THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Where have all the forests gone?

Quantifying pantropical deforestation drivers

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Pasture on land that was once rainforest, in Paragominas, Brazil. © Alexander C. Lees.

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Abstract

Deforestation across the tropics continues to be a major source of greenhouse gas emissions and the largest threat to biodiversity on land. With strengthened commitments to reduce deforestation from countries and companies alike, it is crucial that renewed investments for reducing deforestation be guided by a sound understanding of what drives deforestation. This thesis gives a comprehensive picture of the amount of deforestation and concomitant carbon emissions driven by the expansion of agricultural commodities across the tropics and its link to international trade. The included papers show that pasture and a handful of crops drive a large share of the deforestation resulting in the expansion of productive agriculture. The main demand for these commodities is domestic consumption; even so, imports of food commodities associated with deforestation can still constitute a large part of the consumer countries' carbon emissions due to consumption (e.g., in the EU). This thesis contributes empirical evidence relating to forest transition theories by showing that many countries with increasing forest cover tend to import products associated with deforestation elsewhere, thereby offsetting around one-third of their forest gains. The thesis also introduces a conceptual distinction between two categories of agriculture-driven deforestation, based on whether it results in productive agricultural land or not. Though almost all deforestation is agriculture-driven, one-third to one-half of agriculture-driven deforestation occurs without the expansion of productive agricultural land. Instead, it may be due to several potential mechanisms, such as land speculation, tenure issues, or fires. Put together, these results indicate that it is crucial that policies to curb deforestation go beyond focusing only on trade in specific commodities, to help foster concerted action on rural development, territorial governance, and land-use planning. This thesis also highlights key evidence gaps on the links between deforestation and agriculture: (i) the attribution of deforestation to specific commodities currently often relies on coarse or outdated data, (ii) there is a need for improved data on deforestation trends, and (iii) our understanding of deforestation drivers is systematically poorer for dry forests and Africa.

Keywords: Deforestation, Agriculture, Carbon emissions, International trade, Telecoupling, Carbon footprints, Land use change, Forest transitions, Land system science, Consumption-based accounting

LIST OF PUBLICATIONS

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

Paper I Pendrill, F., & Persson, U. M. (2017). Combining global land cover datasets to quantify agricultural expansion into forests in Latin America: Limitations and challenges. *PLOS ONE,* 12(7). doi:10.1371/journal.pone.0181202

UMP conceived the study, with contributions from FP. FP collected and processed the data, carried out the analyses and wrote the paper, the latter with contributions from UMP.

Paper II Pendrill, F., Persson, U. M., Godar, J., & Kastner, T. (2019). Deforestation displaced: trade in forest-risk commodities and the prospects for a global forest transition. *Environmental Research Letters,* 14(5). doi:10.1088/1748-9326/ab0d41

UMP conceived the study, with contributions from FP. FP and UMP carried out the deforestation drivers analyses. TK carried out the trade analyses. FP and UMP analysed the results and wrote the paper with contributions from TK and JG.

Paper III Pendrill, F., Persson, U. M., Godar, J., Kastner, T., Moran, D., Schmidt, S., & Wood, R. (2019). Agricultural and forestry trade drives large share of tropical deforestation emissions. *Global Environmental Change,* 56, 1–10. doi:10.1016/j.gloenvcha.2019.03.002

UMP conceived the study, with contributions from FP. FP and UMP carried out the deforestation drivers and carbon emissions analyses. TK and SS carried out the trade analyses. FP analysed the results and wrote the paper with contributions from UMP, TK, JG, DM and RW.

Paper IV Pendrill, F., Gardner, T. A., Meyfroidt, P., Persson, U. M., Adams, J., Azevedo, T., Bastos Lima, M. G., Baumann, M., Curtis, P. G., De Sy, V., Garrett, R., Godar, J., Goldman, E. D., Hansen, M. C., Heilmayr, R., Herold, M., Kuemmerle, T., Lathuillière, M. J., Ribeiro, V., Tyukavina, A., Weisse, M. J. and West, C. (2022) 'Disentangling the numbers behind agriculture-driven tropical deforestation', Science, 377(6611), pp. eabm9267. doi: 10.1126/science.abm9267

TAG, JA, PM, FP, and UMP conceptualized the study. FP (lead), TAG, PM and UMP (support) designed the study and the methodology, performed the analysis, and wrote the initial manuscript. All co-authors reviewed and edited the manuscript. FP curated the data with support from UMP, VDS, EDG, and MJW, on the pan-tropical data, and support RH, RG, UMP and VR on the regional and national data.

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Finally, I am grateful, too, for the love, support, and patience of my family and friends.

Contents

1. Introduction

Every year in the tropics, forests amounting to an area larger than the size of the Netherlands (~5–10 million hectares) are cut down or burned (Hansen *et al.*, 2013; Curtis *et al.*, 2018; FAO, 2020b). This contributes to climate change: deforestation not only accounts for up to around a tenth of anthropogenic carbon emissions (Baccini *et al.*, 2017; IPCC, 2019) but also changes temperature, evaporation and rainfall patterns, so that when forests disappear, it affects the climate locally as well as globally (Ellison *et al.*, 2017; Maeda *et al.*, 2021). Deforestation also impacts the livelihoods of people depending on the forest (Sunderlin *et al.*, 2005; Chhatre & Agrawal, 2009) and threatens the habitats of a multitude of species, making land-use change the leading driver of biodiversity loss on land (Newbold *et al.*, 2015; Barlow *et al.*, 2016; Tilman *et al.*, 2017; IPBES, 2019).

These impacts, combined with the stubbornly high deforestation rates across much of the tropics, have sparked unprecedented attention and multiple national and international efforts, both in the public and private sectors, urgently seeking to reduce pressures on forests. At the United Nations Framework Convention on Climate Change (UNFCCC) climate conference of parties (COP26) in late 2021, governments across much of the world pledged renewed efforts to reduce deforestation in The Glasgow Leaders' Declaration on Forests and Land Use. Deforestation is also set to be a key point of discussion at the upcoming negotiations at the UN Biodiversity Conference (COP15, Part 2) in December 2022. Previously, the UNFCCC has developed REDD+ (Reducing Emissions from Deforestation and forest Degradation) as a mechanism to support climate change mitigation, providing results-based financial incentives to developing countries for leaving forests standing. And, also at the climate COP26, the EU along with several other high-income countries made a Global Forest Finance Pledge to "provide US$12 billion for forest-related climate finance" in the next few years. In the private sector, multiple companies and financial institutions are committing to look over their supply chains and investment portfolios in order to rid them of products and assets contributing to deforestation (Gardner *et al.*, 2018; Lambin *et al.*, 2018; ACTIAM *et al.*, 2021; Consumer Goods Forum, 2021; Luciano *et al.*, 2021).

With agriculture being the dominant direct driver of tropical deforestation (Hosonuma *et al.*, 2012; Curtis *et al.*, 2018; FAO, 2022; Pendrill *et al.*, 2022a), many of these emerging policies focus on eliminating deforestation associated with agricultural commodities, such as palm oil, soybeans, beef and cocoa (Ellis & Weatherer, 2022). Additionally, international supply chains supplying these commodities to consumers across the world have gained increasing interest as governments and consumers across the world are increasingly concerned about the impacts of their consumption abroad. For example, there is currently legislation proposed within the EU, the UK, and the US that aim to limit the deforestation due to imported agricultural and forestry commodities (European Commission, 2021; Schatz, 2021; UK Public General Acts, 2021).

However, past ambitious commitments to halt deforestation have fallen short of their goals: The New York Declaration on Forests, endorsed by many governments and companies alike, aimed to halve deforestation by 2020 and halt it by 2030, and, even more ambitiously, the United Nations' Sustainable Development Goals (SDGs) aimed to halt deforestation already by 2020; a goal that has clearly not been met. In face of the urgency of this challenge, it is crucial that efforts to reduce deforestation are designed in an effective way. This requires a solid evidence base on the relative importance of different drivers.

However, though it has been well-established that agriculture is the primary direct cause of deforestation across the tropics, agriculture-driven deforestation can take many forms. And there has been a limited understanding of the relative role of different agricultural land uses or commodities as well as the role of domestic demand vis-à-vis international trade patterns. My PhD research has aimed to reduce these knowledge gaps.

1.1. Aim and research questions

The overarching aim of this thesis is to identify and quantify the causes of deforestation across the tropics. More specifically, the papers in this thesis aim to evaluate:

1. How much tropical deforestation is driven by agriculture?
2. In what ways does agriculture drive deforestation in tropical countries? In particular, to what extent does the expansion of different crops, pastures and tree plantations contribute to deforestation and related CO_2 emissions?
3. What is the relative role of domestic and international demand in driving deforestation?

In answering these questions, the aim is also to assess our current understanding of these questions and identify limitations in the existing knowledge base.

The precise geographic and temporal scope varies between the papers in this thesis; however, they all focus on 21st-century deforestation in tropical and subtropical areas. These areas are where most agricultural expansion into native vegetation occurs (Curtis *et al.*, 2018) and where the impacts on biodiversity and carbon stocks are expected to be the greatest (Myers *et al.*, 2000; Saatchi *et al.*, 2011; Avitabile *et al.*, 2016).

1.2. Thesis structure

This thesis is structured into six chapters, framed around the three research questions listed above. Before we can delve into assessing the drivers of deforestation, we need to know where and how much deforestation is happening. Following Chapter 1 (this Introduction), Chapter 2, therefore, opens with a brief introduction to remote sensing and discusses the question of how much deforestation there is across the tropics. Chapter 3 addresses research questions 1 and 2, focusing on the ways in which agriculture drives deforestation and concomitant CO_2 emissions. Chapter 4 explores research question 3 on the role of international trade and domestic demand. Chapters 2–4 all follow the same basic structure, starting with a *Background*, followed by a brief summary of the *Approach* taken in appended papers to address the question at hand, and finishing with an overview of the *Main findings* from the appended papers. Some of the background sections are in part based on Paper IV and on my licentiate thesis (from which some parts are also excerpted). Chapter 5 presents some of the key limitations and knowledge gaps that currently hamper our understanding of the links between agriculture and deforestation. Finally, Chapter 6 concludes this thesis by discussing the main contributions of my research to science and to policies for curbing deforestation.

2. How much deforestation is there across the tropics?

2.1. Background

2.1.1. A brief introduction to satellite remote sensing

The papers in this thesis all rely on datasets based on satellite remote sensing to some extent. The possibilities of satellite remote-sensing data are continuously improving through new sensors and satellites, enhanced processing capabilities, and increased availability and openness of data (Finer *et al.*, 2018; Masolele *et al.*, 2021). These developments have led to a flurry of new datasets on, for example, land cover, biomass, and, to some extent, land-cover changes and the extent of specific crops.

Remote sensing typically makes use of electromagnetic radiation, actively or passively. Just looking at something with our own eyes can be considered a simple form of remote sensing. More typically, the term refers to the use of a sensor that, as in the case of satellite remote sensing, detects the intensity of radiation within a narrow range of wavelengths emanating from the Earth (or, indeed, another celestial body) (Campbell & Wynne, 2011). These intensity values are gathered in a collection of pixels, which can be used to create images of the area, such as a true colour composite combining data collected in visible wavelengths. This remote sensing permits surveying larger (or remote) areas of the Earth than would otherwise be feasible. However, the advantages of satellite remote sensing do not stop there: using and combining different wavelengths – and not necessarily only within the visible part of the spectrum – can enhance the detection of certain features even better than traditional imagery (Campbell & Wynne, 2011). For example, near-infrared wavelengths are useful for distinguishing the chlorophyll of vegetation (Tucker, 1979).

When it comes to remote sensing, several types of resolution are relevant: spatial (i.e., the pixel size), temporal (how frequently the satellite passes over and collects data) and spectral (the number and width of the wavelength bands sampled) (Campbell & Wynne, 2011). Typically, trade-offs exist between these properties (or with costs): a better spatial and spectral resolution generally comes at the cost of poorer temporal resolution (or by using more expensive sensors or multiple satellites).

A common further step in using remote sensing data is to convert the intensity values into data that tell us something further about the area we are interested in, such as the type of land cover, the land surface temperature, the elevation, or the above-ground biomass. For continuous variables (such as carbon stocks or the percentage of tree cover), an algorithm could be used to "translate" the intensity values into values of the variable of interest (e.g., based on training data points where the value of the variable is known). For data with categories, like land cover maps, this is done by classifying the data, i.e., identifying and then labelling groups of pixels that are similar in a way relevant to the purpose at hand, such as distinguishing pixels with forests from those with bare ground (Campbell & Wynne, 2011). Somewhat simplified, this entails using an algorithm to label pixels with similar spectral properties (e.g., high-intensity values in one wavelength range, low intensity in another). In the resulting classified map (dataset), each pixel is typically assigned to a single class, although sometimes several classes and percentages are assigned (Campbell & Wynne, 2011). The classification requires that the classes one wants to separate are sufficiently distinct in the set of wavelengths used. This can sometimes be challenging, e.g., in some regions, pasture and cropland have resembling spectral properties, thus making them difficult to differentiate (Müller *et al.*, 2015; Oliveira *et al.*, 2020).

Another important step is to assess the accuracy of the resulting classification (Olofsson *et al.*, 2014). A set of validation (or reference or ”ground truth”) data, for example from field visits, higher resolution data or crowdsourcing, provides independent classifications for a number of locations (pixels) (Olofsson *et al.*, 2014; Wulder *et al.*, 2018). For each pixel, the classification in the validation set is compared with that of the main map/dataset. The comparison results are compiled in an error/confusion matrix (Table 1 gives an illustrative example), quantifying how many pixels in each class were correctly classified or not. [In doing this, one assumes the validation set to be entirely "true", which is generally a simplification (Foody, 2002; Olofsson *et al.*, 2013).]

The data in the confusion matrix are commonly summarised to estimate the overall accuracy (i.e., number of correct pixels divided by the total number of pixels), and often also producer's- and user's accuracies for each class (Story & Congalton, 1986; Foody, 2002). The producer's accuracy expresses what share of the pixels was correctly classified; in the example given in Table 1, the validation data had 100 forest pixels, of which the classified map correctly identified only 75, so the producer's accuracy for forest would be 75%. The user's accuracy expresses the share of pixels that are what the map classification says they are (Story & Congalton, 1986); in the Table 1 example, only half of the pixels the map classifies as forest were indeed forests (75 of 150), giving a user's accuracy of 50%. (These concepts are related to errors of omission and commission, respectively). The different types of accuracies can vary quite a lot between each other and between classes (as illustrated in Table 1), so the reliability of the map can depend to a significant degree on which classes are of interest for the purpose at hand.

Table 1. An illustrative example of a simple error matrix.

		Validation set			
		Forest	Not forest	Total	User's
Classified map	Forest	**75**	75	150	50%
	Not forest	25	**225**	250	90%
	Total	100	300	**400**	
	Producer's	75%	75%		Overall: 75%

Overall accuracies of existing global- and continental-scale land cover and forests datasets, such as the Global Forest Change data (Hansen *et al.*, 2013) and GlobeLand30-2010 data (Chen *et al.*, 2015) used in some of the papers of this thesis, commonly lie around 80–90%. However, the accuracy can vary significantly between classes and between places, for example, due to the fact that different types of vegetation or land covers (and their changes) are not equally easy to distinguish with remote sensing (Pérez-Hoyos *et al.*, 2017; Rufin *et al.*, 2022)., and that because places vary in the availability of reliable satellite observations (e.g., depending on differences in cloud cover) (Vancutsem *et al.*, 2021).

2.1.2. What is deforestation?

Alongside the technical challenges in assessing deforestation (and its drivers), more fundamental challenges are the conceptual ones. Before setting out to determine the causes of deforestation, a key point is to decide what to consider as deforestation in the first place. This, in turn, depends in part on what we consider a forest. And there is no single way to unequivocally distinguish between forest and non-forest, nor between deforestation and forest degradation, because different definitions serve different purposes (Chazdon *et al.*, 2016).

In land system science, it is common to distinguish between land cover and land use. While land cover is a biophysical description of the properties of the land (e.g., What type of vegetation is there? Are there any buildings and roads?), land use describes how or for what purpose(s), the land is used by people (Gregorio & Jansen, 2005; Lund, 2006). This distinction between land cover and land use is fundamental when discussing forests and deforestation.

What is a forest?
So, what is a forest? Not surprisingly, it depends on who you ask: there are several hundred official definitions (Lund, 2006). Some definitions rely on the intended use (the land use), whereas others rely solely on biophysical properties (the land cover), such as the degree of canopy cover, tree height and patch size. As hinted at above, this manifoldness of forest definitions results from them serving different purposes (Chazdon *et al.*, 2016). There are also no clearly defined natural thresholds for canopy cover threshold and patch size (Sexton *et al.*, 2016). Different definitions can yield wildly varying pictures on the extent of forests and serve different purposes; for example, a land-cover based approach will probably give a better insight into the current carbon content of the biomass than a land-use based one (Chazdon *et al.*, 2016; Sexton *et al.*, 2016; Fernández-Montes de Oca *et al.*, 2021).

A couple of commonly used forest definitions are:

- the FAO Forest Resources Assessment, which uses: “land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use” (Keenan *et al.*, 2015; FAO, 2016) and
- the UNFCCC, whose definition allows countries to use minimum canopy cover thresholds ranging from 10 to 30% (UNFCCC Conference of the Parties (COP), 2002).

It is also worth noting that, under some land-use based definitions, a piece of land considered a forest might not have any actual tree cover (e.g., it might be a recently cleared rotation forest which is intended to regrow). Vice versa, a piece of land considered a forest using a land-cover based definition might not be considered a forest according to some land-use definitions; for example, despite fulfilling the biophysical criteria, an oil palm plantation is not considered forest by the UN Food and Agriculture Organisation (FAO) Forest Resources Assessment (FRA) (FAO, 2016).

What is deforestation?

Given that there is no clear consensus on what a forest is, there is also no clear consensus on what constitutes deforestation. The question, therefore, again goes back to the intended purpose, and there is no uniquely correct definition (Chazdon *et al.*, 2016). For defining deforestation, there are several things to consider. As discussed above, one question is whether to assess deforestation as a change in land cover or a change in land use. These two perspectives are sometimes terminologically distinguished as tree cover (or forest) loss for a land-cover change and deforestation for a land-use change.

The conceptual challenges of defining forest loss further include, at least if the definition relies primarily on land cover, selecting appropriate minimum thresholds on canopy cover (Sexton *et al.*, 2016) and patch size to delineate forests prior to loss (Chazdon *et al.*, 2016; Griffiths *et al.*, 2018). Minimum canopy-cover thresholds used to define forests prior to loss typically lie within the range of 10%–30% (Paper IV) in line with what is allowed in UNFCCC's REDD+ process (UNFCCC Conference of the Parties (COP), 2002). Minimum forest patch size typically varies more between different assessments: e.g., if we look at the recent pantropical assessments of agriculture-driven deforestation, minimum patch size ranges from a single Landsat pixel (30 m by 30 m – around 0.1 ha) in Curtis *et al.* (2018); Goldman *et al.* (2020) and all papers included in this thesis, and up to >5 ha (in De Sy *et al.*, 2019). The differences in canopy cover thresholds likely have an overall minor impact on the results: in the GFC tree-cover loss data, the difference is small between a >10% and a >30% canopy-cover threshold: the global average GFC tree-cover loss is estimated at 22.2 Mha per year with a >10% threshold compared with 20.6 Mha per year with a >30% threshold (2001–2020) (Hansen *et al.*, 2013). However, the differences in patch size can have a larger impact on measures of deforested area extent (Griffiths *et al.*, 2018; Nomura *et al.*, 2019).

Defining forest loss also requires deciding how much loss of canopy cover (and reduced patch size) counts as forest loss rather than as forest degradation (Sasaki & Putz, 2009; Fernández-Montes de Oca *et al.*, 2021). For example, let's say we have chosen a minimum threshold of 30% canopy cover to consider something a forest. Should we then consider a reduction in canopy cover to be forest loss if (a) canopy cover is reduced by a certain amount, even if the remaining canopy cover exceeds the threshold to count as forest (e.g., if canopy cover is reduced by 50 percentage points, from e.g., 90% to 40%); (b) canopy cover falls below the chosen threshold (in this case 30%; i.e., a reduction from 31% to 29% would count as forest loss); (c) canopy cover falls below another specific threshold; or (d) only if the canopy cover is entirely removed?

In many circumstances, it is appropriate to adapt the thresholds to different regions and types of forests, rather than using fixed thresholds for the whole world (e.g., Chazdon *et al.*, 2016; Galiatsatos *et al.*, 2020). The broader conceptual challenges in defining forests and their loss are discussed at length in Chazdon *et al.* (2016); Sexton *et al.* (2016); and Fernández-Montes de Oca *et al.* (2021).

Table 2. An overview of the main pantropical datasets on tree-cover loss and deforestation.

Dataset or study	Forest	Deforestation	Resolution	Underlying data and methods
FAO Forest Resources Assessment (FAO, 2020a)	"Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use" (Keenan *et al.*, 2015; FAO, 2016)	Focuses on land-use change, where deforestation is considered to be a change of land use from forestry towards agriculture or other land uses, but not if tree cover is expected to regenerate or if the land is replanted so that the land remains under forestry use (FAO, 2020b). This means that the conversion of a natural forest to, e.g., a tree plantation, is not considered deforestation in the FRA.	Country-level 5–10 year averages, from 1946 to 2020.	The FRA is compiled from country reports based on a variety of methods including forest inventories, remote sensing as well as desk studies (FAO, 2020b; Nesha *et al.*, 2021) Countries report forest resources extents and disturbances as part of a reporting process to the FAO Forest Resources Assessment.
Global Forest Change (GFC) tree-cover loss dataset (Hansen *et al.*, 2013)	Forests are defined based on their biophysical properties. A base map provides information on the percent tree cover in each pixel in the year 2000, for trees or other vegetation exceeding a height of 5 m (Hansen *et al.*, 2013). The user then selects one of several choices of minimum canopy cover threshold to define "forests", and may also choose to further limit the minimum patch size or apply additional constraints with the	Focuses on land-cover change, specifically *tree cover loss,* defined as: "a stand-replacement disturbance or the complete removal of tree cover canopy" (Hansen *et al.*, 2013) Not all tree-cover loss constitutes deforestation. For example, tree-cover loss includes harvesting of tree crops, clearing within tree plantations as part of normal forestry practices, and losses from fire and logging patches (Hansen *et al.*, 2013)	30-by-30 m pixels Annual data from 2001 to 2021	Satellite remote sensing (Landsat)

	help of other geographical datasets.			
(Vancutsem *et al.*, 2021)	Tropical moist forests only. Defines undisturbed tropical moist forest "as a closed evergreen or semi-evergreen forest without any disturbance observed over the full Landsat historical dataset" (Vancutsem *et al.*, 2021).	"Deforested land […] is defined as a permanent conversion from moist forest cover to another land cover" (Vancutsem *et al.*, 2021). A key feature of this dataset is that it assesses the sequential dynamics of the changes. As such, it not only distinguishes loss of forest cover but also the extent to which short-term (<2.5 years) forest degradation preceded deforestation and whether regrowth occurred.	30-by-30 m pixels 1990–2019	Satellite remote sensing (Landsat)
(Carter *et al.*, 2018)	Uses the FAO forest definition.	Estimates gross deforestation following the FAO definition by taking steps to harmonise the different input datasets towards this.	Country level Five-year averages between 1990 and 2015	Produced by making an uncertainty-weighted average of four sources of deforestation data: the FAO FRA 2015; GFC tree-cover loss (Hansen *et al.*, 2013); Kim *et al.* (2015), and a 2012 Remote Sensing Survey from FAO and JRC.

In Paper IV of this thesis, *deforestation* is defined as a persistent conversion of natural forest to any other land use, such as agriculture or human settlements, or to tree plantations. *Natural forest* is defined as a forest that "*resembles – in terms of species composition, structure and ecological function – one that is or would be found in a given area in the absence of major human impact*" (Accountability Framework, 2020). Natural forests include primary and intact forests but also regenerated (second-growth) forests and partially-degraded forests, provided they fulfil the definition of natural forest (Accountability Framework, 2020). These definitions were chosen to align with the aims of many policies focused on the loss of natural forests and concomitant losses of biodiversity, carbon stocks and other ecosystem services, and build upon the Accountability Framework initiative's definitions (Accountability Framework 2020). That said, when these definitions are operationalised to quantify deforestation rates in numbers, we are constrained by what is possible to describe with the data that are available. In Papers I–III, we were, in principle, interested in that type of deforestation as well, but we did not express it or assess it quite as explicitly: put roughly, Papers I–III quantify deforestation where tree cover loss (under some additional constraints) can be attributed to a subsequent agricultural land use (i.e., cropland, pasture; and, in Papers II–III, also to tree plantations) – this is detailed further in Section 2.1.3.

Table 2 provides an overview of datasets that quantify some aspect of deforestation or tree cover loss for the past decade or two (and often further back). As discussed in Paper IV, none of these comprehensively assess deforestation in terms of the persistent conversion of natural forest to any other land use for all of the tropics and including both humid and dry forests. Several assessments of pantropical deforestation drivers, including all the papers in this thesis, rely and build on the Global Forest Change dataset – originally described in Hansen *et al.* (2013) – on tree cover loss.

2.1.3. Moving from tree-cover loss data towards deforestation data

Though not all tree cover loss constitutes deforestation, there are ways to process tree cover loss data, such as that from GFC, to align closer with what we consider deforestation.

There are two main challenges in distinguishing deforestation from tree cover loss. First, we need to ensure that we capture only the loss of the forests that we are interested in; typically, we want to capture loss of some kind of "natural forest" (at least if our primary concern is the conservation of natural forests and ecosystems) and we don't want to capture loss within already existing forestry systems or within stable shifting cultivation systems (which would instead reflect regular rotations within these systems rather than what we would consider deforestation under most definitions). A first step towards capturing losses within the type of forest of interest – based on biophysical properties – can be done with the GFC data, by limiting tree cover loss only to those with a certain minimum canopy cover and patch size. However, this would still leave us with a mix of natural forests and tree plantations. Unfortunately, there is currently no comprehensive pan-tropical map of natural forest; if we had such a map of all forests of interest, we could simply choose to select only tree cover loss within those areas. As a step towards this, however, there are maps of primary forest extents (Turubanova *et al.*, 2018) for the tropics and intact forest landscapes (Potapov *et al.*, 2017) for the world. Any loss within these regions is likely deforestation (at least under the definition used in this thesis). A similar map for the dry tropics, such as the Cerrado, Chaco and Miombo, would help identify loss of valuable "natural" ecosystems. Additionally, for many countries, there are maps of tree plantation extent in the Spatial Database of Planted Trees (SDPT) (Harris, Goldman and Gibbes, 2019). As these tree plantation data best represent plantation extents 2013–2015, they are primarily useful for more recent tree cover loss – after the mid-2010s – as they can be used to identify tree cover loss that is likely not deforestation because it occurred within existing tree plantations. (For tree cover loss prior to the mid-2010s, these data cannot help us distinguish whether the tree cover loss was deforestation to establish a new plantation or whether the clearing was done as part of forest management within an already existing plantation). Recently (in April 2022), the SDPT has been complemented by a global map detailing the planting year of tree plantations (between 1982 and 2020) (Du *et al.*, 2022). This could probably be combined with the SDPT to help establish whether or not tree cover loss occurred within existing plantations. A further step toward improving the monitoring of deforestation is to map the forests or other ecosystems of interest – such as those with high carbon stock (HCS) or high conservation value (HCV) (Leijten *et al.*, 2020) – to support easier identification of changes.

Second, we want to determine whether or not the loss of forest is persistent over time. Ideally, this could be established by monitoring or surveying the use of the land at multiple points in time over multiple years, and there is progress towards this; for example, the Vancutsem *et al.* (2021) data on moist tropical forest changes assess forest regrowth alongside forest removal. However, comprehensive pantropical maps of land use are typically not available with such dense temporal resolution. Assessments of deforestation drivers (including the papers in this thesis) thus rely on alternative ways to determine whether the forest loss is persistent. Often this is done in conjunction with determining the driver of the forest loss; for example, if a soy extent map shows soy in an area that was previously forest, one can assume that the forest loss occurred for soy – and also that the forest is unlikely to grow back, thus likely constituting deforestation. This is the approach taken by, e.g., Goldman *et al.* (2020) (in their "detailed approach method"). Using a similar logic, Paper I in this thesis relies on a map (Globeland30-2010) showing the extent of cultivated land and grassland in a single year (approximately 2010, but differing from place to place); within these "agricultural" extents, any tree cover loss that occurred prior to the land cover data year is assumed to constitute deforestation.

Table 3 provides an overview and comparison of how deforestation and deforestation drivers are assessed in each of the papers included in this thesis. While not spatially explicit, Papers II and III use a model that relies on the assumption that if agriculture is expanding within a country (or a subnational division) and there was tree cover loss in the preceding years, a certain amount of deforestation was due to expanding agriculture (thus, in somewhat of a circumventing way, determining the persistence of the forest loss). Other ways exist for establishing where the conversion is persistent; e.g., Curtis *et al.* (2018) use decision tree models trained on high-resolution imagery from Google Earth to classify dominant drivers of tree-cover loss, some of which constitute persistent deforestation.

Table 3. A summary of how each of the papers in this thesis assesses deforestation and an overview of the data used to assess the drivers of deforestation. All of the papers use the Global Forest Change (GFC) data on percentage tree cover and tree cover loss data (Hansen *et al.*, 2013), where "forest" extent refers to tree cover (exceeding 5m height) in the year 2000 within 30-by-30 metre pixels. The minimum canopy cover threshold to define forests (in the year 2000) prior to loss is specified for each paper in the table, as it varies somewhat between them.

Paper	**Deforestation**	**Driver assessment data**
Paper I	GFC tree cover loss with a minimum canopy cover threshold of 30% prior to loss	GlobeLand30 land cover data (based on Landsat satellite data) on the extent of Cultivated land and Grassland.
Paper II & III	GFC tree cover loss with a minimum canopy cover threshold of 25% prior to loss Tree plantation extents for seven countries: (Petersen *et al.*, 2016) Primary forest extents in Indonesia for the year 2000: (Margono *et al.*, 2014) Deforestation is only attributed where our land balance model can attribute tree cover loss to expanding cropland, pasture, or tree plantations.	Agricultural statistics: FAOSTAT and subnational statistics from Brazilian and Indonesian statistics agencies. Brazil pasture data: Extents of pastures at three points in time were taken from the agricultural census 1995 and 2006 and from Parente *et al.* (2017) for 2015. Between these years pasture area was estimated based on the number of heads from the Brazilian Institute of Geography and Statistics. Data on gross loss of cropland and grassland from (Li *et al.*, 2018) based on remotely sensed land cover data from ESA's Climate Change Initiative (CCI).
A dataset developed further from Papers II & III, posted on Zenodo, v.1.1. (Pendrill *et al.*, 2022b)	GFC tree cover loss with a minimum canopy cover threshold of 25% prior to loss Tree plantation extents for a subset of countries: Spatial Database of Planted Trees, Version 1.0 (Harris *et al.*, 2019) Primary forest extents: (Turubanova *et al.*, 2018) Deforestation is only attributed where our land balance model finds expanding cropland, pasture, or tree plantations	Agricultural statistics: FAOSTAT and subnational statistics from Brazilian and Indonesian statistics agencies. Brazil pasture extents: Mapbiomas v. 5.0. Data on gross loss of cropland and grassland from (Li *et al.*, 2018) based on remotely sensed land cover data from ESA's Climate Change Initiative (CCI).

Paper IV	Varies between the studies reviewed, but the synthesized estimates are based on: GFC tree cover loss with a minimum canopy cover threshold of 25% prior to loss Tree plantation extents for a subset of countries: Spatial Database of Planted Trees, Version 1.0 (Harris *et al.*, 2019) Primary forest extents: Pantropical, updated version of (Turubanova *et al.*, 2018) Data on dominant drivers of tree cover loss from (Curtis *et al.*, 2018) Data on deforestation resulting in agricultural production from (Pendrill *et al.*, 2022b)	Varies between the studies reviewed, but the synthesized estimates are based on: Data on dominant drivers of tree cover loss from (Curtis *et al.*, 2018) Data on deforestation resulting in agricultural production from (Pendrill *et al.*, 2022b) Data on deforestation attributed to commodities from (Pendrill *et al.*, 2022b) and (Goldman *et al.*, 2020)

When evaluating the trends in deforestation over time using the GFC tree cover loss data, there are two additional and interrelated challenges. First, the GFC tree-cover loss data have evolved to become more effective at detecting small and temporary forest disturbances post-2011 and especially post-2015 due to both improved methods and improved satellite data (Global Forest Watch, 2021; University of Maryland, 2021). Efforts are underway to reprocess the GFC tree-cover loss data with a consistent methodology throughout the time series (Global Forest Watch, 2021). However, such efforts will not be able to correct for inconsistencies in the Landsat satellite record, including the improved sensitivity of Landsat 8, launched in 2013, and the variable availability of cloud-free images over time, which means that the next version of the data will still not have full internal temporal consistency (Global Forest Watch, 2021). This is likely to be true for any satellite data products that cover a wide time span as sensors and coverage improve. The use of sample-based approaches in combination with satellite-based products such as the GFC data can help correct for inconsistencies and build confidence in reported trends (e.g., Song *et al.*, 2021; Zalles *et al.*, 2021; Potapov *et al.*, 2022).

Second, this effect is enhanced by an increasing importance of forest degradation of standing forests as a source of tree-cover loss in the last decade (Vancutsem *et al.*, 2021), meaning that forest degradation contributes more to the total tree-cover loss data in recent years than it did in the period before 2011. That is, the GFC tree-cover loss data include a higher proportion of forest degradation and a lower proportion of deforestation in recent years compared to the period before 2011, both because the data have become more effective at detecting forest degradation and because there has been an actual increase in forest degradation. Particularly after 2015, the GFC tree-cover loss appears to have increased considerably, likely related to the record

El Niño 2015–2016, which led to losses due to massive droughts and fires (Berenguer *et al.*, 2021; Vancutsem *et al.*, 2021). Indeed, there is evidence showing that forest degradation, especially from fires, has increased in many parts of the tropics in recent years (especially around 2015–2016) – driven by the combined effects of climate change, forest fragmentation and unsustainable timber extraction (Brando *et al.*, 2019; Gao *et al.*, 2020; Matricardi *et al.*, 2020; Berenguer *et al.*, 2021; van Wees *et al.*, 2021; Vancutsem *et al.*, 2021). This varying contribution of forest degradation in the data makes it more difficult to draw firm conclusions on whether deforestation is accelerating or decelerating in more recent years.

When considering the impacts that forest changes have on, e.g., carbon stocks or biodiversity, it is also worthwhile remembering that deliberate deforestation is not the sole change that happens to forests. Smaller changes (for example, from a higher to a lower canopy cover not captured by a given definition of forest loss), as well as changes in management, can also have a large impact (see, e.g., Erb *et al.* (2017a)). On longer time scales, deforestation to date may, together with other contributions to climate change, lead to future forest loss (i.e., a positive feedback): its contribution to global and local climate change may bring about further forest loss or disturbance caused by changing temperature and precipitation patterns, and by more extreme events, e.g., droughts, flooding and fire (Lawrence & Vandecar, 2014; Nobre *et al.*, 2016; Zemp *et al.*, 2017; Silva Junior *et al.*, 2020; Maeda *et al.*, 2021).

2.2. Approach

All papers included in this thesis rely on data on forest loss, using the GFC tree cover loss data in combination with several other sources to quantify agriculture-driven deforestation, listed in Table 3 and discussed further in Chapter 3.

Paper IV additionally and explicitly assesses pan-tropical deforestation (i.e., not just deforestation driven by agriculture) in two ways. First, it compares existing pantropical estimates of forest loss for the past 20 years or so (2000–2020) harmonised to a common set of 87 countries. These reviewed datasets differ in what they strive to measure, and none of them defines deforestation fully in the way sought in that paper. Second, in Paper IV, we, therefore, derive an updated likely range of the total extent of pantropical deforestation by combining multiple sources, including the GFC tree cover loss data, to align more closely with this definition.

2.3. Main findings

There are two key results from Paper IV: we (i) find that consistent pantropical data on deforestation trends is lacking and (ii) estimate that the total extent of tropical deforestation likely lies within the range of 6.5 to 9.5 Mha per year.

The comparison of existing datasets reveals considerable differences between estimates, both in terms of rates and trends of deforestation over time (Figure 1). Some differences are expected due to methodological and conceptual differences (Table 2); at a general level the GFC tree-cover loss (Hansen *et al.*, 2013), the FRA deforestation (FAO, 2020a) and Vancutsem *et al.* (2021)

differ in the type of forest loss they assess and in their coverage of humid and dry forests, with none of them comprehensively describing the trends in deforestation sought here.

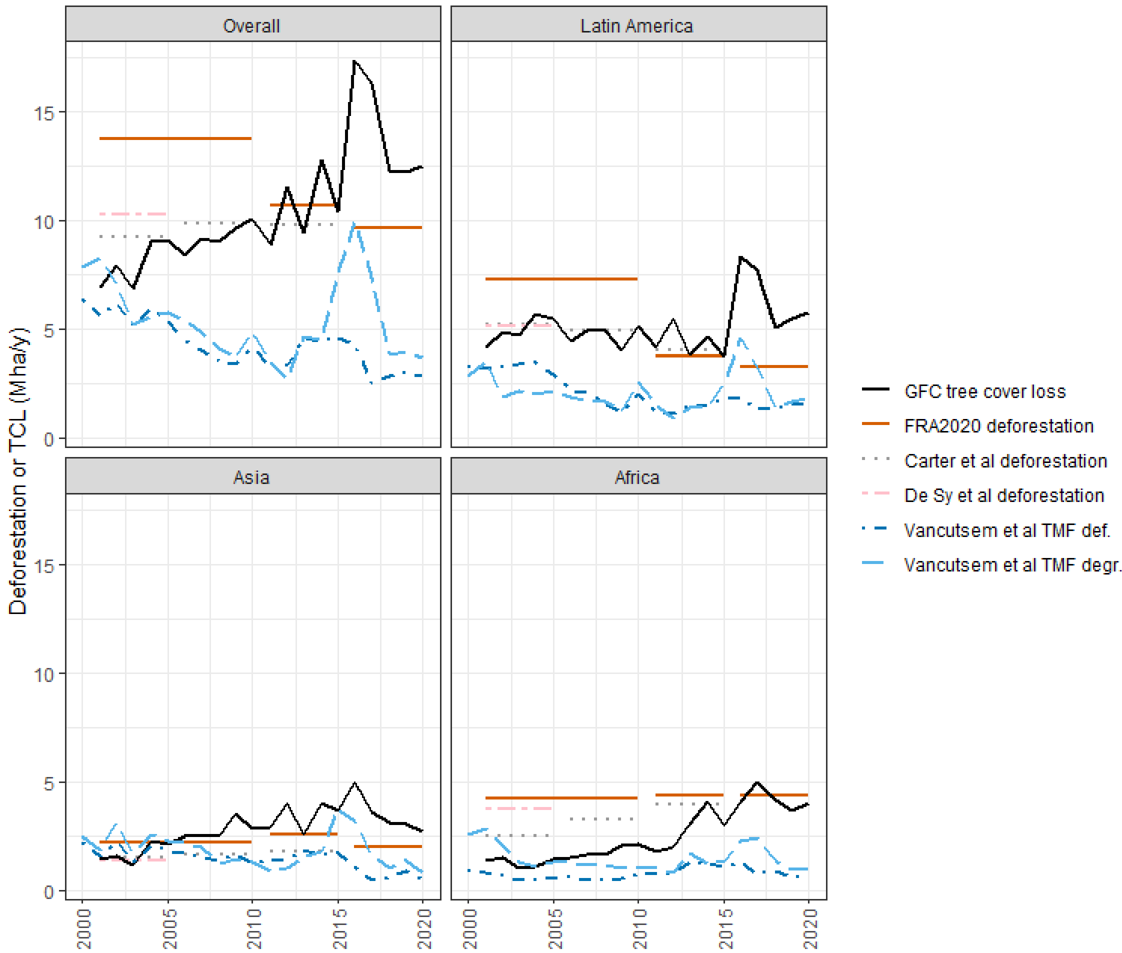

Figure 1. Pan-tropical estimates of tree-cover loss and deforestation. Estimated extents and trends of (sub-)tropical tree-cover loss and deforestation (in millions of hectares per year) vary between studies. This reflects uncertainties as well as conceptual differences. The data on tree-cover loss (TCL) are from global forest change (GFC) (Hansen *et al.* (2013)); on deforestation from the FAO FRA 2020 (FAO, 2020a), Carter *et al.* (2018); De Sy *et al.* (2019) and Vancutsem *et al.* (2021). The FRA deforestation and the Carter *et al.* (2018) deforestation data are averages over 5–10-year time periods. Abbreviations used: "def" = deforestation, TMF = Tropical Moist Forest. The data have been aligned to the same set of 87 (sub-)tropical countries (minor exceptions listed in table S2 of Paper IV), except for the data from Vancutsem *et al.* (2021) data. The Vancutsem *et al.* (2021) data covers disturbances only within tropical moist forests and is presented just for the 33 countries within our set with at least 4 Mha of tropical moist forest cover. This figure is reused from supplementary Figure S2 in Paper IV.

Some differences are more puzzling. Based on their definitions (Table 2), we would in general expect the GFC tree cover loss rates to exceed the FAO FRA deforestation rates: the FAO FRA uses a narrower definition of deforestation and also reports mainly net rather than gross deforestation rates for many countries, whereas the GFC reports gross tree cover loss. However, in the data, this is not always what we see (Figure 1). From 2011 to 2015, GFC TCL rates averaged 10.6 Mha per year in the tropics while the FAO FRA 2020 estimated deforestation to be 10.7 Mha per year. The differences are even greater for the preceding years of the 2000s, with the FAO FRA deforestation rates greatly exceeding GFC tree cover loss, especially for Africa.

Even more perplexing is that the two main datasets show opposing pantropical trends between 2001 to 2010 and 2011 to 2020 with GFC tree cover loss increasing as the FRA deforestation declines. This is especially pronounced for Latin America (Figure 1). Part of the explanation for their diverging trends is likely that these approaches capture differently distinct trends in the relative proportions of different kinds of forest loss over time. As not all tree-cover loss constitutes deforestation (neither as assessed in this paper, nor as FAO FRA deforestation), an increase in the "non-deforestation" proportion of tree-cover loss may be part of the explanation, as this would lead to an increase in the rates of tree-cover loss without a concomitant increase in FRA deforestation rates. This can involve multiple dynamics including, in particular, the increased sensitivity of GFC tree-cover loss to forest degradation enhanced by a growing importance of forest degradation in many parts of the tropics.

3. How much tropical deforestation is driven by agriculture? And in what ways does agriculture drive deforestation?

3.1. Background

3.1.1. What are the causes of deforestation?

The question of what causes deforestation can be answered in many ways, as most land-use changes depend on complex interactions between human (or socio-technical) and natural (or ecological) dynamics at multiple levels (Geist & Lambin, 2002; Meyfroidt, 2016; Busch & Ferretti-Gallon, 2017). The dominating direct driver of tropical deforestation is agriculture (Gibbs *et al.*, 2010; Hosonuma *et al.*, 2012; Jayathilake *et al.*, 2020; FAO, 2022; Pendrill *et al.*, 2022a). Quantifying the extent of deforestation driven by agriculture and some of the different ways through which agriculture drives deforestation is the core topic of this thesis. That said, as deforestation is driven by many interrelated processes, ascribing deforestation a single driver will only reflect part of the causal chains (Geist & Lambin, 2002; Meyfroidt, 2016; Busch & Ferretti-Gallon, 2017).

In the context of deforestation, it is common to distinguish between direct (or proximate) drivers and underlying (or indirect) causes of the land-use change (Geist & Lambin, 2002; Hersperger *et al.*, 2010; Meyfroidt, 2015). At the most immediate level, an actor decides to change the use of land from one purpose to another. For example, a farmer converts a plot of forest into pasture for grazing cattle. In this case, we might say that the expansion of pasture caused the land-use change. This would be an example of direct land-use change (which might make us say that pasture expansion was a direct driver of land-use change). But this is of course only part of a much wider – and far more complex – story, which can span multiple domains. In our simple example, the reason that our farmer bought a new plot of land might not be an increased demand for cattle after all. It might instead be that the farmer needed to find new land for their grazing cattle because their previous grazing land was bought up by, e.g., an agribusiness wanting to meet increased demand for soy or bioenergy. This is sometimes called *indirect* land-use change, or iLUC, in contrast with *direct* land-use change (Lapola *et al.*, 2010; Ostwald & Henders, 2014; Richards *et al.*, 2014).

The distinction between direct and indirect land-use change, though, is still not the whole story: while indirect land-use change may be one of the underlying causes behind the deforestation, there are likely further or other underlying (or indirect) causes. An underlying cause in this type of context is "*a factor which causes the proximate causes of land cover […] change*" (Meyfroidt, 2016, p. 7). For example, to continue with the story above, there are lots of unanswered questions: Did changes to the prices of land, or of beef and soy, affect the decisions of the farmer and the agribusiness? What influenced those changes in prices and profitability? Why is the farmer a farmer and not working with something else? Moreover, who wanted the soy and the beef in the first place? Or maybe the point of the grazing land was not so much the beef, as it was to claim the rights to the land? In short, the direct land-use change did not happen in a vacuum but was probably influenced by several underlying causes arising from demographic, economic, cultural, political, institutional, and technological factors (Geist & Lambin, 2002; Hertel, 2018). The underlying causes may range from geographically local to global: for example – via international trade – the underlying demand for the commodities may arise far from the deforestation itself ((Friis *et al.*, 2016; Eakin *et al.*, 2017; Tramberend *et al.*, 2019); Papers II–IV). Geographically distal drivers and feedbacks between them are sometimes explored as telecouplings (Liu *et al.*, 2013; Bruckner *et al.*, 2015; Friis *et al.*, 2016). A structured telecoupling framework, proposed by Liu *et al.* (2013), includes identifying "sending", "receiving" and "spillover" systems and, in general, the telecoupling approach is developed to help analyse coupled human and environment systems that are separated in space, especially as land use becomes more globalised (Liu *et al.*, 2013; Eakin *et al.*, 2014; MacDonald *et al.*, 2015; Friis *et al.*, 2016; Friis & Nielsen, 2019), by paying "*attention to the place-based, as well as the flow-based human-environment processes shaping land use in specific places*" (Friis & Nielsen, 2019, p. 2).

There might thus be multiple underlying – and interacting – causes of deforestation; and one way of conceptualising this is to view them as a causal chain consisting of a series of interlinked causal mechanisms (Lambin & Meyfroidt, 2011; Meyfroidt, 2015; Meyfroidt *et al.*, 2018). Therefore, when the expansion of agriculture is the direct driver of deforestation, this is but one of the relevant parts of a complex causal chain (also, agricultural expansion is neither a necessary, nor sufficient, cause of deforestation) (Meyfroidt, 2016). So, when I say that my research shows that agricultural commodities or land uses cause deforestation, I mean this in the sense that "X [expansion of cropland for a commodity] is part of a possible combination of factors that suffices to cause Y [deforestation in country A]" (Meyfroidt, 2016, p. 503). The further up the causal chain, the more difficult it might be to establish the causality, especially as multiple causes may interact and there may be feedbacks between them (Efroymson *et al.*, 2016; Meyfroidt, 2016; Friis & Nielsen, 2019).

Hence, this thesis focuses primarily on the direct (or proximate) drivers of deforestation. Indirect (or underlying) causes are mainly explored in terms of (part of) the role of international trade underlying the demand for the products driving the deforestation (Papers II–IV). Paper IV also touches briefly on some ways in which agriculture indirectly drives deforestation, for example by contributing to land speculation that drives deforestation, or when fires used for agricultural land management or clearing escape into adjacent forests.

This thesis thus deals with a piece of the puzzle of what drives deforestation, but not the whole picture. Assessing various types of underlying causes requires a different set of methods and tools (such as regression, panel studies, causal inference approaches, econometrics, land system modelling, interviews and case studies) (Rounsevell *et al.*, 2012; Ferraro & Hanauer, 2014; Meyfroidt, 2016; Busch & Ferretti-Gallon, 2017; Game *et al.*, 2018) than those used in this thesis.

3.1.2. Some reflections on the relationship between scale and causality

Though the focus of this thesis lies on agriculture as a *direct* driver of deforestation, limitations in and choices about the *spatial and temporal scale* of the analysis affect *which part of the causal chain* the results will describe. For example, the land-balance model used to attribute deforestation to expanding pastures and crop cultivation in Papers II–III (and summarized in section 3.2.1. below), does not fully distinguish between direct and indirect land-use change: because of its spatial aggregation (i.e., primarily country-level), it cannot distinguish between commodities directly expanding on recently deforested land, and those "pushing" other land uses into forests. Some of the decisions about scale are made in response to imperfect data, but others cut to deeper conceptual questions about what we should consider to be the causes of deforestation.

The spatial scale of the analysis is thus one aspect that can affect whether the results reflect direct or indirect land-use changes. In general, the finer the spatial scale, the more likely we are to capture the direct land use changes. For example, if we have a sequence of maps with both high spatial and temporal resolution, it can be possible to establish that the forest in a pixel was replaced by soy not too long after it was cleared (this is, for example, what Song *et al.* (2021) do), and then further infer that soy expansion was the direct driver of the deforestation. The coarser the resolution gets, the less certain we can be that we capture the direct land-use changes. With our land-balance model, for example, where we look at which agricultural land uses are expanding at the national (or subnational) level, the direct drivers of deforestation will be captured only to the extent to which the commodities expanding at the national (or subnational) level are the same as those that are expanding where deforestation is happening. This will differ between contexts. How much the spatial scale matters is thus an interaction between the analysis scale and how spatially heterogeneous the land-use dynamics are (within the spatial units studied; e.g., within a grid cell, a province, or a country). The more spatially heterogeneous the land-use dynamics and the coarser the scale, the more indirect land-use change will be mixed in with our deforestation driver results. If we were to take this to the extreme to consider the whole world as a single interconnected unit, we would then be assuming that the agricultural commodities expanding at the global level are the (likely mainly indirect) drivers of deforestation. This would thus entail putting some rather strong assumptions about indirect land-use change between countries and continents (also, at this scale, data only showing net changes would mask a lot of important changes which might still be "visible" in net data at finer spatial scales). At some point it would probably make more sense to go into the mechanisms through which agricultural expansion, change, or loss in one place might affect expansion, change, and loss in another (e.g., the elasticities of e.g., intensification and demand (Angelsen, 2010; Hertel, 2011).

The temporal scale of the analysis is another "lever" (or aspect) that can affect whether the results reflect direct or indirect land-use changes. Again, in an ideal case, if we have a sequence of maps with both high spatial and temporal resolution, it will, in general, be easier to distinguish between the direct and indirect drivers, because we can see for each pixel what the land is used for after it was deforested. However, even if we had perfect data on the sequences of land use, the question of how to allocate deforestation between land uses remains. Part of this question can be answered by knowledge about the typical time dynamics for the establishment of different crops and pasture in different places: for example, in Brazil, cropland, e.g., for soy can expand –

and be detected – quite rapidly after deforestation (Morton *et al.*, 2006; Song *et al.*, 2021), whereas oil palm takes longer and sometimes isn't planted until after several years of degraded land after deforestation (Gaveau *et al.*, 2016). This is the purpose of the time lag in our land-balance model: it intends to reflect that a certain amount of time is assumed to pass between the clearing of the forest and the establishment of subsequent land uses (though, as noted above, the suitable time lag may differ considerably between crops and regions, which is not yet reflected in our model).

However, part of the question of which land uses, or crops, to attribute deforestation to is more a matter of judgement (Davis *et al.*, 2014; Persson *et al.*, 2014) (this relates to the allocation problem used, for example, in life-cycle assessment (Baumann & Tillman, 2004)): We need to infer which of the products stemming from the cleared land were the drivers of the deforestation – and for how many years of subsequent production. There are several potential challenges here. First, some of the products produced on deforested land might not be the reason (or a very small part of the reason) for why the forest was cleared. For example, in South America, rice is sometimes planted for a year or two to prepare the land for subsequent soy cultivation (Brown *et al.*, 2013). Should any deforestation be attributed to that rice? Second, the drivers of deforestation are often interrelated and there might be multiple products being produced on the cleared land (e.g., through double- or triple-cropping (Galford *et al.*, 2008; Spera *et al.*, 2014) or in sequence over somewhat longer periods of time). For example, in Latin America, pasture is often the first agricultural land use following deforestation. However, increased demand for beef (or leather) is not always the only, or even the main, reason behind the expansion for pasture: instead, pasture expansion is often connected with soy, both as a result of indirect land use change where soybean cultivation has replaced pasture elsewhere (Barona *et al.*, 2010; Song *et al.*, 2021), and because the pasture and soy sectors are sometimes interconnected through capital and actors (Gasparri & le Polain de Waroux, 2015; Arima *et al.*, 2017; Richards & Arima, 2018). In time series data of land cover (or use), this might show as soy appearing after a few years (e.g., Song *et al.* (2021) find almost as much soy established more than three years after deforestation as they find soy that was established within three years). Third, non-land-use drivers of deforestation will not be apparent with this approach but can present similar allocation problems. Logging and timber harvesting can occur in conjunction with cropland expansion (and the relative economic rationale between them likely varies)(Gaveau *et al.*, 2013; Tarigan *et al.*, 2015; IUFRO, 2016). Should the deforestation then be split between soy and pasture, and between the timber and the crops, when there is such joint causality? And, if so, how? For some purposes, it is possible to attribute deforestation to multiple drivers (i.e., the same deforestation hectares or emissions are allocated to more than one product), but for others, it is important not to double count (e.g., consumption-based accounting, life-cycle assessment).

The choice of time lag is one way in which we can choose what part we see in the sequences of land uses following deforestation. In the examples above, a short time lag might tend to capture more rice and pasture, whereas a somewhat longer one might capture more soy. There is thus some a relationship between the time lag and whether the results will capture direct or indirect commodity drivers of deforestation. However, this relationship is neither unequivocal nor linear; certainly, we would not infer that the bare land (and also perhaps not the rice) following rather immediately after deforestation was the driver. To select an ideal time lag, we would already need to know quite a lot about the typical land-use dynamics in the region, including how long time it takes for different crops (or pasture) to become established (and observable in the data, be it remotely sensed or in agricultural statistics), about driver interrelationships and how they play out over time (such as pasture and soy in Latin America), and perhaps also which crops are the main motivation for clearing the land.

How specific one can be about the time lag and whether one can distinguish direct and indirect land-use drivers will depend on the temporal and spatial scale of the available data. If one has annual data (like the agricultural statistics we use in our land balance model, and as Song *et al.* (2021) have for soy), there is clearly more choice than when one uses single-year extent or land cover maps (like we use in Paper I, and like Goldman *et al.* (2020) use for a few drivers). However, to be able to give a good account on the land-use dynamic at the local scale, high resolution in both time and space is needed: for example, with our land balance model, even though we have an annual resolution of the input agricultural statistics, we still cannot separate direct and indirect drivers because of the poor spatial resolution.

Additionally, the deforestation was likely done with anticipation of returns for more than one year. This is the purpose of amortization in our land-balance model (it is sometimes called annualization: it deals with the choice of how many years of production to assign deforestation to (and whether to distribute it equally over the years, or tonnes produced, or in some other way); this becomes especially important when further attributing deforestation to commodities being produced from the agricultural land, e.g., when we want to connect them to trade (Cederberg *et al.*, 2011; Ponsioen & Blonk, 2012; Davis *et al.*, 2014; Hörtenhuber *et al.*, 2014; Persson *et al.*, 2014).

Another way of dealing with such temporal issues – both the time lag and the amortization – is to consider any commodity (and potentially derivatives) produced on land deforested after a given "cut-off date" as linked to deforestation. This is the approach taken by many recent zero-deforestation commitments and, e.g., in the proposed legislation on deforestation-free products in the EU (under which "*no commodities and products in the scope of the regulation would be allowed to enter or exit the EU market if they were produced on land subject to deforestation or forest degradation after that date [31 December 2020]*") (European Commission Directorate-General for Environment, 2021, p. 11).

Multiple decisions relating to spatial and temporal scale, and to allocation between drivers, will thus affect whether the deforestation attributed to commodities is direct or indirect. That said, most commodity drivers, at least as discussed in the type of research done here, are still rather close towards the end of the causal chain, compared with broader underlying drivers in the sense of, say demographic or institutional factors.

3.2. Approach

3.2.1. Attributing deforestation to agriculture, commodities, or other drivers

All papers included in this thesis provide quantifications of deforestation drivers, thus contributing to the aim of examining the causes of deforestation in the tropics. The approach used, however, differs between the papers (Table 3). Paper I presents a spatially explicit analysis, using global maps on forest loss and subsequent land cover to quantify to what extent forest loss is directly followed by cropland and pastures, respectively. Papers II and III attribute deforestation to more detailed groups of agricultural commodities, but at a coarser spatial scale, using a simple land-balance model with input data primarily summarised at the country level (Figure 2).

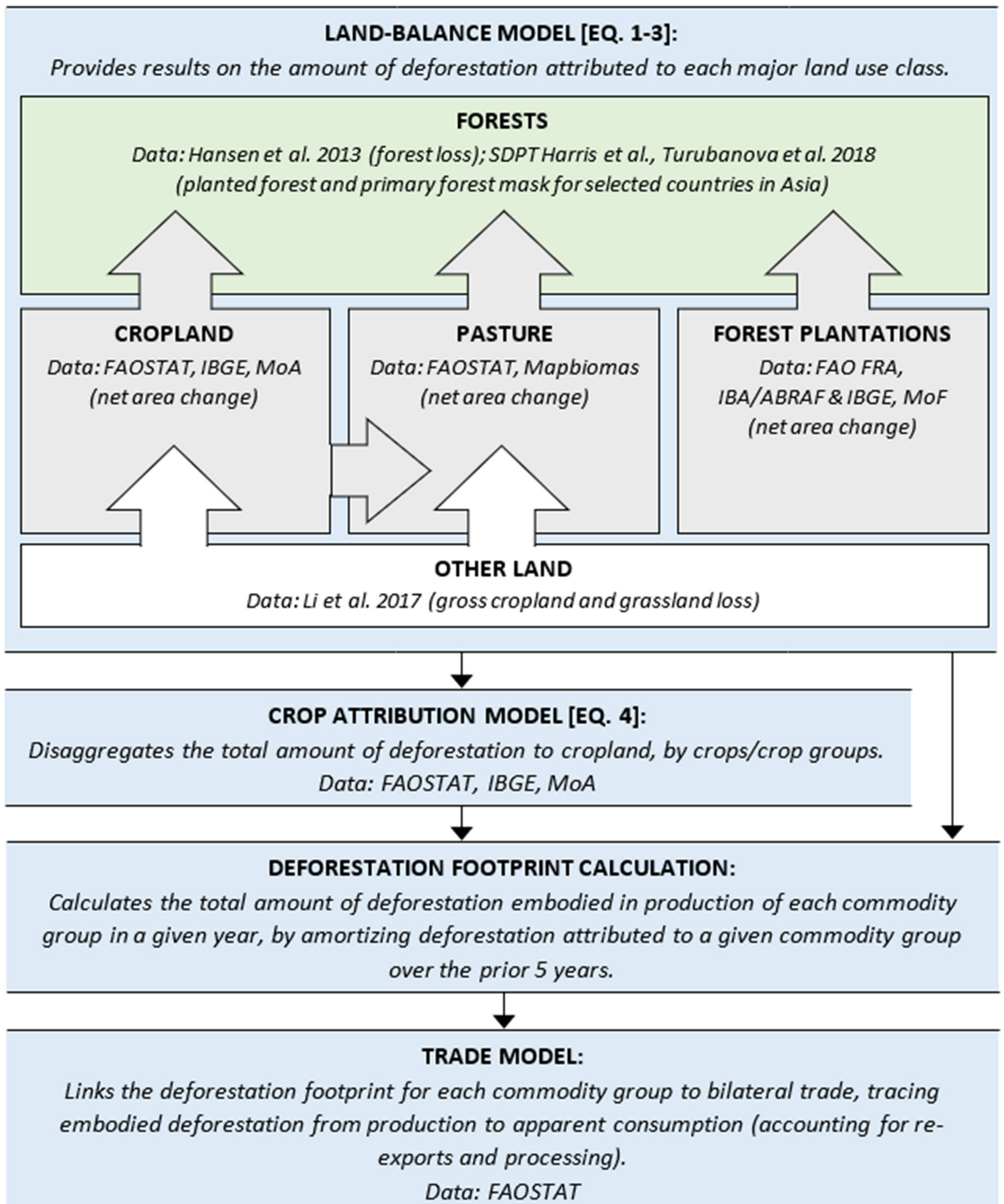

Figure 2. An overview of the main analysis steps of the land-balance model that was first introduced in Papers II & III, subsequently improved for Pendrill *et al.* (2022b), and used in Paper IV. This figure is an updated version of Figure 1 in Paper II, where the data sources have been updated to reflect the most recent version (Pendrill *et al.*, 2022b)

The basic assumption (based on the literature) that underlies this model is that if there is forest loss in a country, and pasture or cropland is expanding, the deforestation was due to the expanding agriculture. It is designed to reflect the predominant land-use transitions relating to tropical deforestation. The input data used for Paper II include those based on remote sensing, as well as agricultural statistics. Since the publication of Paper II, we have also developed and updated our land-balance model further, attributing deforestation to all individual crops in the FAOSTAT database (rather than to a more limited number of crop groups), which we have made available online on Zenodo (Pendrill *et al.*, 2022b). Results from this enhanced version of the model are included in Paper IV.

Paper IV reviews existing pantropical datasets as well as the literature, to quantify the direct expansion of productive agricultural land and, also, assesses more broadly the links between agriculture and land-use dynamics (e.g., land speculation). These papers all focus on tropical and subtropical areas: Paper I on Latin America, while Paper II and IV span, respectively, 156 and 87 countries across Latin America, Asia and Africa.

3.2.2. Attributing carbon emissions to commodity drivers

While the deforestation area associated with different agricultural drivers indicates the main causes of deforestation, the further consequences of these land-use changes also matter. Paper III seeks to identify further carbon emissions associated with the land-cover change from forest to something else.

In Paper III, the carbon emissions are quantified by estimating the changes to carbon stocks as a piece of land is changed from one type to another. Carbon is stored in biomass above ground (above-ground biomass, or AGB) as well as below ground (below-ground biomass, or BGB) and also in organic matter in the soil (soil organic carbon, or SOC) including in peatlands.

The knowledge and data available for different carbon reservoirs vary; the best described is generally AGB, while there is considerable uncertainty when it comes to BGB, and even more so for SOC. For changes in AGB, there are multiple spatially-explicit estimates based on remote sensing (e.g., Saatchi *et al.*, 2011; Baccini *et al.*, 2012; Harris *et al.*, 2012; Achard *et al.*, 2014; Tyukavina *et al.*, 2015; Avitabile *et al.*, 2016; Baccini *et al.*, 2017), which agree reasonably well at the continental level but diverge more at the regional level (Mitchard *et al.*, 2013; Avitabile *et al.*, 2016). For BGB, most studies follow an approach similar to the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) combining ratios between AGB and BGB with typical values from the literature. In Paper III, therefore, carbon stock change is estimated with different levels of precision and with varying levels of uncertainty, ranging from 30-m remote-sensing based data on the AGB stocks prior to forest loss (Zarin *et al.*, 2016) to estimates from the literature on typical SOC changes when a broad land-use category changes to another broad category (Don *et al.*, 2011). Thus, while the results indicate the carbon emissions associated with deforestation, significant improvements to the estimates of carbon stock (or carbon-stock changes) would be needed to quantify the actual emissions associated with each land-cover change.

3.3. Main findings

3.3.1. How much tropical deforestation is driven by agriculture?

The review in Paper IV revealed that existing pantropical estimates of the extent of agriculture-driven deforestation vary greatly, between 4.3 and 9.6 million hectares per year (on average from 2011–2015). A key explanation behind this seemingly large uncertainty is that agriculture contributes to deforestation in different ways, and the amount varies between estimates in part because they differ in what type of causality they assess.

A key contribution of Paper IV is that it explicitly distinguishes between (and quantifies) some of these different ways in which deforestation is driven by agriculture. First, it defines *agriculture-driven deforestation* as "*Deforestation for which agriculture, directly or indirectly, is a cause*". This definition was chosen to reflect that deforestation drivers often interact; even where agriculture is a driver of deforestation, there are always underlying (or indirect) drivers (Geist & Lambin, 2002; Meyfroidt, 2016). There may also be interacting direct drivers, e.g., deforestation might be directly due to both demand for agricultural expansion and demand for timber (Gaveau *et al.*, 2013; Tarigan *et al.*, 2015; IUFRO, 2016). We estimate that around 6.4–8.8 Mha/y, or 90–99%, of tropical deforestation is agriculture-driven in this sense.

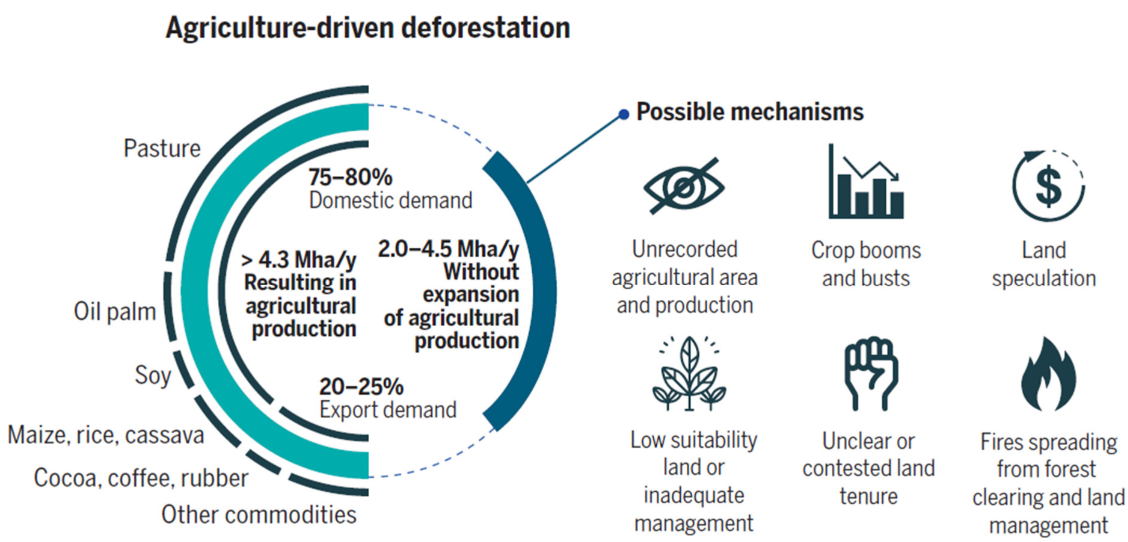

Figure 3. Agriculture contributes to deforestation in many, often interacting, ways. The overwhelming majority of tropical deforestation is *agriculture-driven deforestation* (the whole circle). Part of this constitutes *deforestation resulting in agricultural production* (left). However, there is also *agriculture-driven deforestation without expansion of agricultural production*, which can occur through several mechanisms (right). (Figure reused from Paper IV.)

Paper IV then subdivides this agriculture-driven deforestation into two mutually exclusive categories: (i) *Deforestation resulting in agricultural production* and (ii) *Agriculture-driven deforestation without expansion of agricultural production* (Figure 3). The first – *deforestation resulting in agricultural production* – is used for deforestation that can be attributed to the expansion of land under active agricultural production systems. This is often the kind of deforestation envisaged when we talk about deforestation driven by agriculture, where forests are cleared and replaced by some agricultural land use producing for example a crop, or cattle. This is also the kind of deforestation we quantify with our land-balance model, first presented in Paper II (and subsequently used in Papers III and IV), which amounts to at least 4.3 Mha/y on average from 2011–2015.

The second category – *agriculture-driven deforestation without expansion of agricultural production* – is used for deforestation occurring in landscapes where agriculture is the dominant driver of forest loss, but that does not result in recorded, productive, and actively-managed agricultural land. Based on multiple lines of evidence, Paper IV presents several potential mechanisms through which agriculture may drive deforestation without resulting in productive agricultural land. Such potential mechanisms include unclear or contested land tenure; land speculation; crop booms and busts; fires used for forest clearing or land management that spread to adjacent forests; and short-lived or abandoned agriculture, e.g., due to low suitability of the land or inadequate management. Incomplete records of agricultural area and production might also explain some of the deforestation currently in this category; this should then thus fall under *deforestation resulting in agricultural expansion* if monitoring systems improve. We find that around 2.0–4.5 Mha per year of agriculture-driven deforestation occurs without the expansion of agricultural production. Put together, this means that around one-third to one-quarter of agriculture-driven deforestation ends up not actually being used for agricultural production.

Though the main contribution of Paper I lies in highlighting some important limitations of combining global datasets/maps for assessing the drivers of deforestation (see Chapter 5), Paper I does also quantify deforestation that was driven by agriculture across Latin America. It uses a more spatially-explicit approach, determining where tree cover loss was replaced by cultivated land or grassland for the time period 2001–2011. Its estimates are reasonably similar to those found in Paper IV (Table 4), at least for the countries with the highest deforestation rates.

Using the distinctions from Paper IV, most of the deforestation attributed to agriculture in Paper I – at least for the expansion of cultivated land – would probably fall under *deforestation resulting in agricultural production* rather than *agriculture-driven deforestation without expansion of agricultural production*. That said, GlobeLand30's Cultivated land-class does also include abandoned arable lands (Chen *et al.*, 2015) and its Grassland-class (used in Paper I to identify pasture expansion into cleared forests) does not explicitly say whether or not the land is used for grazing. Part of it might thus instead be *agriculture-driven deforestation without expansion of agricultural production*, but that would not be readily distinguishable.

It is also possible that *agriculture-driven deforestation without expansion of agricultural production* might appear in additional classes in the GlobeLand30 following tree cover loss, such as shrubland or forest. Indeed, one of the challenges in interpreting the results in Paper I is that quite a large share (around one-third on average) of the GFC tree cover loss is still classified as Forest in the GlobeLand30 data in the years after the tree cover loss. One potential explanation for this could then be that it is due to *agriculture-driven deforestation without expansion of agricultural production,* which has been abandoned or not taken into use, thus resulting rapidly in enough regrowth for it to count as forest in GlobeLand30. However, without additional analyses, that would be pure speculation; there is currently not much there to say anything about the causality and establish whether GFC tree cover loss followed by GlobeLand30 Forest (or Shrubland) was agriculture-driven or not. Additionally, for most countries in Paper I, the data do not show an increase over time in the proportion of forest following the tree cover loss event; it is therefore not evident that regrowth is a large explanation for this. This could be explored further, for example, by comparing the spatially explicit results in Paper I to data on the dominant drivers of tree cover loss (Curtis *et al.*, 2018); to the by-country extents of agriculture-driven deforestation without expansion of agricultural production in Paper IV; and to the Vancutsem *et al.* (2021) data on tropical moist forest cover changes that show both short-lived forest disturbances and regrowth. That said, I think the main explanation discussed in Paper I still holds: that errors compound when datasets are combined and that this is further exacerbated by that the accuracy of remotely sensed data is lower when land cover is heterogeneous and forest losses are fragmented or small-scale.

Table 4. Comparison between estimated rates of agriculture-driven deforestation from pan-tropical studies for four Latin American countries. Rates are summarized across different time periods (in millions of hectares per year), for the four Latin American countries with the highest deforestation rates in 2011–2015. Note that deforestation rates have fluctuated over the years; for example, in Brazil the rates have fluctuated considerably, seeing a large decline after 2004, though rates began increasing again during the mid-2010s (Hansen *et al.*, 2013; INPE, 2022). Abbreviations used: "agr." = Agriculture, "def." = deforestation, "prod" = production, deforestation.

		Agr.-driven def.		**Def. resulting in agr. prod.**	**Deforestation replaced by cultivated land or grassland**
		Paper IV		**Paper IV, (Pendrill *et al.*, 2022b)**	**Paper I**
	Year	**L**	**H**		
Brazil	2001–2011				1.94
	2011–2015	1.54	2.01	1.21	
Argentina	2001–2011				0.26
	2011–2015	0.27	0.31	0	
Paraguay	2001–2011				0.20
	2011–2015	0.36	0.38	0.25	
Bolivia	2001–2011				0.15
	2011–2015	0.20	0.24	0.05	

3.3.2. Which commodities drive deforestation?

The results from our land-balance model, presented in Papers II and IV, show that much of the tropical deforestation resulting in agricultural production was associated with just a handful of commodities and land uses (Table 5, Figure 4). Pasture expansion is the dominant land use following deforestation by far, accounting for around half of the deforestation resulting in agricultural production (and forest plantations). The expansion of oil palm and soybean cultivation together accounts for approximately another fifth. Expansion of tree plantations is found to account for at least 8% (average 2016–2018), though there are indications that this is an underestimate (cf. Goldman *et al.*, 2020) (and it should be noted that this number does not comprehensively quantify the role of the demand for timber and other wood products, as only the role of expanding tree plantations is included; thus, e.g., the role of logging of natural forest that can precede the deforestation for the expansion of agriculture and other land uses is not captured). Much of the remainder of deforestation resulting in agricultural production is likely due to just six other commodities and crops: rubber, cocoa, coffee, rice, maize, and cassava (Figure 3), though these estimates are less reliable than for oil palm and soy.

Table 5. Deforestation attribution to commodities – aggerated into groups – by region. Rates are in thousands of hectares per year, on average for 2016–2018. Data from our land-balance model, version 1.1 (Pendrill *et al.*, 2022b). This is the same version of the data as used in Paper IV, though here presented from a larger set of 135 countries and a different time period.

Commodity / region:	**Brazil**	**Rest of Americas**	**Indonesia**	**Rest of Asia-Pacific**	**Rest of Africa**	**Total**
Cattle products	1 261	221	21	387	958	**2 849**
Palm oil	3	67	689	11	6	**775**
Forest plantation	187	123	4	110	30	**453**
Vegetables, fruit, nuts	40	124	57	75	99	**396**
Cereal grains nec	81	81	100	15	52	**329**
Crops nec	14	125	55	39	37	**269**
Soybeans	185	44	21	0	5	**255**
Paddy rice	9	31	121	60	22	**244**
Oil seeds	22	8	1	20	31	**82**
Total	1 802	824	1 070	718	1 239	**5 652**

The variation between countries is large, however. In the Asia-Pacific region, palm oil and tree plantations together accounted for just under half of the deforestation resulting in agricultural production (or tree plantation expansion) during 2016–2018, while in Latin America, cattle meat alone accounted for more than half of the deforestation resulting agricultural production (Table 5, Figure 4). Paper I also assesses the relative roles of cropland and pasture expansion in replacing forests across Latin America. It also shows large variations in the dominating land uses following deforestation between – and within – countries.

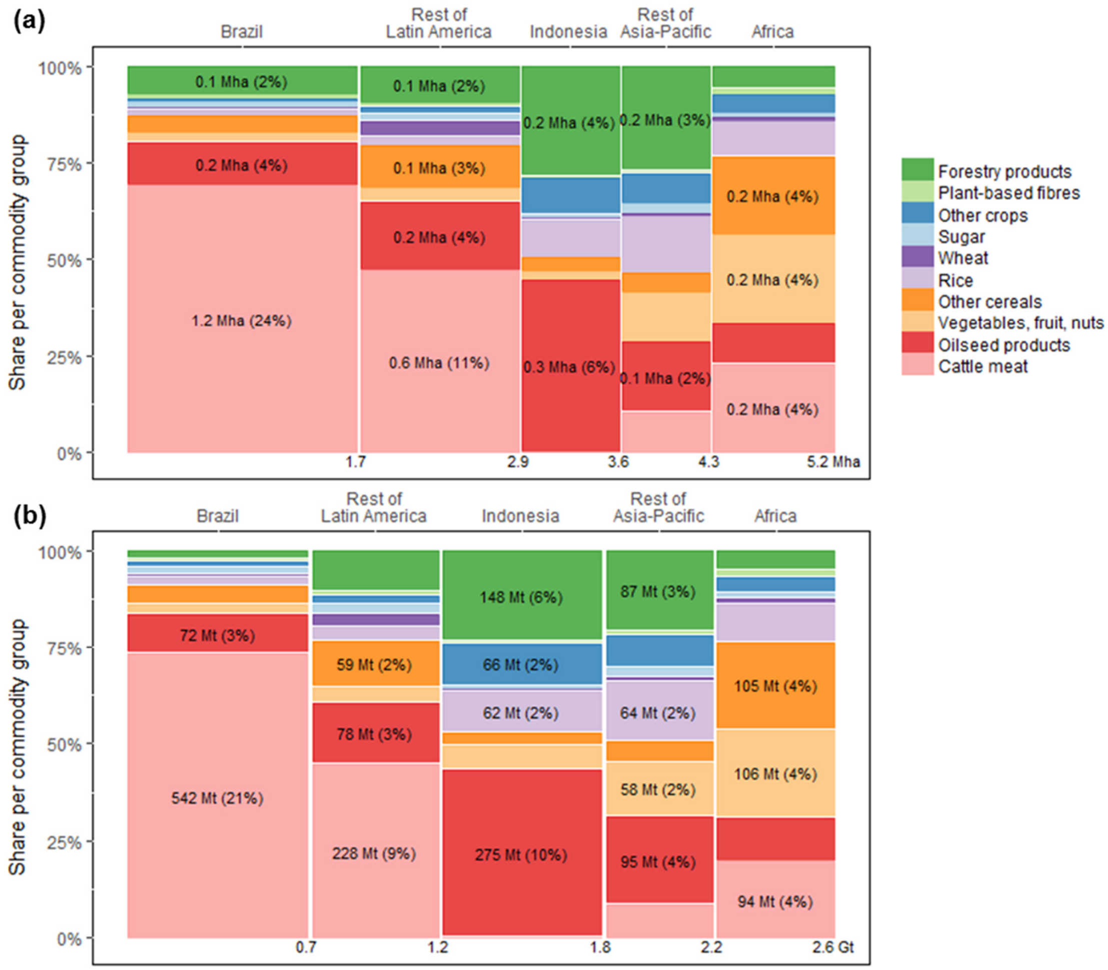

Figure 4. Attribution of deforestation area (in millions of hectares) **(a)** and carbon dioxide emissions (in megatonnes of CO_2) **(b)** per year (on average for the period 2011–2014) to commodities and regions from Papers II and III. The width of a region on the x-axes corresponds to the total deforestation area/emissions attributed to that region, whereas the y-axes show the relative proportion within each country/region attributed to each commodity group. The area of the rectangles in the figure thus represents the deforestation area/emissions attributed to each region-commodity group combination, and the percentages within them indicate each combination's proportion of the embodied deforestation area/emissions. (The data for Paper II have been modified to match the commodity groups and set of countries used in Paper III.)

In general, less deforestation is attributed to grassland in Paper I than to pasture in Paper II. This difference is probably largely due to the incomplete separation between cropland and pasture in the dataset used in Paper I; instead of distinct classes for pasture and cropland, it has classes for Grassland and Cultivated land, which both include certain pasture types. Overall, therefore, though the papers provide quite a coherent picture of the area of forest loss driven by the expansion of agriculture, the results from our land-balance model likely provide a better representation of deforestation attributed to pasture and cropland than does Paper I. Paper IV further compares the results from our land-balance model with other studies; most notably, Goldman *et al.* (2020), but also several regional or national-specific studies for key commodities and countries.

The uncertainty varies considerably between commodities. Paper IV discusses several sources of uncertainty in estimates of commodity-driven deforestation, including the availability and quality of underlying data; interrelated drivers [e.g., deforestation for pasture in Latin America is often interlinked with other drivers, including crops and land speculation (Richards *et al.*, 2014; Gasparri & le Polain de Waroux, 2015; Gibbs *et al.*, 2015b; Miranda *et al.*, 2019)]; and to what extent the methods are able to adequately describe the dynamics of different deforestation drivers. Some key results from this are discussed in Chapter 5.

Another valuable output from the research for this thesis is also the dataset itself (Pendrill *et al.*, 2022b) attributing deforestation across the tropics to all individual commodities in the FAOSTAT data for every year from 2005 to 2018. This dataset is produced using our land-balance model (introduced in Paper II) and is one of the first and, currently, the most comprehensive, sources describing the extent and type of commodity-driven tropical deforestation (Pendrill *et al.*, 2022a). This dataset has been used by non-governmental organisations (e.g., WWF (Pacheco *et al.*, 2021) and Ceres (Richards *et al.*, 2020)), government agencies, e.g., in the UK (Croft *et al.*, 2021) and Denmark (Energistyrelsen, 2021), and by the EU Commission (European Commission Directorate-General for Environment, 2021).

3.3.3. Attributed deforestation compared to attributed deforestation emissions

The results from Paper II and Paper III can be used to investigate how the choice of indicator – here hectares of deforestation versus CO_2 emissions resulting from the land-use change – can influence the result. While the main commodities associated with deforestation-related carbon emissions in Paper III are similar to the commodities associated with deforestation area in Paper II, the relative importance of countries and commodities differ somewhat (Figure 4). In the deforestation-area attribution, Brazil is the dominating country by far (33% of the total). In the attribution of the associated carbon emissions, Brazil is still dominant; however, its relative role is smaller (around a quarter), while the relative role of Indonesia is notably larger (from around a seventh of the deforestation-area attribution, to almost a quarter for the carbon-emission attribution). Similarly, cattle meat is the dominant commodity irrespective of the indicator, but less markedly so for the deforestation carbon emissions than for deforestation area. Conversely, the relative role of oilseeds is greater from an emissions perspective, especially for Indonesia and the rest of the Asia-Pacific region.

In short, while the broad picture is similar concerning drivers of deforestation and its concomitant carbon emissions, there are some notable differences in the relative role of both countries and individual commodities. As such, deforestation area is an incomplete indicator of the carbon emissions associated with deforestation. For other impact categories, such as biodiversity and changes to local climate and hydrology, the differences can potentially be larger (and almost certainly different), making it important to be aware that single indicators give but a limited view of the full impacts of deforestation.

4. What is the contribution of international trade to driving deforestation and associated CO_2 emissions?

4.1. Background

4.1.1. Following embodied deforestation and emissions through trade to consumption

The previous parts of this thesis have focussed on analysing drivers of deforestation in the vicinity of where forests are being lost. However, the patterns of demand are becoming more complex and spatially disconnected from the supply, as products are increasingly traded internationally, often in multi-stage supply chains (Lambin & Meyfroidt, 2011; Yu *et al.*, 2013; Wood *et al.*, 2018). It is therefore vital not only to consider the causes of deforestation at the point of production but also to understand where – and for what purpose – the demand is arising.

There is, therefore, increasing recognition that only evaluating impacts from the production side can be limiting, especially when responsibility is to be assigned and where policies do not cover the entire system of interest (Munksgaard & Pedersen, 2001; Peters, 2008; Duus-Otterström & Hjorthen, 2019). A prominent example of this is that countries committing to reduce their carbon emissions under the United Nations Framework Convention on Climate Change and the Kyoto Protocol (sometimes referred to as Annex-I or Annex-B countries) report only emissions occurring within their national/territorial boundaries (IPCC, 2006). There are indications that this territorial approach has resulted in (at least weak) carbon leakage: developed Annex-I countries seeking to reduce their domestic emissions tend to be net importers of embodied carbon emissions, thus meeting part of their consumption needs by relying on imports from (primarily developing) countries not covered by the emissions-reduction commitments (non-Annex I/B countries) (Peters & Hertwich, 2008; Peters, 2010; Peters *et al.*, 2011; Kanemoto *et al.*, 2014). (However, this trend may be changing: net emissions transfers between OECD and non-OECD countries peaked and then plateaued after 2006, as did emissions embodied in both production and consumption in OECD countries (Wood *et al.*, 2019). Still, developed countries do remain net importers of embodied emissions.) Also, as the capacity to act towards reducing impacts lies not only at the point of production but potentially also along the supply chain all the way to the point of consumption (e.g., by reducing demand in the first place), there is increasing attention brought to the value of complementing production-based approaches with different perspectives, including consumption-based ("downstream") ones, as well as those sharing responsibility between producers and consumers (Lenzen & Murray, 2010; Steininger *et al.*, 2016; Duus-Otterström & Hjorthen, 2019).

The role of international trade and consumption in driving deforestation and deforestation emissions has gained increasing attention in recent years. There are multiple supply chain initiatives to reduce deforestation in the private sector (Lambin *et al.*, 2018; Ellis & Weatherer, 2022) and the public sector is following suit. The EU, the UK, and the US all current have proposed legislation focused on regulating the import of agricultural and forestry commodities stemming from deforested land (European Commission, 2021; Schatz, 2021; UK Public General Acts, 2021). A few countries, including the UK (Croft *et al.*, 2021) and Sweden (Miljömålsberedningen, 2022), are additionally considering and experimenting with indicators on their consumption-based impacts on climate and on the environment more broadly (including those from deforestation). Indeed, the research in this thesis partly aimed at contributing to a research project on "*Policy-Relevant Indicators for National Consumption and Environment*" (PRINCE) funded by Swedish Environmental Protection Agency (Steinbach *et al.*, 2018).

Trade models enable the evaluation of impacts from consumption-based perspectives, thus complementing production-based assessments (Peters, 2008; Lenzen & Murray, 2010; Wiedmann *et al.*, 2011; Wiedmann & Lenzen, 2018). They are frequently used for calculating the embodied, upstream impacts associated with the consumption of a product (similar to the goal of a life-cycle assessment), or for looking at the trade of environmental impacts between countries (trade models, in general, are also widely used outside the environmental domain) (Miller & Blair, 2009; Minx *et al.*, 2009; Kitzes, 2013; Wiedmann & Lenzen, 2018).

A common use of trade models thus lies in carbon footprinting and consumption-based accounting of CO_2 emissions (e.g., Peters, 2008; Davis & Caldeira, 2010; Peters *et al.*, 2011), environmental (Weinzettel *et al.*, 2014) and material footprinting (Wiedmann *et al.*, 2015), along with a range of other impacts embodied in trade (Wiedmann & Lenzen, 2018), including water consumption (Lutter *et al.*, 2016), biomass (Erb *et al.*, 2009), biodiversity loss and species threats (Moran & Kanemoto, 2017; Sun *et al.*, 2022), and health impacts of air pollution (Zhang *et al.*, 2017). Closer to the area of interest in this thesis, there have been several studies assessing land use embodied in trade (e.g., Meyfroidt *et al.*, 2010; Steen-Olsen *et al.*, 2012; Weinzettel *et al.*, 2013). However, prior to my research, there were very few studies of land-use *change* embodied in trade. At that point, studies were limited to a few countries and commodities (Saikku *et al.*, 2012; Karstensen *et al.*, 2013; Henders *et al.*, 2015) or of highly limited temporal resolution and availability (Cuypers *et al.*, 2013). In the past few years, there have come multiple studies exploring more detailed deforestation and trade relationships (frequently based on the Trase data, e.g., (Escobar *et al.*, 2020; zu Ermgassen *et al.*, 2020a; zu Ermgassen *et al.*, 2020b; Leijten *et al.*, 2022)), but there are still very few studies that cover a comprehensive set of agricultural commodities across the whole tropics (the main exception is Nguyen and Kanemoto (2021)). In this thesis, Papers II and III seek to fill part of this gap, by quantifying pan-tropical deforestation embodied in trade.

By examining where the demand for the products stems from, trade models present one way of beginning to "unpack" the sources of the demand behind the direct drivers of deforestation. We might find out from where – geographically – the demand originates. With some types of trade models, we can also gain information on which sector of the economy (e.g., cattle farming, manufacturing, or retail) generates the demand. In this way, we can learn more about the linkages between consumption and a range of environmental impacts associated with the production (Kitzes, 2013; Henders & Ostwald, 2014).

The most common types of trade models used for examining environmental linkages range from (a) direct adoption of bilateral trade statistics and (b) (bio-)physical trade models, to (c) multi-regional input-output (MRIO) models (Kitzes, 2013; Henders & Ostwald, 2014; Bruckner *et al.*, 2015; Schaffartzik *et al.*, 2015; Hubacek & Feng, 2016). The boundaries between the different types are not fixed, and hybrid approaches exist to varying extents. These models have several commonalities and some key differences. They differ particularly in the type of metric used (economic, i.e., dollars, in the typical MRIOs, versus physical units, e.g., kilograms, in the physical trade models) and in how far down the supply chain the embodied impacts are followed (Kitzes, 2013; Henders & Ostwald, 2014; Bruckner *et al.*, 2015; Schaffartzik *et al.*, 2015; Hubacek & Feng, 2016).

These approaches thus reflect different views on what constitutes (the place of) consumption; in complex supply chains, there can be many points at which a product (e.g., soy) can be traded, re-exported, used as an input for further processing, or consumed (e.g., in a service sector). For example, a ton of soy can be exported from Brazil to the Netherlands, re-exported to Germany, where it is crushed and subsequently exported to Spain, fed to pigs, ending up as ham on a frozen pizza produced in Italy, eaten by workers in a French factory producing cars subsequently sold to a final consumer in the UK. In addition to the point of final consumption (which is primarily identified in MRIO models), there can therefore also be many points of intermediate consumption, which for some purposes – e.g., those seeking to address deforestation through international supply chains – may be more relevant than final consumption. Different trade model approaches seek to portray these different levels of consumption, and the different models are therefore suitable for different research questions and policy purposes (Kitzes, 2013; Bruckner *et al.*, 2015; Schaffartzik *et al.*, 2015; Hubacek & Feng, 2016).

Direct adoption of bilateral trade statistics is the most basic method of linking production to consumers through trade. As an example, this is the method adopted by the Trase platform (www.trase.earth) for selected commodity production and export systems (e.g., soy and beef from several countries in South America (zu Ermgassen *et al.*, 2020a; zu Ermgassen *et al.*, 2020b)). With this type of approach, the point of first import is considered the point of demand; i.e., in the example above, this would be in the Netherlands.

Physical trade models, sometimes also called biophysical trade models, (bio-)physical accounting, go one or a few steps further towards accounting also for the fact that products (i) that have been imported may be exported again, either in the same form as they were originally imported (re-exported), and (ii) may have been further processed before original or subsequent export (Bruckner *et al.*, 2015; Schaffartzik *et al.*, 2015; Hubacek & Feng, 2016). Accounting for re-exports and processing requires choices about how to deal with imbalances in trade statistics and – when accounting for derived forms – how to link processed materials back to their raw equivalents (Kastner *et al.*, 2011; Bruckner *et al.*, 2019). Whilst some of these models (e.g., Kastner *et al.*, 2011; Croft *et al.*, 2018; Bruckner *et al.*, 2019) can account for some level of processing, processing into more complex products or their use within, e.g., services, is typically not included. They thus model the supply chain to a point of intermediate, rather than final, consumption; i.e., in the example above, this would be in Germany or Spain.

Multi-regional input-output (MRIO) models aim to model supply chain flows to the point of final consumption. They thus seek to comprehensively account for intermediate inputs and processing through all (or most) sectors of the economy, in order to identify the final (rather than an intermediate) point of consumption of products or services (Kitzes, 2013); i.e., in the example above, this would be in the UK. Alongside the frequent use of MRIOs to assess the trade in various environmental impacts, input-output modelling was originally developed outside of the environmental domain and remains widely used for many other purposes (Miller & Blair, 2009). Examples of MRIOs include Eora (Lenzen *et al.*, 2012a; Lenzen *et al.*, 2013b), Exiobase (Stadler *et al.*, 2018) and GTAP (Aguiar *et al.*, 2019)).

The type of trade model, consequently, affects the type/level of driver that the results will describe, and the choice of model should, therefore, be made with consideration for the research questions or policy aims (Bruckner *et al.*, 2015; MacDonald *et al.*, 2015; Hubacek & Feng, 2016). Understanding the country-to-country trade flows using a physical trade model (or, ideally, with even higher spatial resolution within a country) is probably more relevant for actors such as companies, investors and governments wanting to reduce deforestation through direct supply chain interventions such as due diligence requirements on imported products, commodity moratoria, zero-deforestation commitments, and other demand-side and supply chain measures. For example, unless a piece of legislation intends to require due diligence on very highly processed products or on services, an MRIO is likely less suitable. However, for consumption-based accounting, using an MRIO analysis to follow embodied impacts further through the supply chain to the point of final demand is more useful for understanding better the underlying drivers (Peters, 2008; Wiedmann & Barrett, 2013; Hubacek & Feng, 2016). Thus, the choice of methods for the attribution of deforestation drivers and the choice of trade model affects the type of driver and level of causality described.

4.1.2. A primer to input-output trade models

Here I will give a brief and simplified introduction to input-output modelling. This is the basis for MRIOs, and parts also apply to physical trade models. For a more thorough introduction, see, e.g., Kitzes (2013) and Miller and Blair (2009).

In essence, trade models describe interrelationships between sectors and between regions (e.g., countries). Sectors (and regions) are not only producers of goods (outputs), but also consume goods (inputs) while producing their outputs (Miller & Blair, 2009). Thus, in order to meet a given level of final/external demand, the total output from sectors needs to cover not only the final demand but also the demand for intermediary products (as inputs) in various production sectors (Miller & Blair, 2009; Kitzes, 2013). To take an example (illustrated in Figure 5a), imagine a very simple economy consisting of two sectors: agriculture and industry. To produce output, the agriculture sector uses various inputs, both from its own sector (e.g., feed for cattle) and from the industry sector (e.g., machinery and fertiliser). These intermediary products also need to be produced, which in turn require further inputs, and so on, and so forth. Input-output modelling provides a way to summarise all of these "upstream" inputs, without double counting them, to find the total output needed to meet a certain level of final demand (Kitzes, 2013).

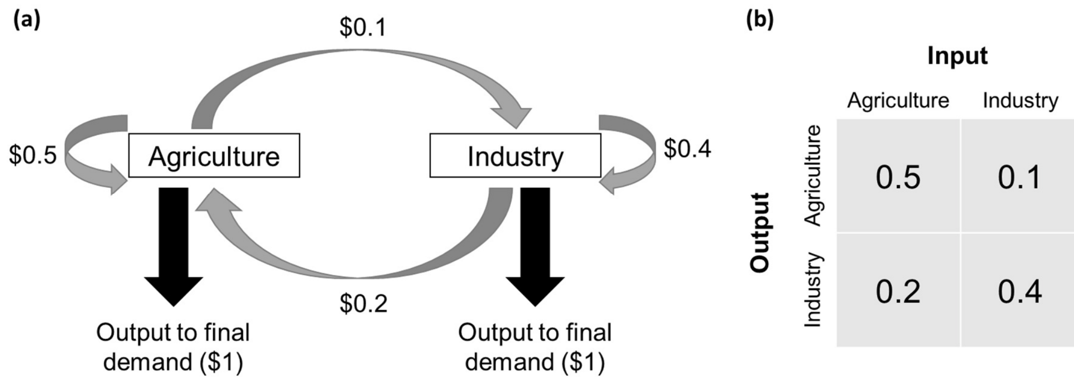

Figure 5. A simplified example of input-output sector interrelationships. **(a)** Schematic illustration of two sectors consuming inputs and producing output both for final demand and for use as inputs in other sectors (intermediary products). The dollar values show the amounts of input needed to produce $1 of output to final demand. In this example, producing $1 of agricultural output requires $0.5 of input from agriculture as well as $0.2 from industry. **(b)** A corresponding technical coefficients matrix (**A**) shows the same thing. The technical coefficients matrix, in essence, gives a ”recipe” of the inputs needed to create $1 of output from each sector. Viewed in another way, **A** also shows the share of output from one sector going to another; here, for example, 10% of the output from agriculture is consumed by the industry sector.

This is accomplished using a set of vectors, matrices and linear algebra equations, at the core of which lies the technical coefficients matrix, **A***,* which describes the interrelationships between sectors (and regions) mentioned above (Miller & Blair, 2009; Kitzes, 2013) (an example is illustrated in Figure 5b). The technical coefficients matrix shows both where the outputs from each sector go (if reading the rows) and what inputs are needed by the sector (if reading the columns) (Miller & Blair, 2009). So, element a_{ij} of **A** shows the share of output from sector i that is consumed by sector j. The Leontief Input-Output model (named by its creator),

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}$$

can then be used to find the total output vector **x**, depending on the level of final demand expressed in vector **y** (each with one element for each sector) (Miller & Blair, 2009). (**I** is an identity matrix, and $(\mathbf{I} - \mathbf{A})^{-1}$ is sometimes called the Leontief matrix.)

A *multi-regional* input-output analysis (MRIO) works the same way, but where each element corresponds to *sector-region* combinations, rather than just between sectors (Miller & Blair, 2009). The type of physical trade model used in Papers II–IV also uses similar mathematics to describe trade between countries (export shares) by assuming that domestic production and imports are distributed proportionally between consumption as well as exports (Kastner *et al.*, 2011).

Environmental input-output analysis – that is, connecting some kind of environmental impact to the trade – expands the Leontief model described above by accounting also for some type(s) of environmental impacts associated with the total output needed to meet a level of final demand (or, e.g., for a single product bought by a consumer). This is done by introducing (pre-multiplying by) an intensity vector listing the environmental impacts (e.g., tonnes of carbon emissions) associated with \$1 (or, e.g., 1 tonne, 1 kcal, or 1 gram of protein, if it is a model using physical units) of sector output for each sector (Wiedmann *et al.*, 2011; Kitzes, 2013).

4.1.3. Limitations of trade models

One central limitation shared by all trade models is an assumption of homogeneity. All products within the same sector (or sector-region combination) are assumed to be exported to the same extent (that specified in **A**). They are also assumed to have the same environmental impact (per unit of measure; e.g., per dollar, in the case of MRIOs, or, e.g., per kilo or calorie of product, in the case of physical trade models) (Kitzes, 2013; Bruckner *et al.*, 2015). These are oversimplifications, further exacerbated by the fact that commodity categories, and sometimes also regions, are in many cases quite aggregated, especially for global MRIOs (Bouwmeester & Oosterhaven, 2013; Majeau-Bettez *et al.*, 2016). For example, EXIOBASE3, the MRIO database used in Papers III and IV has a joint category for "other crops". This category mixes cash crops (such as cocoa, coffee and tea) with subsistence products (such as cassava) (Stadler *et al.*, 2018; Weinzettel & Wood, 2018), which clearly differ in the extent to which they are exported and quite likely also in the environmental impact of their production. EXIOBASE is one of the global MRIOs with the highest resolution for food sectors, though the most recent version of GTAP (10) has a higher sectoral resolution for agriculture (Aguiar *et al.*, 2019).

Another limitation of trade models lies in the quality of the input data (Kitzes, 2013; Tukker *et al.*, 2018). The values in matrix **A** describing the interrelationships between sectors and countries/regions are based on observed economic data (and thus limited by the time frames for which such data are available) (Miller & Blair, 2009; Wiedmann *et al.*, 2011; Kitzes, 2013). These data are often compiled from multiple sources, which may not be using the same standards, introducing additional uncertainties. For MRIOs, transactions between sectors within countries are often based on data from supply-and-use tables compiled by national statistics offices; for trade between countries, a common data source is the UN Commodity Trade Statistics Database (Comtrade) (Tukker & Dietzenbacher, 2013). Comtrade collates trade statistics from official records (*What is UN Comtrade?* , 2020), and these vary considerably in quality. Those compiling global MRIOs often need to reconcile conflicting data as well as infer data where they are missing, and many MRIOs also have some "rest-of-the-world" regions, grouping together multiple countries which may differ considerably in their trade patterns (Wiedmann *et al.*, 2011; Tukker & Dietzenbacher, 2013; Tukker *et al.*, 2018). For physical trade models focused on agricultural trade, data from the UN FAO's FAOSTAT are often used. For this, the FAO compiles data from a combination of sources, including the United Nations Statistics Division (UNSD, which manages UN Comtrade), Eurostat, and national authorities (FAO, 2017). The source data are checked for outliers, and trade partner data is used for non-reporting countries or missing data, but this means that – in contrast to UN Comtrade – many entries are based on trade-partner records or unofficial figures.

4.2. Approach

To examine further where the demand for commodities associated with deforestation stems from, Papers II and III use trade models to trace the commodities with embodied deforestation (Paper II) and concomitant emissions (Paper III) through international supply chains to consumers across the world. The use of trade models permits an examination of the relative roles of domestic and international demand, as well as the identification of major consumer countries and regions.

In both Papers II and III, a physical trade model by Kastner *et al.* (2011) was used to follow country-to-country trade flows to where commodities were physically consumed as food or in industrial processes. Paper III additionally used a state-of-the-art multi-regional input-output model (MRIO), EXIOBASE3 (Wood *et al.*, 2015; Stadler *et al.*, 2018). The MRIO provides a complementary perspective by following the embodied deforestation and deforestation emissions further through monetary trade flows in all sectors of the economy (although with less detailed regional and commodity resolution). The MRIO data thus includes embodied deforestation initially utilized domestically and subsequently exported in different forms, such as protein and biodiesel, as well as more indirectly, e.g., in services. Paper IV also summarises the relative roles of domestic and export demand, using data from our updated data on deforestation (and deforestation emissions) risk embodied in production and consumption uploaded to Zenodo (Pendrill *et al.*, 2022b), based on both the trade model approaches (the Kastner *et al.* (2011) physical trade model and the EXIOBASE MRIO).

Looking at deforestation embodied in international trade also permits widening the focus to include a consumption perspective on deforestation, in addition to more conventional production-side perspectives.

For deforestation, in Paper II, we relate imports of embodied deforestation to trends and changes in forest cover within the importing countries. In particular, we do this in light of their stage of *forest transition*. Forest transitions is a concept used to describe where regions (or countries), as they develop, tend to shift from decreasing their (net) forest area to increasing it instead (Mather, 1992; Rudel *et al.*, 2005). Thus, we first distinguish between countries in different stages of forest transition, depending on their rate of forest change and current forest cover. We then assess whether countries that are increasing their forest cover or reducing their deforestation rates (i.e., countries that have gone through or are undergoing a forest transition), also tend to import commodities that are contributing to deforestation in other countries. We also calculate to what extent such imports of embodied deforestation offset the forest gains made by countries that have undergone a forest transition.

For deforestation emissions, in Paper III, we make several consumption-side comparisons. We compare the imports of embodied deforestation by developed (Annex I) countries to the size of domestic (territorial) agricultural emissions as reported to the UNFCCC. We also calculate deforestation/land-use change carbon footprints: per capita, for countries' food consumption, and per kilogram of product, for key forest risk commodities.

4.3. Main findings

4.3.1. Role of international trade and domestic consumption

Papers II and III in this thesis were among the first to quantify the relative roles of domestic and export demand that underlies the commodity-driven deforestation, revealing that around three-quarters of commodities with embodied deforestation area and emissions are primarily consumed domestically. Though domestic consumption thus dominates, there is still a substantial share, especially of some commodities, which are destined for export markets and eventually consumed outside the producing country, and thus outside the country where the deforestation impacts took place.

As noted above, the choice of the type of trade model will affect the results. On average (2011–2015) for the physical trade model 24% of deforestation embodied in agricultural commodity production was exported (based on Pendrill *et al.* (2022b), which presents updated estimates of deforestation embodied in trade building on the model introduced in Papers II and III)). The results from MRIO show that on average 35% of deforestation attributed to agricultural commodity production is ultimately linked to final consumption in countries other than that of production.

The relative importance of domestic and international demand varies considerably between commodities. Beef is primarily consumed domestically (international demand accounting for only 12% in the physical trade model, 24% in the MRIO), while palm oil and soy are primarily linked to international demand (physical trade model, soy: 69%, palm oil: 58%, MRIO: oilseeds 75%) (Pendrill *et al.*, 2022b) (Figure 6).

The share of embodied deforestation and concomitant emissions attributed to international demand varies significantly not only between commodities but also between countries. For countries in the Asia-Pacific region, nearly half of the embodied deforestation and deforestation emissions were attributed to international demand (on average, 39% and 44% exported, respectively), whereas for countries in Africa, the demand for commodities with embodied deforestation and deforestation emissions was primarily domestic (on average, 10% and 9% exported, respectively).

Though domestic consumption remains the dominant underlying source of demand, the share of deforestation embodied in international trade (around 35% in the results from the MRIO) is still substantial compared with most other types of environmental impacts [excepting the extraction of raw materials, ores, and coal (Wiedmann & Lenzen, 2018)]. The equivalent share in MRIO studies assessing varying environmental impacts are, for example, 23–26% of fossil carbon emissions (Davis and Caldeira (2010); Peters *et al.* (2011), 22% of health impacts of air pollution (Zhang *et al.* (2017)), 25–28% of nitrogen pollution (Oita *et al.* (2016)), 24–32% of water consumption (Lenzen *et al.* (2013a)), 30% of global species threat (Lenzen *et al.* (2012b)), 25% of all agro-food emissions (based on physical product flows) (Piñero *et al.*, 2022), and 22% of agricultural land and 27% of land use emissions (Hong *et al.*, 2022). This is a key result of Paper III, which is further pronounced if looking solely at crops, where the share exported is 48%.

Paper II shows that this high export share of embodied deforestation stems mainly from Brazil, Indonesia, and Argentina, which are high-deforestation countries, and export much of their crops (27–74%) and especially those with embodied deforestation (49–76%).

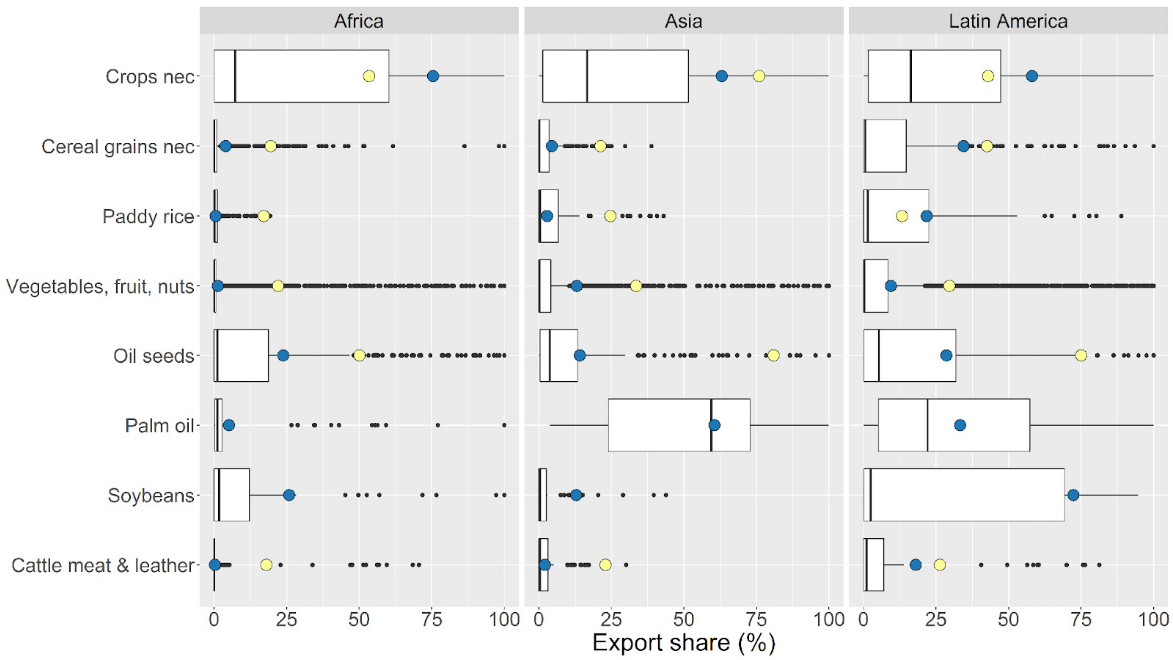

Figure 6. Country-level distribution of the share of deforestation embodied in commodity production that is exported, by commodity groups and major tropical regions for the period 2011–2015, based on a physical trade model Kastner *et al.* (2011). Data is taken from Pendrill *et al.* (2022b). The boxplots are based on country-year values within each region and represent the median, first and third quartiles, with whiskers showing the maximum and minimum values (though extending no further than 1.5 times the interquartile range; black dots indicate outliers). The blue coloured circles show the weighted average export share for the physical trade model (Kastner), and the yellow circles show the average export share for the multiregional input-output model EXIOBASE (there are no boxplots for this model, as the regional aggregation implies there are only a couple of data points per region). The fact that the average export share for the physical model is typically higher (by margin) than the median share, reflects the fact that major producers of each commodity tend to export larger shares. Note that the results from the two models are not directly comparable, due to differences in system boundaries and model structure (see Chapter 4.1 for a discussion on differences between trade model types). This figure and caption are reused from the supporting material of Paper IV.

4.3.2. Consumption of traded deforestation

Although domestic consumption remains the key driver of demand for the agricultural commodities contributing to deforestation, the results in both Papers II and II show that, from a consumption perspective, imports of embodied deforestation can still be sizeable. It is also possible that the international trade flows may have an outsized role in driving landscape-scale land-use dynamics, though this is not something I have explored in my thesis.

In Paper II, we found that a majority (79%) of exported deforestation is consumed in countries that are currently increasing their forest cover (post-forest transition countries), thus partly offsetting some of the net forest gains made by these countries. For many countries, imports of embodied deforestation rivalled or exceeded domestic gains in forest area: for example, for India, deforestation abroad offset almost 60% of forest gains. On average, imports of embodied deforestation offset around a third of the net forest gains made in the countries that have undergone a forest transition. The net forest area saved in the post-forest transition countries is potentially larger, though, as imports may also have prevented domestic deforestation (in addition to enabling forests to expand). However, the results do indicate (in line with Pfaff and Walker (2010)), that achieving a global forest transition will be more challenging than achieving local or regional ones since there is no "outside region" that can help facilitate a global forest transition by supplying land-demanding products.

In Paper III, we found that, for many developed countries, the imports of embodied deforestation emissions are of a similar order of magnitude as the domestic emissions from agriculture. On average, for the Annex I countries to the UNFCCC, deforestation emissions embodied in imports amount to 17–31% of the reported territorial agricultural emissions. For key forest-risk commodities, such as palm oil and beef, we found carbon footprints from deforestation and peatland drainage to be in the same order of magnitude as non-land-use change emission footprint. The per capita deforestation carbon footprint of food consumption was found to be highest for Brazil (2.6 tCO_2 cap^{-1} yr^{-1}; primarily due to domestic beef consumption). For emerging economies (China, India, South Africa), the footprints are generally low (< 0.1 tCO_2 cap^{-1} yr^{-1}), while for most developed countries they lie around 0.3 tCO_2 cap^{-1} yr^{-1}. For the EU, this implies that deforestation emissions in the period 2010–2014 constituted a substantial share (around 15%) of the total carbon footprint of an average EU diet. Thus, although the overall contribution of EU consumption on the total extent of tropical deforestation is fairly small, it remains a relatively large share of the climate impact of the EU's food consumption.

5. What are the current key limitations & knowledge gaps for assessing the drivers of deforestation?

The research for this thesis – and especially the summary of our current understanding of the ways in which agriculture drives deforestation in Paper IV – also serves to reveal a few crucial data gaps. This includes (i) a lack of consistent data on deforestation trends over time, (ii) multiple and interrelated uncertainties in assessing commodity-specific land-use dynamics, and (iii) an overall, systematically poorer understanding of deforestation and its drivers in dry forests and across the African continent.

5.1 Consistent data on deforestation rates and trends are lacking

First, although we do know that deforestation is falling in some areas of the tropics (strengthened by regional analyses), the overall trend in tropical deforestation, surprisingly, remains somewhat unresolved (Figure 1). A lack of consistent pan-tropical data on deforestation, covering both dry and wet tropical forests, currently impedes our capacity to make meaningful comparisons of the extent of conversion between regions and agricultural systems. Thus, while there is a growing body of evidence on the impact of local-to-regional policy interventions on reducing deforestation (Bastos Lima *et al.*, 2019; Börner *et al.*, 2020; Meyfroidt *et al.*, 2020), there remains a need for improved and consistent pantropical data on deforestation rates over time to evaluate the effectiveness of policy measures towards net reductions of deforestation.

Our capacity to assess the extent of deforestation, its drivers, and the progress towards reducing its negative impacts would thus be strengthened by further improvements to deforestation data. In particular, it would be valuable to ensure that there are deforestation data that are as consistent as possible over time and that assess losses of natural forests in both the dry and wet tropics.

That said, deforestation metrics can only ever provide a crude proxy for multiple, interacting changes in land cover and land use and their underlying drivers. Their impacts vary significantly between biomes: one hectare of forest lost may result in vastly different environmental impacts depending on the type of ecosystem and how much of it remains standing. The impact will of course also depend on the type and intensity of the subsequent land use (Phalan *et al.*, 2011; Kehoe *et al.*, 2015; Newbold *et al.*, 2015; Erb *et al.*, 2017b). Improved monitoring of the impacts, such as biodiversity loss, carbon emissions and changes to the local and regional climate, might resolve some of the challenges arising from the lack of a clear line between forest degradation and deforestation and between forests and other valuable ecosystems (Sexton *et al.*, 2016). After all, forest conversion can have a rather different impact on the environment if it takes place in a highly biodiverse or carbon-dense biome, compared to one that is less so.

5.2 Attributing deforestation to commodities still faces considerable challenges

There are multiple uncertainties and potential for improving the evidence base in terms of identifying the agricultural drivers of deforestation (detailed more extensively in the supplementary material S6d of Paper IV).

First, one of the bottlenecks towards improving the identification of pantropical agricultural deforestation drivers is the availability of accurate subnational or spatially-explicit data on the extent of specific crops and of pasture and how these are changing over time. Aside from oil palm and soy, which have been reasonably mapped for most of their production areas (Descals *et al.*, 2021; Song *et al.*, 2021), the attribution of deforestation to pasture and individual crops is typically based on sources of considerably lower fidelity (see, e.g., Table 1 in Paper IV for an overview of the data quality of the underlying data). The sources used include agricultural statistics at coarse – often national – scale and which are frequently based on unofficial estimates or imputation, as well as single-year, often outdated, maps of pasture and (often modelled) crop extents at 10-km resolution (in contrast, tree cover loss is assessed for 30-m pixels). The situation is particularly dire for pasture: most global land cover and use datasets do not specifically distinguish pasture (at best, providing separate classes for grassland and agriculture) (Joshi *et al.*, 2016; Li *et al.*, 2018; Oliveira *et al.*, 2020) and the only dedicated global pasture map (Ramankutty *et al.*, 2008) outside Latin America is available only for the year 2000. For crops and cropland, the MapSPAM initiative collects and disaggregates agricultural statistics into maps (currently available for 2000, 2005 and 2010), but the input crop statistics are generally only available at the national level (Yu *et al.*, 2020).

Paper I also highlights the need to exercise care that the classification of land cover/use matches the purpose at hand. The "Cultivated land" class of the global land cover dataset used (GlobeLand30) in Paper I, which several studies interpret and use as cropland, in fact also contains significant amounts of planted pastures. Second, it shows that forest loss identified by one dataset was frequently still identified as forest in a land cover dataset over the same area a few years later. This indicates that combining datasets to identify land-cover transitions can suffer from limited accuracy (as errors compound when maps are combined (Fuller *et al.*, 2003)), especially in areas with heterogeneous land cover or small-scale forest loss.

To better capture the sequences of commodities following deforestation and distinguishing the direct and indirect land use changes, requires annual data – or at least data that are consistent over multiple points in time – covering all major crops (accounting also for multiple harvests) and pasture area at least at the subnational level. These data do not need to cover the whole tropics, provided they do include the regions where deforestation is occurring. Hopefully, the increased availability of high-resolution data and improved methods for analysing them (Masolele *et al.*, 2021) can facilitate this; indeed, there has been considerable progress in just the past couple of years, with the release of maps for soy for Latin America (Song *et al.*, 2021), as well as high-resolution global maps on oil palm plantations (Descals *et al.*, 2021) and on cropland extents and changes over time (Potapov *et al.*, 2022).

There is likely also further progress that can be made in the methods used for establishing which commodities were the cause of the deforestation. For example, interacting drivers and land uses (e.g., soy and pasture dynamics in Brazil) are currently rarely dealt with except at a cursory level.

Improvements can also relate to more technical specificities, such as examining and making more explicit the impact of methods choices, including spatial scale and temporal aspects; and, though technical, these specificities are intertwined with the type of causality the approach will reflect. For example, Paper II explored the effects of increasing the spatial scale of the analysis for Brazil and Indonesia, from national-level (as used for all other countries) to subnational level, showing that increased spatial resolution led to better representation of the land-use dynamics in the deforestation regions. The subsequent trade analysis would also benefit from improved spatial resolution, but, in practice, this is frequently limited by data availability on subnational trade patterns (Gardner *et al.*, 2018). Coarser-grained analyses will, therefore, likely be needed to prioritise where acquiring additionally detailed data is warranted (Godar *et al.*, 2016).

There is thus an ongoing need for developing robust methods, standards, and definitions on how to attribute deforestation to different drivers. This would also benefit from increased awareness that different methods – and thus numbers – highlight potential responsibility in different ways, thus making them more useful for different types of policies (Meyfroidt, 2016). The increasing availability of regional data sources could also help validate the performance of the global approaches in different regions.

5.3 The uncertainties are systematically poorer for dry forests and Africa

The uncertainties around deforestation rates and its drivers are not evenly distributed over the tropics. There are several reasons for this and – put together – they result in us knowing less about the extent and causes of deforestation in dry (rather than wet) forests and across the African continent. First, remote sensing is more challenging where vegetation is heterogeneous, e.g., where tree cover is varied or intermediate, where deforestation is done in smaller patches, and where there is a mix of agriculture and natural vegetation (Hansen *et al.*, 2013; Pérez-Hoyos *et al.*, 2017; Rufin *et al.*, 2022). Second, agricultural statistics are, in general, less reliable for subsistence and small agricultural holdings (FAO, 2021), and the capacity to collect agricultural statistics is especially limited for many agencies across Africa (Ramankutty *et al.*, 2008; World Bank, 2010). Third, land use change research, in general, has focused less on dry forests compared with wet forests (Bastin *et al.*, 2017; Schröder *et al.*, 2021) and less on Africa compared with other continents (Busch & Ferretti-Gallon, 2017). This is also reflected in the results of a literature search done for Paper IV, where we found only a handful of national-level studies assessing deforestation resulting in agricultural production (6 studies identified for the whole of Africa, compared with > 25 each for Latin America and Asia). With a considerable part (around a third) of dry forests currently in active deforestation frontiers (Buchadas *et al.*, 2022), this systematically poorer understanding of deforestation and its drivers in these regions is particularly concerning.

5.4 Further steps towards understanding the mechanisms behind deforestation

There are of course further steps that can be taken towards improving our understanding of the mechanisms behind deforestation and thus the evidence base on which measures to reduce deforestation can be based. (The following points are hinted at in Paper IV, though not discussed in much detail.)

Effectively tackling deforestation depends on understanding who deforests and why. Is deforestation dominated by large- or smallholders, and are they producing for semi-subsistence or commercial demand? And how much clearing is illegal? To these questions, there are currently few and only partial answers at national and regional, never mind pantropical, scales. This is partly because of the challenge of determining such drivers based on remote sensing.

Quantifying the role of timber extraction and logging in driving deforestation across the tropics is another area which would improve our understanding of deforestation drivers. These are generally also considered important direct drivers of deforestation (Pacheco *et al.*, 2021), and can occur in conjunction with or as a precursor to agricultural expansion into forests (Gaveau *et al.*, 2013; Tarigan *et al.*, 2015; IUFRO, 2016). Though we know that timber extraction has a considerable impact on forest degradation (Pearson *et al.*, 2014; Pearson *et al.*, 2017; Matricardi *et al.*, 2020), the role of logging in driving deforestation has yet to be consistently quantified across the tropics.

Furthermore, the various mechanisms underlying the broader (and more indirect) roles that agriculture has in driving deforestation remain to be quantified. Given that around one-third to one-half of agriculture-driven deforestation does not result in active agricultural production (a main finding of Paper IV), further research on the possible mechanisms behind this – including quantifying their relative importance in different places – would be valuable to help support the design of policies or other measures to reduce also such deforestation.

6. Discussion, policy relevance, and closing words

This thesis and its appended papers have aimed at improving our knowledge of what drives deforestation across the tropics, focusing especially on the manifold ways through which agriculture contributes to causing deforestation. My PhD research has made some contributions to science as well as some contributions that are relevant to addressing deforestation in practice and policy.

As I see it, this thesis has contributed to science in three main ways. First, it has advanced our knowledge of deforestation drivers. It is among the first to provide a comprehensive picture of the amount of deforestation (and associated carbon emissions) that is driven by the expansion of different agricultural commodities across the whole tropics (though still at a rather coarse resolution, and, woefully, often based on data of limited quality). This thesis has also advanced our knowledge of the relative importance of international and domestic markets in fuelling the demand for the commodities associated with deforestation.

Second, this thesis has shown a few areas where improving the evidence base is needed. Paper I lays out some of the challenges to using global remote sensing datasets for assessing the drivers of deforestation, showing that, even when individual land cover (change) datasets have high accuracy, when they are combined their joint accuracy may still be too poor to be able to consistently quantify post-forest land use with sufficient discrimination between pastures and cropland, especially in heterogeneous landscapes. Paper IV elaborates further on knowledge gaps, showing (i) that there remains a need for improved pantropical data on deforestation rates and trends, (ii) that attributing deforestation to commodities still faces substantial challenges, including considerable data gaps, especially for pastures outside of Latin America and for non-cash crops, and (iii) that the uncertainties around the rates and drivers of deforestation are systematically poorer for dry forests and across the African continent.

Third, this thesis makes a couple of contributions which support more theoretical or conceptual aspects of land system science. First, in Paper III, we provide empirical evidence relating to forest transition theories, by assessing to what extent countries that have undergone a forest transition – and have begun to increase their net forest cover – instead import commodities that have caused deforestation somewhere else. We find that nearly 80% of the deforestation embodied in international trade ends up being consumed in these post-forest transition countries and that their imports offset on average one-third of their domestic forest area gains. Second, Paper IV introduces a distinction between agriculture-driven deforestation that either (i) results in agricultural production (i.e., it can be attributed to the expansion of land under active agricultural production systems) or (ii) occurs without resulting in the expansion of recorded and productive agricultural land. This distinction might serve as a useful framework; it might also help open up an avenue for future research in terms of efforts to assess and quantify the various indirect mechanisms (such as land speculation and tenure issues) through which agriculture causes deforestation but without producing much benefit (at least not in terms of agricultural production).

This thesis also has several implications and can be useful for designing more effective policies and efforts to curb deforestation. First, our dataset on deforestation risk embodied in the production and consumption of different agricultural commodities (which was first developed for Papers II and III, and further used in Paper IV) can, in and of itself, help both private and public actors seeking to identify deforestation risk. Commodity buyers and traders, as well as investors (see, e.g., (Richards *et al.*, 2020)), can use these (comparatively coarse-level) data to triage which countries and commodities likely carry more deforestation risk for them, thus potentially requiring further attention and more detailed assessments. The deforestation carbon emissions data are, for example, currently being used as part of climate risk assessments of different sectors by a Dutch bank. They can also be explored as part of countries' consumption-based accounting. This dataset is also being used, e.g., as one basis for the due diligence provisions in the UK's Environment Act, and to inform the product scope in the impact assessment for the EU's proposed legislation on deforestation-free products (European Commission Directorate-General for Environment, 2021).

Second, Papers II, III and IV, show that only a small number of agricultural commodities drive a large share of the deforestation attributed to the expansion of agricultural production (confirming the findings of previous studies, e.g., Henders *et al.* (2015)). At the surface, this indicates that supply-chain and demand-side efforts to reduce deforestation may address a relatively large part of the deforestation by focusing only on a limited set of commodities. Brazil's Soy Moratorium provided a prime successful example of this (Nepstad *et al.*, 2014; Gibbs *et al.*, 2015a; Gibbs *et al.*, 2015b; Gollnow *et al.*, 2022). This is currently the approach intended by, e.g., the EU's proposed legislation on deforestation-free products, where due-diligence requirements are set to apply only to a handful of commodities. It is also the approach of companies making zero-deforestation commitments targeting key commodities such as palm oil, beef, and high-value crops, such as cocoa and coffee (Donofrio *et al.*, 2017; Lambin *et al.*, 2018; Garrett *et al.*, 2019; Bager & Lambin, 2022). One concern with these approaches, however, is that – unless the underlying demand is addressed – their effectiveness may be undermined by leakage (le Polain de Waroux *et al.*, 2017; Lambin *et al.*, 2018) or by supply-chain "bifurcation", whereby the deforestation-free production simply goes to conscious consumers, and deforestation continues largely unabated unless the majority of a commodity's consumption is covered by deforestation-free requirements (Garrett *et al.*, 2019; Lyons-White *et al.*, 2020; Gollnow *et al.*, 2022).

Third, in Paper IV we argue that there are some fundamental limits to what can be directly accomplished by focusing solely on stamping out the trade or imports of commodities produced on recently deforested land. The first reason for this is that around one-third to one-half of agriculture-driven deforestation does not result in active agricultural production (as shown in Paper IV). Since no commodities are produced from this land, commodity-specific initiatives are mainly moot for addressing this type of agriculture-driven deforestation. The second reason for the limits of policies promoting deforestation-free international supply chains is that international demand is behind just around a quarter of the deforestation resulting in agricultural production. Therefore, even though imports from, e.g., the EU and the US, drive quite a large share of the deforestation associated with international trade, their share of total agriculture-driven deforestation is considerably smaller. Instead, effectively curbing agriculture-driven deforestation therefore needs to address also domestic demand as well as the broader and underlying parts of agriculture-driven deforestation (such as land speculation, tenure issues, and fires). That said, in Papers II and III, we show that the role of international demand in driving deforestation exceeds that of many other environmental impacts and that the carbon emissions associated with deforestation still constitute a considerable share of the carbon footprint of food. Addressing deforestation abroad therefore remains an important strategy for, e.g., the EU, in order to reduce their impacts. Put together, this indicates that curbing deforestation will likely require a combination of measures that also go beyond specific commodities, towards partnerships between producer and consumer markets and governments. New measures to prohibit imports of commodities linked to deforestation in consumer markets, such as those under negotiation in the EU, the UK, and the US, represent a major step forward from largely voluntary efforts to combat deforestation to date. But although commodity-specific initiatives to combat deforestation can be invaluable (e.g., as seen with the soy moratorium in Brazil), the goal of achieving reduced deforestation on the ground is more likely to be achieved if they can further help foster concerted action on rural development, territorial governance, and land-use planning. The mechanisms through which this can be achieved remains a research frontier.

I hope and believe that this thesis has contributed to increasing our knowledge about the role and importance of agriculture in driving deforestation. And I hope it does so in a way that can help contribute to the design of more effective policies and private-sector efforts to stop it. At this unique moment in time, where there is unprecedented acknowledgement that we need to curb deforestation, but where deforestation rates keep remaining obstinately high, we urgently need to act and find ways to feed and fuel the Earth without undermining its capacity to continue to do so.

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