and enforced at large scale, thus resulting in potentially large environmental benefits. Given the goals of the New York Declaration on Forests and the Convention on Biological Diversity, this should motivate the international community to increase the uptake, but also the enforcement of ZDCs.

6

Synthesis

The overarching objective of this thesis was to investigate what insights can be gained from applying different methodological approaches for assessing the effectiveness of Zero-Deforestation Commitments (ZDCs) and the degree of complementarity between these different approaches. In Chapters 2 – 5, several approaches were presented to assess ZDCs that differ in three ways: the degree to which quasi-experimental methods were employed, the degree to which simulation models were employed and the degree to which geospatial data were used and generated. In the following, I will revisit the sub-research questions presented in Chapter 1 and discuss remaining scientific challenges for future research. In addition, I will discuss the broader implications of the research, thereby providing concrete recommendations as to how the design and the assessment of ZDCs could be improved.

6.1. Revisiting the research questions

6.1.1. How can geospatial analysis be leveraged to advance assessments (ex-post or ex-ante) of ZDCs?

There are three distinct geospatial techniques that have been repeatedly applied throughout the chapters; these are overlay analysis, proximity analysis and spatial econometrics. These techniques provide an essential toolkit for assessing ZDCs. For example, they have been applied to map the coverage of ZDCs (Chapter 2), identify potential spillover areas (Chapter 3), analyse sourcing patterns at the level of individual firms (Chapter 4) and downscale projections of geographically coarse simulation models (Chapter 5). In the absence of geospatial analysis, inferences on the effectiveness of ZDCs need to be based on aggregated datasets, thus giving rise to the ecological inferences problem (Anselin and Tam Cho 2002). For example, the direction and magnitude of subnational spillover effects in the wake of anti-deforestation policies (see Chapter 3) cannot be detected from national-level datasets, thus precluding comprehensive assessments of ZDC effectiveness.

In addition to circumventing the ecological inference problem, geospatial analysis is also key for validating aggregate-level data. Aggregate-level statistics are known to be often biased by double counts, especially when statistics are aggregated across space (Ma *et al* 2014). As shown in Chapter 2, the risk of double counting is particularly high when estimating the impact of ZDCs on forest protection as the areas covered by ZDCs tend to overlap with legally protected areas. Failing to account for spatial overlap could thus result in gross overestimates of the impact of ZDCs on forest protection.

Although geospatial analysis has been increasingly adopted in the literature on ZDC effectiveness, the role of spatial heterogeneity is still often overlooked. For example, many studies do not differentiate between types of forests in their assessment of the effectiveness of ZDCs (Mosnier *et al* 2017, zu Ermgassen *et al* 2020). However, the evidence set forth in Chapter 2 indicates that ZDC coverage is likely to be highly variable across different forest types. In addition, many quasi-experimental studies on the effectiveness of ZDCs fail to account for the degree of forest fragmentation across space. This could lead to biased estimates of how effective ZDCs have been in reducing deforestation if the degree of forest fragmentation correlates with the adoption of ZDCs across space. Spatial weight matrices such as in Chapter 3 may mitigate the risk of such confounding bias, thus advancing future assessments of ZDCs.

In addition to the geospatial techniques discussed above, there are other techniques that have not been applied in this thesis that could enhance future ZDC assessments. For example, airborne Light Detection and Ranging (LiDAR) data facilitate much more accurate mapping of High Carbon Stock forests (Asner *et al* 2018). Although such data are typically only available for very small regions, precluding their use for global assessments, they would help to make local studies on ZDC effectiveness more rigorous and could be used as training data for predictive models, thereby enabling assessments across larger regions. In addition, downscaling assessments such as Chapter 5 should capitalize on anticipated increases in (cloud) computing power and memory storage, which will enable geospatial processing at much higher resolutions than currently possible. This will help to reduce the problem of ecological inference and to unlock the potential of quasi-experimental assessments and simulation models for assessing ZDC effectiveness at high spatial resolutions.

6.1.2. How do the insights from quasi-experimental assessments of the effectiveness of ZDCs differ from ex-ante simulation modelling assessments?

Both quasi-experimental and ex-ante simulation modelling assessments involve counterfactual modelling to ascribe causality to a particular policy or intervention. However, where quasi-experimental assessments are concerned with exploring historic causal relationships over certain periods of time (see Chapters 3 & 4), simulation modelling involves exploring possible scenarios that could be realized if certain assumptions are met (see Chapter 5). The benefit of employing quasi-experimental methods over simulation models to assess past effectiveness is that they are designed in a way that 'allow the data to speak for themselves'. For example, in both Chapters 3 and 4, fixed effects models are leveraged to account for a wide variety of unobserved confounding factors such as market dynamics or political economy factors without imposing any deterministic assumptions as to how deforestation is influenced by such factors. This makes quasi-experimental analysis an invaluable tool for monitoring progress against ZDCs.

However, a drawback of quasi-experimental analysis is that the conclusions are context-dependent and only apply to certain areas or periods of time. For instance, insights on the direction and magnitude of local spillover effects in the wake of the Indonesian forest moratorium (Chapter 3) do not directly carry over to other regions or to future time periods.

Thus, the conclusions of quasi-experimental analysis have limited external validity whenever causal relationships vary across space and time (Greenstone and Gayer 2009).

Simulation models incorporate systems thinking to attribute deforestation outcomes to individual policies or interventions, which is why they have the potential to extract insights that are relevant for a wide variety of contexts. The modelling design presented in Chapter 5 enables exploring the way in which ZDCs could play out in terms of land use while accounting for expected baseline changes in the economy. Such insights are hard to obtain from quasi-experimental methods as they do not incorporate systems theory to capture evolving dependencies and feedback loops.

At the same time, the degree to which simulation models are capable of generating plausible predictions depends on the validity of the assumptions upon which they are based. This has proven to be an area of controversy as many ex-ante assessments of land use policies rely on contradicting assumptions. For example, literature estimates of the amount of indirect land use change associated with biofuel expansion are sensitive to assumptions on the degree to which world markets are (perfectly) integrated, which helps to explain the large variation in these estimates (Taheripour and Tyner 2020). Furthermore, the large variation may be partially driven by the different assumptions underpinning land use models regarding the supply of agricultural land. Many frequently used land use models such as MAgPIE (Dietrich *et al* 2019), GCAM (Chen *et al* 2020b), or GLOBIOM (IIASA 2014) are predicated on the assumption that the supply of agricultural land is fixed and independent of land rents. Previous studies have argued that such models are unlikely to capture the dynamics of land systems (Eickhout *et al* 2009, Tabeau *et al* 2006), which is why endogenous land supply curves have been developed. The methodology set forth in Chapter 5 tries to improve on previous efforts to account for endogenous land supply curves (Overmars *et al* 2014, Johnson *et al* 2021) by reconstructing land supply curves that explicitly account for multiple cropping systems. In addition, rather than drawing on downscaled national-level statistics, they incorporate remotely sensed datasets that have been shown to give a more accurate representation of the current spatial distribution of croplands in many countries of the world (Fritz *et al* 2019, Pérez-Hoyos *et al* 2017).

Given the wide variation in assumptions underpinning ex-ante simulation models, it is key to empirically test the validity of the assumptions, to whatever extent possible. For example, the most appropriate method for disaggregating oil crop projections in Chapter 5 is selected based on the performance of each method against historic data. While such an approach does not safeguard against the risk of non-stationarity, it mitigates the risk that simulation outcomes are primarily driven by theoretical assumptions that do not hold true in reality.

6.1.3. What is the degree of complementarity between the different approaches?

The preceding chapters have shown that none of the approaches adopted in the thesis are by themselves sufficiently flexible to assess all aspects of ZDCs. However, when combined, these approaches may interact in synergistic ways and pave the way towards a more holistic understanding of ZDC effectiveness. A schematic overview of the interdependent links between the three different methodological approaches is shown in Figure 1.

Quasi-experimental methods are invaluable tools for inferring causal relationships and can be used to validate predictions made my simulation models. For example, the methodology employed in Chapter 3 could be leveraged to assess the empirical evidence of local spillover effects predicted by CLUMondo in Chapter 5. Similar methods employing fixed effects regressions could be used to validate of the assumptions and parameters underlying both GTAP-AEZ and CLUMondo, especially with respect to the incorporated land supply elasticities and land resistance factors (see e.g., Roberts and Schlenker 2013). ..These could in turn be adjusted in a way to improve the performance of both models over historic periods. Such an iterative approach could help to improve the reliability of ex-ante simulation models, assuming historic trends provide a reasonable approximation of how the future may unfold.

While quasi-experimental methods suffer from risks of endogeneity, such risks can be mitigated by incorporating insights from simulation models into their design (see Figure 1). For example, the GTAP-AEZ model employed in Chapter 5 highlights the importance of land rents as a driver of land use change, but also its endogenous relationship with the availability of suitable agricultural land. Accounting for such relationships in quasi-experimental assessments is key to obtain unbiased estimates of the impact of ZDCs on deforestation outcomes. In the absence of data on local land rents, the potential confounding relationship between ZDCs and land rents in Chapter 4 is accounted for by including the unprotected suitable area within each company's sourcing area as a proxy variable in the regression model.

Finally, given the large spatial variation in the coverage of ZDCs, both quasi-experimental and ex-ante simulation assessments would benefit from a deeper integration of geospatial analysis. Such analysis is key for providing more spatial granularity to both types of assessments, thus providing insights into the conditions under which ZDCs are likely to be effective or not. This is illustrated in Chapter 3, where spatial differences in economic development, agro-ecological suitability and the coverage of the Indonesian forest moratorium are exploited to disaggregate estimates of the deforestation spillover effects.

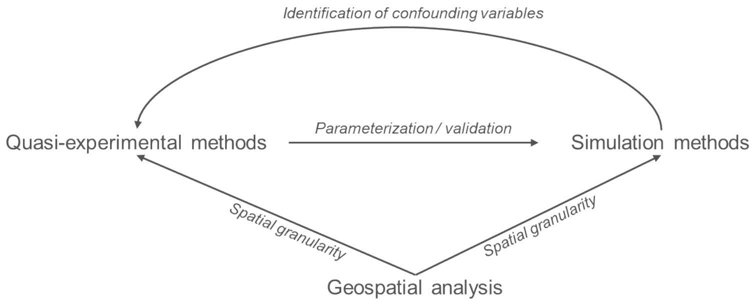

Figure 1 – Interdependent links between the different methodological approaches to assess ZDC effectiveness.

While these three methodological approaches provide a rigorous framework for assessing ZDCs, there are many additional approaches originating from a wide range of scientific disciplines that could enhance assessments of ZDCs that have not been discussed in this thesis. First, assessments of ZDCs are likely to benefit from a deeper integration of ecological field work. Ecological field work constitutes an invaluable approach for mapping the likely distribution of High Conservation Value Forests (HCVFs) and High Carbon Stock Forests (HCSFs), as well as enabling effective monitoring of the ecological impacts of ZDCs at the local scale. For example, Deere *et al* (2020) employ detection/non-detection data from camera-traps deployed across the island of Borneo to test the capacity for the High Carbon Stock Approach (HCSA) to prioritize forest remnants that sustain mammal diversity. Such insights are hard to derive from remotely sensed datasets and are indispensable for advancing our understanding of how ZDCs may affect local ecosystems.

In addition, there is a wealth of literature that employs qualitative research methods to assess the criteria under which ZDCs may be effective at reducing deforestation and the challenges for implementation (e.g., Austin *et al.*, 2021; Garrett *et al.*, 2019; Grabs *et al.*, 2021; Lyons-White and Knight, 2018). Typical qualitative research techniques involve surveying a panel of experts or conducting semi-structured, in-depth interviews with major decision-makers. Such techniques would complement the quantitative approaches adopted in this thesis as they may uncover non-trivial insights that are typically hard to derive from quantitative datasets (Shah and Corley 2006). For example, they could be employed to test the accuracy of supply chain stickiness as a proxy for the underlying power dynamics present in value chains. As the influence of such underlying factors are typically hard to measure, there is a need for appropriate proxy variables to incorporate more realistic assumptions into future assessments of ZDC effectiveness. While qualitative research techniques are by definition not appropriate for expressing the effectiveness of ZDC in quantitative terms, they have an important role to play in examining contextual conditions under which ZDCs are likely to be effective and identifying appropriate proxy variables, which could in turn be leveraged to strengthen the robustness of both quasi-experimental and simulation modelling assessments.

The preceding indicates that each of the methodological approaches discussed in this section are highly complementary and fit for different purposes. The applicability of each approach depends on a range of factors, including the geographic scope of the analysis (i.e., local, regional or global) and the type of analysis (i.e., ex-ante or ex-post). When combined, they constitute a rigorous portfolio of approaches that enables researchers to assess ZDCs under a wide range of conditions (Young *et al* 2006). Moreover, when the results of the different methodological approaches generate conclusions that concur with each other, they inspire more confidence in their robustness than when they are applied in isolation.

6.1.4. What do the different approaches tell us about the (potential) effectiveness of ZDCs?

Overall, there is a high degree of complexity involved in ZDC assessments and a high level of sensitivity of results to assumptions about the coverage of ZDCs. The starting assumption in Chapters 2 and 5 is that all industries and world regions are fully covered by ZDCs. Chapter 2 drew on a wide range of spatial datasets to map the likely extent of forests protected under this assumption. In a scenario where these forests are indeed protected by ZDCs, the results from Chapter 5 reveal that ZDCs are likely to have significant land-sparing effects that extend beyond the forests within their scope. This suggests that ZDCs have the potential to deliver large environmental benefits, even in areas that are not necessarily covered by ZDCs. However, the results from Chapters 3 and 5 also showed that due to the incomplete protection of forests and other biomes, there are likely to be major displacement effects to forests, shrublands and grasslands outside the scope of ZDCs. Thus, while it is commonly held that ZDCs are designed to eliminate all deforestation (Pirard *et al* 2015), the results of the thesis show that even in a scenario of full adoption and enforcement, many forests are unlikely to be protected by ZDCs and displacement effects could (partially) undermine their overall effectiveness in curbing deforestation and nature loss. Although the global land-sparing effects identified in Chapter 5 are projected to be much larger than the displacement effects, there is significant spatial heterogeneity in terms of effectiveness, implying large differences in the potential environmental benefits across regions.

What is more, the large land-sparing effects are, to a large extent, driven by the increase in agricultural yields as a result of increasing land rents. Depending on the technology through which such yield increases are realized, this may partly come at the expense of the broader societal goals to which many companies have committed, for example to improve human health, protect biodiversity, or improve water management (Donofrio *et al* 2019). Furthermore, the results from Chapter 5 also hint at major implications for human livelihoods given the increases in commodity prices and reduction in consumption, which conflicts with other societal goals such as to reduce poverty or malnutrition. It should be noted, though, that these effects can be reduced through multilateral development initiatives that reward stakeholders for conserving nature, as is currently done under the REDD+ program (Roopsind *et al* 2019). Also, previous research has found that nature conservation may improve human livelihoods as it facilitates access to invaluable ecosystem services for which no substitutes exist in many parts of the world (Johnson *et al* 2020). Thus, while major trade-offs exist, these findings suggest that ZDCs have the potential to accelerate progress towards a wide variety of societal goals if global cooperation can be enhanced.

The critical assumption underpinning these findings from Chapters 2 and 5 is that ZDCs are fully adopted and enforced across industries and regions. The actual coverage of ZDCs is much lower and highly concentrated in a limited number of sectors and regions (Donofrio *et al* 2019, Jopke and Schoneveld 2018). This constitutes a major hurdle for ZDC effectiveness as attempts to implement ZDCs are likely undermined by a wide range of displacement effects. In addition to spatial displacement effects to different areas (see Chapter 3), this could include displacement effects to other supply chains – within the same industry or outside – with no ZDCs in place. Such intra-, or inter-industry leakage effects could help explain why many studies on ZDC effectiveness – including Chapter 4 of this thesis – have failed to find evidence of successfully implemented ZDCs. However, it is also possible that the absence of evidence on ZDC effectiveness is due to a lack of ambition to implement ZDCs (Schulte *et al* 2019, zu Ermgassen *et al* 2020, Villoria 2021). A notable exception of a ZDC that is considered highly effective in curbing deforestation is the Amazon Soy Moratorium (ASM) in Brazil, which is estimated to have prevented nearly 20,000 km^2 of deforestation over its first decade, with relatively modest displacement effects (2006 – 2016; Heilmayr *et al.*, 2020b). However, due to a wide range of political and socio-economic factors, the effectiveness of the ASM has steadily decreased since 2016 and deforestation levels in the Brazilian Amazon in 2021 were estimated to be at their highest since 2006 (TerraBrasilis 2021).

In conclusion, while the ex-ante simulation results suggest that ZDCs have the potential to deliver major benefits if they are fully adopted and enforced, the empirical evidence suggests that ZDCs are unlikely to live up to their potential given their incomplete adoption across regions and industries. Therefore, ambitions to implement ZDCs need to be ramped up across industries and regions if societal targets to eliminate deforestation are to be achieved.

6.2. Broader implications of the research

The findings of this thesis could support decision makers in the public and private sectors to design effective anti-deforestation strategies and anticipate likely spillover effects. In light of the recently adopted pledge at the Glasgow Climate Change Conference in 2021 to end deforestation by 2030, the three following recommendations are made. First, given the large uncertainties regarding the spatial coverage of ZDCs (see Chapter 2), companies and governments are encouraged to abide by standardized definitions and criteria as to what constitutes a forest and thus deforestation. This would eliminate uncertainties on the qualifying areas and likely consequences of ZDCs for forests across the globe, thus enabling civil society to monitor progress against international deforestation goals and identify complementary strategies for meeting related societal goals on biodiversity conservation and poverty reduction (Oxfam 2021). There has already been some progress in this space: the definitions and criteria put forward by the Accountability Framework (2018) initiative have been increasingly adopted across public and private sectors, thereby easing the implementation of ZDCs.

Second, the findings of the thesis lend support to the notion that increasing the uptake of ZDCs is a necessary condition for increasing their effectiveness. While ZDCs have been widely embraced in a number of industries and geographies, the uptake has stagnated in recent years (Haupt *et al* 2018). Imposing mandatory due diligence rules for importers into major destination markets of deforestation-risk commodities, as currently discussed by the European Union, United Kingdom and United States (Mongabay 2022), could encourage the further uptake of ZDCs and increase their effectiveness. Care should be taken to manage societal trade-offs that could arise as a result of anti-deforestation policies, such as between forest protection and economic development, especially in developing countries.

Finally, this thesis has made the case that the different approaches adopted in the literature to assess ZDC effectiveness are complementary and act in synergistic ways. It is therefore recommended that future assessments of ZDCs employ a wide variety of methods. Not only will such a portfolio approach help to identify weaknesses in the analyses and explore the robustness of the results, but it will also help to advance the growing field of sustainability science. This will help policy makers, companies, and civil society to make more informed decisions as to how different societal targets can be reconciled and pave the way towards a more sustainable future.

7

References

Abadie A and Cattaneo M D 2018 Econometric Methods for Program Evaluation Annual Review of Economics 10

Abatzoglou J T, Dobrowski S Z, Parks S A and Hegewisch K C 2018 TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015 Scientific Data

Accountability Framework 2018 The Accountability Framework Terms and Definitions DRAFT FOR WORKSHOPPING Online: www.accountability-framework.org%7Ccontact@accountability-framework.org

Aguiar A, Chepeliev M, Corong E L, McDougall R and van der Mensbrugghe D 2019 The GTAP Data Base: Version 10 Journal of Global Economic Analysis

Akkermans H 2001 Emergent Supply Networks: System Dynamics Simulation of Adaptive Supply Agents Proceedings of the 34th Hawaii International Conference on System Sciences pp 1–11

Alix-Garcia J and Gibbs H K 2017 Forest conservation effects of Brazil's zero deforestation cattle agreements undermined by leakage Global Environmental Change

Allison, P.D., Waterman, R.P., 2002. Fixed-effects negative binomial regression models. Sociol. Methodol. https://doi.org/10.1111/1467-9531.00117

Amatulli G, Domisch S, Tuanmu M N, Parmentier B, Ranipeta A, Malczyk J and Jetz W 2018 Data Descriptor: A suite of global, cross-scale topographic variables for environmental and biodiversity modeling Scientific Data 5

Angelsen A, Brockhaus M, Duchelle A E, Larson A, Martius C, Sunderlin W D, Verchot L, Wong G and Wunder S 2017 Learning from REDD+: a response to Fletcher *et al*. Conservation Biology 31

Angelsen, A., Kaimowitz, D., 1999. Rethinking the causes of deforestation: Lessons from economic models. World Bank Res. Obs. https://doi.org/10.1093/wbro/14.1.73

Angrist, J.D., Pischke, J.S., 2008. Mostly harmless econometrics: An empiricist's companion, Mostly Harmless Econometrics: An Empiricist's Companion. https://doi.org/10.1111/j.1475-4932.2011.00742.x

Anselin L and Tam Cho W K 2002 Spatial Effects and Ecological Inference Political Analysis 10

Areendran G, Sahana M, Raj K, Kumar R, Sivadas A, Kumar A, Deb S and Gupta V D 2020 A systematic review on high conservation value assessment (HCVs): Challenges and framework for future research on conservation strategy Science of the Total Environment 709

Asner G P, Brodrick P G, Philipson C, Vaughn N R, Martin R E, Knapp D E, Heckler J, Evans L J, Jucker T, Goossens B, Stark D J, Reynolds G, Ong R, Renneboog N, Kugan F and Coomes D A 2018 Mapped aboveground carbon stocks to advance forest conservation and recovery in Malaysian Borneo Biological Conservation 217

Atmadja, S., Verchot, L., 2012. A review of the state of research, policies and strategies in addressing leakage from reducing emissions from deforestation and forest degradation (REDD+). Mitig. Adapt. Strateg. Glob. Chang. 17, 311–336. https://doi.org/10.1007/s11027-011-9328-4

Aukland L, Costa P M and Brown S 2003 A conceptual framework and its application for addressing leakage: The case of avoided deforestation Climate Policy 3

Austin K G, González-Roglich M, Schaffer-Smith D, Schwantes A M and Swenson J J 2017 Trends in size of tropical deforestation events signal increasing dominance of industrial-scale drivers Environmental Research Letters 12

Austin K G, Heilmayr R, Benedict J J, Burns D N, Eggen M, Grantham H, Greenbury A, Hill J K, Jenkins C N, Luskin M S, Manurung T, Rasmussen L v., Rosoman G, Rudorff B, Satar M, Smith C and Carlson K M 2021 Mapping and Monitoring zero-deforestation commitments BioScience 71

Austin K G, Lee M E, Clark C, Forester B R, Urban D L, White L, Kasibhatla P S and Poulsen J R 2017 An assessment of high carbon stock and high conservation value approaches to sustainable oil palm cultivation in Gabon Environ. Res. Lett. 12 014005 Online: http://stacks.iop.org/1748-9326/12/i=1/a=014005?key=crossref.f95de1bc99ee48f5f7aeb90c12a18a64

Austin, K., Alisjahbana, A., Darusman, T., Boediono, R., Budianto, B.E., Purba, C., Indrarto, G.B., Pohnan, E., Putraditama, A., Stolle, F., 2014. Indonesia's Forest Moratorium: Impacts And Next Step. Washington, DC.

Austin, K., Sheppard, S., Stolle, F., 2012. Indonesia's moratorium on new forest concessions: key findings and next steps, WRI Working Paper.

Austin, P.C., 2011. Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. Pharm. Stat. https://doi.org/10.1002/pst.433

Avitabile V, Herold M, Heuvelink G B M, Lewis S L, Phillips O L, Asner G P, Armston J, Ashton P S, Banin L, Bayol N, Berry N J, Boeckx P, de Jong B H J, Devries B, Girardin C A J, Kearsley E, Lindsell J A, Lopez-Gonzalez G, Lucas R, Malhi Y, Morel A, Mitchard E T A, Nagy L, Qie L, Quinones M J, Ryan C M, Ferry S J W, Sunderland T, Laurin G V, Gatti R C, Valentini R, Verbeeck H, Wijaya A and Willcock S 2016 An integrated pan-tropical biomass map using multiple reference datasets Glob. Chang. Biol.

Baccini A, Goetz S J, Walker W S, Laporte N T, Sun M, Sulla-Menashe D, Hackler J, Beck P S A, Dubayah R, Friedl M A, Samanta S and Houghton R A 2012 Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps Nat. Clim. Chang.

Bager S and Lambin E F 2020 Sustainability strategies in the global coffee sector Business Strategy and the Environment

Bah E M, Faye I and Geh Z F 2018 Unlocking Land Markets and Infrastructure Provision Housing Market Dynamics in Africa

Bair J 2008 Analysing economic organization: Embedded networks and global chains compared Economy and Society 37 339–64

Baldassarri D and Abascal M 2017 Field experiments across the social sciences Annual Review of Sociology 43

Barnett M L and Hoffman A J 2008 Beyond Corporate Reputation: Managing Reputational Interdependence Corporate Reputation Review

Bartholomé E and Belward A S 2005 GLC2000: A new approach to global land cover mapping from earth observation data Int. J. Remote Sens.

Bastos Lima M G and Persson U M 2020 Commodity-Centric Landscape Governance as a Double-Edged Sword: The Case of Soy and the Cerrado Working Group in Brazil Frontiers in Forests and Global Change 3 1–17

Bastos Lima M G, Persson U M and Meyfroidt P 2019 Leakage and boosting effects in environmental governance: a framework for analysis Environmental Research Letters 14

Bebber, D.P., Butt, N., 2017. Tropical protected areas reduced deforestation carbon emissions by one third from 2000-2012. Sci. Rep. https://doi.org/10.1038/s41598-017-14467-w

Bentivoglio D, Finco A, Bucci G and Zolin M B 2018 Asian Palm Oil Production and European Vegetable Oil Market: What Can We Learn in Terms of Sustainability? Asian Nations and Multinationals

Bergé L 2018 Efficient estimation of maximum likelihood models with multiple fixed-effects: the R package FENmlm CREA Discussion Paper 2018 - 13

Bergé L 2020 Fast Fixed-Effects Estimations [R package fixest version 0.3.1]

BirdLife International 2018 Digital boundaries of Important Bird and Biodiversity Areas from the World Database of Key Biodiversity Areas. February 2018 Version. Online: http://datazone.birdlife.org/site/requestgis

Blackman A, Goff L and Rivera Planter M 2018 Does eco-certification stem tropical deforestation? Forest Stewardship Council certification in Mexico Journal of Environmental Economics and Management

Bontemps S, Defourny P, Bogaert E Van, Arino O, Kalogirou V and Perez J R 2016 ESA CCI Land cover website Online: https://www.esa-landcover-cci.org/

Börner, J., Baylis, K., Corbera, E., Ezzine-de-Blas, D., Ferraro, P.J., Honey-Rosés, J., Lapeyre, R., Persson, U.M., Wunder, S., 2016. Emerging evidence on the effectiveness of tropical forest conservation. PLoS One. https://doi.org/10.1371/journal.pone.0159152

Boserup E 1965 The Conditions of Agricultural Growth

Bouguen A, Huang Y, Kremer M and Miguel E 2019 Using Randomized Controlled Trials to Estimate Long-Run Impacts in Development Economics Annual Review of Economics 11

Brandão F, Schoneveld G, Pacheco P, Vieira I, Piraux M and Mota D 2021 The challenge of reconciling conservation and development in the tropics: Lessons from Brazil's oil palm governance model World Development

Brown E, Dudley N, Lindhe A, Muhtaman D R, Stewart C and Synnott T 2013 Common Guidance for the Identification of High Conservation Values Online: www.hcvnetwork.org

Brown, S., Zarin, D., 2013. What does zero deforestation mean? Science (80-.). 342, 805–807. https://doi.org/10.1126/science.1241277

Bruggeman, D., Meyfroidt, P., Lambin, E.F., 2018. Impact of land-use zoning for forest protection and production on forest cover changes in Bhutan. Appl. Geogr. https://doi.org/10.1016/j.apgeog.2018.04.011

Buchhorn M, Smets B, Bertels L, Lesiv M, Tsendbazar N-E, Herold M and Fritz S 2019 Copernicus Global Land Service: Land Cover 100m: epoch 2015: Globe. Dataset of the global component of the Copernicus Land Monitoring Service 2019.

Burfisher M E 2011 Introduction to computable general equilibrium models

Burgess, R., Hansen, M., Olken, B.A., Potapov, P., Sieber, S., 2012. The political economy of deforestation in the tropics. Q. J. Econ. https://doi.org/10.1093/qje/qjs034

Busch J, Amarjargal O, Taheripour F, Austin K G, Siregar R N, Koenig K and Hertel T W 2022 Effects of demand-side restrictions on high-deforestation palm oil in Europe on deforestation and emissions in Indonesia Environmental Research Letters 17

Busch, J., Ferretti-Gallon, K., 2017. What drives deforestation and what stops it? A meta-analysis. Rev. Environ. Econ. Policy 11, 3–23. https://doi.org/10.1093/reep/rew013

Busch, J., Ferretti-Gallon, K., Engelmann, J., Wright, M., Austin, K.G., Stolle, F., Turubanova, S., Potapov, P. V., Margono, B., Hansen, M.C., Baccini, A., 2015. Reductions in emissions from deforestation from Indonesia's moratorium on new oil palm, timber, and logging concessions. Proc. Natl. Acad. Sci. U. S. A. https://doi.org/10.1073/pnas.1412514112

Byerlee D, Falcon W P and Naylor R L 2016 The Tropical Oil Crop Revolution

Carlson, K.M., Heilmayr, R., Gibbs, H.K., Noojipady, P., Burns, D.N., Morton, D.C., Walker, N.F., Paoli, G.D., Kremen, C., 2018a. Effect of oil palm sustainability certification on deforestation and fire in Indonesia. Proc. Natl. Acad. Sci. 115, 121–126. https://doi.org/10.1073/pnas.1704728114

Carlson, K.M., Heilmayr, R., Gibbs, H.K., Noojipady, P., Burns, D.N., Morton, D.C., Walker, N.F., Paoli, G.D., Kremen, C., 2018b. RSPO-certified oil palm supply bases in Indonesia [WWW Document]. URL https://www.arcgis.com/sharing/rest/content/items/6be15bdb5fb643f48114de6b54f6627d/info/metadata/metadata.xml?format=default&output=html (accessed 3.20.20).

Carrasco L R, Larrosa C, Milner-Gulland E J and Edwards D P 2014 A double-edged sword for tropical forests: Contrary to expectation, high-yield tropical crops may cause forest loss in the tropics Science (1979)

Carvalho W D, Mustin K, Hilário R R, Vasconcelos I M, Eilers V and Fearnside P M 2019 Deforestation control in the Brazilian Amazon: A conservation struggle being lost as agreements and regulations are subverted and bypassed Perspectives in Ecology and Conservation 17

Cattau, M.E., Marlier, M.E., DeFries, R., 2016. Effectiveness of Roundtable on Sustainable Palm Oil (RSPO) for reducing fires on oil palm concessions in Indonesia from 2012 to 2015. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/11/10/105007

Chaplin-Kramer R, Sharp R P, Weil C, Bennett E M, Pascual U, Arkema K K, Brauman K A, Bryant B P, Guerry A D, Haddad N M, Hamann M, Hamel P, Johnson J A, Mandle L, Pereira H M, Polasky S, Ruckelshaus M, Shaw M R, Silver J M, Vogl A L and Daily G C 2019 Global modeling of nature's contributions to people Science (80-.).

Chateau J, Corong E, Lanzi E, Carrico C, Foure J and Laborde D 2020 Characterizing supply-side drivers of structural change in the construction of economic baseline projections Journal of Global Economic Analysis 5

Chazdon R L, Brancalion P H S, Laestadius L, Bennett-Curry A, Buckingham K, Kumar C, Moll-Rocek J, Vieira I C G and Wilson S J 2016 When is a forest a forest? Forest concepts and definitions in the era of forest and landscape restoration Ambio

Chen G, Li X, Liu X, Chen Y, Liang X, Leng J, Xu X, Liao W, Qiu Y, Wu Q and Huang K 2020a Global projections of future urban land expansion under shared socioeconomic pathways Nature Communications 11

Chen M, Vernon C R, Graham N T, Hejazi M, Huang M, Cheng Y and Calvin K 2020b Global land use for 2015–2100 at 0.05° resolution under diverse socioeconomic and climate scenarios Scientific Data 7

Chen, B., Kennedy, C.M., Xu, B., 2019. Effective moratoria on land acquisitions reduce tropical deforestation: Evidence from Indonesia. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/ab051e

Cheyns E, Silva-Castañeda L and Aubert P-M 2019 Missing the forest for the data? Conflicting valuations of the forest and cultivable lands Land use policy Online: https://www.sciencedirect.com/science/article/pii/S0264837717309249

CIESIN 2018 Gridded Population of the World, Version 4 (GPWv4): Basic Characteristics, Revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). Columbia University Center for International Earth Science Information Network (CIESIN) - Columbia University

Corley R H V 2009 How much palm oil do we need? Environ. Sci. Policy

Corley R H V and Tinker P B 2015 The Oil Palm: Fifth Edition

Corong E, Thomas H, Robert M, Tsigas M and van der Mensbrugghe D 2017 The Standard GTAP Model, version 7 Journal of Global Economic Analysis 2 1–119 Online: https://jgea.org/resources/jgea/ojs/index.php/jgea/article/view/47

Crespo Cuaresma J, Fengler W, Kharas H, Bekhtiar K, Brottrager M and Hofer M 2018 Will the Sustainable Development Goals be fulfilled? Assessing present and future global poverty Palgrave Communications 4

Cuaresma, J.C., Heger, M., 2019. Deforestation and economic development: Evidence from national borders. Land use policy. https://doi.org/10.1016/j.landusepol.2018.12.039

Curtis P G, Slay C M, Harris N L, Tyukavina A and Hansen M C 2018 Classifying drivers of global forest loss Science (1979) 361 1108–11

Dargavel J and Williams M 2004 Deforesting the Earth: From Prehistory to Global Crisis Environmental History 9

Darmawan, R., Klasen, S., Nuryantono, N., 2015. Migration and deforestation in Indonesia. Courant Res. Cent. Poverty, Equity Growth - Discuss. Pap.

Dauvergne P and Lister J 2013 Eco-Business: A Big-Brand Takeover of Sustainability (MIT Press Books)

de Sousa L, Poggio L, Batjes N, Heuvelink G, Kempen B, Riberio E and Rossiter D 2020 SoilGrids 2.0: producing quality-assessed soil information for the globe SOIL Discussions

Deere N J, Guillera-Arroita G, Platts P J, Mitchell S L, Baking E L, Bernard H, Haysom J K, Reynolds G, Seaman D J I, Davies Z G and Struebig M J 2020 Implications of zero-deforestation commitments : Forest quality and hunting pressure limit mammal persistence in fragmented tropical landscapes Conservation Letters

Defourny P, Bontemps S, Lamarche C, Brockmann C, Boettcher M, Wevers J, Kirches G, Santoro M and ESA 2017 Land Cover CCI Product User Guide - Version 2.0 ESA

Descals A, Wich S, Meijaard E, Gaveau D, Peedell S and Szantoi Z 2021 High-resolution global map of smallholder and industrial closed-canopy oil palm plantations Earth System Science Data Discussions

Di Lallo, G., Mundhenk, P., López, S.E.Z., Marchetti, M., Köhl, M., 2017. REDD+: Quick assessment of deforestation risk based on available data. Forests. https://doi.org/10.3390/f8010029

Diamond, A., Sekhon, J.S., 2013. Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. Rev. Econ. Stat. https://doi.org/10.1162/REST_a_00318

Dietrich J P, Bodirsky B L, Humpenöder F, Weindl I, Stevanović M, Karstens K, Kreidenweis U, Wang X, Mishra A, Klein D, Ambrósio G, Araujo E, Yalew A W, Baumstark L, Wirth S, Giannousakis A, Beier F, Meng-Chuen Chen D, Lotze-Campen H and Popp A 2019 MAgPIE 4-a modular open-source framework for modeling global land systems Geoscientific Model Development 12

Disdier A-C and Head K 2008 The Puzzling Persistance of the Distance Effect on Bilateral Trade Review of Economics and Statistics 90 37–48

Doelman J C, Stehfest E, Tabeau A, van Meijl H, Lassaletta L, Gernaat D E H J, Hermans K, Harmsen M, Daioglou V, Biemans H, van der Sluis S and van Vuuren D P 2018 Exploring SSP land-use dynamics using the IMAGE model: Regional and gridded scenarios of land-use change and land-based climate change mitigation Glob. Environ. Chang. 48 119–35 Online: https://www.sciencedirect.com/science/article/pii/S0959378016306392

Donofrio S, Rothrock P, Associate S, Calderon C, Assistant R, Hamrick K and Weatherer L 2019 Targeting Zero Deforestation: Company Progress On Commitments That Count, 2019 A Collaborative Analysis Between Forest Trends And Ceres Based Upon Supply Change Data Editors Authors Contributors In Partnership With Online: https://www.forest-trends.org/wp-content/uploads/2019/06/2019.06.05-Supply-Change-Targeting-Zero-Deforestation-Report-Final.pdf

Dou, Y., da Silva, R.F.B., Yang, H., Liu, J., 2018. Spillover effect offsets the conservation effort in the Amazon. J. Geogr. Sci. 28, 1715–1732. https://doi.org/10.1007/s11442-018-1539-0

Edwards, D.P., Socolar, J.B., Mills, S.C., Burivalova, Z., Koh, L.P., Wilcove, D.S., 2019. Conservation of Tropical Forests in the Anthropocene. Curr. Biol. https://doi.org/10.1016/j.cub.2019.08.026

Eickhout B, Meijl H van, Tabeau A and Stehfest E 2009 The impact of environmental and climate constraints on global food supply Economic Analysis of Land Use in Global Climate Change Policy

Eitelberg D A, van Vliet J and Verburg P H 2015 A review of global potentially available cropland estimates and their consequences for model-based assessments Global Change Biology 21

Eklund J, Blanchet F G, Nyman J, Rocha R, Virtanen T and Cabeza M 2016 Contrasting spatial and temporal trends of protected area effectiveness in mitigating deforestation in Madagascar Biological Conservation 203

Ellis E A, Sierra-Huelsz J A, Ceballos G C O, Binnqüist C L and Cerdán C R 2020a Mixed effectiveness of REDD+ subnational initiatives after 10 years of interventions on the Yucatan Peninsula, Mexico Forests 11

Ellis E C, Beusen A H W and Goldewijk K K 2020b Anthropogenic biomes: 10,000 BCE to 2015 CE Land (Basel) 9

Ewers, R.M., Rodrigues, A.S.L., 2008. Estimates of reserve effectiveness are confounded by leakage. Trends Ecol. Evol. https://doi.org/10.1016/j.tree.2007.11.008

FAO 2012 FRA 2015 Terms and Definitions (Rome) Online: www.fao.org/forestry/fra

FAO 2018 The State of the World's Forests 2018 - Forest pathways to sustainable development. (Rome)

FAO 2020 Global Forest Resources Assessment, a main report

FAOSTAT 2021 FAOSTAT - Crops Online: http://www.fao.org/faostat/en/#data/QC

Fares M, Magrini M B and Triboulet P 2012 Transition agroécologique, innovation et effets de verrouillage Le rôle de la structure organisationnelle des filières Cahiers Agricultures 21 34–45

Fernandes L, Dias O, Dias D V and Magnusson W E 2015 Influence of Environmental Governance on Deforestation in Municipalities of the Brazilian Amazon Online: http://www.ibge.gov.br/home/estatistica/economia/perfilmunic/defaulttab1_perfil.

Ferraro P J, Hanauer M M, Miteva D A, Canavire-Bacarreza G J, Pattanayak S K and Sims K R E 2013 More strictly protected areas are not necessarily more protective: Evidence from Bolivia, Costa Rica, Indonesia, and Thailand Environmental Research Letters

Ferraro, P.J., Miranda, J.J., 2017. Panel Data Designs and Estimators as Substitutes for Randomized Controlled Trials in the Evaluation of Public Programs. J. Assoc. Environ. Resour. Econ. https://doi.org/10.1086/689868

Fouré J, Bénassy-Quéré A and Fontagné L 2013 Modelling the world economy at the 2050 horizon Economics of Transition 21

Freebairn L, Atkinson J, Kelly P, McDonnell G and Rychetnik L 2016 Simulation modelling as a tool for knowledge mobilisation in health policy settings: A case study protocol Health Research Policy and Systems 14

Freedman D A, Klein S P, Ostland M, Roberts M R and King G 1998 A Solution to the Ecological Inference Problem J Am Stat Assoc 93

Fritz S, See L, Bayas J C L, Waldner F, Jacques D, Becker-Reshef I, Whitcraft A, Baruth B, Bonifacio R, Crutchfield J, Rembold F, Rojas O, Schucknecht A, van der Velde M, Verdin J, Wu B, Yan N, You L, Gilliams S, Mücher S, Tetrault R, Moorthy I and McCallum I 2019 A comparison of global agricultural monitoring systems and current gaps Agricultural Systems 168

Fuller, C., Ondei, S., Brook, B.W., Buettel, J.C., 2019. First, do no harm: A systematic review of deforestation spillovers from protected areas. Glob. Ecol. Conserv. https://doi.org/10.1016/j.gecco.2019.e00591

FUNAI 2020 FUNAI - Fundação Nacional do Índio. I3GEO (Interface Integrada para Internet de Ferramentas de Geoprocessamento). Bases de dados espaciais de terras indígenas. 46169

Furumo P R and Aide T M 2017 Characterizing commercial oil palm expansion in Latin America: Land use change and trade Environmental Research Letters

Furumo P R and Lambin E F 2020 Scaling up zero-deforestation initiatives through public-private partnerships: A look inside post-conflict Colombia Global Environmental Change

Gao J 2017 Downscaling Global Spatial Population Projections from 1/8-degree to 1-km Grid Cells NCAR Technical Note

Gardner T A, Benzie M, Börner J, Dawkins E, Fick S, Garrett R, Godar J, Grimard A, Lake S, Larsen R K, Mardas N, McDermott C L, Meyfroidt P, Osbeck M, Persson M, Sembres T, Suavet C, Strassburg B, Trevisan A, West C and Wolvekamp P 2019 Transparency and sustainability in global commodity supply chains World Development 121 163–77

Garnett S T, Burgess N D, Fa J E, Fernández-Llamazares Á, Molnár Z, Robinson C J, Watson J E M, Zander K K, Austin B, Brondizio E S, Collier N F, Duncan T, Ellis E, Geyle H, Jackson M V., Jonas H, Malmer P, McGowan B, Sivongxay A and Leiper I 2018 A spatial overview of the global importance of Indigenous lands for conservation Nature Sustainability 1 369–374

Garrett R D, Levy S, Carlson K M, Gardner T A, Godar J, Clapp J, Dauvergne P, Heilmayr R, le Polain de Waroux Y, Ayre B, Barr R, Døvre B, Gibbs H K, Hall S, Lake S, Milder J C, Rausch L L, Rivero R, Rueda X, Sarsfield R, Soares-Filho B and Villoria N 2019 Criteria for effective zero-deforestation commitments Glob. Environ. Chang. 54 135–47 Online: https://www.sciencedirect.com/science/article/pii/S0959378018306654

Gaveau, D.L.A., Locatelli, B., Salim, M.A., Yaen, H., Pacheco, P., Sheil, D., 2018. Rise and fall of forest loss and industrial plantations in Borneo (2000–2017). Conserv. Lett. https://doi.org/10.1111/conl.12622

Geldmann, J., Manica, A., Burgess, N.D., Coad, L., Balmford, A., 2019. A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. Proc. Natl. Acad. Sci. U. S. A. https://doi.org/10.1073/pnas.1908221116

GeoLab - USP 2017 Aptidão agrícola. Mapa de aptidão agrícola do Brasil composta por nove variáveis de solo, relevo e clima.

Ghosh A and Fedorowicz J 2008 The role of trust in supply chain governance Business Process Management Journal 14 453–70

Gilbert M, Nicolas G, Cinardi G, van Boeckel T P, Vanwambeke S O, Wint G R W and Robinson T P 2018 Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010 Scientific Data 5

Giudice, R., Börner, J., Wunder, S., Cisneros, E., 2019. Selection biases and spillovers from collective conservation incentives in the Peruvian Amazon. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/aafc83

Global Forest Watch, 2019a. Indonesia logging concessions | Global Forest Watch Open Data Portal [WWW Document]. URL https://mapforenvironment.org/layer/info/329/Indonesia-Logging-Concessions#5.24/-1.289/118.16 (accessed 1.7.20).

Global Forest Watch, 2019b. Indonesia oil palm concessions | Global Forest Watch Open Data Portal [WWW Document]. URL http://data.globalforestwatch.org/datasets/f82b539b9b2f495e853670ddc3f0ce68_2 (accessed 1.7.20).

Global Forest Watch, 2019c. Indonesia wood fiber concessions | Global Forest Watch Open Data Portal [WWW Document]. URL https://data.globalforestwatch.org/datasets/05c3a7ee17df4f69bf3c4f974a8bece9_0 (accessed 1.7.20).

Global Forest Watch, 2019d. Universal Mill List | Global Forest Watch Open Data Portal [WWW Document]. URL http://data.globalforestwatch.org/datasets/universal-mill-list (accessed 10.6.19).

Godar J, Persson U M, Tizado E J and Meyfroidt P 2015 Towards more accurate and policy relevant footprint analyses: Tracing fine-scale socio-environmental impacts of production to consumption Ecological Economics 112 25–35

Godar J, Suavet C, Gardner T A, Dawkins E and Meyfroidt P 2016 Balancing detail and scale in assessing transparency to improve the governance of agricultural commodity supply chains Environmental Research Letters 11 035015

Gollnow F, Hissa L de B V, Rufin P and Lakes T 2018 Property-level direct and indirect deforestation for soybean production in the Amazon region of Mato Grosso, Brazil Land Use Policy 78 377–85

Golub A A and Hertel T W 2012 Modeling land-use change impacts of biofuels in the gtap-bio framework Climate Change Economics 3

Grabs J, Cammelli F, Levy S A and Garrett R D 2021 Designing effective and equitable zero-deforestation supply chain policies Global Environmental Change 70

Granovetter M 1985 Economic Action and Social Structure : The Problem of Embeddedness The American Journal of Sociology 91 481–510

Grassini P, Eskridge K M and Cassman K G 2013 Distinguishing between yield advances and yield plateaus in historical crop production trends Nature Communications 4

Greenpeace, 2021. Global Mapping Hub by Greenpeace [WWW Document]. URL https://maps.greenpeace.org/

Greenstone M and Gayer T 2009 Quasi-experimental and experimental approaches to environmental economics Journal of Environmental Economics and Management 57

Griscom B W, Adams J, Ellis P W, Houghton R A, Lomax G, Miteva D A, Schlesinger W H, Shoch D, Siikamäki J v., Smith P, Woodbury P, Zganjar C, Blackman A, Campari J, Conant R T, Delgado C, Elias P, Gopalakrishna T, Hamsik M R, Herrero M, Kiesecker J, Landis E, Laestadius L, Leavitt S M, Minnemeyer S, Polasky S, Potapov P, Putz F E, Sanderman J, Silvius M, Wollenberg E and Fargione J 2017 Natural climate solutions Proc Natl Acad Sci U S A 114

Gumbricht T, Roman-Cuesta R M, Verchot L, Herold M, Wittmann F, Householder E, Herold N and Murdiyarso D 2017 An expert system model for mapping tropical wetlands and peatlands reveals South America as the largest contributor Glob. Chang. Biol. 23 3581–99 Online: http://doi.wiley.com/10.1111/gcb.13689

Haberl H, Erb K H, Krausmann F, Gaube V, Bondeau A, Plutzar C, Gingrich S, Lucht W and Fischer-Kowalski M 2007 Quantifying and mapping the human appropriation of net primary production in earth’s terrestrial ecosystems Proc Natl Acad Sci U S A 104

Haddad S, Britz W and Börner J 2019 Economic impacts and land use change from increasing demand for forest products in the European bioeconomy: A general equilibrium based sensitivity analysis Forests

Hadush M, Holden S T and Tilahun M 2019 Does population pressure induce farm intensification? Empirical evidence from Tigrai Region, Ethiopia Agricultural Economics (United Kingdom) 50

Hansen M C, Potapov P V., Moore R, Hancher M, Turubanova S A, Tyukavina A, Thau D, Stehman S V., Goetz S J, Loveland T R, Kommareddy A, Egorov A, Chini L, Justice C O and Townshend J R G 2019 Hansen Global Forest Change v1.6 (2000-2018) | Earth Engine Data Catalog | Google Developers Online: https://developers.google.com/earth-engine/datasets/catalog/UMD_hansen_global_forest_change_2018_v1_6

Hansen, M.C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science (80-.). https://doi.org/10.1126/science.1244693

Harris N L, Goldman E, Gabris C, Nordling J, Minnemeyer S, Ansari S, Lippmann M, Bennett L, Raad M, Hansen M and Potapov P 2017 Using spatial statistics to identify emerging hot spots of forest loss Environmental Research Letters 12

Haupt F, Bakhtary H, Schulte I, Galt H and Streck C 2018 Progress on Corporate Commitments and their Implementation - Progress on Corporate Commitments and their Implementation Online: https://www.tfa2020.org/wp-content/uploads/2018/06/Progress-on-Corporate-Commitments-and-their-Implementation.pdf

Hawkins D M 2004 The Problem of Overfitting Journal of Chemical Information and Computer Sciences

Heilmayr R, Carlson K M and Benedict J J 2020a Deforestation spillovers from oil palm sustainability certification Environmental Research Letters in press

Heilmayr R, Rausch L L, Munger J and Gibbs H K 2020b Brazil’s Amazon Soy Moratorium reduced deforestation Nature Food 1 801–10

Henders S, Persson U M and Kastner T 2015 Trading forests: Land-use change and carbon emissions embodied in production and exports of forest-risk commodities Environ. Res. Lett. 10

Henderson J, Dicken P, Hess M, Coe N and Wai-Chung Yeung H 2002 Global production networks and the analysis of economic development vol 9

Heron T, Prado P and West C 2018 Global Value Chains and the Governance of ‘Embedded’ Food Commodities: The Case of Soy Global Policy 9 29–37

Herrera, D., 2015. Protected Areas’ Deforestation Spillovers and Two Critical Underlying Mechanisms: An Empirical Exploration for the Brazilian Amazon. Univ. Progr. Environ. Policy Duke Univ. https://doi.org/10.1017/CBO9781107415324.004

Hertel T W 1997 Global Trade Analysis: Modeling and Applications Cambridge University Press New York

Hertel T W 2018 Economic perspectives on land use change and leakage Environ. Res. Lett.

Hertel T W, West T A P, Börner J and Villoria N B 2019 A review of global-local-global linkages in economic land-use/cover change models Environmental Research Letters 14

High Carbon Stock Approach Steering Group 2019 Summary Progress and Highlights - November 2016 to January 2019 Online: http://highcarbonstock.org/wp-content/uploads/2019/01/HCSA-Summary-Highlights-Brochure-Jan-2019-final.pdf

Hilbe J M 2009 Logistic Regression Models (CRS Press - Taylor & Francis Group, LLC)

Hilbe J M 2011 Negative binomial regression, second edition

Hill S L L, Arnell A, Maney C, Butchart S H M, Hilton-Taylor C, Ciciarelli C, Davis C, Dinerstein E, Purvis A and Burgess N D 2019 Measuring Forest Biodiversity Status and Changes Globally Front. For. Glob. Chang.

Ho Y and Lin C 2012 An Empirical Study on Taiwanese Logistics Companies ' Attitudes toward Environmental Management Practices Advances in Management & Applied Economics

Ho, D.E., Imai, K., King, G., Stuart, E.A., 2007. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Polit. Anal. https://doi.org/10.1093/pan/mpl013

Hoffman M, Koenig K, Bunting G, Costanza J and Williams K J 2016 Biodiversity Hotspots (version 2016.1) [Data set] Online: https://zenodo.org/record/3261807#.Xk_J1Wj7SUk

Hosonuma N, Herold M, De Sy V, De Fries R S, Brockhaus M, Verchot L, Angelsen A and Romijn E 2012 An assessment of deforestation and forest degradation drivers in developing countries Environmental Research Letters

Huang B and Wang J 2020 Big spatial data for urban and environmental sustainability Geo-Spatial Information Science 23

ICMBio 2020 ICMBio - Instituto Chico Mendes de Conservação da Biodiversidade. Mapas Temáticos e Dados Geoestatísticos das Unidades de Conservação.

IIASA 2014 Globiom model International Instutute for Applied Systems Analysis

IIASA/FAO 2012 Global Agro-ecological Zones (GAEZ v3.0). (Rome, Italy) Online: http://www.gaez.iiasa.ac.at/

INCRA 2020 INCRA - Instituto Nacional de Colonização e Reforma Agrária. Acervo Fundiário. Bases espaciais de assentamentos rurais e áreas de quilombolas

Ingalls M L, Meyfroidt P, To P X, Kenney-Lazar M and Epprecht M 2018 The transboundary displacement of deforestation under REDD+: Problematic intersections between the trade of forest-risk commodities and land grabbing in the Mekong region Global Environmental Change 50

International Food Policy Research Institute 2019 Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 1.0 - IFPRI HarvestChoice Dataverse https://doi.org/10.7910/DVN/PRFF8V, Harvard Dataverse, V1 Online: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PRFF8V

International Food Policy Research Institute/Food and Agriculture Organization, 2012. Global Agro-ecological Zones (GAEZ v3.0). Rome, Italy.

Jarvis, A., Reuter, H.I., Nelson, A., Guevara, E., 2008. Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database: http://srtm.csi.cgiar.org. [WWW Document]. URL https://cgiarcsi.community/data/srtm-90m-digital-elevation-database-v4-1/ (accessed 1.7.20).

Jasinski E, Morton D, DeFries R, Shimabukuro Y, Anderson L and Hansen M 2005 Physical landscape correlates of the expansion of mechanized agriculture in Mato Grosso, Brazil Earth Interactions 9

Jayachandran S, de Laat J, Lambin E F, Stanton C Y, Audy R and Thomas N E 2017 Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation Science (1979) 357

Johnson J A, Ruta G, Baldos U, Cervigni R, Chonabayashi S, Corong E, Gavryliuk O, Gerber J, Hertel T, Nootenboom C and Polasky S 2021 The Economic Case for Nature: A global Earth-economy model World Bank Publications

Johnson J, Roxburgh T, Andrew Johnson J and Polasky S 2020 Global Trade Analysis Project Modelling the global economic impacts of environmental change to support policy-making Online: www.cleancanvas.co.uk

Johnston C M T 2016 Global paper market forecasts to 2030 under future internet demand scenarios J. For. Econ. 25 14–28 Online: https://www.sciencedirect.com/science/article/pii/S1104689916300186

Jones, K.W., Lewis, D.J., 2015. Estimating the counterfactual impact of conservation programs on land cover outcomes: The role of matching and panel regression techniques. PLoS One. https://doi.org/10.1371/journal.pone.0141380

Jopke P and Schoneveld G C 2018 Corporate commitments to zero deforestation An evaluation of externality problems and implementation gaps Online: http://www.cifor.org/publications/pdf_files/OccPapers/OP-181.pdf

Keele, L., 2008. Semiparametric Regression for the Social Sciences, Semiparametric Regression for the Social Sciences. https://doi.org/10.1002/9780470998137

Kepaptsoglou K, Karlaftis M G and Tsamboulas D 2010 The Gravity Model Specification for Modeling International Trade Flows and Free Trade Agreement Effects: A 10-Year Review of Empirical Studies The Open Economics Journal 3 1–13

Krippner G R and Alvarez A S 2007 Embeddedness and the Intellectual Projects of Economic Sociology Annual Review of Sociology 33 219–40

Kuik O 2014 REDD+ and international leakage via food and timber markets: A CGE analysis Mitigation and Adaptation Strategies for Global Change

Kummu, M., Taka, M., Guillaume, J.H.A., 2018. Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015. Sci. Data 5, 180004. https://doi.org/10.1038/sdata.2018.4

Kyalo Willy D, Muyanga M and Jayne T 2019 Can economic and environmental benefits associated with agricultural intensification be sustained at high population densities? A farm level empirical analysis Land Use Policy 81

Lake S, Rosenbarger A and Winchester C 2016 Palm Risk Assessment Methodology: Prioritizing Areas, Landscapes, And Mills Online: www.wri.org/

Lam W Y, Kulak M, Sim S, King H, Huijbregts M A J and Chaplin-Kramer R 2019 Greenhouse gas footprints of palm oil production in Indonesia over space and time Science of the Total Environment 688

Lambin E F and Meyfroidt P 2011 Global land use change, economic globalization, and the looming land scarcity Proc. Natl. Acad. Sci.

Lambin E F, Gibbs H K, Ferreira L, Grau R, Mayaux P, Meyfroidt P, Morton D C, Rudel T K, Gasparri I and Munger J 2013 Estimating the world's potentially available cropland using a bottom-up approach Global Environmental Change 23

Lambin E F, Gibbs H K, Heilmayr R, Carlson K M, Fleck L C, Garrett R D, le Polain De Waroux Y, McDermott C L, McLaughlin D, Newton P, Nolte C, Pacheco P, Rausch L L, Streck C, Thorlakson T and Walker N F 2018 The role of supply-chain initiatives in reducing deforestation Nature Climate Change 8 109–116

Lancaster T 2000 The incidental parameter problem since 1948 Journal of Econometrics

Lee H L, Hertel T W, Sohngen B and Ramankutty N 2005 Towards an integrated land use database for assessing the potential for greenhouse gas mitigation vol 25

Leijten F, dos Reis T N P, Sim S, Verburg P H and Meyfroidt P 2022 The influence of company sourcing patterns on the adoption and effectiveness of zero-deforestation commitments in Brazil's soy supply chain Environmental Science & Policy 128

Leijten F, Sim S, King H and Verburg P 2020 Which forests could be protected by corporate zero deforestation commitments? A spatial assessment. - IOPscience Environmental Research Letters Online: https://iopscience.iop.org/article/10.1088/1748-9326/ab8158/meta

Leijten F, Sim S, King H and Verburg P H 2021 Local deforestation spillovers induced by forest moratoria: Evidence from Indonesia Land Use Policy 109 105690

Liebsch D, Marques M C M and Goldenberg R 2008 How long does the Atlantic Rain Forest take to recover after a disturbance? Changes in species composition and ecological features during secondary succession Biological Conservation 141

Lim, F.K.S., Roman Carrasco, L., McHardy, J., Edwards, D.P., 2019. Land rents drive oil palm expansion dynamics in Indonesia. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/ab2bda

Liu X, Yu L, Li W, Peng D, Zhong L, Li L, Xin Q, Lu H, Yu C and Gong P 2018 Comparison of country-level cropland areas between ESA-CCI land cover maps and FAOSTAT data International Journal of Remote Sensing 39

Lloyd C T 2016 WorldPop Archive global gridded spatial datasets. Version Alpha 0.9. 100m base topography (tiled) Harvard Dataverse, V1 https://do

Longley P A, Goodchild M F, Maguire D J, and Rhind D W 2020 Geographic Information Science and Systems International Encyclopedia of Human Geography

Ludena C E, Hertel T W, Preckel P v., Foster K and Nin A 2007 Productivity growth and convergence in crop, ruminant, and nonruminant production: Measurement and forecasts Agricultural Economics 37

Lyons-White J and Knight A T 2018 Palm oil supply chain complexity impedes implementation of corporate no-deforestation commitments Global Environmental Change 50 303–13 Online: https://www.sciencedirect.com/science/article/pii/S0959378017310117

Ma B, Song G, Zhang L and Sonnenfeld D A 2014 Explaining sectoral discrepancies between national and provincial statistics in China China Economic Review 30

Magliocca, N., Khuc, Q. Van, de Bremond, A., Ellicott, E., 2019. Direct and indirect land-use change caused by large-scale land acquisitions in Cambodia. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/ab6397

Masuda T and Goldsmith P D 2009 World Soybean Production : Area Harvested , Yield , and Long-Term Projections 12 143–62

McCullough B D 2009 The Devil is in the Detail: Hints for Practical Optimisation - A Comment Economic Analysis and Policy

McGill R, Tukey J W and Larsen W A 1978 Variations of box plots American Statistician

McGrath L F 2015 Estimating Onsets of Binary Events in Panel Data Political Analysis

Melitz M J 2002 The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity NBER working paper No. 8881

Mellino S, Buonocore E and Ulgiati S 2015 The worth of land use: A GIS-emergy evaluation of natural and human-made capital Science of the Total Environment 506–507

Mermoz S, Bouvet A, Le Toan T and Herold M 2018 Impacts of the forest definitions adopted by African countries on carbon conservation Environ. Res. Lett 13 104014 Online: https://doi.org/10.1088/1748-9326/aae3b1

Meyfroidt P, Roy Chowdhury R, de Bremond A, Ellis E C, Erb K H, Filatova T, Garrett R D, Grove J M, Heinimann A, Kuemmerle T, Kull C A, Lambin E F, Landon Y, le Polain de Waroux Y, Messerli P, Müller D, Nielsen J, Peterson G D, Rodriguez García V, Schlüter M, Turner B L and Verburg P H 2018 Middle-range theories of land system change Global Environmental Change 53 52–67

Meyfroidt, P., Lambin, E.F., 2009. Forest transition in Vietnam and displacement of deforestation abroad. Proc. Natl. Acad. Sci. U. S. A. 106. https://doi.org/10.1073/pnas.0904942106

Ministry of Environment and Forestry of The Republic of Indonesia, 2010. Indonesia legal classifications [WWW Document]. 'Landuse maps (provincial Plan. maps/Forest L. Use by Consens. maps (TGHK)', Gen. Direktorat Planning, Minist. For. URL https://data.globalforestwatch.org/datasets/04f797199b9441a28490410f91336b38_13?geometry=65.830%2C-10.215%2C170.376%2C5.104

Ministry of Environment and Forestry of The Republic of Indonesia, 2021. Archive Indicative Moratorium Map (PIPPIB) [WWW Document]. Digit. by Greenpeace. URL https://geoportal.menlhk.go.id/webgis/index.php/en/map/pippib

Ministry of Environment and Forestry, 2016. National Forest Reference Emission Level For Deforestation And Forest Degradation In the Context of Decision 1/CP.16 para 70 UNFCCC (Encourages developing country Parties to contribute to mitigation actions in the forest sector).

Miranda M, Burris P, Bingcang J F, Shearman P, Oliver J, Antonio B, Viña L A, Menard S, Kool J, Miclat S, Mooney C and Resueño A 2003 Mining And Critical Ecosystems: Mapping the Risks (Washington DC)

7

Miranda, J., Börner, J., Kalkuhl, M., Soares-Filho, B., 2019. Land speculation and conservation policy leakage in Brazil. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/ab003a

Moffette F and Gibbs H 2019 Agricultural Displacement and Deforestation Leakage in the Brazilian Legal Amazon

Molotoks A, Stehfest E, Doelman J, Albanito F, Fitton N, Dawson T P and Smith P 2018 Global projections of future cropland expansion to 2050 and direct impacts on biodiversity and carbon storage Global Change Biology 24

Mongabay 2022 To cooperatively stop deforestation for commodities, navigating 'legal' vs 'zero' is key (commentary)

Mongabay, 2019a. Indonesia forest-clearing ban is made permanent, but labeled 'propaganda' [WWW Document]. URL https://news.mongabay.com/2019/08/indonesia-forest-clearing-ban-is-made-permanent-but-labeled-propaganda/ (accessed 10.6.19).

Mongabay, 2019b. Indonesian president signs 3-year freeze on new oil palm licenses [WWW Document]. URL https://news.mongabay.com/2018/09/indonesian-president-signs-3-year-freeze-on-new-oil-palm-licenses/ (accessed 3.16.20).

Mosnier A, Boere E, Reumann A, Yowargana P, Pirker J and Havlík P 2017 Palm oil and likely futures plantations in Indonesia 1–8

Murdiyarso, D., Dewi, S., Lawrence, D., Seymour, F., 2011. Indonesia's forest moratorium: A stepping stone to better forest governance? https://doi.org/10.17528/cifor/003561

Narasimhan R, Nair A, Griffith D A, Arlbjørn J S and Bendoly E 2009 Lock-in situations in supply chains: A social exchange theoretic study of sourcing arrangements in buyer-supplier relationships Journal of Operations Management 27 374–89

Newton P and Benzeev R 2018 The role of zero-deforestation commitments in protecting and enhancing rural livelihoods Curr. Opin. Environ. Sustain. 32 126–33 Online: https://www.sciencedirect.com/science/article/pii/S1877343517301550

Neyman J and Scott E L 1948 Consistent Estimates Based on Partially Consistent Observations Econometrica

Nolte, C., le Polain de Waroux, Y., Munger, J., Reis, T.N.P., Lambin, E.F., 2017. Conditions influencing the adoption of effective anti-deforestation policies in South America's commodity frontiers. Glob. Environ. Chang. https://doi.org/10.1016/j.gloenvcha.2017.01.001

Noojipady, P., Morton, D.C., Schroeder, W., Carlson, K.M., Huang, C., Gibbs, H.K., Burns, D., Walker, N.F., Prince, S.D., 2017. Managing fire risk during drought: The influence of certification and El Ninõ on fire-driven forest conversion for oil palm in Southeast Asia. Earth Syst. Dyn. https://doi.org/10.5194/esd-8-749-2017

O'Neill B C, Kriegler E, Riahi K, Ebi K L, Hallegatte S, Carter T R, Mathur R, Van Vuuren D P, Kriegler E, Riahi K, Ebi K L, Hallegatte S, Carter T R, Mathur R and Van Vuuren D P 2014 A new scenario framework for climate change research: the concept of shared socioeconomic pathways Clim. Change 122 387–400 Online: https://rd.springer.com/content/pdf/10.1007%2Fs10584-013-0905-2.pdf

OECD and FAO 2020 Chapter 4. Oilseeds and oilseed products OECD-FAO AGRICULTURAL OUTLOOK 2020-2029

OECD/FAO 2021 OECD-FAO Agricultural Outlook 2021-2030 (OECD Publishing Paris, /Food and Agriculture Organization of the United Nations, Rome) Online: http://www.fao.org/documents/card/en/c/cb5332en

OECD-FAO 2018 OECD-FAO Agricultural Outlook 2018-2027 (OECD Publishing Paris, /Food and Agriculture Organization of the United Nations, Rome) Online: http://dx.doi.org/10.1787/agr-outl-data-en.

Overmars K P, Stehfest E, Tabeau A, van Meijl H, Beltrán A M and Kram T 2014 Estimating the opportunity costs of reducing carbon dioxide emissions via avoided deforestation, using integrated assessment modelling Land Use Policy 41

Oxfam 2021 Tightening the net. Net zero climate targets – implications for land and food equity

Pailler, S., 2018. Re-election incentives and deforestation cycles in the Brazilian Amazon. J. Environ. Econ. Manage. https://doi.org/10.1016/j.jeem.2018.01.008

Panlasigui, S., Rico-Straffon, J., Pfaff, A., Swenson, J., Loucks, C., 2018. Impacts of certification, uncertified concessions, and protected areas on forest loss in Cameroon, 2000 to 2013. Biol. Conserv. https://doi.org/10.1016/j.biocon.2018.09.013

Payo A, Becker P, Otto A, Vervoort J and Kingsborough A 2016 Experiential Lock-In: Characterizing Avoidable Maladaptation in Infrastructure Systems Journal of Infrastructure Systems 22 02515001

Pellegrini P and Fernández R J 2018 Crop intensification, land use, and on-farm energy-use efficiency during the worldwide spread of the green revolution Proc Natl Acad Sci U S A 115

Pendrill F, Persson U M, Godar J and Kastner T 2019 Deforestation displaced: trade in forest-risk commodities and the prospects for a global forest transition Environmental Research Letters 14 055003

Pérez-Hoyos A, Rembold F, Kerdiles H and Gallego J 2017 Comparison of global land cover datasets for cropland monitoring Remote Sensing 9

Pfaff, A., Robalino, J., 2017. Spillovers from Conservation Programs. Annu. Rev. Resour. Econ. https://doi.org/10.1146/annurev-resource-100516-053543

Pirard R, Fishman A, Gnych S, Obidzinski K and Pacheco P 2015 The challenge of implementation- An application to Indonesia Online: http://www.cifor.org/publications/pdf_files/WPapers/WP181Pirard.pdf

Pirker J, Mosnier A, Kraxner F, Havlík P and Obersteiner M 2016 What are the limits to oil palm expansion? Global Environmental Change 40 73–81

Plevin R J, Beckman J, Golub A A, Witcover J and O'Hare M 2015 Carbon accounting and economic model uncertainty of emissions from biofuels-induced land use change Environmental Science and Technology 49

Polanyi K 1944 The Great Transformation (New York: Beacon Press Books)

Potapov P, Yaroshenko A, Turubanova S, Dubinin M, Laestadius L, Thies C, Aksenov D, Egorov A, Yesipova Y, Glushkov I, Karpachevskiy M, Kostikova A, Manisha A, Tsybikova E and Zhuravleva I 2008 Mapping the world's intact forest landscapes by remote sensing Ecol. Soc.

Potapov P, Yaroshenko A, Turubanova S, Dubinin M, Laestadius L, Thies C, Aksenov D, Egorov A, Yesipova Y, Glushkov I, Karpachevskiy M, Kostikova A, Manisha A, Tsybikova E and Zhuravleva I 2017 Intact Forest Landscapes 2016 Online: http://www.intactforests.org/data.ifl.html

Potoski M and Prakash A 2013 Green Clubs: Collective Action and Voluntary Environmental Programs Annual Review of Political Science 16 399–419

President of Indonesia, 2011. Instruksi Presiden Republik Indonesia Nomor 10 Tahun 2011 Tentang Penundaan Pemberian Izin Baru Dan Penyempurnaan Tata Kelola Hutan Alam Primer Dan Lahan Gambut (in Indonesian) [Instruction Of The President Of The Republic Of Indonesia Number 10 Of 2011 A. Jakarta, Indonesia.

Qaim M, Sibhatu K T, Siregar H and Grass I 2020 Environmental, Economic, and Social Consequences of the Oil Palm Boom Annual Review of Resource Economics 12 Online: https://www.annualreviews.org/doi/abs/10.1146/annurev-resource-110119-024922

R Core Team 2020 R software: Version 4.0.2 R Foundation for Statistical Computing

Ramankutty N, Evan A T, Monfreda C and Foley J A 2010 Global Agricultural Lands: Pastures, 2000. Palisades, NY NASA Socioecon. Data Appl. Cent. (SEDAC). https//doi.org/10.7927/H47H1GGR. n/a-n/a Online: http://doi.wiley.com/10.1029/2007GB002952

Reis T N P dos, Meyfroidt P, zu Ermgassen E K H J, West C, Gardner T, Bager S, Croft S, Lathuillière M J and Godar J 2020 Understanding the Stickiness of Commodity Supply Chains Is Key to Improving Their Sustainability One Earth 3 100–15

Richards P D, Myers R J, Swinton S M and Walker R T 2012 Exchange rates, soybean supply response, and deforestation in South America Global Environmental Change

7

Rist L, Feintrenie L and Levang P 2010 The livelihood impacts of oil palm: Smallholders in Indonesia Biodiversity and Conservation 19

Robalino, J., Pfaff, A., Villalobos, L., 2017. Heterogeneous Local Spillovers from Protected Areas in Costa Rica. J. Assoc. Environ. Resour. Econ. https://doi.org/10.1086/692089

Roberts M J and Schlenker W 2013 Identifying Supply and Demand Elasticities of Agricultural Commodities : American Economic Review 103

Romijn E, Ainembabazi J H, Wijaya A, Herold M, Angelsen A, Verchot L and Murdiyarso D 2013 Exploring different forest definitions and their impact on developing REDD+ reference emission levels: A case study for Indonesia Environ. Sci. Policy

Roopsind, A., Sohngen, B., Brandt, J., 2019. Evidence that a national REDD+ program reduces tree cover loss and carbon emissions in a high forest cover, low deforestation country. Proc. Natl. Acad. Sci. U. S. A. https://doi.org/10.1073/pnas.1904027116

Rosoman G, Sheun S S, Opal C, Anderson P and Trapshah R 2017 The HCS Approach - Putting no deforestation into practice (Singapore) Online: www.forestdeclaration.org

RSPO 2018 RSPO P&C for the Production of Sustainable Palm Oil Online: http://www.rspo.org/file/RSPO Statutes.pdf

Rubin D B 2008 For objective causal inference, design trumps analysis Annals of Applied Statistics 2

Rudel T K, Defries R, Asner G P and Laurance W F 2009 Changing drivers of deforestation and new opportunities for conservation Conservation Biology 23

Rueda X, Garrett R D and Lambin E F 2017 Corporate investments in supply chain sustainability: Selecting instruments in the agri-food industry Journal of Cleaner Production

Santeramo F G, di Gioia L and Lamonaca E 2021 Price responsiveness of supply and acreage in the EU vegetable oil markets: Policy implications Land Use Policy 101

Santoro M and Cartus O 2019 Dataset Record: ESA Biomass Climate Change Initiative (Biomass_cci): Global datasets of forest above-ground biomass for the year 2017, v1 Cent. Environ. Data Anal. Online: https://catalogue.ceda.ac.uk/uuid/bedc59f37c9545c981a839eb552e4084

Šavrič B, Jenny B, White D and Strebe D R 2015 Cartography and Geographic Information Science User preferences for world map projections User preferences for world map projections Online: https://www.tandfonline.com/action/journalInformation?journalCode=tcag20

Schaaf, C., Wang Z 2015 MCD43A4 V006 | LP DAAC :: NASA Land Data Products and Services Online: https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q1_v006

Schepaschenko D, See L, Lesiv M, McCallum I, Fritz S, Salk C, Moltchanova E, Perger C, Shchepashchenko M, Shvidenko A, Kovalevskyi S, Gilitukha D, Albrecht F, Kraxner F, Bun A, Maksyutov S, Sokolov A, Dürauer M, Obersteiner M, Karminov V and Ontikov P 2015 Development of a global hybrid forest mask through the synergy of remote sensing, crowdsourcing and FAO statistics Remote Sens. Environ.

Schleicher J, Eklund J, D. Barnes M, Geldmann J, Oldekop J A and Jones J P G 2020 Statistical matching for conservation science Conservation Biology 34

Schmitz T, Schweiger B and Daft J 2016 The emergence of dependence and lock-in effects in buyer-supplier relationships - A buyer perspective Industrial Marketing Management

Schneider A, Friedl M A and Woodcock C E 2003 Mapping urban areas by fusing multiple sources of coarse resolution remotely sensed data IGARSS 2003. 2003 IEEE International Geoscience and Remote Sensing Symposium. Proceedings (IEEE Cat. No.03CH37477) vol 4 (IEEE) pp 2623–5 Online: http://ieeexplore.ieee.org/document/1294530/

Schulte I, Streck C and Roe S 2019 Protecting and Restoring Forests A Story of Large Commitments yet Limited Progress Progress on the New York Declaration on Forests forestdeclaration.org FIVE-YEAR ASSESSMENT REPORT

Schulze K, Malek Ž and Verburg P H 2019 Towards better mapping of forest management patterns: A global allocation approach Forest Ecology and Management 432 776–85

Schulze K, Malek Ž and Verburg P H 2021 How will land degradation neutrality change future land system patterns? A scenario simulation study Environmental Science and Policy 124

Searchinger T, Heimlich R, Houghton R A, Dong F, Elobeid A, Fabiosa J, Tokgoz S, Hayes D and Yu T H 2008 Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change Science (1979) 319

Senior M J M, Brown E, Villalpando P and Hill J K 2015 Increasing the Scientific Evidence Base in the "High Conservation Value" (HCV) Approach for Biodiversity Conservation in Managed Tropical Landscapes Conserv. Lett. 8 361–7 Online: http://doi.wiley.com/10.1111/conl.12148

Sexton J O, Noojipady P, Song X P, Feng M, Song D X, Kim D H, Anand A, Huang C, Channan S, Pimm S L and Townshend J R 2016 Conservation policy and the measurement of forests Nat. Clim. Chang.

Sexton J O, Song X P, Feng M, Noojipady P, Anand A, Huang C, Kim D H, Collins K M, Channan S, DiMiceli C and Townshend J R 2013 Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error Int. J. Digit. Earth

Seymour F and Busch J 2016 Why Forests? Why Now?: The Science, Economics, and Politics of Tropical Forests and Climate Change

Shah S K and Corley K G 2006 Building better theory by bridging the quantitative-qualitative divide Journal of Management Studies 43

Shevade V S and Loboda T v. 2019 Oil palm plantations in Peninsular Malaysia: Determinants and constraints on expansion PLoS ONE

Shimada M, Itoh T, Motooka T, Watanabe M, Shiraishi T, Thapa R and Lucas R 2014 New global forest/non-forest maps from ALOS PALSAR data (2007-2010) Remote Sens. Environ.

Shimada M, Itoh T, Motooka T, Watanabe M, Shiraishi T, Thapa R and Lucas R 2019 New global forest/non-forest maps from ALOS PALSAR data (2007–2010) Online: https://developers.google.com/earth-engine/datasets/catalog/JAXA_ALOS_PALSAR_YEARLY_FNF

Siebert S, Kummu M, Porkka M, Döll P, Ramankutty N and Scanlon B R 2015 A global data set of the extent of irrigated land from 1900 to 2005 Hydrology and Earth System Sciences 19

Siebert S, Portmann F T and Döll P 2010 Global patterns of cropland use intensity Remote Sensing

Sinclair, B., Mcconnell, M., Green, D.P., 2012. Detecting Spillover Effects: Design and Analysis of Multilevel Experiments. Am. J. Pol. Sci. https://doi.org/10.1111/j.1540-5907.2012.00592.x

Skandrani H, Triki A and Baratli B 2011 Trust in supply chains, meanings, determinants and demonstrations Qualitative Market Research: An International Journal 14 391–409

Sloan, S., 2014. Indonesia's moratorium on new forest licenses: An update. Land use policy 38, 37–40. https://doi.org/10.1016/J.LANDUSEPOL.2013.10.018

Sloan, S., Edwards, D.P., Laurance, W.F., 2012. Does Indonesia's REDD+ moratorium on new concessions spare imminently threatened forests? Conserv. Lett. https://doi.org/10.1111/j.1755-263X.2012.00233.x

Smit H H, Meijaard E, van der Laan C, Mantel S, Budiman A and Verweij P 2013 Breaking the Link between Environmental Degradation and Oil Palm Expansion: A Method for Enabling Sustainable Oil Palm Expansion PLoS ONE

Soterroni A C, Ramos F M, Mosnier A, Fargione J, Andrade P R, Baumgarten L, Pirker J, Obersteiner M, Kraxner F, Câmara G, Carvalho A X Y and Polasky S 2019 Expanding the Soy Moratorium to Brazil's Cerrado Science Advances 5 eaav7336

Srinivasan U, Velho N, Lee J S H, Chiarelli D D, Davis K F and Wilcove D S 2021 Oil palm cultivation can be expanded while sparing biodiversity in India Nature Food 2

Stammann A 2017 Fast and Feasible Estimation of Generalized Linear Models with High-Dimensional k-way Fixed Effects arXiv

7

Stehfest E, van Vuuren D, Kram T, Bouwman L, Alkemade R, Bakkenes M, Biemans H, Bouwman A, Den Elzen M, Janse J, Alkemade R, Bakkenes M, Biemans H, Bouwman A, Den Elzen M, Janse J, Lucas P, van Minnen J, Muller C and Prins A G 2014 Integrated assessment of global environmental change with IMAGE 3.0 - Chapter 7.6

Steinweg T, Drennen Z, Advisers C and Rijk G 2017 Unsustainable Palm Oil Faces Increasing Market Access Risks | Unsustainable Palm Oil Faces Increasing Market Access Risks: NDPE Sourcing Policies Cover 74 Percent of Southeast Asia's Refining Capacity (Updated Version) Figure 1: Indonesian and Malaysian refining capacity covered by NDPE Sourcing Policies Online: www.chainreactionresearch.com

Stevens, F.R., Gaughan, A.E., Linard, C., Tatem, A.J., 2015. Disaggregating census data for population mapping using Random forests with remotely-sensed and ancillary data. PLoS One. https://doi.org/10.1371/journal.pone.0107042

Stuart, E.A., 2010. Matching methods for causal inference: A review and a look forward. Stat. Sci. https://doi.org/10.1214/09-STS313

Suwarno, A., van Noordwijk, M., Weikard, H.P., Suyamto, D., 2018. Indonesia's forest conversion moratorium assessed with an agent-based model of Land-Use Change and Ecosystem Services (LUCES). Mitig. Adapt. Strateg. Glob. Chang. 23, 211–229. https://doi.org/10.1007/s11027-016-9721-0

Tabeau A, Eickhout B and Meijl H van 2006 Endogenous agricultural land supply : estimation and implementation in the GTAP model Gtap

Tacconi, L., Muttaqin, M.Z., 2019. Reducing emissions from land use change in Indonesia: An overview. For. Policy Econ. https://doi.org/10.1016/j.forpol.2019.101979

Taheripour F and Tyner W E 2020 US biofuel production and policy: Implications for land use changes in Malaysia and Indonesia Biotechnology for Biofuels 13

Taheripour F, Hertel T W and Ramankutty N 2019 Market-mediated responses confound policies to limit deforestation from oil palm expansion in Malaysia and Indonesia Proc Natl Acad Sci U S A

Taheripour, F., Zhao, X., Tyner, W.E., 2017. The impact of considering land intensification and updated data on biofuels land use change and emissions estimates. Biotechnol. Biofuels. https://doi.org/10.1186/s13068-017-0877-y

Tamayo-Torres I, Gutierrez-Gutierrez L and Ruiz-Moreno A 2019 Boosting sustainability and financial performance: the role of supply chain controversies International Journal of Production Research

Taubert, F., Fischer, R., Groeneveld, J., Lehmann, S., Müller, M.S., Rödig, E., Wiegand, T., Huth, A., 2018. Global patterns of tropical forest fragmentation. Nature. https://doi.org/10.1038/nature25508

Tayleur C and Phalan B T 2018 Spatial Data Are Key to Sustainability Standards Increasing and Demonstrating Their Impact Tropical Conservation Science 11

Taylor R and Streck C 2018 The Elusive Impact Of The Deforestation-Free Supply Chain Movement Ending Tropical Deforestation: A Stock-Take Of Progress And Challenges Online: http://supply-change.org.

ten Kate A, Kuepper B and Piotrowski M 2020 NDPE Policies Cover 83% of Palm Oil Refineries; Implementation at 78% Online: https://chainreactionresearch.com/wp-content/uploads/2020/04/NDPE-Policies-Cover-83-of-Palm-Oil-Refining-Market.pdf

TerraBrasilis 2021 Filtros - Amazônia Legal / Estados / Todos Online: http://terrabrasilis.dpi.inpe.br/app/dashboard/deforestation/biomes/legal_amazon/rates

Thorlakson T, de Zegher J F and Lambin E F 2018 Companies' contribution to sustainability through global supply chains. Proc Natl Acad Sci U S A 115 2072–7

Thornton P K 2010 Livestock production: recent trends, future prospects Philos. Trans. R. Soc. B Biol. Sci. 365 2853–67 Online: http://www.royalsocietypublishing.org/doi/10.1098/rstb.2010.0134

Trase 2020a Brazil soy data. SEI-PCS v2.4 Online: https://trase.earth/

Trase 2020b How Trase assesses 'commodity deforestation' and 'commodity deforestation risk'

Trase 2020c Key indicators

Tropek, R., Sedláček, O., Beck, J., Keil, P., Musilová, Z., Šímová, I., Storch, D., 2014. Comment on "High-resolution global maps of 21st-century forest cover change." Science (80-.). 344, 981. https://doi.org/10.1126/science.1248753

UNEP-WCMC 2017 World Database on Protected Areas Online: https://www.protectedplanet.net/

UNEP-WCMC and IUCN 2018 Protected Planet: The World Database on Protected Areas (WDPA)/ The Global Database on Protected Areas Management Effectiveness (GD-PAME)] [On-line], [23/11/2018]

UNFCCC 2006 Definitional issues related to reducing emissions from deforestation in developing countries

Uzzi B 1997 Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness Administrative Science Quarterly 42 35–67

van Asselen S and Verburg P H 2013 Land cover change or land-use intensification: Simulating land system change with a global-scale land change model Global Change Biology

van der Ven, H., Rothacker, C., Cashore, B., 2018. Do eco-labels prevent deforestation? Lessons from non-state market driven governance in the soy, palm oil, and cocoa sectors. Glob. Environ. Chang. https://doi.org/10.1016/j.gloenvcha.2018.07.002

Van Velthuizen H, Huddleston B, Fischer G, Salvatore M, Ataman E, Nachtergaele F O, Zanetti M, Bloise M, Gis F, Antonicelli A, Bel J, De Liddo A, De Salvo P and Franceschini G 2007 Mapping biophysical factors that influence agricultural production and rural vulnerability Online: http://www.fao.org/docrep/pdf/010/a1075e/a1075e00.pdf

van Vuuren D P, Stehfest E, Gernaat D E H J, Doelman J C, van den Berg M, Harmsen M, de Boer H S, Bouwman L F, Daioglou V, Edelenbosch O Y, Girod B, Kram T, Lassaletta L, Lucas P L, van Meijl H, Müller C, van Ruijven B J, van der Sluis S and Tabeau A 2017 Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm Global Environmental Change 42 237–50 Online: https://www.sciencedirect.com/science/article/pii/S095937801630067X?via%3Dihub

Vancutsem C, Achard F, Pekel J F, Vieilledent G, Carboni S, Simonetti D, Gallego J, Aragão L E O C and Nasi R 2021 Long-term (1990–2019) monitoring of forest cover changes in the humid tropics Science Advances 7

Vanloqueren G and Baret P V. 2009 How agricultural research systems shape a technological regime that develops genetic engineering but locks out agroecological innovations Research Policy 38 971–83

Venter O, Sanderson E W, Magrach A, Allan J R, Beher J, Jones K R, Possingham H P, Laurance W F, Wood P, Fekete B M, Levy M A and Watson J E 2018 Last of the Wild Project, Version 3 (LWP-3): 2009 Human Footprint, 2018 Release NASA Socioeconomic Data and Applications Center 3

Verburg P H, van de Steeg J, Veldkamp A and Willemen L 2009 From land cover change to land function dynamics: A major challenge to improve land characterization Journal of Environmental Management 90

Verburg, P.H., Eickhout, B., Meijl, H., 2008. A multi-scale, multi-model approach for analyzing the future dynamics of European land use. Ann. Reg. Sci. https://doi.org/10.1007/s00168-007-0136-4

Vijay V, Pimm S L, Jenkins C N and Smith S J 2016 The Impacts of Oil Palm on Recent Deforestation and Biodiversity Loss PLoS One

Villoria N 2021 Lack of Ambition, Not Leakage, is What Can Make Brazil's Soybean Supply-Chain Zero Deforestation Commitments Ineffective Online: https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=6317

Villoria N B and Hertel T W 2011 Geography matters: International trade patterns and the indirect land use effects of biofuels American Journal of Agricultural Economics 93 919–35

Virah-Sawmy M, Durán A P, Green J M H, Guerrero A M, Biggs D and West C D 2019 Sustainability gridlock in a global agricultural commodity chain: Reframing the soy–meat food system Sustainable Production and Consumption 18

Waha K, Dietrich J P, Portmann F T, Siebert S, Thornton P K, Bondeau A and Herrero M 2020 Multiple cropping systems of the world and the potential for increasing cropping intensity Global Environmental Change

Weber A K and Partzsch L 2018 Barking up the right tree? NGOs and corporate power for deforestation-free supply chains Sustain.

Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T.C.D., Howes, R.E., Tusting, L.S., Kang, S.Y., Cameron, E., Bisanzio, D., Battle, K.E., Bhatt, S., Gething, P.W., 2018. A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature 553, 333–336. https://doi.org/10.1038/nature25181

West T A P, Börner J, Sills E O and Kontoleon A 2020 Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon Proc Natl Acad Sci U S A 117

West T A P, Grogan K A, Swisher M E, Caviglia-Harris J L, Sills E, Harris D, Roberts D and Putz F E 2018 A hybrid optimization-agent-based model of REDD+ payments to households on an old deforestation frontier in the Brazilian Amazon Environmental Modelling and Software 100

Wijaya, A., Chrysolite, H., Ge, M., Wibowo, K.C., Pradana, A., Utami, A.F., Austin, K., 2017. How Can Indonesia Achieve Its Climate Change Mitigation Goal? An Analysis Of Potential Emissions Reductions From Energy And Land-Use Policies.

Woittiez L S, van Wijk M T, Slingerland M, van Noordwijk M and Giller K E 2017 Yield gaps in oil palm: A quantitative review of contributing factors European Journal of Agronomy

Wolf C, Levi T, Ripple W J, Zárrate-Charry D A and Betts M G 2021 A forest loss report card for the world's protected areas Nature Ecology and Evolution 5

Wolff S, Schrammeijer E A, Schulp C J E and Verburg P H 2018 Meeting global land restoration and protection targets: What would the world look like in 2050? Global Environmental Change 52

Wolosin M and Harris N 2018 Tropical forests and climate change: the latest science Ending tropical deforestation

Woltjer G B and Kuiper M H 2014 The MAGNET model: Module description Wageningen: LEI 877 Wageningen UR.

World Resources Institute, 2019. Indonesia Is Reducing Deforestation, but Problem Areas Remain [WWW Document]. URL https://www.wri.org/blog/2019/07/indonesia-reducing-deforestation-problem-areas-remain

Wunder S, Kaimowitz D, Jensen S and Feder S 2021 Coronavirus, macroeconomy, and forests: What likely impacts? Forest Policy and Economics 131

Young O R, Lambin E F, Alcock F, Haberl H, Karlsson S I, McConnell W J, Myint T, Pahl-Wostl C, Polsky C, Ramakrishnan P S, Schroeder H, Scouvart M and Verburg P H 2006 A portfolio approach to analyzing complex human-environment interactions: Institutions and land change Ecology and Society 11

Yusuf, A.A., Roos, E.L., Horridge, J.M., 2018. Indonesia's moratorium on palm oil expansion from natural forests: Economy-wide impacts and the role of international transfers. Asian Dev. Rev. https://doi.org/10.1162/adev_a_00115

Zabel F, Putzenlechner B and Mauser W 2014 Global agricultural land resources - A high resolution suitability evaluation and its perspectives until 2100 under climate change conditions PLoS ONE 9

Zhu A-X, Richardson D, Castree N, Goodchild M F, Kobayashi A, Liu W and Marston R A 2017 Resampling, raster Online: https://onlinelibrary.wiley.com/doi/pdf/10.1002/9781118786352.wbieg0878

zu Ermgassen E K H J, Ayre B, Godar J, Bastos Lima M G, Bauch S, Garrett R, Green J, Lathuillière M J, Löfgren P, MacFarquhar C, Meyfroidt P, Suavet C, West C and Gardner T 2020 Using supply chain data to monitor zero deforestation commitments: an assessment of progress in the Brazilian soy sector Environmental Research Letters 15 035003

Appendix A

Table 1 – List of High Conservation Value categories, their formal definitions, the indicators used to identify High Conservation Value Forest, the rationale for selecting each indicator and their corresponding datasets. The last column indicates whether the datasets are publicly available or not. The official High Conservation Value category definitions are derived from Brown *et al* (2013).

HCV category	**Official definition**	**Indicator**	**Rationale**	**Analysis**	**Datasets**	**Publicly available**
HCV 1 Species diversity	Concentrations of biological diversity including endemic species, and rare, threatened or endangered (RTE) species that are significant at global, regional or national levels.	Biodiversity Hotspots	Are estimated to support more than half of the world's plant species as endemics and nearly 43% of bird, mammal, reptile and amphibian species as endemics (Conservation International 2020).	Converted to 1 km^2 raster format using the majority resampling approach.	Hoffman *et al* (2016)	Yes
		Key Biodiversity Areas	Contribute significantly to the global persistence of biodiversity (IUCN 2016). In comparison with the IUCN Red List Species range maps (IUCN 2019), the Key Biodiversity Areas are less likely to suffer from commission errors, i.e. when species are erroneously thought to be present even though they are not (Kullberg *et al* 2019).		BirdLife International (2018)	On request
		World Database of Protected Areas	Known to harbour significant levels of biodiversity (UNEP-WCMC 2019) and includes, among other things, IUCN recognized Protected Areas, UNESCO World Heritage Sites and Ramsar Sites. Both are explicitly listed in the HCV guidelines as indicators of HCV1 (Brown *et al* 2013).		UNEP-WCMC and IUCN (2018)	Yes

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HCV category	**Official definition**	**Indicator**	**Rationale**	**Analysis**	**Datasets**	**Publicly available**
HCV 2 Landscape-level ecosystems and mosaics and Intact Forest Landscapes	Large landscape-level ecosystems, ecosystem mosaics and Intact Forest Landscapes (IFL), that are significant at global, regional or national levels, and that contain viable populations of the great majority of the naturally occurring species in natural patterns of distribution and abundance.	Intact Forest Landscapes	Listed in the HCV guidelines as an official indicator of HCV2 (Brown *et al* 2013). Intact Forest Landscapes are defined as a seamless mosaic of forest and naturally treeless ecosystems with no signs of human activity detected via remote sensing and a minimum area of 500 km^2 (Potapov *et al* 2017).		Potapov *et al* (2008)	Yes
HCV 3 Ecosystems and habitats	Rare, threatened, or endangered ecosystems, habitats or refugia.	Forest Biodiversity Significance	Represent the contribution of each ~30m forest raster cell toward the global extent of suitable habitat for several forest-dependent mammals, amphibians, birds and conifers, based on data from the IUCN Red List (www.iucnredlist.org). Areas with high significance represent rare or endangered ecosystems.	Reclassified to a binary raster using the fifth quintile (80% to 100% highest values), thus capturing typical HCV 3 forests including the Madagascar Lowland Forest, the Atlantic Forest and the Kerala Forest.	Hill *et al* (2019)	On request

Table 1 – List of High Conservation Value categories, their formal definitions, the indicators used to identify High Conservation Value Forest, the rationale for selecting each indicator and their corresponding datasets. The last column indicates whether the datasets are publicly available or not. The official High Conservation Value category definitions are derived from Brown *et al* (2013). (continued)

HCV category	Official definition	Indicator	Rationale	Analysis	Datasets	Publicly available
HCV 4 Ecosystem services	Basic ecosystem services in critical situations including protection of water catchments and control of erosion of vulnerable soils and slopes.	Coastal Risk Reduction Crop Pollination	These ecosystem services are considered typical examples of HCV4, according to the HCV guidelines (Brown *et al* 2013). Note that some of these datasets are subject to large uncertainties.	Reclassified and resampled to a 1 km^2 binary raster using the fifth quintile (80% to 100% highest values) of the combined distribution of people's needs and nature's contributions.	Chaplin-Kramer *et al* (2019)	Yes
		Erosion Protection Reduction of Flood Risk		Reclassified and resampled to a 1 km^2 binary raster using the fifth quintile (80% to 100% highest values) of the combined distribution of ecosystem service values and rural population density in 2020, following the methods described in Chaplin-Kramer *et al* (2019).	Stehfest *et al* (2014); CIESIN (2018)	Stehfest *et al* (2014): on request CIESIN (2018): yes
		Water Quality Regulation		Reclassified and resampled to a 1 km^2 binary raster using the fifth quintile (80% to 100% highest values) of the combined distribution of people's needs and nature's contributions.	Chaplin-Kramer *et al* (2019)	Yes
		Water Supply Regulation		Reclassified and resampled to a 1 km^2 binary raster using the fifth quintile (80% to 100% highest values) of the combined distribution of ecosystem service values and rural population density in 2020, following the methods described in Chaplin-Kramer *et al* (2019).	Stehfest *et al* (2014); CIESIN (2018)	On request

Table 1 – List of High Conservation Value categories, their formal definitions, the indicators used to identify High Conservation Value Forest, the rationale for selecting each indicator and their corresponding datasets. The last column indicates whether the datasets are publicly available or not. The official High Conservation Value category definitions are derived from Brown *et al* (2013). (continued)

HCV category	**Official definition**	**Indicator**	**Rationale**	**Analysis**	**Datasets**	**Publicly available**
HCV 5 Community needs	Sites and resources fundamental for satisfying the basic necessities of local communities or indigenous peoples (for example for livelihoods, health, nutrition, water), identified through engagement with these communities or indigenous peoples.	Presence of Indigenous Community	Indigenous communities typically depend on forest resources (Newton *et al* 2016) and hence are indicative of sites that are fundamental for satisfying the basic necessities. Note that areas not mapped as Indigenous may still retain an Indigenous connection.	Converted to 1 km^2 raster format using the majority resampling approach.	Garnett *et al* (2018)	On request
HCV 6 Cultural values	Sites, resources, habitats and landscapes of global or national cultural, archaeological or historical significance, and/or of critical cultural, ecological, economic or religious/sacred importance for the traditional cultures of local communities or indigenous peoples, identified through engagement with these local communities or indigenous peoples.	UNESCO World Heritage Sites (subset of World Database on Protected Areas)	UNESCO World Heritage Sites include cultural and natural heritage around the world considered to be of outstanding value to humanity (UNESCO 2020).	The UNESCO World Heritage Sites are a subset of the World Database on Protected Areas and hence, also included under HCV1. To avoid double counting, these areas were only included once.	UNEP-WCMC and IUCN (2018)	Yes

Table 2 – List of data sources used to identify potential expansion areas for the 4 commodities most commonly covered by corporate zero-deforestation commitments

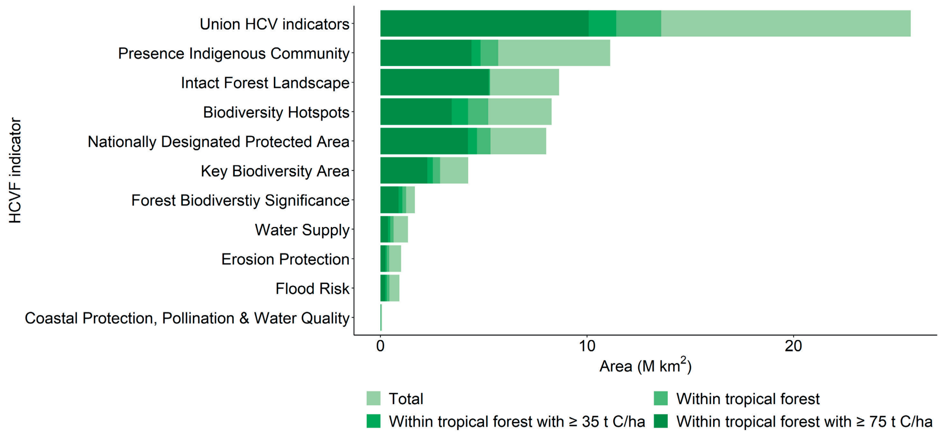
	Suitability estimates		**Areas already under cultivation or used for production**	
	Data description	**Classification method**	**Data description**	**Threshold(s) to distinguish occupied areas**
Forestry	Suitability estimates from Schulze *et al* (2019) at 1 km resolution.	8 quantiles within current production areas	Binary map (production/ no production) from Schulze *et al* (2019) at 1 km resolution.	
Oil Palm	Suitability estimates – classified into 8 classes – sourced from Version 3 of the Global Agro-Ecological Zones (GAEZ) (IIASA/FAO 2012). The data are based on the SRES A1FI emission scenario for the 2020s and control for a CO_2 fertilization effect.		Fraction of grid cell under cultivation from the International Food Policy Research Institute (2019) at 5 minute resolution (approximately 10x10km at the equator)	Figure 3: ≥ 50% of grid cells under cultivation or used as pasture Supplementary material Figure 4: • ≥ 25% of grid cells under cultivation or used as pastureland • ≥ 50% of grid cells under cultivation or used as pastureland • ≥ 75% of grid cells under cultivation or used as pastureland
Pasture	Suitability estimates – classified into 8 classes – sourced from Van Velthuizen *et al* (2007)		Fraction of grid cell used as pasture from Ramankutty *et al* (2010) at 5 minute resolution (approximately 10x10km at the equator)	
Soybean	Suitability estimates – classified into 8 classes – sourced from Version 3 of the Global Agro-Ecological Zones (GAEZ) (IIASA/FAO 2012). The data are based on the SRES A1FI emission scenario for the 2020s and control for a CO_2 fertilization effect.		Fraction of grid cell under cultivation from the International Food Policy Research Institute (2019) at 5 minute resolution (approximately 10x10km at the equator)	

Table 3 – Percentage of overlap between 10 different forest maps in terms of their combined extent of HCVF, HCSF and tropical peatland, based on Jaccard's Similarity index (Intersection over Union). Forests designated as HCV or HCS are here defined as forests with at least 2 overlapping HCV indicators or an AGB threshold of at least 75 t C/ha if located in the tropics. Parentheses denote the upper and lower range of the total extent of HCVF, HCSF and tropical peatland forest using other the criteria to delineate HCVF and HCSF, shown in Figure 1 of Chapter 2 CCT denotes canopy cover threshold.

	Copernicus	**ESA**	**GLC2000**	**Hansen CCT 10%**	**Hansen CCT 30%**	**MODIS**	**Schulze***	**Sexton CCT 10%**	**Sexton CCT 30%**	**Shimada**
Copernicus	-	0.73 (0.65 - 0.79)	0.71 (0.62 - 0.78)	0.83 (0.71 - 0.93)	0.8 (0.66 - 0.9)	0.62 (0.45 - 0.73)	0.76 (0.65 - 0.77)	0.84 (0.72 - 0.91)	0.73 (0.59 - 0.81)	0.77 (0.65 - 0.86)
ESA	0.73 (0.65 - 0.79)	-	0.72 (0.64 - 0.77)	0.7 (0.6 - 0.77)	0.71 (0.61 - 0.76)	0.64 (0.49 - 0.74)	0.72 (0.63 - 0.89)	0.7 (0.6 - 0.76)	0.67 (0.57 - 0.74)	0.69 (0.59 - 0.76)
GLC2000	0.71 (0.62 - 0.78)	0.72 (0.64 - 0.77)	-	0.69 (0.59 – 0.79)	0.7 (0.59 – 0.79)	0.63 (0.46 – 0.74)	0.72 (0.62 – 0.78)	0.7 (0.61 – 0.77)	0.66 (0.54 – 0.74)	0.67 (0.56 – 0.76)
Hansen CCT 10%	0.83 (0.71 – 0.93)	0.7 (0.6 – 0.79)	0.69 (0.59 – 0.78)	-	0.88 (0.78 - 0.96)	0.62 (0.45 - 0.73)	0.73 (0.6 - 0.73)	0.86 (0.77 - 0.94)	0.73 (0.58 - 0.81)	0.75 (0.62 - 0.85)
Hansen CCT 30%	0.8 (0.66 - 0.9)	0.71 (0.61 - 0.79)	0.7 (0.59 - 0.79)	0.88 (0.78 - 0.92)	-	0.69 (0.56 – 0.77)	0.75 (0.64 – 0.86)	0.8 (0.68 – 0.9)	0.8 (0.7 – 0.85)	0.74 (0.61 – 0.83)
MODIS	0.62 (0.45 – 0.73)	0.64 (0.49 – 0.74)	0.63 (0.46 – 0.74)	0.62 (0.45 – 0.73)	0.69 (0.56 – 0.72)	-	0.65 (0.51 - 0.9)	0.58 (0.41 - 0.7)	0.72 (0.63 - 0.78)	0.62 (0.47 - 0.73)
Schulze*	0.76 (0.65 - 0.83)	0.72 (0.63 - 0.77)	0.72 (0.62 - 0.79)	0.73 (0.6 - 0.84)	0.75 (0.64 - 0.87)	0.65 (0.51 - 0.75)	-	0.73 (0.61 – 0.81)	0.72 (0.6 – 0.79)	0.71 (0.59 – 0.79)
Sexton CCT 10%	0.84 (0.72 – 0.91)	0.7 (0.6 – 0.76)	0.7 (0.61 – 0.77)	0.86 (0.77 – 0.95)	0.8 (0.68 – 0.93)	0.58 (0.41 – 0.7)	0.73 (0.61 – 0.67)	-	0.74 (0.59 - 0.84)	0.74 (0.62 - 0.83)
Sexton CCT 30%	0.73 (0.59 - 0.81)	0.67 (0.57 - 0.74)	0.66 (0.54 - 0.74)	0.73 (0.58 - 0.8)	0.8 (0.7 - 0.8)	0.72 (0.63 - 0.78)	0.72 (0.6 - 0.88)	0.74 (0.59 - 0.84)	-	0.68 (0.55 – 0.76)
Shimada	0.77 (0.65 – 0.86)	0.69 (0.59 – 0.76)	0.67 (0.56 – 0.76)	0.75 (0.62 – 0.87)	0.74 (0.61 – 0.88)	0.62 (0.47 – 0.73)	0.71 (0.59 – 0.75)	0.74 (0.62 – 0.83)	0.68 (0.55 – 0.76)	-

* Note: the Schulze *et al* (2019) map is an updated version of the original Schulze *et al* map using data on tree cover loss between 2000 – 2017 and tree cover gain between 2000 – 2012 from Hansen *et al* (2013, 2019).

Figure 1 – Global extent of all indicators used to delineate High Conservation Value Forests.



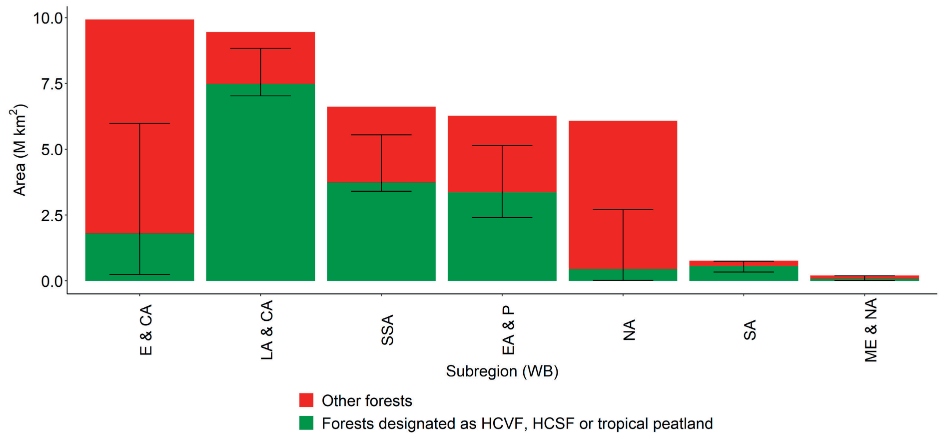


Figure 2 – Regional extent of forest that may be at reduced risk of development due to the corporate zero-deforestation commitments . The acronyms listed on the x-axis denote the following World Bank (WB) regions: E & CA – Europe & Central Asia; LA & C – Latin America & Caribbean; SSA – Sub-Saharan Africa; EA & P – East Asia & Pacific; NA – North America; SA – South Asia; ME & NA – Middle East & North Africa. Forests designated as HCV or HCS are here defined as forests with at least 2 overlapping HCV indicators or at least 75 t C/ha if located in the tropics. Error bars denote the upper and lower range of the total extent of HCVF, HCSF and tropical peatland forest using the other criteria to delineate HCVF and HCSF shown in Figure 1 of Chapter 2.

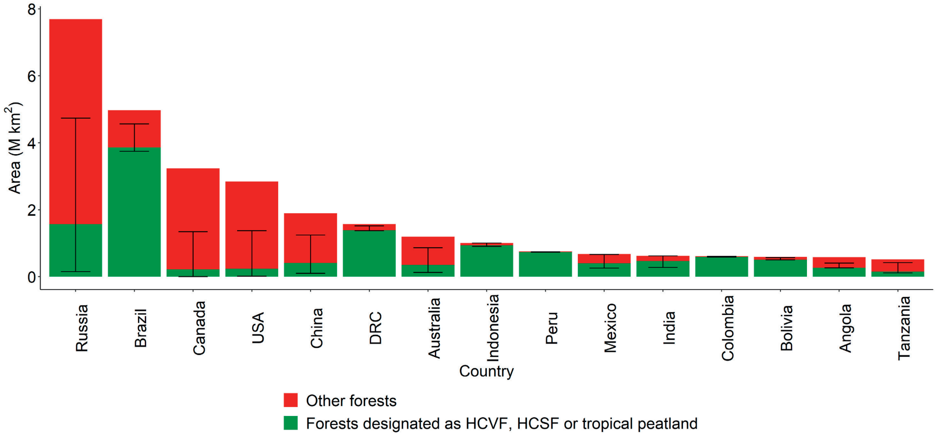


Figure 3 – Extent of forest that may be at reduced risk of development due to the corporate zero-deforestation commitments for the 15 countries with the largest forest areas. The following acronyms or abbreviations are used: USA – United States of America, China - People's Republic of China; DRC – Democratic Republic of Congo. Forests designated as HCV or HCS are here defined as forests with at least 2 overlapping HCV indicators or at least 75 t C/ha if located in the tropics. Error bars denote the upper and lower range of the total extent of HCVF, HCSF and tropical peatland forest using the other criteria to delineate HCVF and HCSF shown in Figure 1 of Chapter 2.

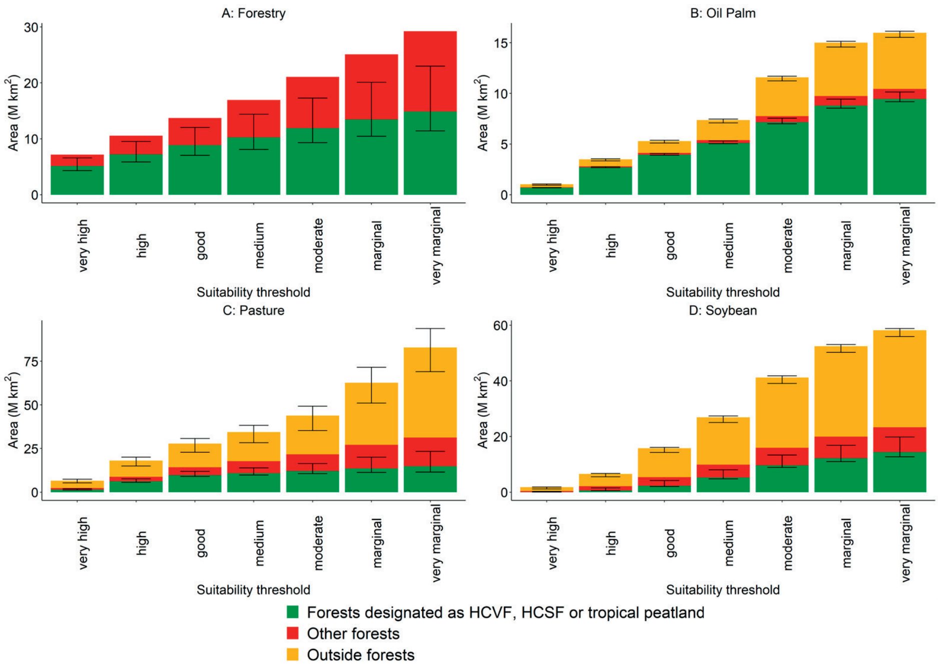


Figure 4 – Overlap of agro-ecological suitability for 4 main deforestation-risk commodities with forests designated as High Conservation Value Forest (HCVF), High Carbon Stock Forest (HCSF) and tropical peatland forest. The error bars in the green bars denote the uncertainty in the total extent of HCVFs, HCSFs and peat forests, while the error bars in the yellow bars denote the uncertainty in the total extent of potential expansion areas if a smaller and higher threshold is used to distinguish areas already under cultivation or used for production (25% and 75%, respectively).

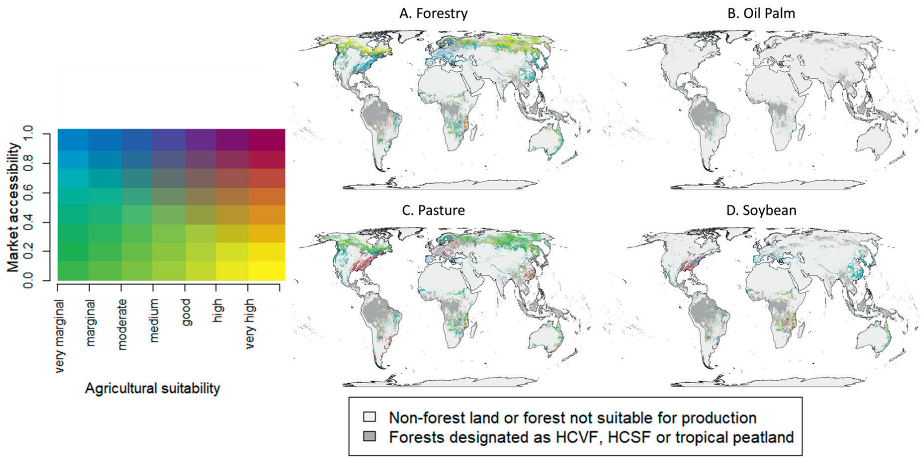


Figure 5 – Joint distribution of market accessibility and agricultural suitability per commodity across forests not designated as HCVF, HCSF or peat forest. Market accessibility is classified into 8 quantiles. Agricultural suitability is determined by taken the highest suitability class for each grid cell.

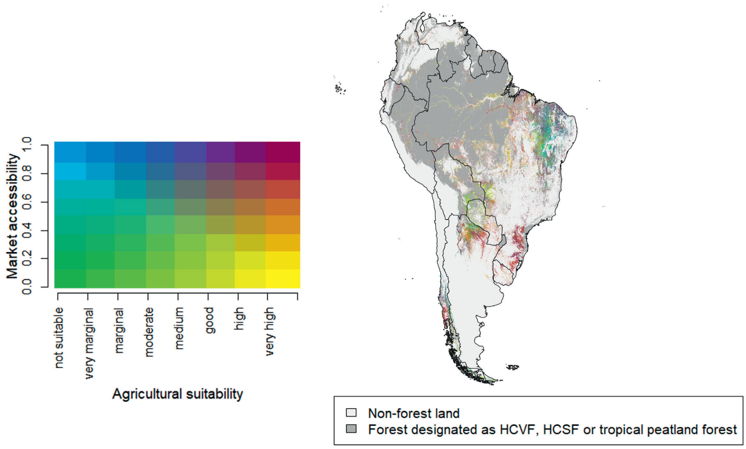


Figure 6a – Joint distribution of market accessibility and agricultural suitability across forests in Latin America that are not designated as HCVF, HCSF or peat forest. Market accessibility is classified into 8 quantiles. Agricultural suitability is determined by taking the highest suitability class for each grid cell after overlaying 4 suitability layers for forestry, oil palm cultivation, soybean cultivation and pastureland – each comprising 8 suitability classes.

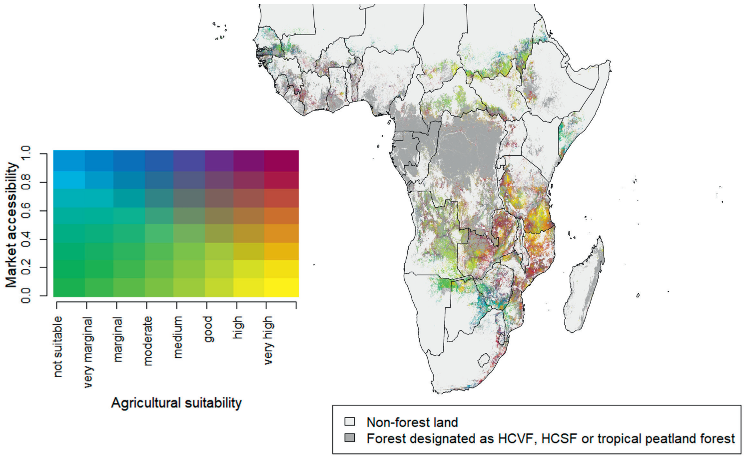


Figure 6b – Joint distribution of market accessibility and agricultural suitability across forests in Sub-Saharan Africa that are not designated as HCVF, HCSF or peat forest. Market accessibility is classified into 8 quantiles. Agricultural suitability is determined by taking the highest suitability class for each grid cell after overlaying 4 suitability layers for forestry, oil palm cultivation, soybean cultivation and pastureland – each comprising 8 suitability classes.

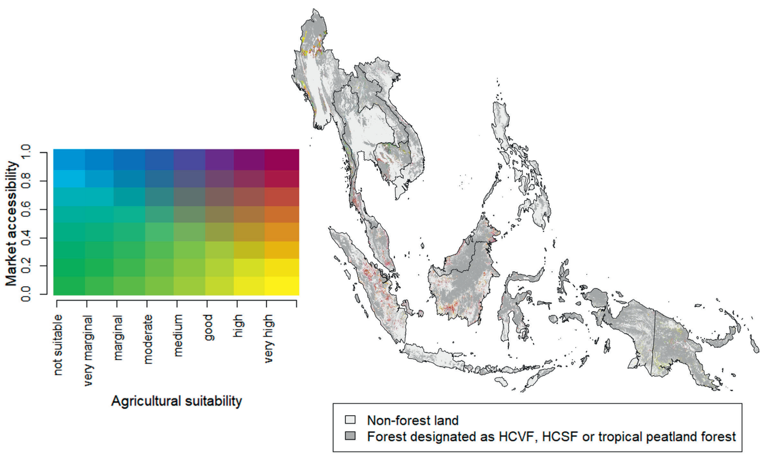


Figure 6c – Joint distribution of market accessibility and agricultural suitability across forests in Southeast Asia that are not designated as HCVF, HCSF or peat forest. Market accessibility is classified into 8 quantiles. Agricultural suitability is determined by taking the highest suitability class for each grid cell after overlaying 4 suitability layers for forestry, oil palm cultivation, soybean cultivation and pastureland – each comprising 8 suitability classes.

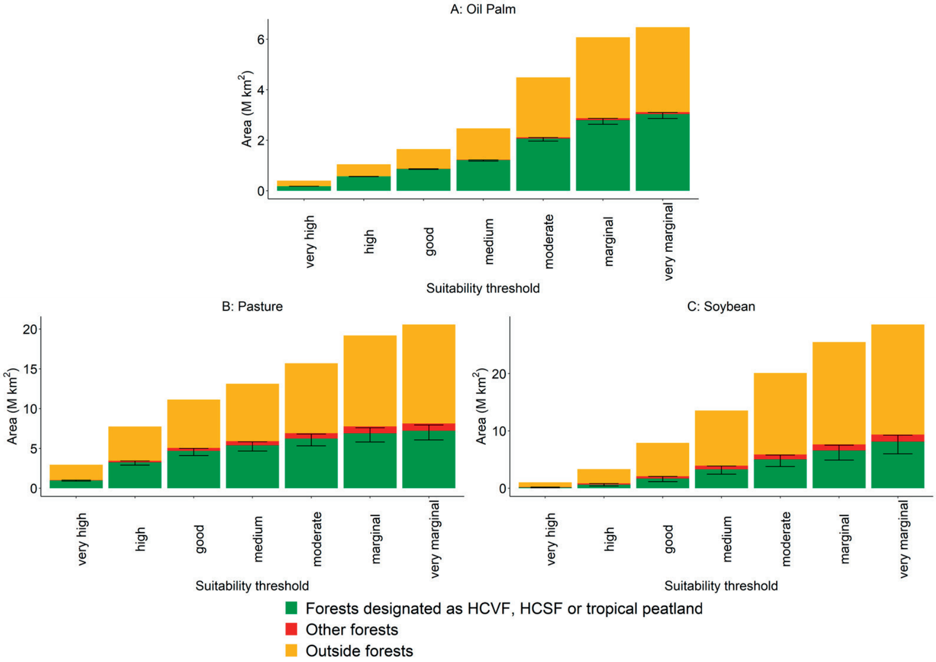


Figure 7 – Overlap of agro-ecological suitability for 3 main deforestation-risk commodities with forests designated as High Conservation Value Forest (HCVF), High Carbon Stock Forest (HCSF) and tropical peatland forest located within areas where agricultural expansion is projected to occur between 2020 to 2030. These projections are based on the IMAGE model. The errors bars denote the uncertainty in the total extent of HCVF, HCSF and tropical peatland forests. Suitable areas outside forests do not include urban areas and areas already under cultivation or used for production.

References for Appendix A

BirdLife International 2018 Digital boundaries of Important Bird and Biodiversity Areas from the World Database of Key Biodiversity Areas. February 2018 Version. Online: http://datazone.birdlife.org/site/requestgis

Brown E, Dudley N, Lindhe A, Muhtaman D R, Stewart C and Synnott T 2013 *Common Guidance for the Identification of High Conservation Values* Online: www.hcvnetwork.org

Chaplin-Kramer R, Sharp R P, Weil C, Bennett E M, Pascual U, Arkema K K, Brauman K A, Bryant B P, Guerry A D, Haddad N M, Hamann M, Hamel P, Johnson J A, Mandle L, Pereira H M, Polasky S, Ruckelshaus M, Shaw M R, Silver J M, Vogl A L and Daily G C 2019 Global modeling of nature's contributions to people *Science (80-.).*

CIESIN 2018 Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 10 *Palisades, NY NASA Socioecon. Data Appl. Cent.*

Conservation International 2020 Biodiversity Hotspots Online: https://www.conservation.org/priorities/biodiversity-hotspots

Garnett S T, Burgess N D, Fa J E, Fernández-Llamazares Á, Molnár Z, Robinson C J, Watson J E M, Zander K K, Austin B, Brondizio E S, Collier N F, Duncan T, Ellis E, Geyle H, Jackson M V., Jonas H, Malmer P, McGowan B, Sivongxay A and Leiper I 2018 A spatial overview of the global importance of Indigenous lands for conservation *Nat. Sustain.*

Hill S L L, Arnell A, Maney C, Butchart S H M, Hilton-Taylor C, Ciciarelli C, Davis C, Dinerstein E, Purvis A and Burgess N D 2019 Measuring Forest Biodiversity Status and Changes Globally *Front. For. Glob. Chang.*

Hoffman M, Koenig K, Bunting G, Costanza J and Williams K J 2016 Biodiversity Hotspots (version 2016.1) [Data set] Online: https://zenodo.org/record/3261807#.Xk_J1Wj7SUk

IIASA/FAO 2012 *Global Agro-ecological Zones (GAEZ v3.0).* (Rome, Italy) Online: http://www.gaez.iiasa.ac.at/

International Food Policy Research Institute 2019 Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 1.0 - IFPRI HarvestChoice Dataverse *https//doi.org/10.7910/DVN/PRFF8V, Harvard Dataverse, V1* Online: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PRFF8V

IUCN 2016 *A Global Standard for the Identification of Key Biodiversity Areas, Version 1.0.* (Gland, Switzerland) Online: www.chadiabi.com

IUCN 2019 IUCN Red List of Threatened Species Online: https://www.iucnredlist.org/resources/spatial-data-download

Kullberg P, Di Minin E and Moilanen A 2019 Using key biodiversity areas to guide effective expansion of the global protected area network *Glob. Ecol. Conserv.*

Newton P, Miller D C, Byenkya M A A and Agrawal A 2016 Who are forest-dependent people? A taxonomy to aid livelihood and land use decision-making in forested regions *Land use policy*

Potapov P, Hansen M C, Laestadius L, Turubanova S, Yaroshenko A, Thies C, Smith W, Zhuravleva I, Komarova A, Minnemeyer S and Esipova E 2017 The last frontiers of wilderness: Tracking loss of intact forest landscapes from 2000 to 2013 *Sci. Adv.*

Potapov P, Yaroshenko A, Turubanova S, Dubinin M, Laestadius L, Thies C, Aksenov D, Egorov A, Yesipova Y, Glushkov I, Karpachevskiy M, Kostikova A, Manisha A, Tsybikova E and Zhuravleva I 2008 Mapping the world's intact forest landscapes by remote sensing *Ecol. Soc.*

Ramankutty N, Evan A T, Monfreda C and Foley J A 2010 Global Agricultural Lands: Pastures, 2000. *Palisades, NY NASA Socioecon. Data Appl. Cent. (SEDAC). https//doi.org/10.7927/H47H1GGR.* n/a-n/a Online: http://doi.wiley.com/10.1029/2007GB002952

Schulze K, Malek Ž and Verburg P H 2019 Towards better mapping of forest management patterns: A global allocation approach *For. Ecol. Manage.*

Stehfest E, van Vuuren D, Kram T, Bouwman L, Alkemade R, Bakkenes M, Biemans H, Bouwman A, Den Elzen M, Janse J, Alkemade R, Bakkenes M, Biemans H, Bouwman A, Den Elzen M, Janse J, Lucas P, van Minnen J, Muller C and Prins A G 2014 *Integrated assessment of global environmental change with IMAGE 3.0 - Chapter 7.6*

UNEP-WCMC 2019 *User Manual for the World Database on Protected Areas and world database on other effective area-based conservation measures: 1.6* (Cambridge, UK) Online: http://wcmc.io/WDPA_Manual

UNEP-WCMC and IUCN 2018 Protected Planet: The World Database on Protected Areas (WDPA)/ The Global Database on Protected Areas Management Effectiveness (GD-PAME)] [On-line], [23/11/2018]

UNESCO 2020 UNESCO World Heritage Centre - World Heritage Online: https://whc.unesco.org/en/about/

Van Velthuizen H, Huddleston B, Fischer G, Salvatore M, Ataman E, Nachtergaele F O, Zanetti M, Bloise M, Gis F, Antonicelli A, Bel J, De Liddo A, De Salvo P and Franceschini G 2007 *Mapping biophysical factors that influence agricultural production and rural vulnerability* Online: http://www.fao.org/docrep/pdf/010/a1075e/a1075e00.pdf

Appendix B

B.1 Overdispersion and the negative binomial model

The negative binomial model is the most popular model when dealing with nonnegative, overdispersed data. Overdispersion occurs when the variance of the response variable exceeds the mean and is a violation of the main assumption underlying the Poisson model. Failing to account for overdispersion may cause standard errors of the parameter estimates to be underestimated, thus increasing the risk of type 1 errors (false positives). Whether the model should be Poisson or not can be formally tested by means of a Boundary Likelihood Ratio (BLR) test (Hilbe, 2011). Using equation (2) of Chapter 5 to compare Poisson and negative binomial models, we overwhelmingly rejected the null hypothesis of no overdispersion (P < 0.001), indicating the negative binomial model is more appropriate. We used the standard parameterization of the negative binomial, which has a variance function of $\mu + \frac{1}{\theta}\mu^2$. Here, μ denotes the conditional expectation of the sample and θ denotes the dispersion parameter, resulting in the following probability density function (see Hilbe, 2011 for further details):

$$f(y, \mu, \theta) = \binom{y_i+\theta-1}{\theta-1}\left(\frac{1}{1+\frac{1}{\theta}\mu_i}\right)^{\theta}\left(\frac{\frac{1}{\theta}\mu_i}{1+\frac{1}{\theta}\mu_i}\right)^{y_i}.$$

To replicate the results of an unconditional negative binomial fixed effects model, we used the fixest software package in R version 4.0.2 (Bergé, 2020, 2018; R Core Team, 2020). The underlying algorithm optimizes only over the parameters of interest, while the fixed effects are dealt with separately in the concentrating likelihood function. As a result, there is no downward bias in the standard errors estimates of the parameters of interest. To hasten convergence of fixed effects coefficients, the algorithm integrates a fixed-point acceleration method, thus outperforming alternative methods in terms of computing time. Simulations by Bergé (2020) and Allison and Waterman (2002) reveal that in contrast to the logistic regression model, the negative binomial model does not suffer from the Incidental Parameters Problem (Lancaster, 2000), indicating that the model provides consistent estimates for the parameters of interest.

B.2 Genetic matching

The goal of matching is to replicate a randomized controlled trial as closely as possible by obtaining treated and control groups with similar covariate distributions (Stuart, 2010). The first step in implementing matching methods is to define ‘closeness’, i.e., a metric used to determine whether two observations can be matched or not. The two most popular distance metrics include Mahalanobis distance and distance between propensity scores (Rosenbaum, 2010). However, matching based on these two metrics can be misleading and may sometimes make balance worse across covariates. Diamond and Sekhon (2013) therefore proposed a metric that generalizes Mahalanobis distance by including an additional weight matrix:

$$d(Z_i, Z_j, W) = \sqrt{(Z_i - Z_j)'(S^{-\frac{1}{2}})' W S^{-\frac{1}{2}}(Z_i - Z_j)},$$

where Z is a matrix consisting of both the propensity score and the underlying covariates X, W is a k x k positive definitive weight matrix and $(S^{-\frac{1}{2}})$ is the Cholesky decomposition of the variance-covariance matrix of X. In order to define W, an iterative search algorithm is used to weight each covariate according to its relative importance for achieving the best overall balance. Balance is iteratively assessed by means of *t*-tests for difference of means and non-parametric (bootstrap) Kolmogorov-Smirnov distributional tests. As such, the algorithm guarantees asymptotic convergence to the optimal matched sample. Genetic matching was performed using the MatchIt package in R version 4.0.2 (Ho *et al.*, 2011; R Core Team, 2020). The key tuning parameters for optimization were left at their default values.

Below, we present the standardized mean differences (Table 2) and empirical Quantile-Quantile (QQ) plots (Figure 10) used to evaluate postmatching covariate balance.

B.3 Tables

Table 1 – Quartile values of various covariates deemed to influence deforestation risk. To explore the sensitivity of the results, grid cells with covariate values below these quartile values were excluded in alternative model runs.

Covariate	**1st Qu.**	**Median**	**3rd Qu.**
Elevation (m)	32.7	68.7	155.3
Gross Domestic Product (2010)	5.8	7.5	11.9
Market Accessibility (hours)	0.7	2.0	5.2
Oil palm agro-ecological suitability	36.3	64.6	82.8
Population Density (2010)	0.2	0.7	2.6
Remaining forest area in ha (2010)	1,269	1,921	2,336
Slope (mean)	1.7	3.0	6.2
Slope (variance)	1.3	4.0	19.0
Travel distance nearest palm oil mill (hours)	0.9	2.2	6.0

Table 2 – Standardized mean differences between treated and control observations within the matched sample, using a caliper width of 0.2 times the standard deviation. Treated observations are those within 10 km of a moratorium border. All other observations are part of the control group. SD denotes standard deviation; Std. Mean Diff. denotes standardized mean difference; and eCDF denotes empirical Cumulative Distribution Function.

Covariate	Means Treated	Means Control	SD Control	Std. Mean Diff.	eCDF Med	eCDF Mean	eCDF Max
Elevation (m)	0.19	0.19	0.00	1.03	0.01	0.03	0.07
GDP at PPP in constant 2011 international US$	9.14	9.14	0.00	1.01	0.01	0.03	0.04
Market accessibility (hours)	5.21	5.17	0.01	1.01	0.01	0.02	0.20
Oil palm suitability (0.01 - 100)	54.91	55.24	-0.01	1.05	0.01	0.03	0.17
Population density (number of persons per grid cell)	6.35	6.32	0.01	0.98	0.01	0.03	0.25
Propensity Score	0.58	0.58	0.00	1.01	0.00	0.01	0.05
Remaining forest area in ha (in 2010)	16.60	16.63	-0.05	1.15	0.01	0.02	0.21
Slope (°)	16.98	16.83	0.01	1.07	0.00	0.02	0.11
Travel time to the nearest oil palm mill (hours)	8.78	8.47	0.02	1.00	0.01	0.03	0.08

Table 3 – Negative binomial regression estimates of deforestation, focussing only on areas with additional protection as of 2011. AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC). Unit of observation is the 5 x 5 km grid cell. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity, based on equation (1) in Chapter 3.

	Dependent variable: Deforestation (canopy cover threshold 30%)					
Subsamples:	All areas with additional protection		Peatland with additional protection		Primary forest with additional protection	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables:						
Within 10 km of border (0/1)	0.01		0.00		0.00	
	(0.05)		(0.07)		(0.07)	
Closeness		-1.29**		-0.68		-1.01**
		(0.56)		(0.68)		(0.50)
ln(forest (ha))	1.75***	1.75***	1.75***	1.75***	1.75***	1.75***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
ln(neighbouring forest (ha))	-0.20	-0.21	-0.20	-0.22	-0.20	-0.16
	(0.23)	(0.22)	(0.23)	(0.21)	(0.23)	(0.21)
RSPO-certification	-0.71	-0.68	-0.71	-0.70	-0.71	-0.72
	(0.60)	(0.58)	(0.60)	(0.60)	(0.60)	(0.60)
Dispersion parameter	0.88	0.88	0.88	0.88	0.88	0.88
Fixed effects:						
Grid cell	Yes	Yes	Yes	Yes	Yes	Yes
Regency x year	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	499,870	499,870	499,870	499,870	499,870	499,870
AIC	3,314,679	3,314,538	3,314,679	3,314,643	3,314,679	3,314,577
BIC	3,690,684	3,690,543	3,690,684	3,690,648	3,690,684	3,690,581
McFadden's adjusted Pseudo R^2	0.15	0.15	0.15	0.15	0.15	0.15

Table 4 – Negative binomial regression estimates of deforestation, using an alternative moratorium map, based on the intersection of the initial moratorium map, published in 2011, and 15th revised map, published in 2018. AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC). Unit of observation is the 5 x 5 km grid cell. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity, based on equation (1) in Chapter 3.

	Dependent variable: Deforestation (canopy cover threshold 30%)							
Proximity to:	All moratorium areas		Conservation Forests		Peatland Forests		Primary Forests	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables:								
Within 10 km of border (0/1)	0.09***		0.08***		0.08		0.12***	
	(0.03)		(0.03)		(0.07)		(0.04)	
Closeness		0.55***		0.69***		-0.61		-1.48***
		(0.15)		(0.13)		(0.44)		(0.48)
ln(forest (ha))	1.74***	1.74***	1.74***	1.74***	1.73***	1.73***	1.73***	1.73***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
ln(neighbouring forest (ha))	-0.15	-0.17	-0.24	-0.18	-0.12	-0.13	-0.12	-0.08
	(0.23)	(0.22)	(0.23)	(0.22)	(0.22)	(0.22)	(0.23)	(0.22)
RSPO-certification	-0.74	-0.74	-0.75	-0.73	-0.75	-0.74	-0.75	-0.75
	(0.61)	(0.61)	(0.61)	(0.60)	(0.61)	(0.60)	(0.60)	(0.60)
Dispersion parameter	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
Fixed effects:								
Grid cell	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Concession type x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regency x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	526,565 526,565	526,565	526,565	526,565	526,565 526,565	526,565	526,565	526,565
AIC	3,453,535	3,453,440	3,453,562	3,453,269	3,453,617	3,453,601	3,453,610	3,453,461
BIC	3,847,904	3,847,809	3,847,931	3,847,637	3,847,986	3,847,970	3,847,979	3,847,830
McFadden's adjusted Pseudo R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Table 5 – Negative binomial regression estimates of deforestation. AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC). Unit of observation is the 5 x 5 km grid cell. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity, based on equation (1) in Chapter 3. Deforestation is here defined as any tree cover loss within tree covered areas with a canopy cover of at least 10%.

	Dependent variable: Deforestation (canopy cover threshold 10%)							
Proximity to:	All moratorium areas		Conservation Forests		Peatland Forests		Primary Forests	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables:								
Within 10 km of border (0/1)	0.07**		0.08***		0.04		0.03	
	(0.03)		(0.03)		(0.08)		(0.06)	
Closeness		1.26***		1.63***		-1.11		-1.13**
		(0.39)		(0.38)		(1.15)		(0.53)
ln(forest (ha))	1.74***	1.74***	1.74***	1.75***	1.74***	1.74***	1.74***	1.73***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
ln(neighbouring forest (ha))	-0.23	-0.25	-0.23	-0.26	-0.20	-0.22	-0.20	-0.16
	(0.23)	(0.23)	(0.24)	(0.22)	(0.23)	(0.21)	(0.23)	(0.21)
RSPO-certification	-0.73	-0.74	-0.73	-0.72	-0.74	-0.73	-0.74	-0.75
	(0.61)	(0.61)	(0.61)	(0.60)	(0.61)	(0.60)	(0.61)	(0.61)
Dispersion parameter	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Fixed effects:								
Grid cell	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Concession type x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regency x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	500,053	500,053	500,053	500,053	500,053	500,053	500,053	500,053
Observations	500,053	500,053	500,053	500,053	500,053	500,053	500,053	500,053
AIC	3,330,841	3,330,782	3,330,836	3,330,624	3,330,891	3,330,862	3,330,893	3,330,766
BIC	3,707,070	3,707,011	3,707,065	3,706,853	3,707,120	3,707,090	3,707,122	3,706,995
McFadden's adjusted Pseudo R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Table 6 – Negative binomial regression estimates of deforestation. AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC). Unit of observation is the 5 x 5 km grid cell. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity, bbased on equation (1) in Chapter 3. Deforestation is here defined as any tree cover loss within tree covered areas with a canopy cover of at least 60%.

	Dependent variable: Deforestation (canopy cover threshold 60%)							
Proximity to:	All moratorium areas		Conservation Forests		Peatland Forests		Primary Forests	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables:								
Within 10 km of border (0/1)	0.07**		0.08***		0.01		0.04	
	(0.03)		(0.03)		(0.07)		(0.06)	
Closeness		1.30***		1.62***		-0.87		-1.12**
		(0.44)		(0.38)		(1.01)		(0.50)
ln(forest (ha))	1.75***	1.75***	1.75***	1.75***	1.74***	1.74***	1.74***	1.74***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
ln(neighbouring forest (ha))	-0.26	-0.28	-0.27	-0.30*	-0.23	-0.25	-0.23	-0.20
	(0.19)	(0.18)	(0.19)	(0.17)	(0.18)	(0.17)	(0.18)	(0.17)
RSPO-certification	-0.61	-0.62	-0.61	-0.60	-0.62	-0.61	-0.62	-0.63
	(0.58)	(0.58)	(0.58)	(0.57)	(0.58)	(0.58)	(0.58)	(0.58)
Dispersion parameter	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Fixed effects:								
Grid cell	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Concession type x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regency x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	499,245	499,245	499,245	499,245	499,245	499,245	499,245	499,245
AIC	3,246,939	3,246,877	3,246,928	3,246,733	3,246,993	3,246,973	3,246,991	3,246,869
BIC	3,622,179	3,622,117	3,622,168	3,621,973	3,622,233	3,622,213	3,622,230	3,622,109
McFadden's adjusted Pseudo R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Table 7 – Negative binomial regression estimates of deforestation using alternative proximity metrics. Results are shown for all moratorium types combined (i.e., Conservation and Protection Forest, Peatland Forest and Primary Forest). Unit of observation is the 5 x 5 km grid cell. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity, based on equation (1) in Chapter 3. AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC).

	Dependent variable: Deforestation (canopy cover threshold 30%)		
	(1)	(2)	(3)
Variables:			
Within 20 km of moratorium areas (0/1)	0.07***		
	(0.03)		
Within 40 km of moratorium areas (0/1)		0.10**	
		(0.05)	
Closeness			-8.25
			(-15.19)
Closeness (squared)			5.18
			(8.25)
ln(forest (ha))	1.76***	1.75***	1.76***
	(0.10)	(0.10)	(0.10)
ln(neighbouring forest (ha))	-0.22	-0.21	-0.25
	(0.23)	(0.22)	(0.23)
RSPO-certification	-0.70	-0.72	-0.70
	(0.60)	(0.60)	(0.60)
Dispersion parameter	0.88	0.88	0.88
Fixed effects:			
Grid cell	Yes	Yes	Yes
Concession type x year	Yes	Yes	Yes
Province x year	Yes	Yes	Yes
Observations	499,870	499,870	499,870
AIC	3,314,626	3,314,634	3,314,565
BIC	3,690,631	3,690,639	3,690,581
McFadden's adjusted Pseudo R2	0.15	0.15	0.15

Table 8 – Negative binomial regression estimates of deforestation after pre-processing the sample by a genetic matching algorithm. Matching was done with replacement and with a caliper width of 0.2 times the standard deviation. Unit of observation is the 5 x 5 km grid cell. Standard errors are clustered at the province level and shown in parentheses. Asterisks indicate the level of statistical significance (*p < 0.10, **p < 0.05, ***p <0.01). The variable 'Closeness' represents a continuous metric of proximity, based on equation (1) in Chapter 3. AIC denotes Akaike Information Criterion and BIC denotes Bayesian Information Criterion (BIC).

	Dependent variable: Deforestation (canopy cover threshold 30%)							
Proximity to:	All moratorium areas		Conservation Forests		Peatland Forests		Primary Forests	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables:								
Within 10 km of border (0/1)	0.05*		0.07*		0.01		0.02	
	(0.03)		(0.04)		(0.07)		(0.06)	
Closeness		1.04*		1.67***		-0.97		-1.06**
		(0.59)		(0.53)		(1.19)		(0.42)
ln(forest (ha))	1.71***	1.71***	1.71***	1.71***	1.70***	1.71***	1.70***	1.70***
	(0.11)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.11)
ln(neighbouring forest (ha))	-0.18	-0.19	-0.19	-0.22	-0.15	-0.17	-0.16	-0.12
	(0.24)	(0.25)	(0.25)	(0.24)	(0.24)	(0.22)	(0.24)	(0.23)
RSPO-certification	-0.38	-0.39	-0.38	-0.37	-0.39	-0.38	-0.39	-0.39
	(0.75)	(0.75)	(0.75)	(0.74)	(0.75)	(0.75)	(0.75)	(0.76)
Dispersion parameter	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Fixed effects:								
Grid cell	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Concession type x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regency x year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	372,194	372,194	372,194	372,194	372,194	372,194	372,194	372,194
AIC	2,386,542	2,386,526	2,386,532	2,386,391	2,386,570	2,386,552	2,386,570	2,386,490
BIC	2,674,025	2,674,009	2,674,015	2,673,874	2,674,053	2,674,035	2,674,053	2,673,973
McFadden's adjusted Pseudo R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

B.4. Figures

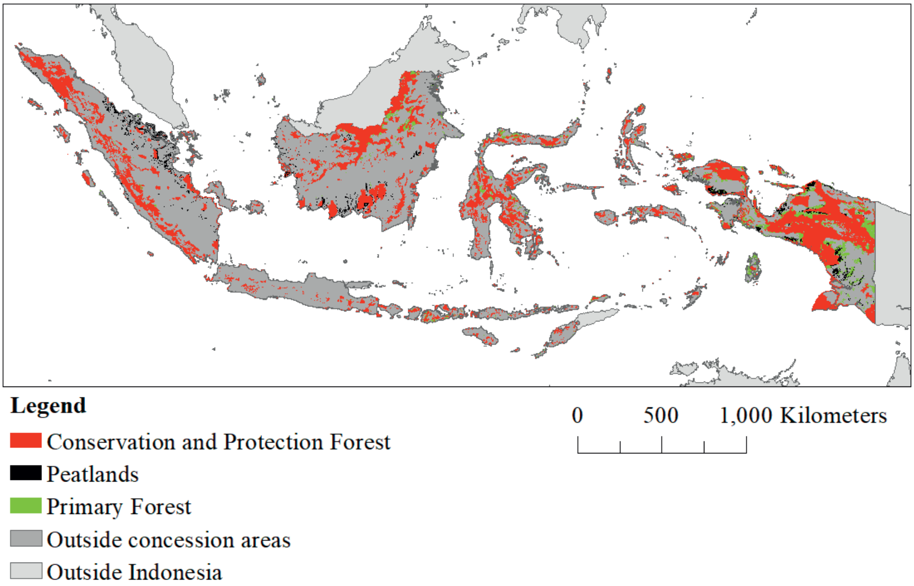


Figure 1 – Map of Indonesia showing the spatial extent of the three different types of areas covered by the moratorium, based on the intersection of the initial moratorium map, published in July 2011, and the 15th revised moratorium published in December 2018. The indicative moratorium maps, as published by the Indonesian Ministry of Environment and Forestry (2021), were digitized by Greenpeace (2021).

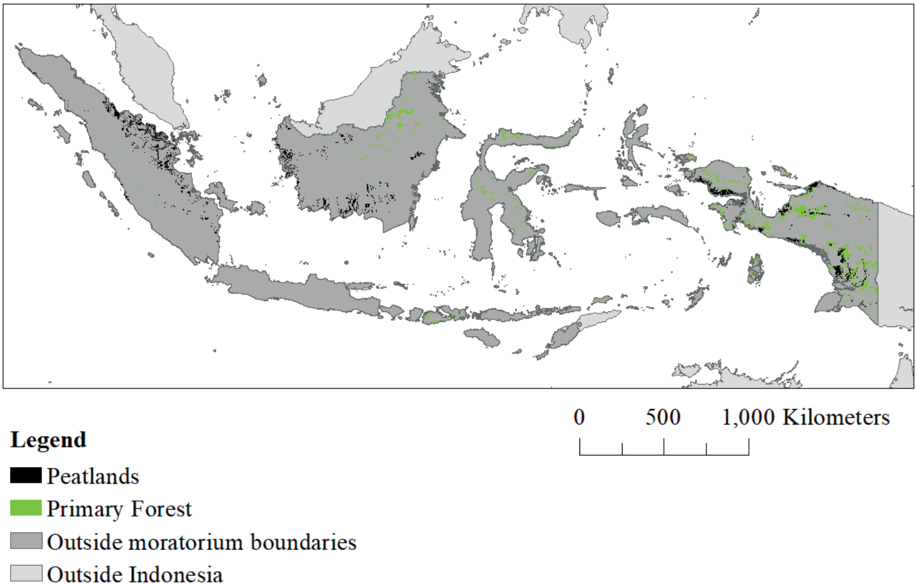


Figure 2 – Map of Indonesia showing the spatial extent of peatland and primary forest that are covered by the moratorium and that constituted additional protection as of 2011, based on the 8th revised moratorium map (Greenpeace, 2021; Ministry of Environment and Forestry, 2021) and the spatial distribution of legally protected areas in 2010 (Ministry of Environment and Forestry, 2010).

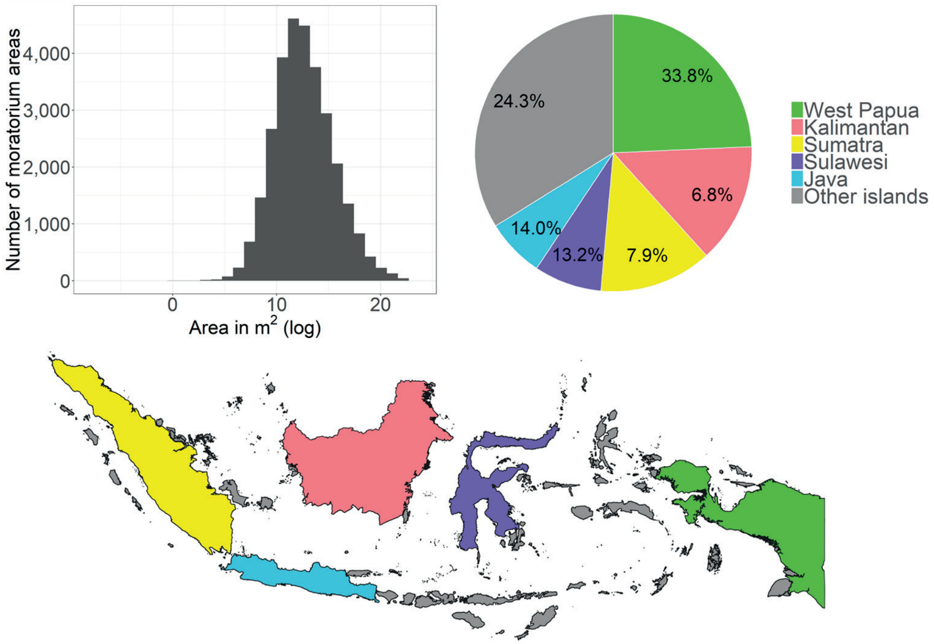


Figure 3 – Distribution of moratorium areas across Indonesia. Figure a) shows their distribution by area after taking the natural logarithm, Figure b) shows their distribution by number across 6 different island groups, and Figure c) maps the spatial extent of the individual island groups.

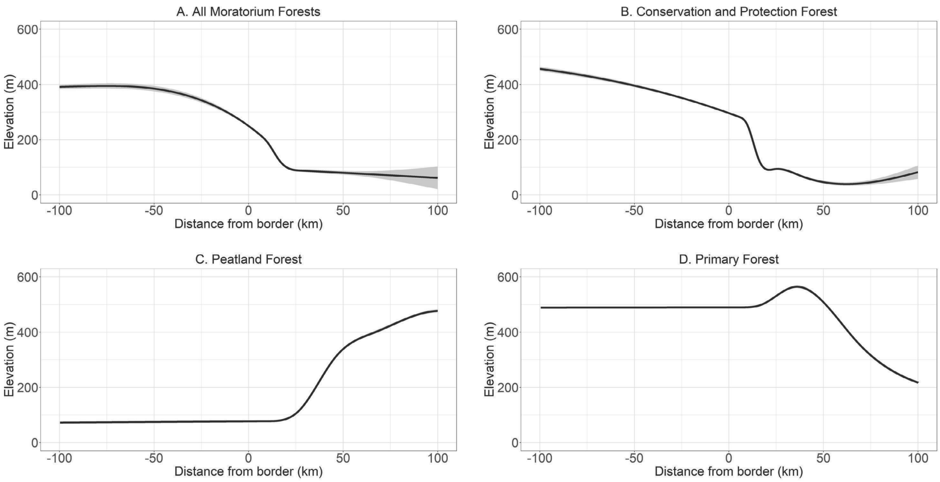


Figure 4 – Smoothed relationship between elevation and distance from moratorium areas within 100 km based on a) all moratorium areas, b) only moratorium areas designated as Conservation and Protection Forest, c) only moratorium areas designated as Peatland Forest and d) only moratorium areas designated as Primary Forest. Moratorium areas smaller than 50 km^2 were not considered. Smoothing was done with a negative binomial one dimensional penalized regression spline with smoothing parameters selected by generalized cross-validation. Deforestation levels and distance indicators are analysed within a 5 x 5 km^2 grid. Negative distances indicate Euclidean distances within moratorium areas to the closest border. Shaded areas denote 95% confidence intervals.

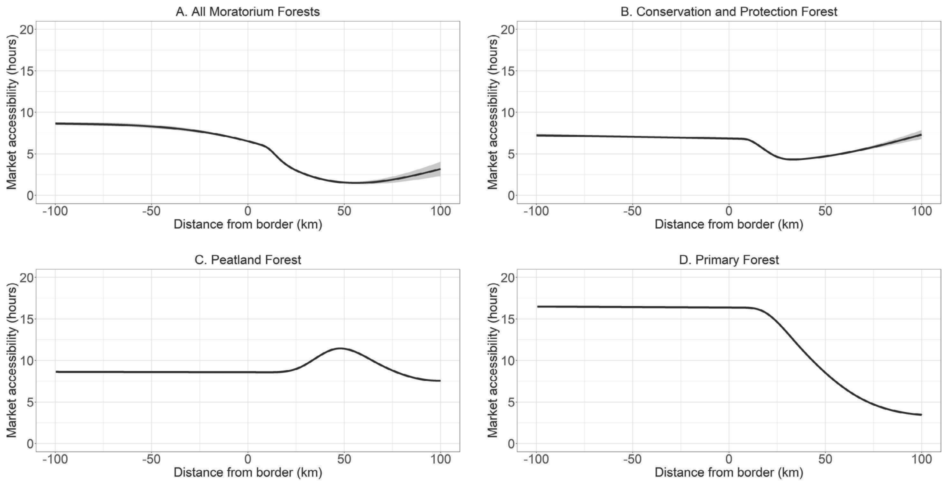


Figure 5 – Smoothed relationship between market accessibility – proxied by travel distance to the nearest city or port – and Euclidean distance from moratorium areas within 100 km period based on a) all moratorium areas, b) only moratorium areas designated as Conservation and Protection Forest, c) only moratorium areas designated as Peatland Forest and d) only moratorium areas designated as Primary Forest. Moratorium areas smaller than 50 km^2 were not considered. Smoothing was done with a negative binomial one dimensional penalized regression spline with smoothing parameters selected by generalized cross-validation. Deforestation levels and distance indicators are analysed within a 5 x 5 km^2 grid. Negative distances indicate Euclidean distances within moratorium areas to the closest border. Shaded areas denote 95% confidence intervals.

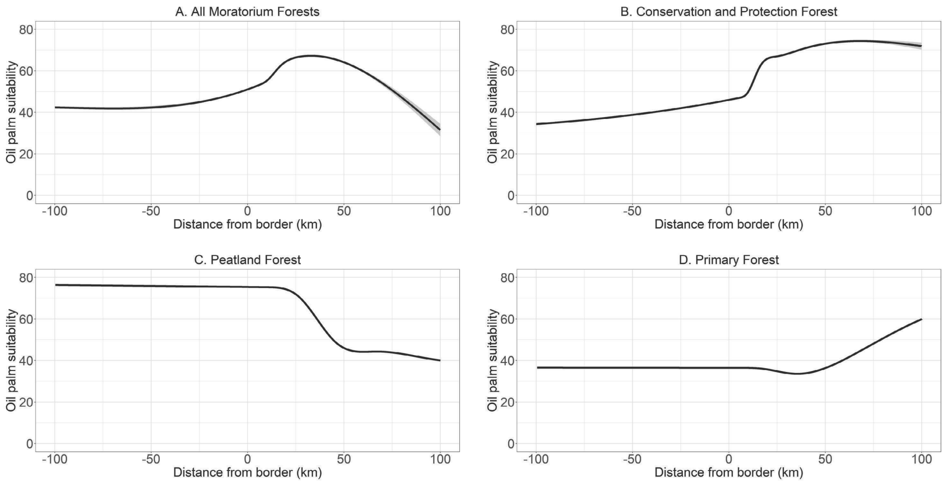


Figure 6 – Smoothed relationship between agro-ecological suitability for oil palm plantations (0 – 100) and distance from moratorium areas within 100 km period based on a) all moratorium areas, b) only moratorium areas designated as Conservation and Protection Forest, c) only moratorium areas designated as Peatland Forest and d) only moratorium areas designated as Primary Forest. Moratorium areas smaller than 50 km^2 were not considered. Smoothing was done with a negative binomial one dimensional penalized regression spline with smoothing parameters selected by generalized cross-validation. Deforestation levels and distance indicators are analysed within a 5 x 5 km^2 grid. Negative distances indicate Euclidean distances within moratorium areas to the closest border. Shaded areas denote 95% confidence intervals.

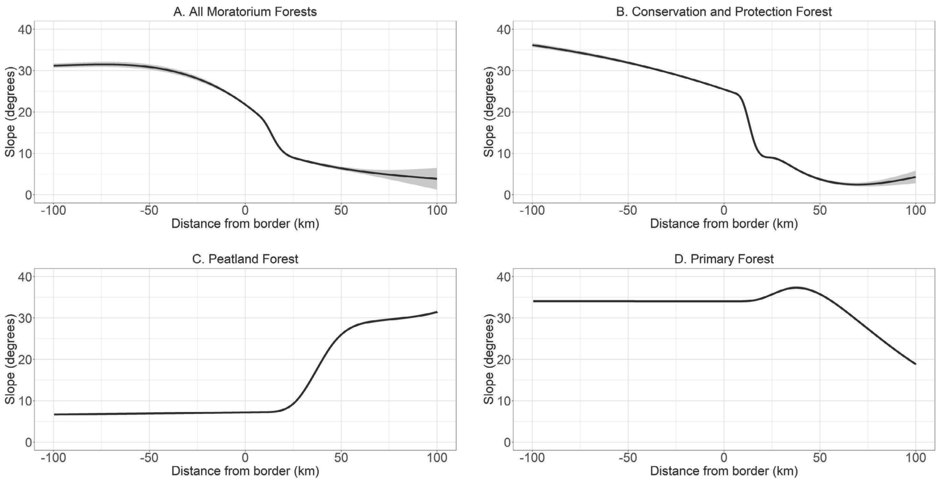


Figure 7 – Smoothed relationship between slope and distance from moratorium areas within 100 km period based on a) all moratorium areas, b) only moratorium areas designated as Conservation and Protection Forest, c) only moratorium areas designated as Peatland Forest and d) only moratorium areas designated as Primary Forest. Moratorium areas smaller than 50 km^2 were not considered. Smoothing was done with a negative binomial one dimensional penalized regression spline with smoothing parameters selected by generalized cross-validation. Deforestation levels and distance indicators are analysed within a 5 x 5 km^2 grid. Negative distances indicate Euclidean distances within moratorium areas to the closest border. Shaded areas denote 95% confidence intervals.

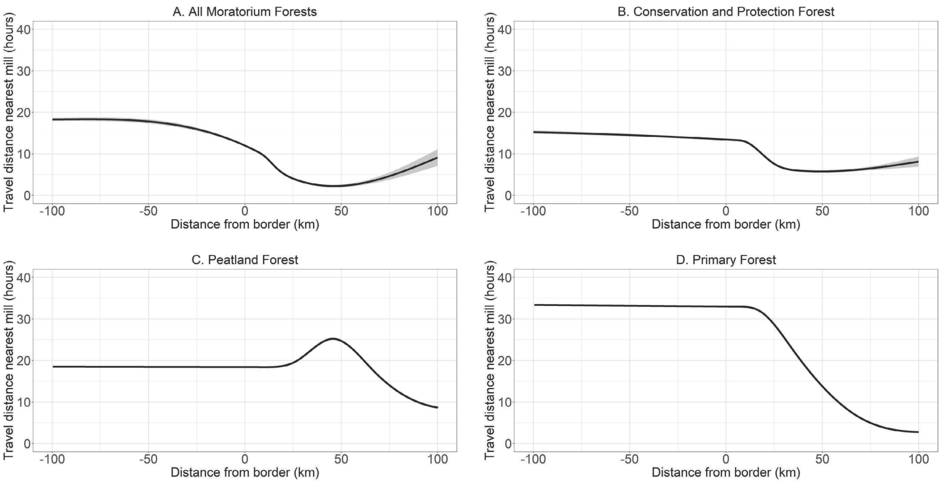


Figure 8 – Smoothed relationship between travel distance to the nearest palm oil mill and Euclidean distance from moratorium areas within 100 km period based on a) all moratorium areas, b) only moratorium areas designated as Conservation and Protection Forest, c) only moratorium areas designated as Peatland Forest and d) only moratorium areas designated as Primary Forest. Moratorium areas smaller than 50 km^2 were not considered. Smoothing was done with a negative binomial one dimensional penalized regression spline with smoothing parameters selected by generalized cross-validation. Deforestation levels and distance indicators are analysed within a 5 x 5 km^2 grid. Negative distances indicate Euclidean distances within moratorium areas to the closest border. Shaded areas denote 95% confidence intervals.

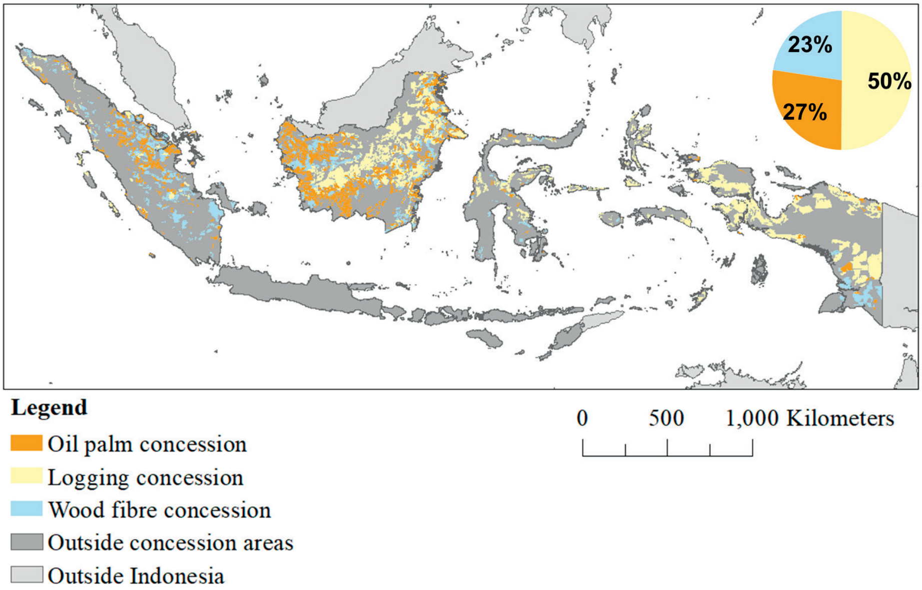
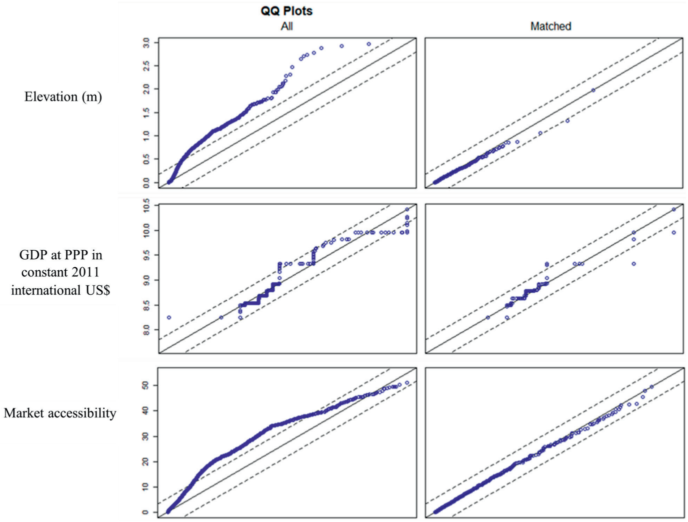
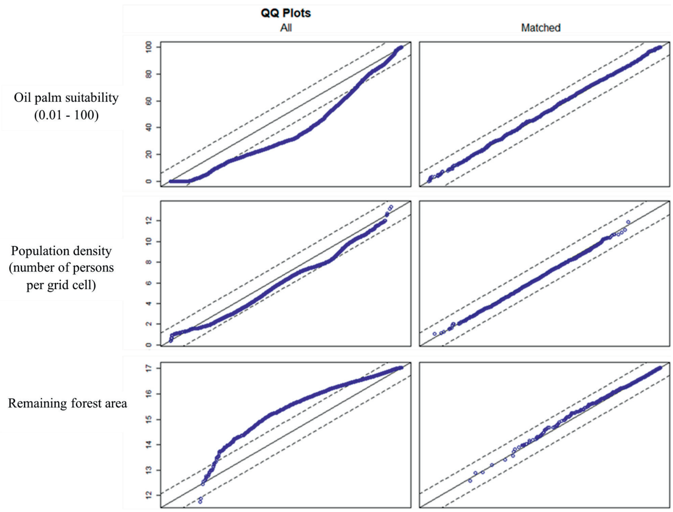


Figure 9 – Map of Indonesia showing the spatial extent of the three different types of concession areas, based on data from (Global Forest Watch, 2019a, 2019b, 2019c). The pie chart presented in the top right of the figure shows the percentage of the different types of concession areas.


QQ Plots
All
Matched
Elevation (m)
GDP at PPP in constant 2011 international US$
Market accessibility


QQ Plots
All
Matched
Oil palm suitability (0.01 - 100)
Population density (number of persons per grid cell)
Remaining forest area

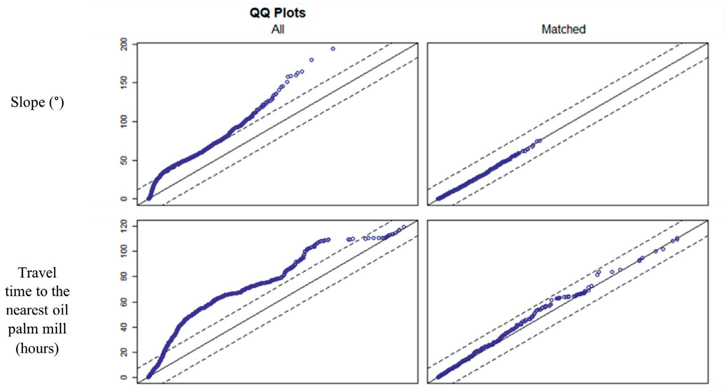


Figure 10 – Empirical quantile-quantile plots of selected covariates for grid cells within 10 km of a moratorium border (treated units) and grid cells located further away (control units) both before and after trimming the data to a matched sample. Matching was done with replacement and with a caliper width of 0.2 times the standard deviation.

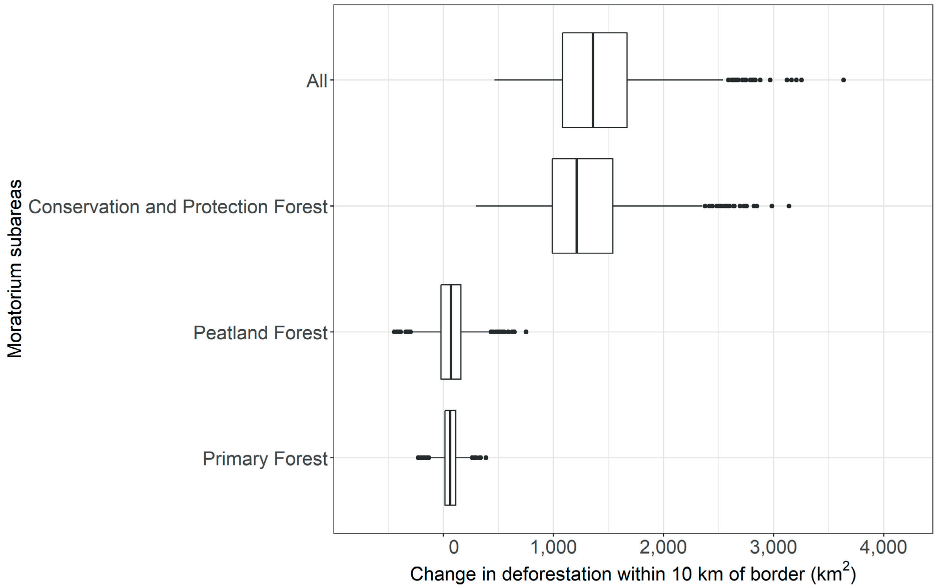


Figure 11 – Results of a Monte-Carlo simulation of the estimated effect of the Indonesian moratorium on deforestation in areas within 10 km of the targeted areas. The box plots display the five-number summary of the simulations, including the minimum, first quartile, median, third quartile and maximum. To run the simulations, the results of equation (2) of the Chapter 5 were first used to predict for each grid cell how much deforestation would have occurred in the period 2011 – 2018 if no moratorium had been in place. These values were then subtracted from the baseline fitted values and aggregated across all grid cells within 10 km of a moratorium areas. Thereafter, the variance-covariance matrix of the regression parameters was used to perform 1,000 iterations, thereby assuming that the regression parameters follow a multivariate normal distribution.

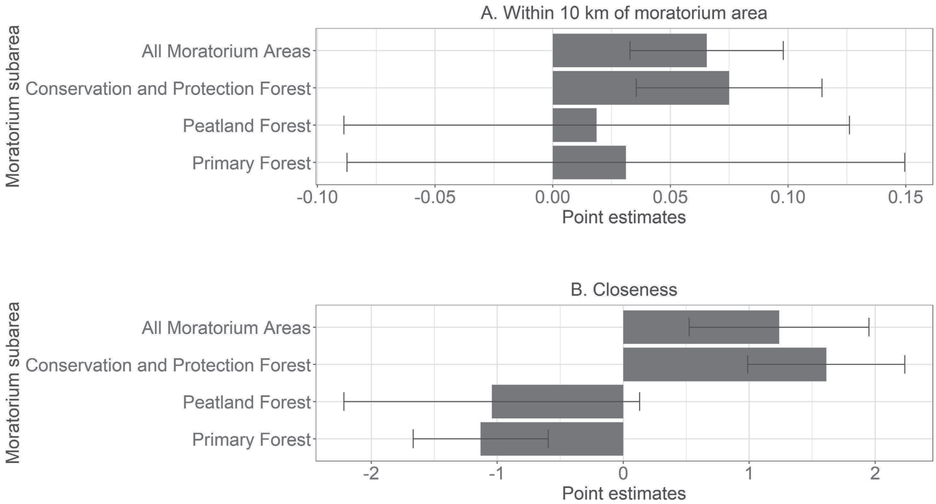


Figure 12 – Point estimates of the estimated effect of the Indonesian moratorium on deforestation in areas within 10 km of the targeted areas. Error bars denote the largest 95% confidence intervals after clustering the standard errors at the regency, province, and island level, respectively.

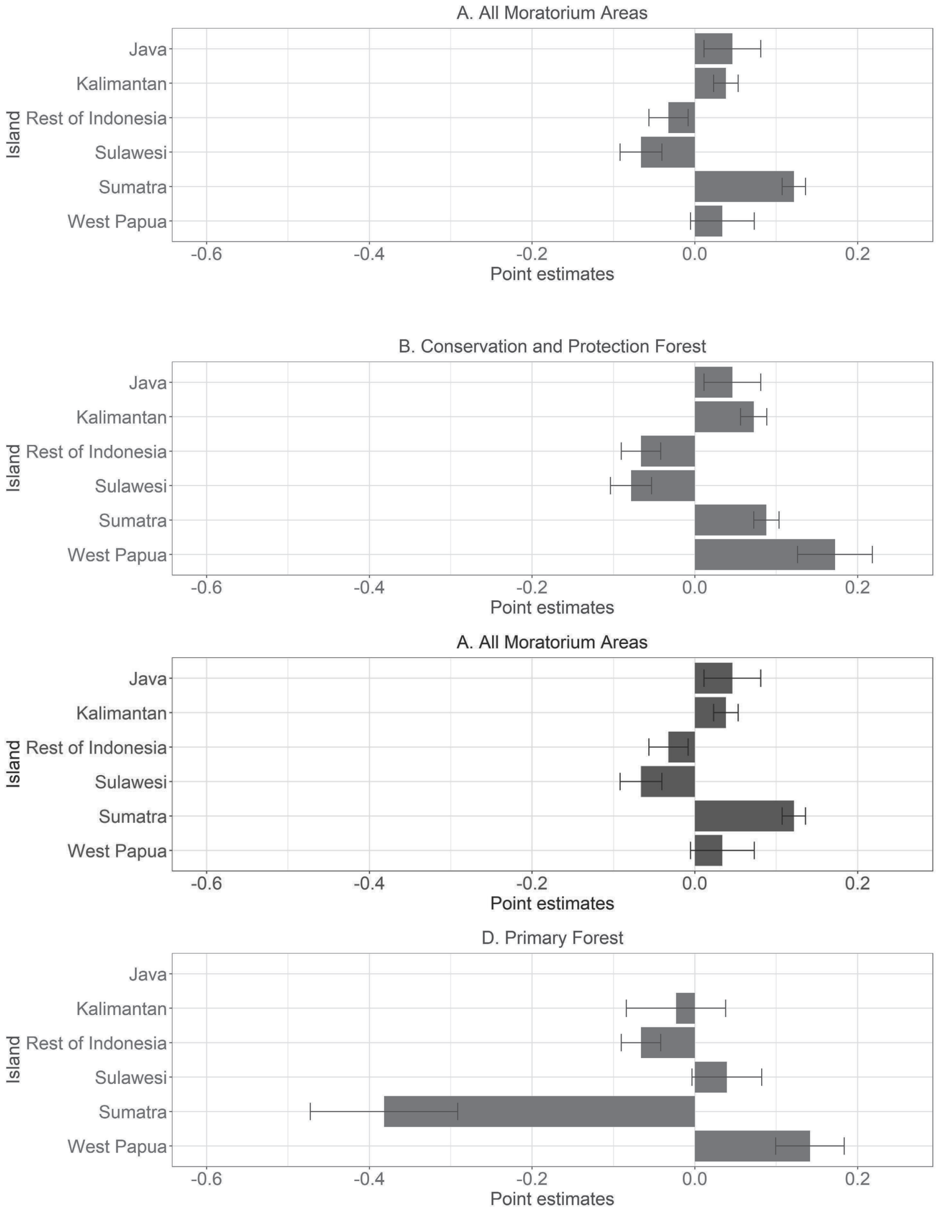


Figure 13 – Point estimates of the estimated effect of the Indonesian moratorium on deforestation in areas within 10 km of the targeted areas for 6 different Indonesian island groups. Error bars denote 95% confidence intervals.

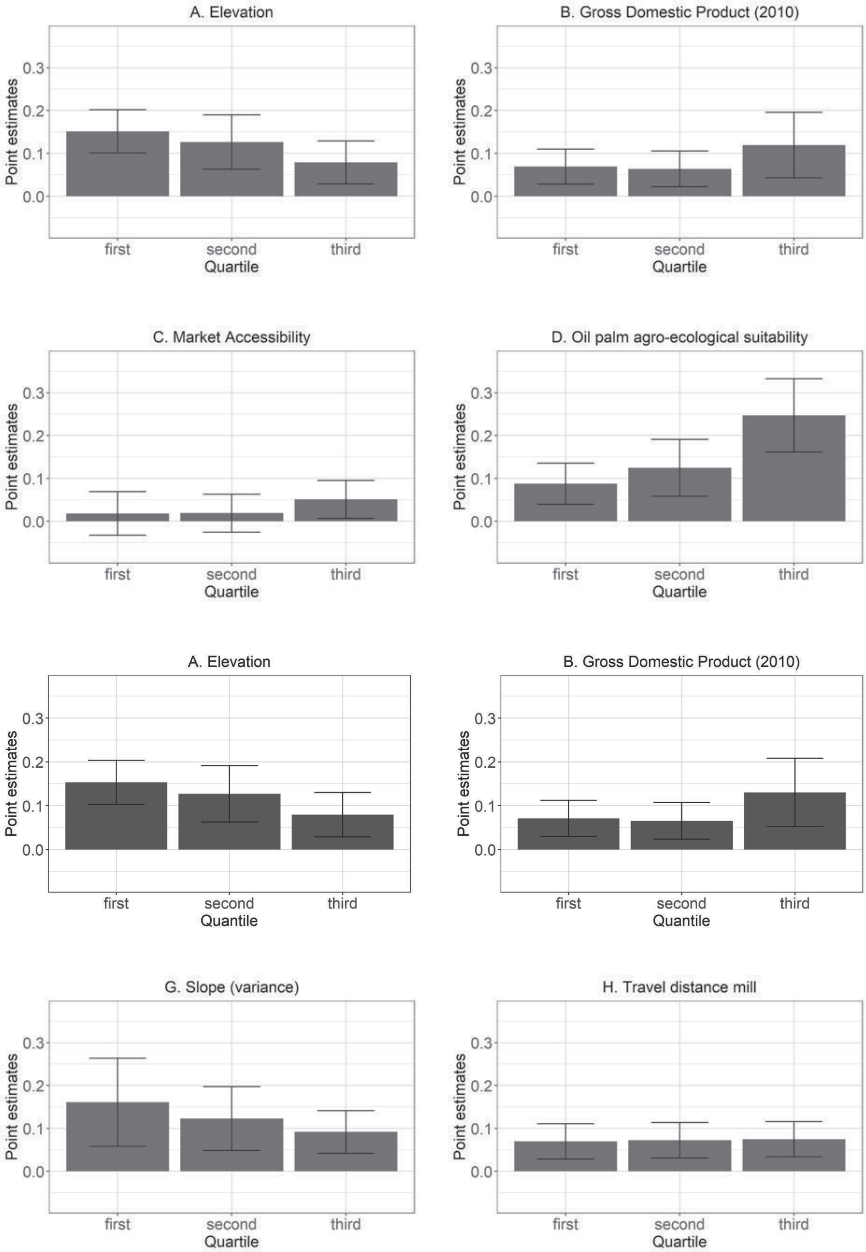


Figure 14 – Point estimates of the estimated effect of the Indonesian moratorium on deforestation in areas within 10 km of the targeted areas after trimming the sample to grid cells with covariate values exceeding a certain threshold, based on quartiles. Threshold values are shown in Table 1. Error bars denote 95% confidence intervals.

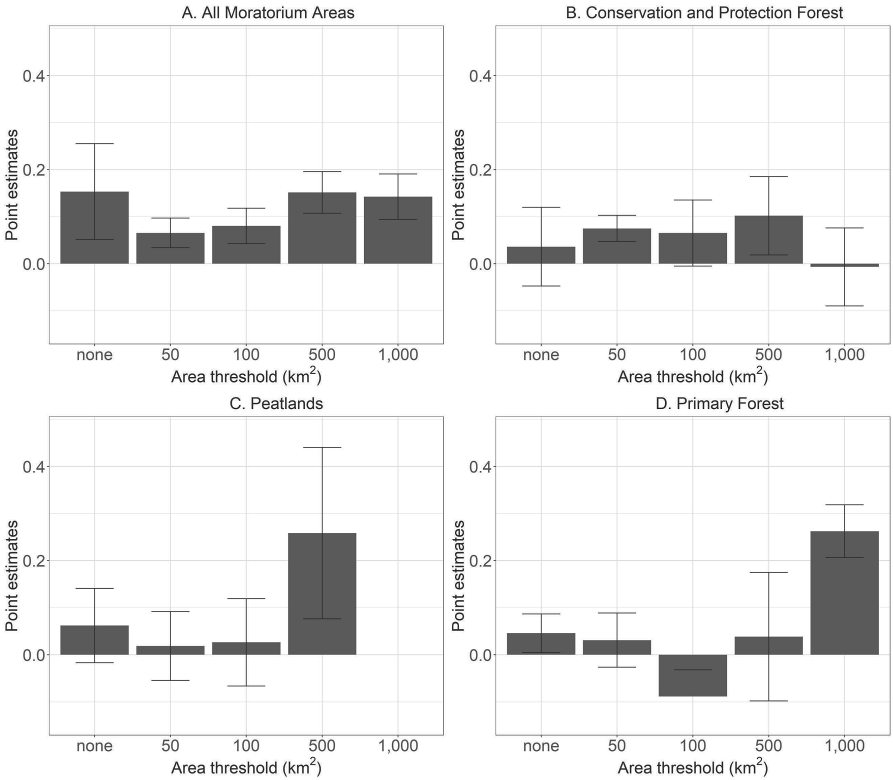


Figure 15 –Point estimates of the estimated effect of the Indonesian moratorium on deforestation in areas within 10 km of a certain moratorium area, after excluding moratorium areas below a certain area threshold. Error bars denote 95% confidence intervals. Note that there are no peatlands exceeding 1,000 km².

B.5 References for Appendix B

Allison, P.D., Waterman, R.P., 2002. Fixed-effects negative binomial regression models. Sociol. Methodol. https://doi.org/10.1111/1467-9531.00117

Bergé, L., 2020. Fast Fixed-Effects Estimations [R package fixest version 0.3.1].

Bergé, L., 2018. Efficient estimation of maximum likelihood models with multiple fixed-effects: the R package FENmlm. CREA Discuss. Pap. 2018 - 13.

Diamond, A., Sekhon, J.S., 2013. Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. Rev. Econ. Stat. https://doi.org/10.1162/REST_a_00318

Global Forest Watch, 2019a. Indonesia logging concessions | Global Forest Watch Open Data Portal [WWW Document]. URL https://mapforenvironment.org/layer/info/329/Indonesia-Logging-Concessions#5.24/-1.289/118.16 (accessed 1.7.20).

Global Forest Watch, 2019b. Indonesia oil palm concessions | Global Forest Watch Open Data Portal [WWW Document]. URL http://data.globalforestwatch.org/datasets/f82b539b9b2f495e853670ddc3f0ce68_2 (accessed 1.7.20).

Global Forest Watch, 2019c. Indonesia wood fiber concessions | Global Forest Watch Open Data Portal [WWW Document]. URL https://data.globalforestwatch.org/datasets/05c3a7ee17df4f69bf3c4f974a8bece9_0 (accessed 1.7.20).

Greenpeace, 2021. Global Mapping Hub by Greenpeace [WWW Document]. URL https://maps.greenpeace.org/

Hilbe, J.M., 2011. Negative binomial regression, second edition, Negative Binomial Regression, Second Edition. https://doi.org/10.1017/CBO9780511973420

Ho, D.E., Imai, K., King, G., Stuart, E.A., 2011. MatchIt: Nonparametric preprocessing for parametric causal inference. J. Stat. Softw. 42. https://doi.org/10.18637/jss.v042.i08

Lancaster, T., 2000. The incidental parameter problem since 1948. J. Econom. https://doi.org/10.1016/S0304-4076(99)00044-5

Ministry of Environment and Forestry of The Republic of Indonesia, 2021. Archive Indicative Moratorium Map (PIPPIB) [WWW Document]. Digit. by Greenpeace. URL https://geoportal.menlhk.go.id/webgis/index.php/en/map/pippib

Ministry of Environment and Forestry of The Republic of Indonesia, 2010. Indonesia legal classifications [WWW Document]. 'Landuse maps (provincial Plan. maps/Forest L. Use by Consens. maps (TGHK)', Gen. Direktorat Planning, Minist. For. URL https://data.globalforestwatch.org/datasets/04f797199b9441a28490410f91336b38_13?geometry=65.830%2C-10.215%2C170.376%2C5.104

R Core Team, 2020. R software: Version 4.0.2. R Found. Stat. Comput.

Rosenbaum, P.R., 2010. Basic Tools of Multivariate Matching. pp. 163–186. https://doi.org/10.1007/978-1-4419-1213-8_8

Stuart, E.A., 2010. Matching methods for causal inference: A review and a look forward. Stat. Sci. https://doi.org/10.1214/09-STS313

Appendix C

Table 1 – Negative binomial regression estimates of the annual amount of soy deforestation risk and territorial deforestation. Columns (1) and (3) assume a ZDC implementation deadline of 2 years, while columns (2) and (4) assume an implementation deadline of 5 years. Sourcing areas outside the Amazon biome are excluded. Heteroskedasticity robust (White-Huber) standard errors in parentheses. Asterisks indicate the level of statistical significance (· $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$). Soy and territorial deforestation are represented in kha.

	Soy deforestation risk	Soy deforestation risk	Territorial deforestation	Territorial deforestation
Stickiness (0 –1)	0.01	0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Commitment (2-year lag)	0.15		-0.10	
	(1.81)		(0.98)	
Stickiness x Commitment (2-year lag)	0.00		0.02.	
	(0.02)		(0.01)	
Commitment (5-year lag)		0.62		-1.79
		(2.22)		(1.40)
Stickiness x Commitment (5-year lag)		-0.02		0.03 *
		(0.03)		(0.02)
Soy volumes (%)	0.21	0.15	0.14 .	0.19 *
	(0.13)	(0.13)	(0.08)	(0.08)
Destination - Europe (%)	1.88	1.43	1.69	1.80
	(1.78)	(1.83)	(1.49)	(1.51)
Destination - Asia (%)	1.44	0.96	1.31	1.42
	(1.61)	(1.62)	(1.48)	(1.50)
Unprotected suitable forest area	0.01	0.01	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Theta (overdispersion)	0.97 ***	1.01 ***	1.31 ***	1.31 ***
	(0.25)	(0.26)	(0.32)	(0.33)
McFadden's Pseudo R^2	0.31	0.32	0.32	0.32
Observations	269	269	336	336
Trader fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
AIC	754.71	752.29	1165.60	1167.60
BIC	1121.38	1118.95	1654.19	1656.19
Log Likelihood	-275.36	-274.14	-454.80	-455.80

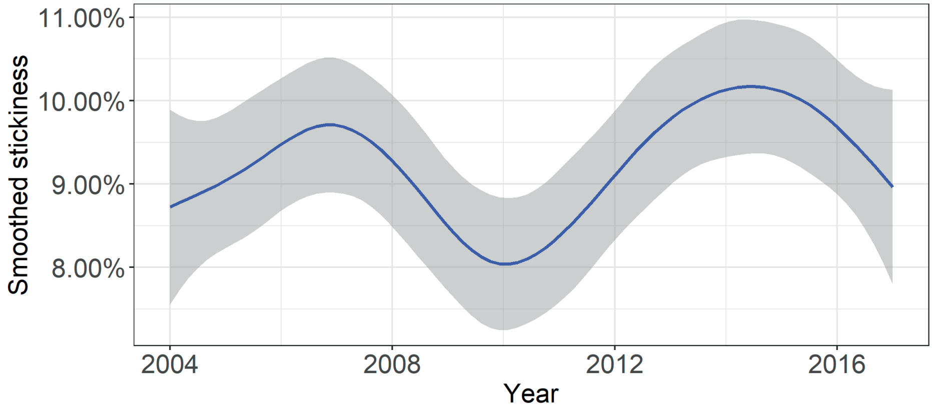


Figure 1 – Smoothed levels of stickiness in the Brazilian soy supply chain between 2004 – 2017, using a penalised cubic regression spline. Grey areas denote 95% confidence intervals.

Appendix D

Table 1 – Overview of the ESA CCI-LC 2014 land cover classes. The last column shows the different classifications that were used to construct the land systems map for the year 2014.

Value	Label	Reclassified into
0	No Data	No Data
10	Cropland, rainfed	Cropland
11	Herbaceous cover	
12	Tree or shrub cover	
20	Cropland, irrigated or post-flooding	
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)	Mosaic cropland
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)	
50	Tree cover, broadleaved, evergreen, closed to open (>15%)	Dense forest
60	Tree cover, broadleaved, deciduous, closed to open (>15%)	
61	Tree cover, broadleaved, deciduous, closed (>40%)	
62	Tree cover, broadleaved, deciduous, open (15-40%)	Open forest
70	Tree cover, needleleaved, evergreen, closed to open (>15%)	Dense forest
71	Tree cover, needleleaved, evergreen, closed (>40%)	
72	Tree cover, needleleaved, evergreen, open (15-40%)	Open forest
80	Tree cover, needleleaved, deciduous, closed to open (>15%)	Dense forest
81	Tree cover, needleleaved, deciduous, closed (>40%)	
82	Tree cover, needleleaved, deciduous, open (15-40%)	Open forest
90	Tree cover, mixed leaf type (broadleaved and needleleaved)	Dense forest
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)	Shrubland; herbaceous cover; lichens and mosses; sparse vegetation; flooded tree cover.
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	
120	Shrubland	
121	Evergreen shrubland	
122	Deciduous shrubland	
130	Grassland	Grassland
140	Lichens and mosses	Shrubland; herbaceous cover; lichens and mosses; sparse vegetation; flooded tree cover.
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)	
151	Sparse tree (<15%)	
152	Sparse shrub (<15%)	
153	Sparse herbaceous cover (<15%)	
160	Tree cover, flooded, fresh or brakish water	
170	Tree cover, flooded, saline water	
180	Shrub or herbaceous cover, flooded, fresh/saline/brakish water	
190	Urban areas	Urban areas
200	Bare areas	Bare areas
201	Consolidated bare areas	
202	Unconsolidated bare areas	
210	Water bodies	No Data
220	Permanent snow and ice	Bare areas

Table 2 – All 44 predictors variables used in the logistic regression analysis. Climatological variables were averaged over the period 2010 – 2019. All raster data were resampled to a 10 x 10 km grid using the bilinear resampling method.

Predictor variable	**Source**	**Predictor variable**	**Source**
Actual evapotranspiration	Abatzoglou *et al* (2018)	Precipitation	Abatzoglou *et al* 2018
Altitude	Amatulli *et al* (2018)	Presence indigenous community	Garnett *et al* (2018)
Aspect cosine	Amatulli *et al* (2018)	Proportion population aged between 15 - 64	CIESIN (2018)
Aspect sine	Amatulli *et al* (2018)	Proportion population female	CIESIN (2018)
Cation exchange capacity	De Sousa *et al* (2020)	Reference evapotranspiration	Abatzoglou *et al* 2018
Clay	De Sousa *et al* (2020)	Runoff	Abatzoglou *et al* 2018
Climate water deficit	Abatzoglou *et al* 2018	Sand	De Sousa *et al* (2020)
Coarse fragments in the soil	De Sousa *et al* (2020)	Shannon index geomorphological landforms	Amatulli (2018)
Downward surface shortwave radiation	Abatzoglou *et al* 2018	Silt	De Sousa *et al* (2020)
Gross Domestic Product per capita	Kummu *et al* (2018)	Slope	Amatulli (2018)
Human Development Index per capita	Kummu *et al* 2018	Snow water equivalent	Abatzoglou *et al* 2018
Human footprint index	Venter *et al* (2018)	Soil bulk density	De Sousa *et al* (2020)
Irrigation	Siebert *et al* (2015)	Soil moisture	Abatzoglou *et al* 2018
Maximum temperature	Abatzoglou *et al* 2018	Soil organic carbon	De Sousa *et al* (2020)
Minimum temperature	Abatzoglou *et al* 2018	Soil pH	De Sousa *et al* (2020)
Nitrogen	de Sousa *et al* (2020)	Suitability plantation forest	Schulze *et al* (2019)
NPP of potential vegetation	Haberl *et al* (2007)	Travel time to nearest city	Weiss *et al* (2018)
Organic carbon density	De Sousa *et al* (2020)	Travel time to nearest palm oil mill	Leijten *et al* (2021)
Organic carbon stock	De Sousa *et al* (2020)	Travel time to nearest port	Weiss *et al* (2018)
Palmer Drought Severity Index	Abatzoglou *et al* 2018	Vapor pressure	Abatzoglou *et al* 2018
Population	Gao (2017)	Vapor pressure deficit	Abatzoglou *et al* 2018
Population - rural	Gao (2017)	Wind-speed	Abatzoglou *et al* 2018

Table 3 – Land conversion matrix used in the CLUMondo simulations.

	Cropland - extensive	Mosaic - extensive	Dense forest	Open forest	Shrubland and herbaceous	Grassland	Urban	Bareland	Oil palm - mosaic	Oil palm	Cropland - medium intensive	Mosaic - medium intensive	Cropland - intensive	Mosaic - intensive	Grazing grassland
Cropland - extensive	1	1	0	0	1	1	1	0	0	0	1	1	1	1	1
Mosaic - extensive	1	1	0	0	1	1	1	0	103	103	1	1	1	1	1
Dense forest	1	1	1	1	0	0	1	0	103	103	1	1	1	1	1
Open forest	1	1	130	1	0	0	1	0	103	103	1	1	1	1	1
Shrubland and herbaceous	1	1	0	120	1	1	1	0	103	103	1	1	1	1	1
Grassland	1	1	0	0	1	1	1	0	103	0	1	1	1	1	1
Urban	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Bareland	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Oil palm - mosaic	1	1	0	0	1	1	1	0	1	103	1	1	0	0	1
Oil palm	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1
Cropland - medium intensive	1	1	0	0	1	1	1	0	0	0	1	1	1	1	1
Mosaic - medium intensive	1	1	0	0	1	1	1	0	103	103	1	1	1	1	1
Cropland - intensive	1	1	0	0	1	1	1	0	0	0	1	1	1	1	1
Mosaic - intensive	1	1	0	0	1	1	1	0	103	103	1	1	1	1	1
Grazing grassland	1	1	0	0	1	1	1	0	103	0	1	1	1	1	1

Table 4 – Conversion resistance elasticities for each land system used in the CLUMondo simulations.

	Cropland - extensive	Mosaic - extensive	Dense forest	Open forest	Shrubland and herbaceous	Grassland	Urban	Bareland	Oil palm - mosaic	Oil palm	Cropland - medium intensive	Mosaic - medium intensive	Cropland - intensive	Mosaic - intensive	Grazing grassland
Angola	0.1	0	0.1	0	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2
Australia	0.1	0	0.1	0	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2
Brazil	0.1	0	0.1	0	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2
Chile	0.1	0	0.1	0	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2
Colombia	0.1	0	0.1	N.A.	0	0	1	N.A.	0.6	1	0.15	0	0.25	0.1	0.2
East Timor - R SE Asia	0.1	0	0.1	N.A.	0	0	1	N.A.	0.6	1	0.15	0	0.25	0.1	0.2
Indonesia	0.1	0	0.1	N.A.	0	N.A.	1	N.A.	0.5	0.7	0.15	0	0.25	0.1	N.A.
Jamaica	0.1	0	0.1	N.A.	0	0	1	N.A.	0.6	1	0.15	0	0.25	0.1	0.2
Kenya	0.1	0	0.1	0	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2
Malaysia	0.1	0	0.1	N.A.	0	N.A.	1	N.A.	0.5	0.7	N.A.	N.A.	N.A.	N.A.	N.A.
Mexico	0.1	0	0.1	N.A.	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2
Nigeria	0.1	0	0.1	0	0	0	1	N.A.	0.6	1	0.15	0	0.25	0.1	0.2
Philippines	0.1	0	0.1	N.A.	0	N.A.	1	N.A.	0.6		0.15	0	0.25	0.1	N.A.
Mosaic - intensive	0.1	0	0.1	0	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2
Grazing grassland	0.1	0	0.1	0	0	0	1	1	0.6	1	0.15	0	0.25	0.1	0.2

Table 5 – List of neighbourhood weight factors by land system

Land system	Neighbourhood weight factor
Cropland - extensive	0.2
Mosaic - extensive	0.1
Dense forest	0.5
Open forest	0.3
Shrubland and herbaceous	0.4
Grassland	0.1
Urban	1
Oil palm - mosaic	0.8
Oil palm	1
Cropland - medium intensive	0.2
Mosaic - medium intensive	0.1
Cropland - intensive	0.2
Mosaic - intensive	0.1
Grazing grassland	0.1

D.2 Figures

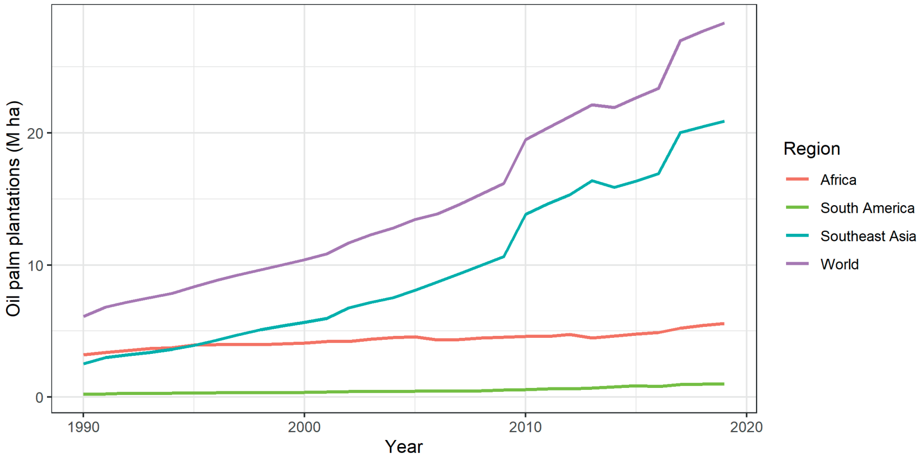


Figure 1 – Evolution of oil palm plantations in Mha per world region between 1990 – 2019

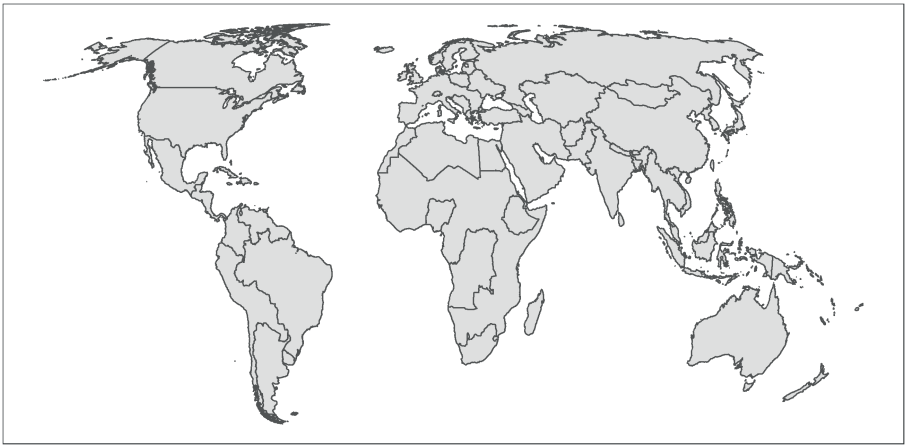


Figure 2 – Spatial overview of the 37 different regions in the GTAP-AEZ database.

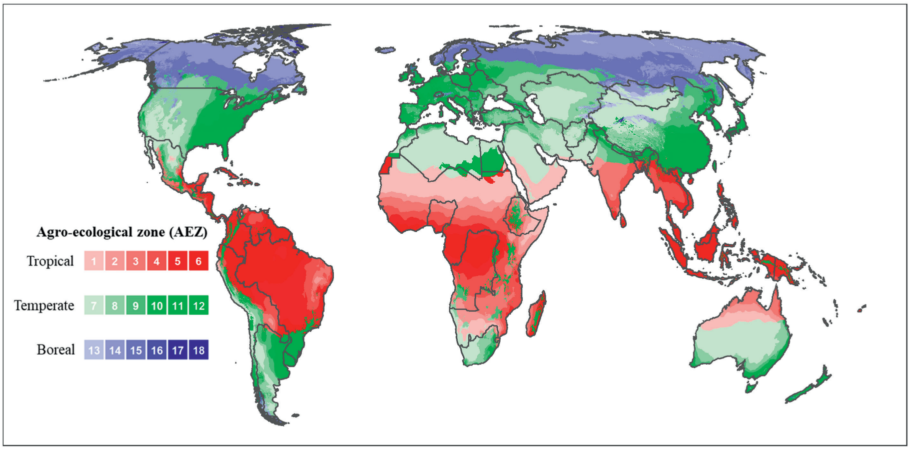


Figure 3 – Spatial overview of the 18 agro-ecological zones (AEZ) in the GTAP-AEZ database AEZs are overlayed on the 37 regions in the GTAP-AEZ database.

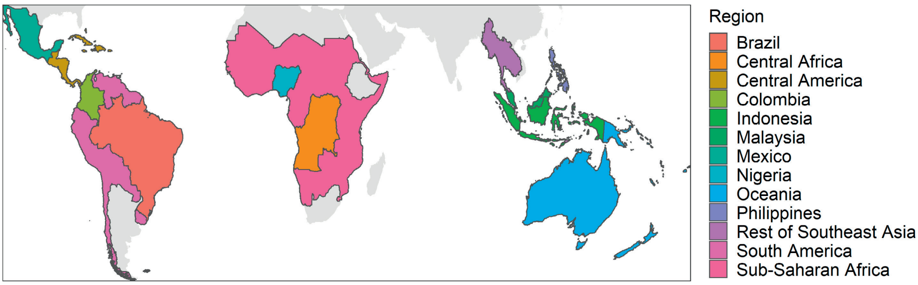
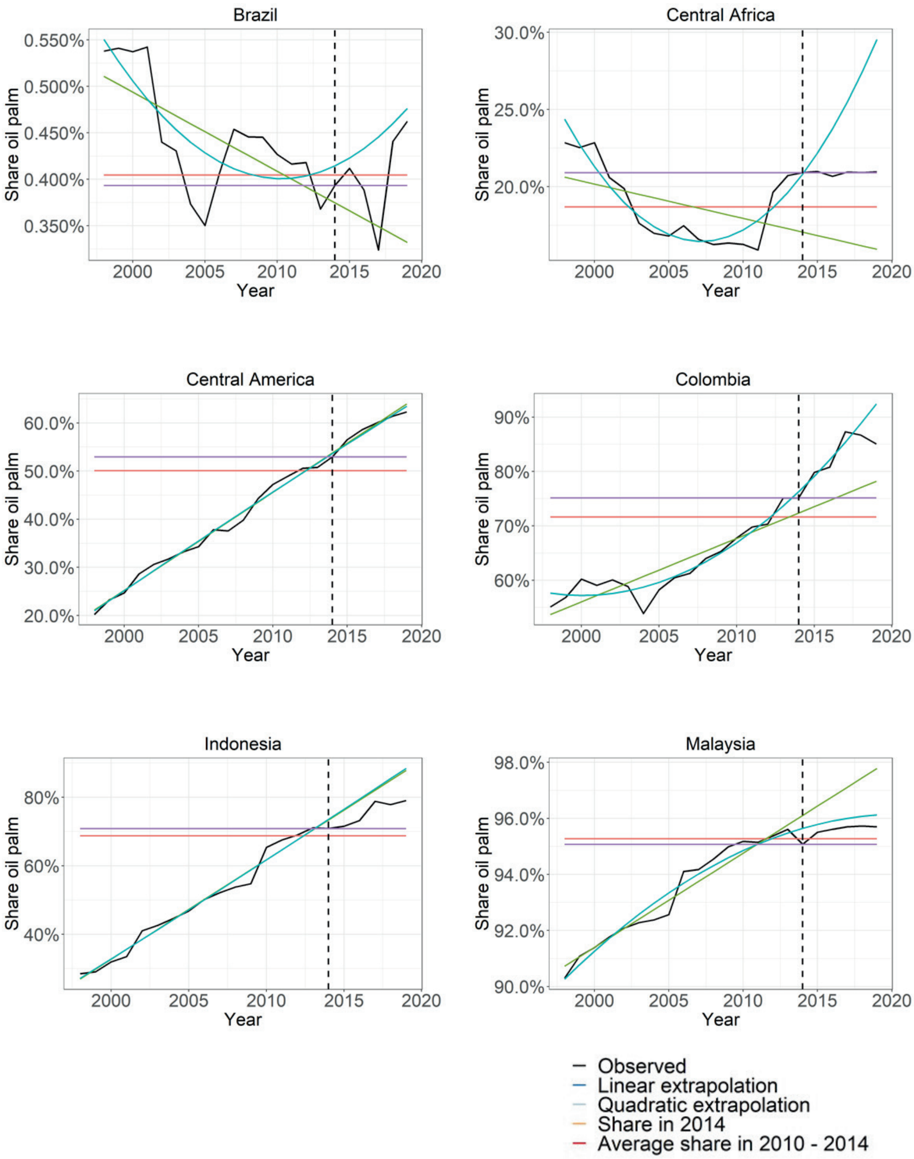
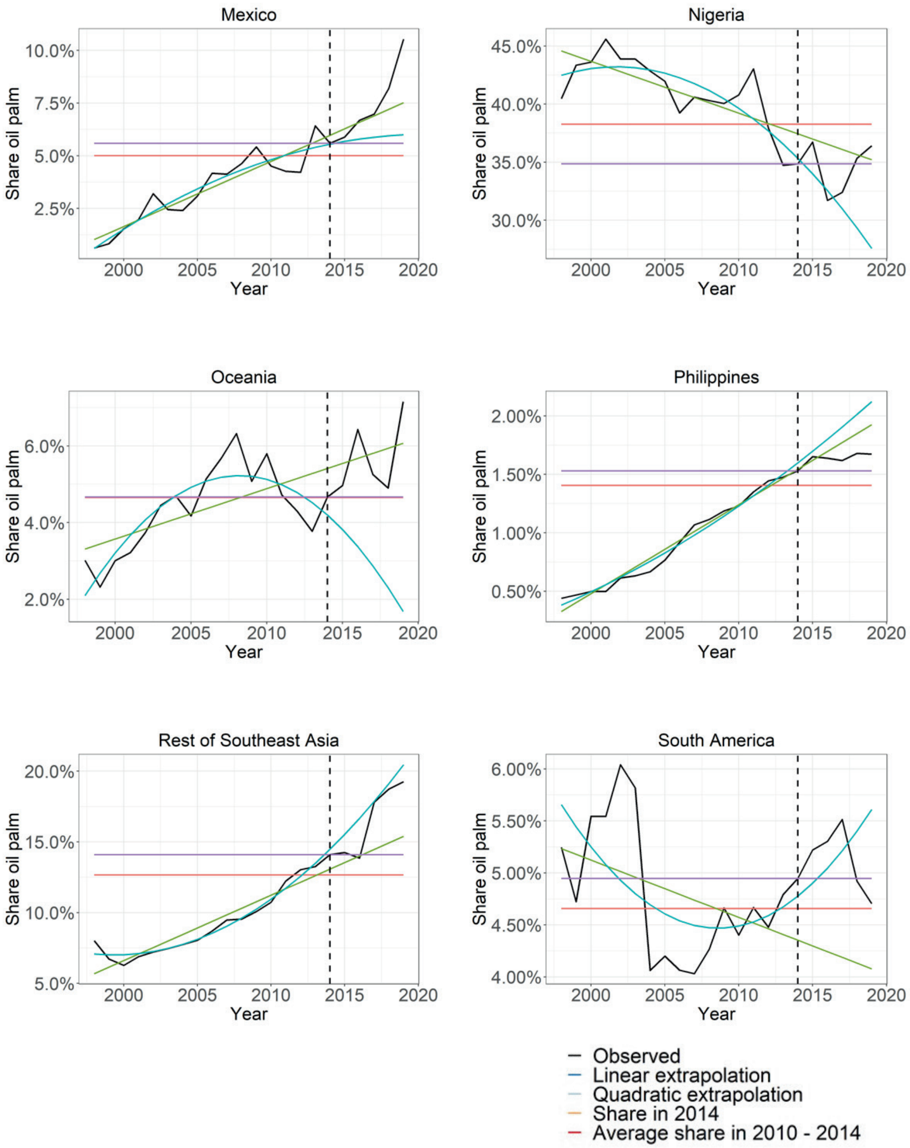


Figure 4 – Spatial overview of the 13-oil palm-producing regions in the GTAP-AEZ database.


Brazil
Central Africa
Central America
Colombia
Indonesia
Malaysia
Share oil palm
Year
0.550%
0.500%
0.450%
0.400%
0.350%
30.0%
25.0%
20.0%
60.0%
50.0%
40.0%
30.0%
20.0%
90%
80%
70%
60%
80%
60%
40%
98.0%
96.0%
94.0%
92.0%
90.0%
2000
2005
2010
2015
2020
Observed
Linear extrapolation
Quadratic extrapolation
Share in 2014
Average share in 2010 - 2014


Mexico
Nigeria
Oceania
Philippines
Rest of Southeast Asia
South America
Share oil palm
Year
Observed
Linear extrapolation
Quadratic extrapolation
Share in 2014
Average share in 2010 - 2014

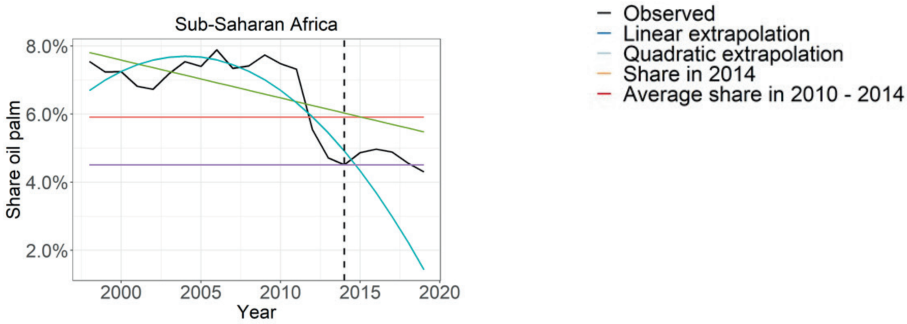


Figure 5 –Evolution of share of oil palm (%) relative to other oil crops for each oil palm producing region in the GTAP-AEZ database. To project the share up until 2030, 4 different approaches are considered and evaluated in terms of their Root Mean Square Error against the period 2015 – 2019. A spatial overview of the different regions is presented in Figure 4.

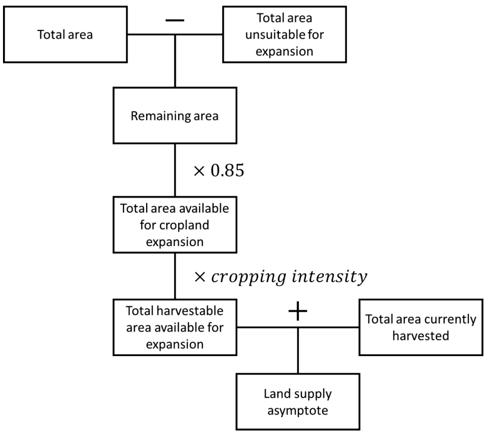


Figure 6 –Flowchart of the methodology to construct new land supply asymptotes within each region-specific agro-ecological zone.

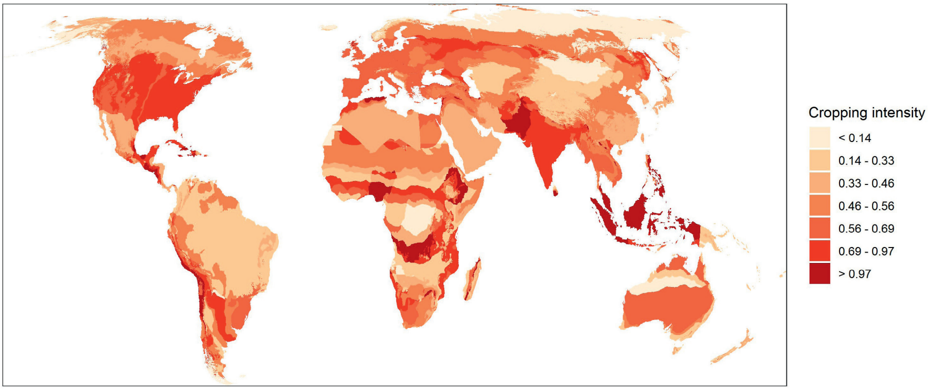


Figure 7 – Spatial overview of the estimated multiple cropping intensities in 2014 within each region-specific agro-ecological zone.

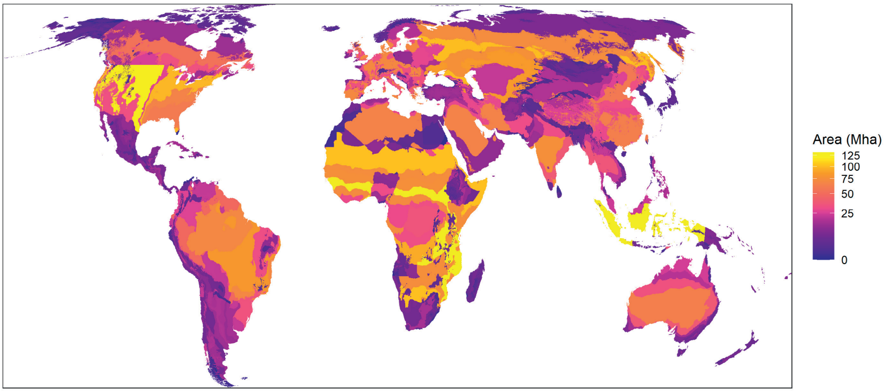


Figure 8a – Estimated land supply asymptotes (total area available for agriculture) as of 2014 assuming no implementation of zero-deforestation commitments

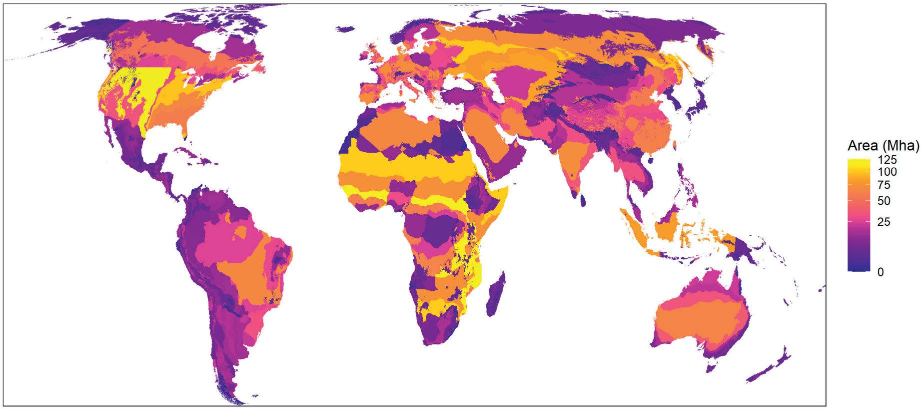


Figure 8b – Estimated land supply asymptotes (total area available for agriculture) as of 2014 assuming full implementation of zero-deforestation commitments

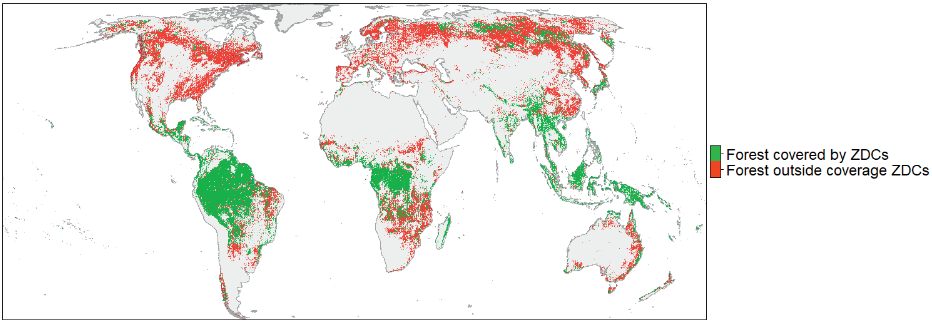


Figure 9 – Estimated coverage of zero-deforestation commitments based on the likely distribution of high conservation value forests and high carbon stock forests. Data obtained from Leijten *et al* (2020).

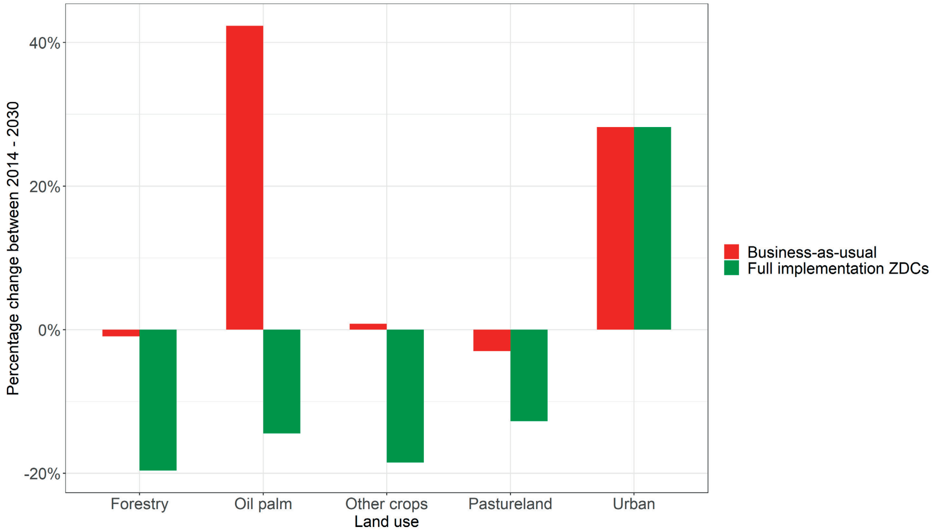


Figure 10 – Percentage changes in land use in the oil palm-producing regions for five different types of demand under both scenarios relative to the area in 2014.

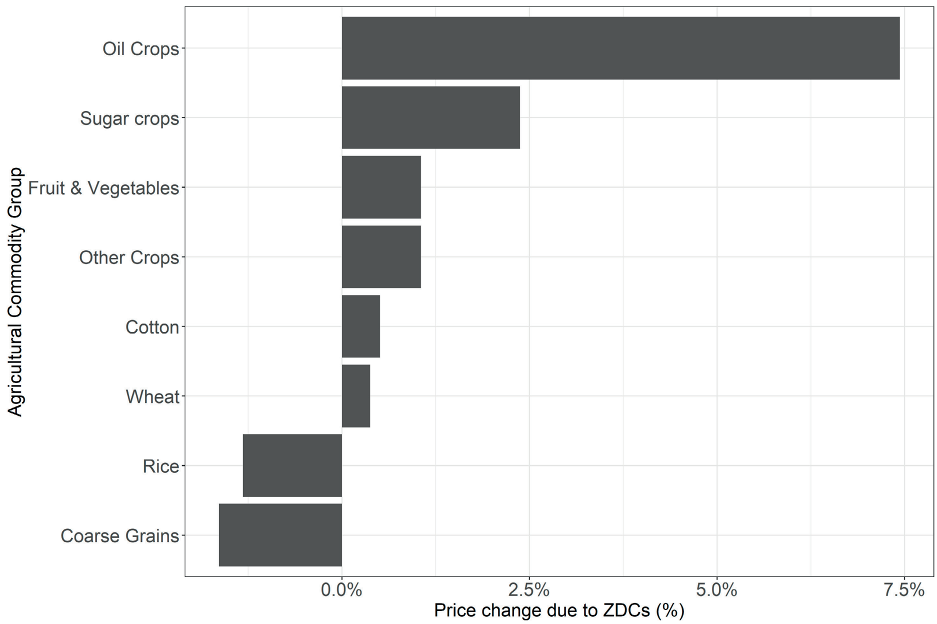


Figure 11 – Projected changes in global commodity prices by agricultural commodity group due to Zero-Deforestation Commitments (ZDCs).

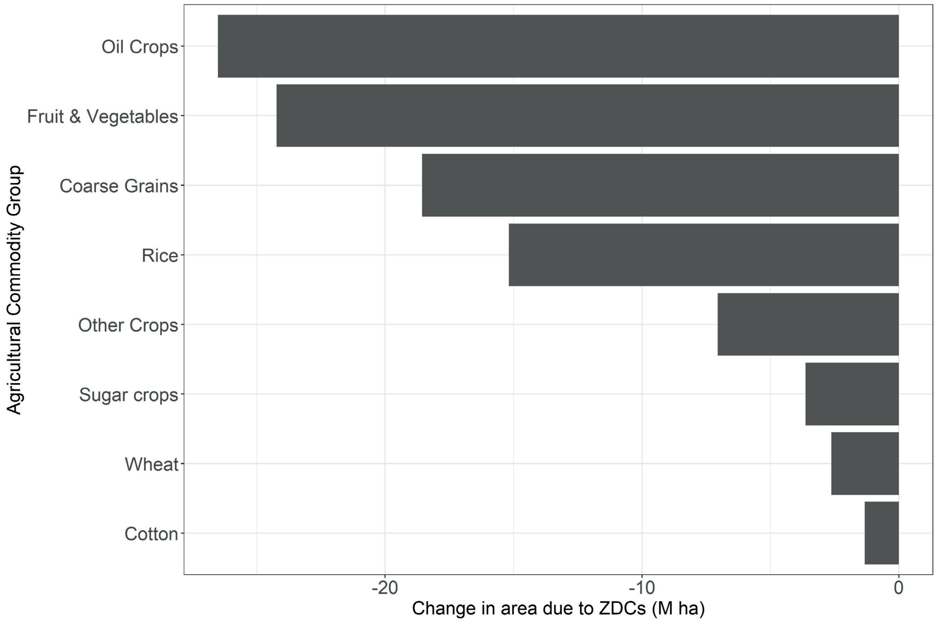
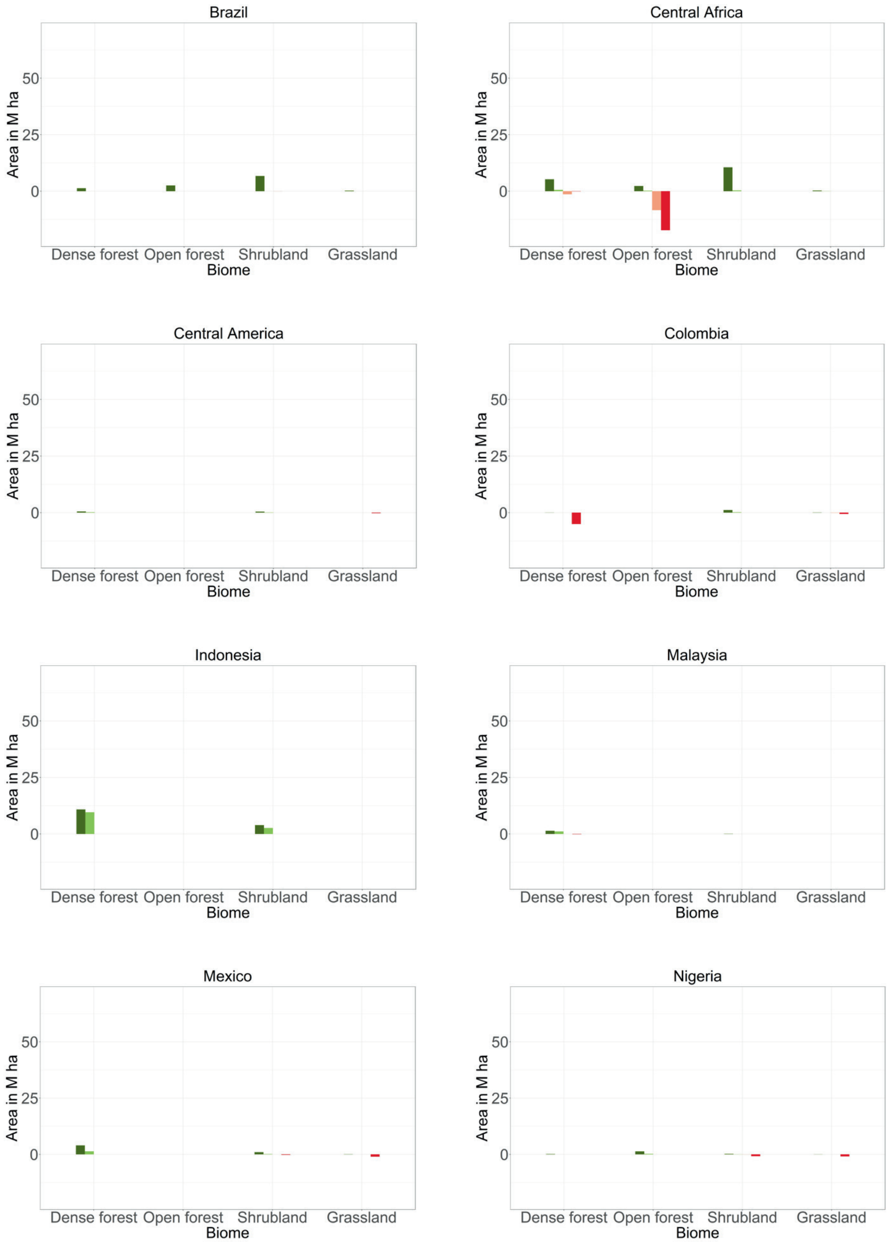


Figure 12 – Projected changes in area by agricultural commodity group within the oil palm-producing world due to Zero-Deforestation Commitments (ZDCs).


Brazil
Central Africa
Central America
Colombia
Indonesia
Malaysia
Mexico
Nigeria
Area in M ha
50
25
0
Dense forest
Open forest
Shrubland
Grassland
Biome

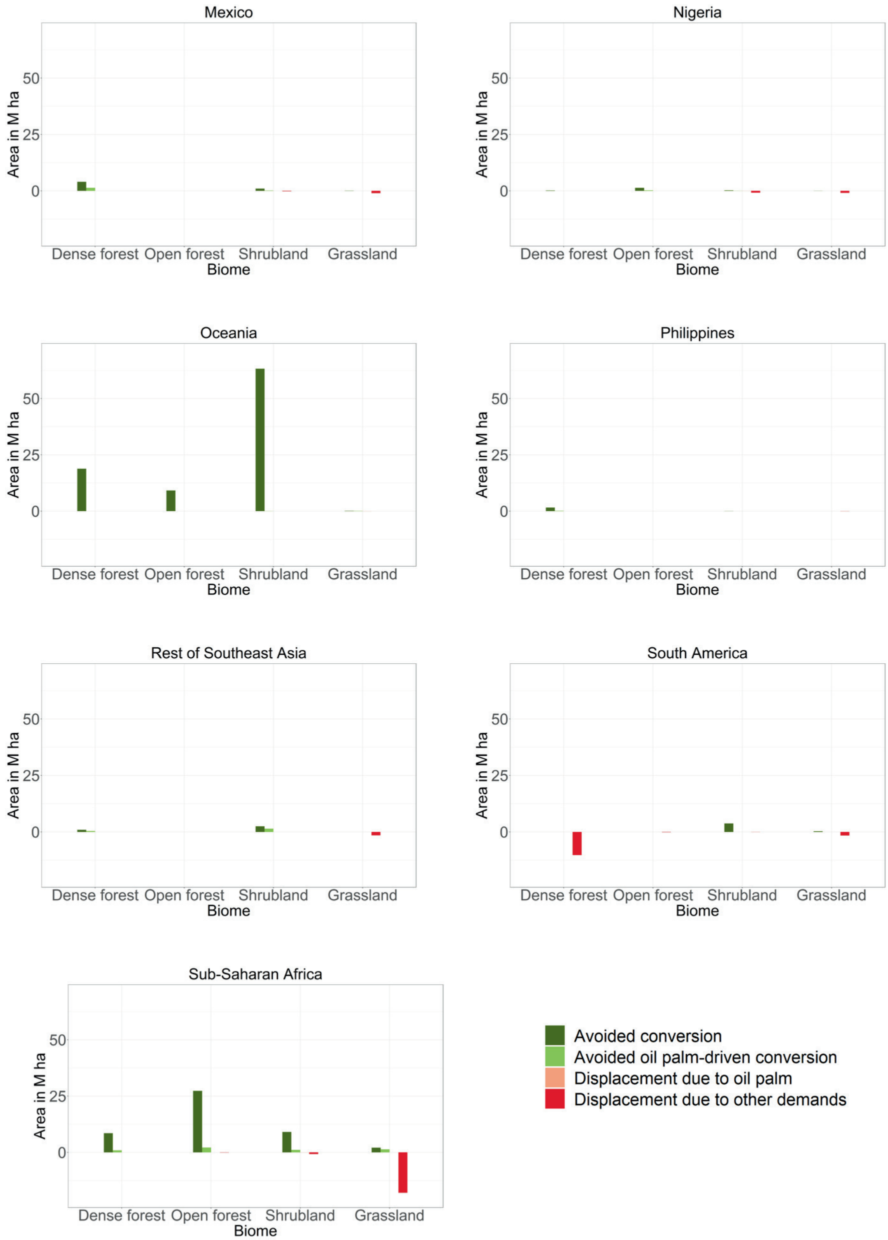


Figure 13 – Absolute area changes within each region as a result of ZDCs within 4 (semi-) natural biomes: dense forests, open forests, shrublands and grasslands. Green coloured bars represent avoided conversions. Red coloured bars represent displacement effects. Light coloured bars indicate absolute area changes that can be directly attributed to changes in the demand for oil palm. A spatial overview of the different regions is presented in Figure 4.

D.3 Constructing land supply asymptotes

To identify area where cropland could possibly expand, we first excluded areas where expansion is impossible or unlikely to occur. To do so, we computed the remaining area within each region-specific AEZ after excluding areas already under cultivation, areas biophysically unsuitable for cropland cultivation (thereby accounting for the predicted effects of climate change), legally protected areas, rough terrains, and urban areas. To harmonize the different input data, all data were resampled to a 1 x 1 km World Eckert IV grid.

We used data from the European Space Agency Climate Change Initiative (ESA-CCI; Defourny *et al.*, 2017) for the year 2014 to identify existing cropland areas and urban areas. Areas classified as "Cropland, rainfed", "Cropland, irrigated or post-flooding" and "Urban areas" were assumed to be unavailable for expansion. The first two of these three classes do not cover all cropland areas as some cropland areas in the ESA-CCI database are subsumed under two mosaic classes ("Mosaic cropland (>50%) / natural vegetation (< 50%)" and "Mosaic natural vegetation (>50%) / cropland (< 50%)"). Following Liu *et al* (2018), we therefore assumed a cropland fraction of 58% and 38% for these two mosaic classes, respectively.

To identify areas biophysically unsuitable for overall cropland expansion, we used data from Zabel *et al* (2014). These data incorporate suitability estimates for the 16 most important food and energy crops and account for the potential impact of climate change under SRES A1B conditions[1]. Areas classified as unsuitable were assumed to be unavailable for expansion.

Furthermore, we excluded areas that are legally protected using data from UNEP-WCMC and IUCN (2018). Although it has been recognized that encroachment may still occur within these areas (Wolf *et al* 2021), it is unlikely that these areas represent future hotspots of agricultural expansion (Molotoks *et al* 2018).

Finally, we excluded rough terrains (here defined as areas with steep slopes) as these areas are less likely to be developed (Busch and Ferretti-Gallon 2017). The extent to which rough terrains can be cultivated depends, however, on the degree of agricultural mechanization (Jasinski *et al* 2005), which varies across space. Therefore, in an attempt to control for the spatially varying levels of agricultural mechanization, we took a region-specific approach to identify areas that are too steep to convert into cropland. Within each of the 37 regions in the GTAP database, we applied a slope threshold, based on the top 5% slope values within existing cropland areas. Slope data were sourced from Lloyd (2016). As this resulted in unreasonably pessimistic slope thresholds in areas that are dominated by flat terrains, we imposed a minimum threshold of 10 degrees.

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1 Under this scenario, economies will rapidly grow, population growth will be small and there will be a rapid introduction of new and more efficient technologies.

D.4 References for Appendix D

Abatzoglou, J.T., Dobrowski, S.Z., Parks, S.A., Hegewisch, K.C., 2018. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015. Scientific Data. https://doi.org/10.1038/sdata.2017.191

Amatulli, G., Domisch, S., Tuanmu, M.N., Parmentier, B., Ranipeta, A., Malczyk, J., Jetz, W., 2018. Data Descriptor: A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. Scientific Data 5. https://doi.org/10.1038/sdata.2018.40

Busch, J., Ferretti-Gallon, K., 2017. What drives deforestation and what stops it? A meta-analysis. Review of Environmental Economics and Policy 11, 3–23. https://doi.org/10.1093/reep/rew013

CIESIN, 2018. Gridded Population of the World, Version 4 (GPWv4): Basic Characteristics, Revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). Columbia University Center for International Earth Science Information Network (CIESIN) - Columbia University.

Defourny, P., Bontemps, S., Lamarche, C., Brockmann, C., Boettcher, M., Wevers, J., Kirches, G., Santoro, M., ESA, 2017. Land Cover CCI Product User Guide - Version 2.0. ESA.

de Sousa, L., Poggio, L., Batjes, N., Heuvelink, G., Kempen, B., Riberio, E., Rossiter, D., 2020. SoilGrids 2.0: producing quality-assessed soil information for the globe. SOIL Discussions. https://doi.org/10.5194/soil-2020-65

Gao, J., 2017. Downscaling Global Spatial Population Projections from 1/8-degree to 1-km Grid Cells. NCAR Technical Note.

Garnett, S.T., Burgess, N.D., Fa, J.E., Fernández-Llamazares, Á., Molnár, Z., Robinson, C.J., Watson, J.E.M., Zander, K.K., Austin, B., Brondizio, E.S., Collier, N.F., Duncan, T., Ellis, E., Geyle, H., Jackson, M. V., Jonas, H., Malmer, P., McGowan, B., Sivongxay, A., Leiper, I., 2018. A spatial overview of the global importance of Indigenous lands for conservation. Nature Sustainability 1, 369–374. https://doi.org/10.1038/s41893-018-0100-6

Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., Gingrich, S., Lucht, W., Fischer-Kowalski, M., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proceedings of the National Academy of Sciences of the United States of America 104. https://doi.org/10.1073/pnas.0704243104

Jasinski, E., Morton, D., DeFries, R., Shimabukuro, Y., Anderson, L., Hansen, M., 2005. Physical landscape correlates of the expansion of mechanized agriculture in Mato Grosso, Brazil. Earth Interactions 9. https://doi.org/10.1175/EI143.1

Kummu, M., Taka, M., Guillaume, J.H.A., 2018. Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015. Scientific Data 5, 180004. https://doi.org/10.1038/sdata.2018.4

Leijten, F., Sim, S., King, H., Verburg, P.H., 2021. Local deforestation spillovers induced by forest moratoria: Evidence from Indonesia. Land Use Policy 109, 105690. https://doi.org/10.1016/j.landusepol.2021.105690

Liu, X., Yu, L., Li, W., Peng, D., Zhong, L., Li, L., Xin, Q., Lu, H., Yu, C., Gong, P., 2018. Comparison of country-level cropland areas between ESA-CCI land cover maps and FAOSTAT data. International Journal of Remote Sensing 39. https://doi.org/10.1080/01431161.2018.1465613

Lloyd, C.T., 2016. WorldPop Archive global gridded spatial datasets. Version Alpha 0.9. 100m base topography (tiled). Harvard Dataverse, V1 https://do. https://doi.org/10.1038/sdata.2017.1

Molotoks, A., Stehfest, E., Doelman, J., Albanito, F., Fitton, N., Dawson, T.P., Smith, P., 2018. Global projections of future cropland expansion to 2050 and direct impacts on biodiversity and carbon storage. Global Change Biology 24. https://doi.org/10.1111/gcb.14459

Schulze, K., Malek, Ž., Verburg, P.H., 2019. Towards better mapping of forest management patterns: A global allocation approach. Forest Ecology and Management 432, 776–785. https://doi.org/10.1016/j.foreco.2018.10.001

Siebert, S., Kummu, M., Porkka, M., Döll, P., Ramankutty, N., Scanlon, B.R., 2015. A global data set of the extent of irrigated land from 1900 to 2005. Hydrology and Earth System Sciences 19. https://doi.org/10.5194/hess-19-1521-2015

UNEP-WCMC and IUCN, 2018. Protected Planet: The World Database on Protected Areas (WDPA)/ The Global Database on Protected Areas Management Effectiveness (GD-PAME)] [On-line], [23/11/2018] [WWW Document]. URL https://www.protectedplanet.net/

Venter, O., Sanderson, E.W., Magrach, A., Allan, J.R., Beher, J., Jones, K.R., Possingham, H.P., Laurance, W.F., Wood, P., Fekete, B.M., Levy, M.A., Watson, J.E., 2018. Last of the Wild Project, Version 3 (LWP-3): 2009 Human Footprint, 2018 Release. NASA Socioeconomic Data and Applications Center.

Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T.C.D., Howes, R.E., Tusting, L.S., Kang, S.Y., Cameron, E., Bisanzio, D., Battle, K.E., Bhatt, S., Gething, P.W., 2018. A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature 553, 333–336. https://doi.org/10.1038/nature25181

Wolf, C., Levi, T., Ripple, W.J., Zárrate-Charry, D.A., Betts, M.G., 2021. A forest loss report card for the world's protected areas. Nature Ecology and Evolution 5. https://doi.org/10.1038/s41559-021-01389-0

Zabel, F., Putzenlechner, B., Mauser, W., 2014. Global agricultural land resources - A high resolution suitability evaluation and its perspectives until 2100 under climate change conditions. PLoS ONE. https://doi.org/10.1371/journal.pone.0107522

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About the author

Floris Leijten was born in Haarlem, the Netherlands, on June 29, 1994. He obtained his bachelor's degree in Earth Sciences and Economics from the Free University (Vrije Universiteit) of Amsterdam in 2017. During his bachelor studies, he was a successful participant of the honours programme and worked as a student assistant at the Institute for Environmental Studies and the Faculty of Economics and Business Administration. Following an internship at PricewaterhouseCoopers Amsterdam, he pursued a Master of Science degree in Environmental Economics and Climate Change at the London School of Economics (LSE) from which he graduated (with distinction) in 2018. His dissertation on the use of satellite data to assess the effectiveness of the Assam Agricultural Competitiveness Project was awarded with the George and Hilda Ormsby Prize for Best Postgraduate Dissertation in the Geography and Environment Department. During his master studies, he also worked as a research assistant at the LSE Cities research centre, which sparked his interest in geospatial analysis and geographic information systems.

Between September 2018 and August 2021, Floris was employed by Unilever in the United Kingdom as an industrial PhD-student. During this period, he wrote most of his PhD thesis on zero-deforestation commitments. His research was carried out in close collaboration with the Environmental Geography group of the Institute for Environmental Studies and the University of Minnesota's Department of Applied Economics. As of September 2021, Floris works as a Senior Knowledge Analyst at McKinsey & Company Amsterdam, where he builds tools and models to advise clients in both the public and private sector on a wide range of sustainability issues.