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Title: Disentangling the numbers behind agriculture-driven tropical deforestation

Authors: Florence Pendrill1[1]*, Toby A. Gardner[2*], Patrick Meyfroidt[3,4], U. Martin Persson[1], Justin Adams[5], Tasso Azevedo[6], Mairon G. Bastos Lima[2], Matthias Baumann[7], Philip G. Curtis[8], Veronique De Sy[9], Rachael Garrett[10], Javier Godar[2], Elizabeth Dow Goldman[11], Matthew C. Hansen[12], Robert Heilmayr[13], Martin Herold[14], Tobias Kuemmerle[7,15], Michael J. Lathuillière[2], Vivian Ribeiro[2], Alexandra Tyukavina[12], Mikaela J. Weisse[11], Chris West[16].

Affiliations:

[1]Department of Space, Earth and Environment, Chalmers University of Technology; Gothenburg, Sweden.

[2]Stockholm Environment Institute (SEI); Stockholm, Sweden.

[3]Georges Lemaître Earth and Climate Research Centre, Earth and Life Institute, UCLouvain; Louvain-la-Neuve, Belgium.

[4]Fonds de la Recherche Scientifique F.R.S.-FNRS; Brussels, Belgium.

[5]Tropical Forest Alliance, World Economic Forum; Geneva, Switzerland.

[6]Observatório do Clima, MapBiomas; São Paulo, Brazil.

[7]Geography Department, Humboldt-Universität zu Berlin; Berlin, Germany.

[8]Juniata Analytics LLC; Denver, CO, United States.

[9]Laboratory of Geo-Information Science and Remote Sensing, Wageningen University and Research; Wageningen, The Netherlands.

[10]Environmental PolicyLab, Department of Humanities, Social, and Political Sciences, ETH Zürich; Zürich, Switzerland.

[11]Global Forest Watch, World Resources Institute; Washington, DC, United States.

[12]Department of Geographical Sciences, University of Maryland, College Park; Maryland, United States.

[13]Environmental Studies Program and Bren School of Environmental Science and Management, University of California, Santa Barbara; Santa Barbara, California, United States.

[14]Helmholz GFZ Research Centre for Geosciences, Section 1.4 Remote Sensing and Geoinformatics, Telegrafenberg; Potsdam, Germany.

[15]Integrated Research Institute for Transformations in Human-Environment Systems (IRI THESys), Humboldt-Universität zu Berlin; Berlin, Germany.

[16]Stockholm Environment Institute York, Department of Environment and Geography, University of York; York, UK.

*Corresponding authors. Email: florence.pendrill@chalmers.se, toby.gardner@sei.org

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Abstract: Tropical deforestation continues at alarming rates, with profound impacts on ecosystems, climate, and livelihoods, prompting renewed commitments to halt it. While it is well established that agriculture is a dominant driver of deforestation, rates and mechanisms remain disputed and often lack a clear evidence base. We synthesize the best available pan-tropical evidence to provide clarity on the ways that agriculture drives deforestation. Although most (90–99%) deforestation across the tropics 2011–2015 was driven by agriculture, only 45–65% of deforested land became productive agriculture within a few years. Therefore, ending deforestation likely requires combining measures to create deforestation-free supply chains with landscape governance interventions. We highlight key remaining evidence gaps, including deforestation trends, commodity-specific land-use dynamics, and data from dry forests and across Africa.

Teaser: A Review disentangles the numbers behind agriculture-driven deforestation and explains the different forms it can take.

Print page summary:

Background

Agricultural expansion is a primary cause of tropical deforestation and, therefore, a key driver of greenhouse gas emissions, biodiversity loss and the degradation of ecosystem services vital to the livelihoods of forest-dependent and rural people. However, agriculture-driven deforestation can take many forms, from the direct expansion of pastures and cropland into forests, to more complex or indirect pathways. A clear understanding of the different ways in which agriculture drives deforestation is essential for designing effective policy responses. To address this need, we provide a review of the literature on pan-tropical agriculture-driven deforestation and synthesize the best available evidence to quantify dominant agricultural land-use changes relating to deforestation. We consider the policy implications of this assessment, especially for burgeoning demand-side and supply-chain interventions seeking to address deforestation.

Advances

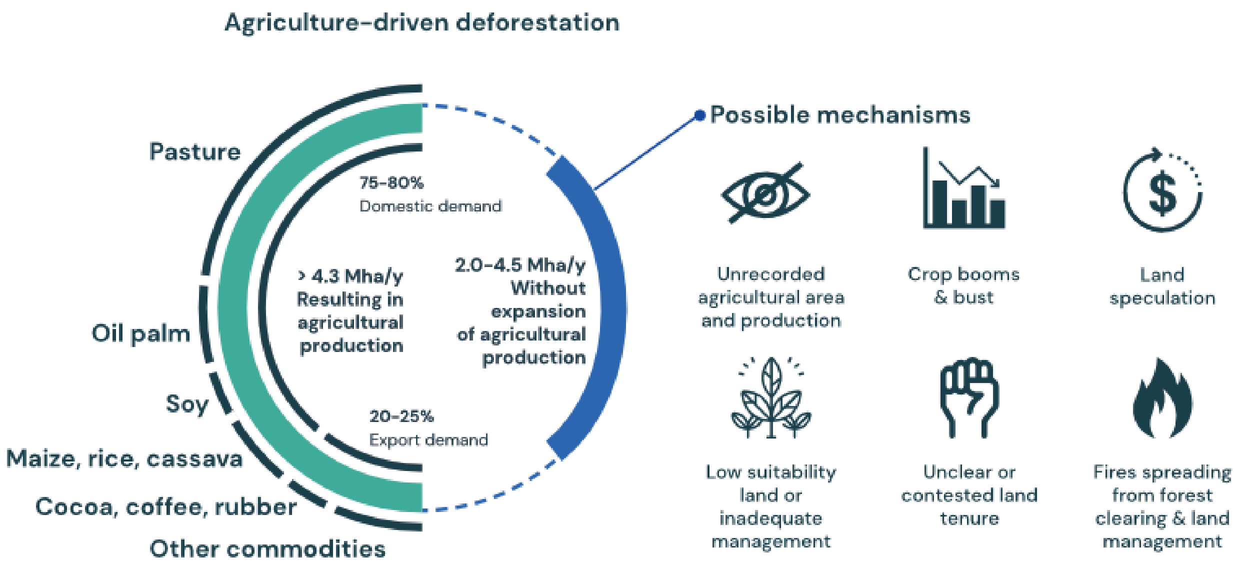
New methods and data have advanced our understanding of deforestation and subsequent land uses. Still, only a handful of studies estimate agriculture-driven deforestation across the whole tropics. While these studies agree that agriculture is the dominant land use following forest clearing, their estimates of pan-tropical rates of agriculture-driven deforestation during the period 2011–2015 vary greatly between 4.3 and 9.6 Mha/y, with our synthesized estimate being 6.4–8.8 Mha/y. This apparent uncertainty in the amount of agriculture-driven deforestation can be disentangled by distinguishing between the different ways in which agriculture contributes to deforestation: we find that while the overwhelming majority (90–99%) of all tropical deforestation occurs in landscapes where agriculture is the dominant driver of tree-cover loss, a smaller share (45–65%) of deforestation is due to the expansion of active agricultural production into forests. Multiple lines of evidence show that the remainder of agriculture-driven deforestation does not result in the expansion of productive agricultural land, but instead is due to activities such as speculative clearing, land tenure issues, short-lived and abandoned agriculture, and agriculture-related fires spreading to adjacent forests.

Different land uses and commodities often interact to drive deforestation. However, pasture expansion is the most important driver by far, accounting for around half of the deforestation resulting in agricultural production across the tropics. Oil palm and soy cultivation together account for at least a fifth, and six other crops—rubber, cocoa, coffee, rice, maize, and cassava—likely account for a majority of the remainder, with large regional variations and higher levels of uncertainty.

Outlook

This review points to three key areas where a stronger evidence base would advance global efforts to curb agriculture-driven deforestation. First, consistent pan-tropical data on deforestation trends are lacking. This limits our ability to assess overall progress on reducing deforestation and account for leakage across regions. Second, excepting soy and oil palm, the attribution of deforestation to forest-risk commodities is often based on coarse-grained agricultural statistics, outdated or modeled maps, or local case studies. Third, uncertainties are greatest in dry and seasonal tropics and across the African continent in particular.

This assessment highlights that while public and private policies promoting deforestation-free international supply chains have a critical role to play, their ability to reduce deforestation on the ground is fundamentally limited. One-third to one-half of the agriculture-driven deforestation does not result in actively-managed agricultural land. Moreover, the majority—approximately three-quarters—of the expansion of agriculture into forests is driven by domestic demand in producer countries, especially for beef, cereals and much of the deforestation across the African continent. These data suggest that the potential for international supply-chain measures to help reduce tropical deforestation is more likely to be achieved through interventions in deforestation-risk areas that focus on strengthening sustainable rural development and territorial governance.



Agriculture contributes to deforestation in many, often interacting, ways. Most tropical deforestation occurs in landscapes where agriculture is the dominant driver. Part of this agriculture-driven deforestation results in agricultural production (left) meeting domestic and export demand. However, agriculture-driven deforestation also occurs without expansion of managed agricultural land through several mechanisms (right). Incomplete agricultural records also explain a share of that deforestation.

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Main Text: Deforestation continues at high rates, mainly in the tropics (*1-4*), and is one of the largest drivers of greenhouse gas emissions, biodiversity loss and the degradation of ecosystem services (*5*). While deforestation is driven by many interrelated processes (*6*), expanding agricultural land use—including cropland, pastures, and tree crops—is the primary direct cause of tropical deforestation (*7-9*).

Currently there is unprecedented attention on curbing tropical deforestation, with renewed commitments to reduce deforestation at the climate COP26 in 2021, upcoming negotiations at the COP15 for the Convention on Biological Diversity and strengthened commitments and legislative proposals from governments (*10-12*), companies (*13, 14*), and financial institutions (*15*). Emerging policies often focus upon eliminating deforestation from international supply chains of agri-food commodities such as palm oil, soybeans, and beef. With the adequacy of past pledges having received damning assessments (e.g., in the New York Declaration on Forests 5-year assessment in 2019), largely due to lack of funding and implementation, it is crucial that renewed investment is guided by the best available evidence on agriculture-driven deforestation. The targeting of limited resources needs to be based on a clear understanding of the scale of the problem, its location, and the relative importance of different drivers.

Yet, at present, policies are being designed and evaluated against a backdrop of widespread uncertainty regarding our understanding of the links between agriculture and deforestation. The focus on agricultural supply-chain policies is commonly premised on statements that agricultural expansion and production drive 80% of tropical deforestation, a number appearing in everything from policy proposals (e.g., by the EU (*10*) and the UK (*16*)), to high-profile research (e.g., *17*), and communications from NGOs and international organizations (e.g., Rainforest Alliance (*18*), Greenpeace (*19*)). This 80% number frequently appears as fact, often without referencing the original source, Hosonuma *et al.* (*20*), or understanding its meaning and limitations. In 2012, the referenced study gave a much-needed "first inventory of what countries identify as relevant and important drivers" (*21*). However, data sources and methods for identifying deforestation and subsequent land uses have since improved considerably (*1, 2, 7, 22-25*). At this critical juncture of the fate of the world's tropical forests, it is essential to take stock of our current understanding of the role agriculture plays in driving deforestation, identifying key data and knowledge gaps.

Here, we aim to provide such a synthesis to disentangle the key rates and mechanisms of agriculture-driven deforestation, organized around three central questions. What is our current understanding of: (i) the rates and trends in deforestation across the tropics? (ii) The role of agriculture in driving deforestation, both in terms of the direct expansion of productive agricultural land and more broadly regarding the links between agriculture and land-use dynamics (e.g., land speculation)? And (iii), the relative importance of different forest-risk commodities in driving deforestation, and to which extent their production is linked to international trade? We assess our ability to address these questions in different regions, clarify the inherent challenges in quantifying the role of agriculture in driving tropical deforestation, and consider the practical implications of existing knowledge for science and policy.

Agriculture and deforestation

The drivers, or causes, of deforestation can be examined in many ways (*26, 27*), and multiple drivers often interact (*6, 9*). This review focuses on agriculture-driven deforestation, here defined broadly as deforestation for which agriculture, whether directly or indirectly, is a cause (Box 1). Importantly, agriculture-driven deforestation is not limited to the direct expansion of commodity production into forests. We review recent pan-tropical assessments of deforestation drivers (table S1) and complement this with a literature search of national-level estimates for eleven countries with the highest deforestation rates (*28*). We harmonized datasets to the same set of 87 tropical and subtropical countries (henceforth: the "tropics"), covering most of Latin America, Africa south of the Sahara, and South & Southeast Asia (*28*) (fig. S1) and focus on the time period of 2011–2015.

Deforestation rates and trends

Estimating deforestation rates across the tropics presents both conceptual and technical challenges. First, there is no single way to distinguish between forests and non-forests, nor between deforestation and forest degradation, so different studies and monitoring systems rely on different definitions (*29-31*). Second, while remote sensing is useful for monitoring forest changes in terms of land cover, not all aspects of deforestation—including its underlying drivers—can be observed from satellites, and technical and practical constraints result in imperfect data (e.g., dealing with cloud cover) (*29, 30*). Forest loss estimates therefore differ between studies (fig. S2), both because of measurement uncertainties (*32*) and because they strive to measure different things.

We define deforestation as "a persistent conversion of natural forest to any other land use, such as agriculture or human settlements, or to tree plantations." (Box 1). This definition aligns 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 builds Accountability Framework initiative's definition (*33*). There is currently no pan-tropically consistent, spatially-explicit dataset that quantifies deforestation as defined above, though Vancutsem *et al.* (*2*) comes close for tropical moist forests (*28*). Therefore, this review combines data from different sources to derive estimates in line with that definition.

The two main global data sources on forest loss, used by a majority in the policy and research communities, are the Global Forest Change (GFC) dataset based on annual, remote-sensing based measures of tree-cover loss (TCL) (*1*)., and the Food and Agriculture Organization (FAO)'s Forest Resources Assessment (FRA) which reports deforestation rates at 5-10 year intervals (*3*). Many recent pan-tropical assessments of deforestation drivers rely partly on GFC. A key challenge for assessing deforestation based on the GFC data is that while all deforestation is in principle captured by tree-cover loss, not all tree-cover loss (a land-cover change) constitutes deforestation in terms of a persistent change in land use away from natural forest (*1, 28*) (Fig. 1A). In particular, tree-cover loss includes clearings within tree plantations, severe forest degradation, and rotational cycles of shifting cultivation (*1, 7*). The FRA uses a more restrictive definition of deforestation than the one used here, where conversion of natural forest to forestry plantation is not considered deforestation. Its usefulness for assessing deforestation drivers is limited as the data are compiled at national-level only and are collected from country reports based on a variety of methods, including remote sensing and inventories (*34*).

For 2011–2015, GFC tree-cover loss rates averaged 10.6 Mha/y in the tropics, while the FAO FRA 2020 estimates deforestation to be 10.7 Mha/y (Fig. 1B), despite the latter applying a more restrictive definition and primarily reporting net (not gross) deforestation for many countries. These aggregated numbers mask considerable regional differences, especially for Africa, where FRA deforestation is estimated at 4.4 Mha/y, while tree-cover loss amounts to 2.8 Mha/y (Fig. 2 and table S3). For some countries, these differences are striking; for India, the FRA (gross) deforestation rate (0.67 Mha/y; based on remote sensing (*3*)) far exceeds the GFC tree-cover loss (0.10 Mha/y). Additionally, the two main datasets show opposing pan-tropical trends between 2001–2010 and 2011–2020, with an increase from 9 to 12 Mha/y in GFC tree-cover loss (*1*), compared to a decrease from 14 to 10 Mha/y in FRA deforestation rates (*3*) (Fig. 1B). While discrepancies in rates are expected as approaches differ in how they define "forests" and "deforestation" (see more discussion in (*1, 2, 32, 35*)), the fact that GFC tree-cover loss and the FRA deforestation data report a difference in the overall direction of the trend is more puzzling.

Uncertainties in trends arise due to several methodological and conceptual challenges, which must be taken into account for drawing conclusions about trends in tree-cover loss or deforestation based on the GFC and FAO FRA datasets, e.g., Curtis *et al.* (*7*), Carter *et al.* (*32*), Goldman *et al.* (*36*), Pendrill *et al.* (*37*), Nguyen and Kanemoto (*38*).

The increasing trend in GFC tree-cover loss presents two main challenges for evaluating temporal trends in deforestation. First, the GFC methodology has become more effective at detecting small and temporary forest disturbances—part of which could be more adequately characterized as forest degradation rather than deforestation—post-2011 and especially post-2015 (*39, 40*) both due to changes in the methodology and increased quality and volume of Landsat satellite data. Caution is thus needed when trying to compare tree-cover loss trends between the pre- and post-2011 or -2015 time periods (*28, 39, 40*). Second, this effect is enhanced by the growing importance of forest degradation, which has increased in many parts of the tropics in recent years due to the combined effects of climate change, fires, forest fragmentation and unsustainable timber extraction (*2, 41, 42*).

For the FRA 2020 deforestation data "*relatively few countries and territories have reliable data over the [full] period*" (*43*). There has been some evidence that "*countries with lower capacities in the past had the tendency to overestimate the area of forest loss*" (*44*). In recent years, the data sources have improved for many tropical countries (*34, 43*), potentially leading to inconsistencies with older data of lower quality. The decreasing trend in the FRA deforestation rates may thus, in part, result from overestimates and uncertainties in earlier years (though decelerating deforestation is also found in the preliminary (global) results from the Remote Sensing Study accompanying the FRA 2020 (*4*)).

Overall, we thus find that consistent pan-tropical data on deforestation trends is lacking, challenging our ability to assess if and where progress is being made.

Agriculture-driven deforestation

There are currently only a handful of pan-tropical estimates of the importance of agriculture in deforestation (*7, 8, 20, 32, 37, 45*) (table S1), all of which agree that agriculture is the dominant land use following deforestation. Estimates of deforestation drivers, e.g., the relative importance of agriculture and of different commodities, are intrinsically less reliable in the most recent years, because time is needed to reveal whether the cleared land will be used for production (and, if so, for what) or allowed to regenerate. Typically, the use of the cleared land is assessed within at least two to four years after forest clearing, though the precise number of years varies between studies (from one year and up to two decades) depending on method and data availability (*28*). For these reasons, we focus our analysis here on the period 2011–2015.

For that period, three studies provide pan-tropical estimates of agriculture-driven deforestation (fig. S3). One (Carter *et al.* (*32*)) assumes a constant fraction of deforestation being agriculture-driven, based on pre-2010 data from other studies (De Sy *et al.* (*8*)) and Hosonuma *et al.* (*20*)). The other two, despite relying on the same GFC tree-cover loss data (*1*), provide vastly different estimates of agriculture-driven deforestation, ranging from 4.3 Mha/y (Pendrill *et al.* (*37*)) up to 9.6 Mha/y (Curtis *et al.* (*7*)) (Fig. 1B and table S4). The variation arises because of methodological differences and because estimates describe different aspects of deforestation and the role of agriculture therein.

By combining these two assessments, Curtis *et al.* (*7*) and Pendrill *et al.* (*37*), with ancillary data (*28*), we estimate total agriculture-driven deforestation across the tropics to be 6.4–8.8 Mha/y (Fig. 1A). As detailed below, this range reflects uncertainties of how much tree-cover loss due to shifting agriculture constitutes deforestation, as opposed to cyclical crop-fallow rotations. With total deforestation ranging between 6.5 and 9.5 Mha/y (table S3), this implies that the vast majority (c.90–99%) of tropical deforestation occurs in landscapes where agriculture is the dominant driver of forest loss (*28*).

The Pendrill *et al.* (*37*) data suggest a much smaller share of tropical deforestation resulting in agricultural production, in the range c.45–65% of our total tropical deforestation estimate (likely at the higher end (*28*)). Pendrill *et al.* (*37*) estimate this by employing a land-balance model to attribute GFC tree-cover loss to expanding cropland and pastures. They evaluate the expansion of cropland and pastures primarily based on national agricultural statistics (FAOSTAT (*46*)); with subnational data for Brazil and Indonesia). A key source of uncertainty in the Pendrill *et al.* (*37*) assessment comes from its reliance on FAOSTAT-recorded agricultural areas. The quality of these data varies considerably between countries and data are often imputed or estimated rather than reported (Table 1)(*46*). This can lead to underestimation of the significance of agriculture as a deforestation driver for countries that are slower to (or simply do not) update their statistics and where the self-reporting by countries incompletely capture some agricultural activities (e.g., shifting cultivation). The Pendrill *et al.* (*37*) estimate of 4.3 Mha/y of deforestation resulting in agricultural production should therefore be considered a conservative estimate (*28*).

In contrast, Curtis *et al.* (*7*) assess the dominant direct drivers of tree-cover loss in 10-by-10 km grid cells using decision-tree models trained on high-resolution imagery in Google Earth. Dominant drivers of GFC tree-cover loss are divided into five classes: commodity-driven deforestation (5.19 Mha/y; primarily for agriculture), shifting agriculture (4.37 Mha/y), forestry (0.93 Mha/y), wildfire (0.02 Mha/y) and urbanization (0.02 Mha/y).

For assessing agriculture-driven deforestation, the Curtis *et al.* (*7*) approach presents two key challenges. First, it does not fully distinguish which of the GFC tree-cover loss is deforestation. Some of the dominant drivers of tree-cover loss correspond to deforestation (i.e., commodity-driven deforestation and urbanization), while others do not (i.e., wildfires potentially resulting in regrowth). Still, the large remainder—i.e., shifting agriculture and forestry—can reflect both the expansion of these systems into natural forests (i.e., deforestation), as well as regular rotations in stable shifting agriculture systems, plantations, or managed forests, which does not constitute deforestation under most definitions (including the one adopted here). Second, the Curtis *et al.* (*7*) approach allocates all tree-cover loss in each grid cell to a single dominant (defined as >50%) driver of tree-cover loss for the whole time period (2001–2020), ignoring drivers that are not dominant. Therefore, even in the grid cells where commodity-driven deforestation or shifting agriculture is the dominant driver of tree-cover loss, not all the tree-cover loss is necessarily directly driven by agriculture. The Curtis *et al.* (*7*) estimate is thus a metric of deforestation occurring in landscapes where agriculture is the dominant direct driver of forest loss (rather than only deforestation resulting in agricultural production per se).

This metric deviates conceptually from our definition of agriculture-driven deforestation, as remote sensing data can never unambiguously distinguish deforestation indirectly driven by agriculture from drivers that are co-located, but causally uncoupled. However, drivers of deforestation often interact (*6, 9, 47*), so in these landscapes where most deforestation is directly due to agriculture, evidence from multiple studies suggest that agriculture typically contributes indirectly also to much of the deforestation that is directly driven by other factors (*6, 48*). For example, in agricultural deforestation frontiers, even if logging or urbanization is the direct driver of some deforestation, it is typically indirectly linked to agriculture, such as where land is logged first but with prospects of converting it to agriculture, which may or may not materialize (*49-51*), or where urbanization is connected to the inflow of laborers into agriculture (*52*). The share of deforestation in pixels where Curtis *et al.* (*7*) classify agriculture as the dominant driver, but which is causally disconnected from agriculture, is therefore likely to be very small. Hence, we take the metric of deforestation occurring in landscapes where agriculture is the dominant direct driver of forest loss as the best-available proxy for estimating agriculture-driven deforestation.

Curtis *et al.* (*7*) put deforestation occurring in landscapes where agriculture is the dominant driver in the range of 5.19 Mha/y (commodity-driven deforestation only) to 9.47 Mha/y (sum of commodity-driven deforestation and shifting agriculture) (Fig. 2). We narrowed this range down to 6.4–8.8 Mha/y (*28*), by excluding tree-cover loss in tree plantations (*53*) and by including deforestation in primary forests (*54*) and deforestation resulting in agricultural production (based on Pendrill *et al.* (*37*))(fig. S4).

Our analysis suggests a large discrepancy (2.0–4.5 Mha/y) between the deforestation resulting in agricultural production (>4.3 Mha/y) and the overarching category of agriculture-driven deforestation (6.4–8.8 Mha/y) (Figs. 1A and 3). This discrepancy is present across all three continents in our country sample, totaling 1.0–2.0 Mha/y in Latin America, 0.0–1.3 Mha/y in Africa, and 1.1–1.2 Mha/y in Asia (Fig. 3), though uncertainties abound and part of the discrepancy is likely due to unrecorded agricultural areas.

The discrepancy reflects the complex role of agriculture as a driver of tropical deforestation and indicates that a around one-third to one-half of agriculture-driven deforestation does not result in recorded agricultural land (though it might be used for other purposes). This is consistent with regional and pan-tropical remote-sensing studies finding large tracts of unused land following forest loss (*8, 24, 28, 55, 56*), including a pan-tropical estimate that 20–30% of agriculture-driven tree-cover loss in the period 2015–2019 showed some shrub or forest regrowth by 2020 (*57*).

There are several mechanisms explaining this large share of agriculture-driven deforestation without expansion of agricultural production. One such mechanism is land speculation, often linked to unclear or contested tenure. This process has been documented for several Latin American countries, including the Brazilian Amazon (*58, 59*) and Costa Rica (*60*), where expectations about future agricultural rents—fueled by planned road infrastructure improvements, uncertainties around future forest conservation policies and the existence of large tracts of undesignated public land—lead to speculative clearing. Other social processes, such as imitation (cf. *61, 62*), create crop booms and potential busts (*63*). This can lead to land being cleared anticipatively but not subsequently being taken into production because the market conditions deteriorate or due to failed operations or diminishing economic viability. For instance, land cleared for speculation in the Brazilian Amazon is typically put under extensive pasture, where animal stocking rates are very low; these pastures are commonly degraded and abandoned within relatively short time periods (*64-66*). Deforestation can also be used to strengthen tenure claims, where laws link land rights to clearing or use (*67, 68*). Moreover, conflicts over land tenure often contribute to deforestation in contested forest frontiers, in excess of clearings purely for productive agriculture (*69, 70*). The extent of land with unclear and contested tenure is not precisely quantified pan-tropically but shown to be very large in some countries (*71*).

Land degradation can also lead to land abandonment, or maintenance of the land at very low levels of productivity, possibly because the deforested land was not suitable to begin with (*72, 73*), or because of deforestation-driven changes in local climate (*74*), inadequate management and lack of know-how, or cultural or structural barriers (*66, 75*).

Another mechanism through which agriculture contributes to deforestation without resulting in productive agricultural land in the near term is from fires started in agricultural lands that spread to adjacent forest areas, leading to forest degradation and, in some cases, complete deforestation. Almost all fires in tropical moist forests are due to human activities (*42*) including to clear forests for new agriculture and as a land management tool (e.g., for weed control and nutrient mobilization) in already-cleared agricultural areas (*42*). This frequently leads to fires spreading into adjacent forest areas, as documented in Brazil (*76*), the Miombo (*77*), and Indonesia (*78*).

Attributing deforestation to commodities and consumers

The evidence on pan-tropical rates of deforestation attributed to cropland, pasture and associated commodity production in more recent years primarily stems from only two approaches: Pendrill *et al.* (*37*) and Goldman *et al.* (*36*). Two other studies have also quantified the role of agricultural commodity production in driving deforestation(*38, 45*), but these primarily cover time periods before 2010 and are thus not discussed in detail here. Pendrill *et al.* (*37*) is the most comprehensive in terms of commodity coverage, with annual data on deforestation followed by pasture and 155 crops, assessed primarily at national level. Given its lack of spatial detail, that method does not unequivocally establish whether these land uses expanded directly on cleared forest land or if they indirectly displaced other land uses into the forest (*37*). Goldman *et al.* (*36*) attribute deforestation to commodities by overlaying GFC tree-cover loss classified as commodity-driven deforestation or shifting agriculture (from Curtis *et al.* (*7*)) with recent spatially-explicit extent maps for oil palm, soy, rubber and pasture for a subset of countries, as well as older, coarse maps for pasture, cocoa and coffee. The coarse estimates are far more uncertain (than those based on recent maps) for two main reasons. First, all tree-cover loss classified as dominated by commodity-driven deforestation or shifting agriculture is assumed to constitute deforestation resulting in agricultural production, which risks over-allocating tree-cover loss as deforestation assigned to commodities. Second, it assumes that the relative shares of commodity area, and thus share of deforestation, in each grid cell remained stable since the year 2000 for pasture and 2010 for crops. This is unlikely to hold, especially in rapidly changing deforestation frontiers.

It is well established that cattle pasture expansion is the single most important deforestation driver by far, alone accounting for around half of the deforestation resulting in agricultural production (*36, 37*). Still, the two available pan-tropical datasets differ considerably in the estimated extent of deforestation attributed to the expansion of pastures (1.9 compared with 2.7 Mha/y, with the lower value from Pendrill *et al.* (*37*) and the higher from Goldman *et al.* (*36*). Most of the deforestation due to the expansion of pastures is found in South America (c.1.2 and 2.1 Mha/y) (Fig. 2), particularly in Brazil. This region has robust data on pasture-driven deforestation at the national or biome-level (table S5). Attributing deforestation to pasture is especially challenging (*28*) because of its complex dynamics with other drivers (e.g., land speculation and crops (*58, 79-81*)); additionally, pastures can be difficult to distinguish from other land covers based on remote sensing because they may appear spectrally similar to cropland or natural vegetation (*82, 83*) and because pastures and their definitions vary considerably (*84, 85*).

Following pasture, the next most important land uses are oil palm and soy cultivation, together accounting for at least a fifth of the deforestation resulting in agricultural production (*36, 37*). Their importance is reflected in the large number of country or biome-wide assessments of these crops (table S5) (*28*). Deforestation attributed to these crops is highly concentrated regionally, in South America for soy and in Southeast Asia for oil palm (Fig. 2, table S6), in particular in Indonesia. Pan-tropical estimates are also the most reliable for these two crops (Table 1), though precise estimates can still differ from, and between, national-specific studies (e.g., for Indonesia (*28*)), underscoring the value of having multiple data sources.

The cultivation of six other crops—rubber, cocoa, coffee, rice, maize, and cassava—account for a majority of the remaining deforestation resulting in agricultural production (*28, 36, 37*)). However, the evidence is currently lacking to confidently estimate their significance or changes in this over time (*37*), and country-level assessments are largely missing (table S5). For these crops, the data are limited or of poor quality (Table 1) and both pan-tropical approaches rely heavily on agricultural statistics. Statistical records are unreliable for cocoa and coffee cultivation (*86*), with further uncertainties as these crops can be shade-grown, in which case their expansion into natural forest can be difficult to detect using remote sensing, and they are also often grown together with other crops in agroforestry systems (*87-89*). Records for staple crops are frequently based on estimates and may underestimate harvested areas in subsistence or smallholder contexts due to minimum harvested area criteria in records (*90*).

Many of the crops discussed above are important export crops—including soybeans, palm oil, rubber, coffee, and cacao—and international trade has been identified as a key driver of deforestation since the 2000s (*89, 91-93*). Three pan-tropical studies assess deforestation associated with trade in commodities: Nguyen and Kanemoto (*38*), Cuypers *et al.* (*45*) and Pendrill *et al.* (*37*). The first two are not discussed further as their deforestation data are primarily for the pre-2010 time period.

The role of international demand in driving deforestation differs depending on how far downstream international supply chains the analysis extends (*94*). A physical trade model, which traces deforestation embodied in raw or lightly processed agricultural commodities, suggests that 20–25% of all deforestation resulting in agricultural production is linked to exports (*37*)(fig. S5). This average, however, hides substantial variation across countries and regions (fig. S6): soybeans, palm oil, and cash crops (e.g., rubber, coffee, cocoa) are primarily destined for export markets, while beef and cereals are typically consumed domestically. An economic, multi-regional input-output model, which traces deforestation all the way to final consumption, raises the share of commodity-driven deforestation linked to international demand to around 35% (*37*)(fig. S5). Thus, despite the remaining limitations and uncertainties in data and current trade models, there is convincing evidence that domestic demand remains a primary underlying driver of deforestation resulting in agricultural production.

While the numbers presented here provide a big-picture indication of the most important forest-risk commodities, commodities often interact in driving deforestation. Deforestation can also be followed by several successive agricultural land uses (*28*). For example, soy expansion in one place has been linked to pasture expansion in others in South America (*79, 81*), while timber harvesting is often a precursor to deforestation, for instance, to oil palm expansion in Indonesia (*49, 95*). Such concurrent and interacting drivers of forest degradation and deforestation are poorly evaluated in continental-scale assessments, which can lead to an overly simplified focus on addressing drivers in isolation (*47, 96*). Additionally, data is largely lacking on the legality of the deforestation and production (*97*), or whether the actors involved are small- or large holders and whether they are producing for subsistence or marketed demand (*98-100*).

Moreover, we have not assessed non-agricultural deforestation drivers. Logging and demand for wood products (e.g., timber and pulp), charcoal, and fuelwood are, alongside agricultural expansion, key direct drivers of deforestation and, even more so, of degradation (*6, 55, 101, 102*). While deforestation due to the expansion of tree plantations is estimated by Goldman *et al.* (*36*) and Pendrill *et al.* (*37*) (0.1 Mha/y and 0.8 Mha/y, respectively, with the former only covering eight countries), deforestation due to logging and timber extraction that sometimes occurs in conjunction with and facilitates agriculture expansion (*49, 50, 95*) is not comprehensively quantified at the pan-tropical level.

Urbanization, mining, and energy infrastructure like hydropower dams are relatively minor direct drivers of deforestation from a pan-tropical perspective—together, they amounted to just 2% of the land uses following forest loss across the (sub-)tropics between 1990 and 2000 (*8*), although they can be important direct drivers locally; e.g., gold mining is a dominant direct cause of deforestation in Guyana (*103*) and in Madre de Dios in Peru (*104*). However, the indirect impacts of these drivers can be considerable (*71, 105-107*). A study of the Brazilian Amazon found that deforestation indirectly induced by mining was 12 times larger than the direct deforestation occurring within mining concessions (*108*).

Improving the evidence base

Our findings point to three key data gaps in our understanding of tropical deforestation and its links to agriculture. Overcoming these gaps can considerably strengthen the evidence base to help accelerate global efforts to curb agriculture-driven deforestation—both in the design of policy responses and in evaluating their effectiveness.

First, the lack of consistent pan-tropical data on deforestation still hampers our ability to assess overall deforestation trends and thus the net impacts of interventions to reduce deforestation while accounting for leakage across regions and biomes (*109-111*). Improvements in deforestation data are needed in three main areas, to i) encompass both dry and wet tropics, ii) provide estimates of deforestation that go beyond tree-cover loss and satisfy the commonly-held definition of a persistent conversion of natural forest to any other land use, and iii) ensure that estimates are consistent across regions and over time. Data on deforestation trends could be improved in several ways to help meet these requirements, including by improving contextual data on tree plantations and shifting agriculture to systematically filter out such temporary tree-cover loss from the GFC data (*1*); or, e.g., expanding the Vancutsem *et al.* (*2*) approach to the dry tropics. Furthermore, deforestation area metrics alone are a crude proxy for the multiple social-ecological impacts, which vary significantly between places (*30*). Improved quantification of these impacts remains needed.

Second, to improve our understanding of the relationships between agricultural drivers and forest loss, and to inform both territorial and supply-chain measures directed at specific commodities, a concerted effort is needed to improve the coverage, quality, and frequency of data on pastures and crops that are replacing forests for all regions where significant deforestation occurs. In contrast to deforestation data, data on drivers need not be pan-tropical, as commodity-specific deforestation frontiers are typically concentrated in specific regions and require responses tailored to their context (*111*). Regional-level datasets that can cover the majority of a given commodity, e.g., soy across South America and oil palm in Southeast Asia, play a key role as, being built on regional knowledge, they are typically not just more accurate but also more regionally- and policy-relevant, e.g., in terms of land use and management characterization (*112*). Currently, however, only oil palm (*113*) and soy (*25*) are mapped for most production areas in the tropics (*36*). The attribution of deforestation and conversion to most forest-risk commodities, especially outside of Brazil and Indonesia, therefore relies on agricultural statistics at a very coarse—often national—scale, on local case studies, or on single-year, modeled maps that are often outdated, potentially leading to misattribution. Despite the fact that pastureland is by far the most prominent driver of deforestation, our understanding of pasture extent is particularly poor, as large-scale assessments outside of South America rely on (often unofficial) agricultural statistics or on a global pasture map for the year 2000 (*28*).

Important recent advances in land-use mapping include multiple biome-scale initiatives such as MapBiomas (*114*); sample-based monitoring tools such as CollectEarth (*115*); and efforts to combine wall-to-wall satellite monitoring and sample-based approaches, including to build confidence in temporal trends in deforestation (*4, 23-25, 116, 117*). Future advances can include improving the collection and organization of sub-national agricultural statistics and further leveraging advances in remote-sensing data and methods (*8, 22*).

Third, there is an urgent need to invest in spatially and temporally explicit assessments of agriculture-driven deforestation tailored to the dry tropics and to deforestation frontiers in Africa, with a focused effort to better characterize deforestation in smallholder shifting agriculture (e.g., (*100*)). Uncertainties around the nature, extent, and drivers of deforestation linked to agriculture are unevenly distributed, as the quality of the data used and the performance of the methods vary between countries and biomes (*1, 2, 7, 32,* *36*)(Table 1). Overall, our understanding of agriculture-driven deforestation is systematically poorer in dry forests and wooded savannas, and across the African continent, in contrast with Latin America and the humid tropics. There are several reasons for this: First, there is a general neglect of land-use change research in Africa (*9*), where, additionally, the capacity of agencies to compile data on agricultural production is particularly limited (*118, 119*). Our literature search found comparatively fewer studies on recent agriculture-driven deforestation in Africa (n = 6), compared to Latin America (n = 27) and Asia (n = 26) (table S5). Tropical dry forests are also less researched than wet forests (*116, 120*). Second, remote-sensing mapping of forests and agricultural land cover and their changes is generally more difficult in heterogeneous landscapes, e.g., where tree cover and canopy structure varies, and where smallholder and shifting agriculture results in small, irregularly-shaped and temporally dynamic patches of cultivated land interspersed with natural vegetation (*1, 121, 122*). These challenges are exacerbated by difficulties in discriminating vegetation types for intermediate levels of tree cover, such as in savannas, shrublands and sparsely forested woodlands, which are more prevalent on the African continent (*30, 77, 116*).

This disparity in our understanding of the dry and seasonal tropics compared to the wet tropics (Table 1) is particularly striking given that about one-third of all tropical dry forests and woodlands are in active deforestation frontiers (*56*). Further emphasis on deforestation in the dry and seasonal tropics would also challenge the disproportionate prioritization of international conservation funding towards moist forest biomes (*123*).

Conclusions

The synthesis of current data on agriculture-driven deforestation provided here challenges conventional wisdom and has profound implications for policy. The central insight from our review is the distinction—and discrepancy—between agriculture-driven deforestation and deforestation resulting in agricultural production. While as much as 90–99% of deforestation occurs in landscapes where agriculture is the main driver of tree-cover loss, only 45–65% of deforestation can be attributed to the expansion of actively-managed cropland, pasture or tree crops. The implications of this discrepancy are wide-ranging for efforts to curb deforestation and to mitigate climate change. The most recent global carbon budget indicates a stagnation or decline in global emissions from land-use change, due most notably to reduced tropical cropland expansion (*124*). However, that assessment does not account for forest degradation or the large share of deforestation not resulting in agricultural production identified here. The discrepancy also highlights two essential conclusions that can shape more effective policy responses to deforestation.

First, while public and private policies promoting deforestation-free international supply chains have a key role to play (*96, 125*), their direct effectiveness in reducing deforestation is fundamentally limited given that (i) international demand represents only a quarter of total deforestation resulting in agricultural production, and (ii) one third to one half of agriculture-driven deforestation does not result in productive agricultural land. Additionally, most supply-chain interventions to date have been focused on direct sourcing and are restricted in their ability to address products associated with deforestation that enter supply chains through intermediaries (*126*). International supply-chain interventions can, in principle, help address some of the indirect ways agriculture drives deforestation (e.g., by discouraging speculative clearings (*127*)). However, tackling deforestation linked with domestic demand as well as the underlying drivers of agriculture-driven deforestation more broadly, such as land-tenure insecurities and conflicts, likely requires broader land governance and rural development interventions (*125, 128*). Tenure reform, land zoning, regulatory reform and enforcement, and extension services supporting farmers, all have an important role to play in slowing agriculture-driven deforestation (*125, 128, 129*). Many of these approaches would likely benefit from closer partnerships between demand and supply-side actors and the scaling up of deforestation-free supply chains to deforestation-free regions and sectors. There is an urgent need to identify and leverage the mechanisms by which demand-side supply-chain policies, including zero-deforestation commitments, can go beyond their immediate impacts and help motivate and catalyze broader changes in territorial governance. This remains a key research frontier.

Second, to effectively reduce deforestation, interventions need to address the systemic interdependencies between the expansion of different commodities, requiring a much stronger focus on more comprehensive, landscape-level approaches. The most prominent example of this is pasture expansion, which is tightly linked to soy expansion and land speculation across Latin America. An excessive focus on individual commodities, which characterize many current policy initiatives, risks undermining the potential to avoid widespread leakage and deliver positive reductions in deforestation on the ground.

The unprecedented focus on forest conservation and nature-based climate solutions in the aftermath of the UNFCCC COP 26 and heading into the UN Biodiversity COP 15 provides a critical moment to ensure that urgent efforts to tackle deforestation are guided and evaluated by an evidence base fit for purpose as this review sets out.

Box 1. Key terms for disentangling agriculture-driven deforestation.

Natural forest: 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*" (*33*). Aside from primary and intact forests, *natural forest* also includes regenerated (second-growth) forests and partially-degraded forests, provided they fulfill the definition above (*33*). As no comprehensive, pan-tropical map of natural forests currently exists, most studies approximate their extent.

Deforestation: A persistent conversion of *natural forest* to any other land use, such as agriculture or human settlements, or to tree plantations.

Agriculture: Agriculture includes cropland, pastures and tree crops, but not forestry (excluding timber, pulp and paper).

Agriculture-driven deforestation: Deforestation for which agriculture, directly or indirectly, is a cause. This includes both *deforestation resulting in agricultural production* and *agriculture-driven deforestation without expansion of agricultural production*. Agriculture-driven deforestation does not necessarily mean that agriculture is the only, or main, cause of deforestation; for example, deforestation may be directly driven by the demand for timber, alongside the demand for agricultural expansion (*49, 50, 95*) and indirect, or underlying, drivers always play a role (*6, 27*).

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Deforestation resulting in agricultural production: Deforestation that can be attributed to the expansion of land under active agricultural production systems.

Agriculture-driven deforestation without expansion of agricultural production: 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. This can be due to several mechanisms and is distinct from forest degradation or other tree-cover loss in the sense that the forest has been fully cleared and there are signs of other land uses, though in practice the boundary can be hard to draw.

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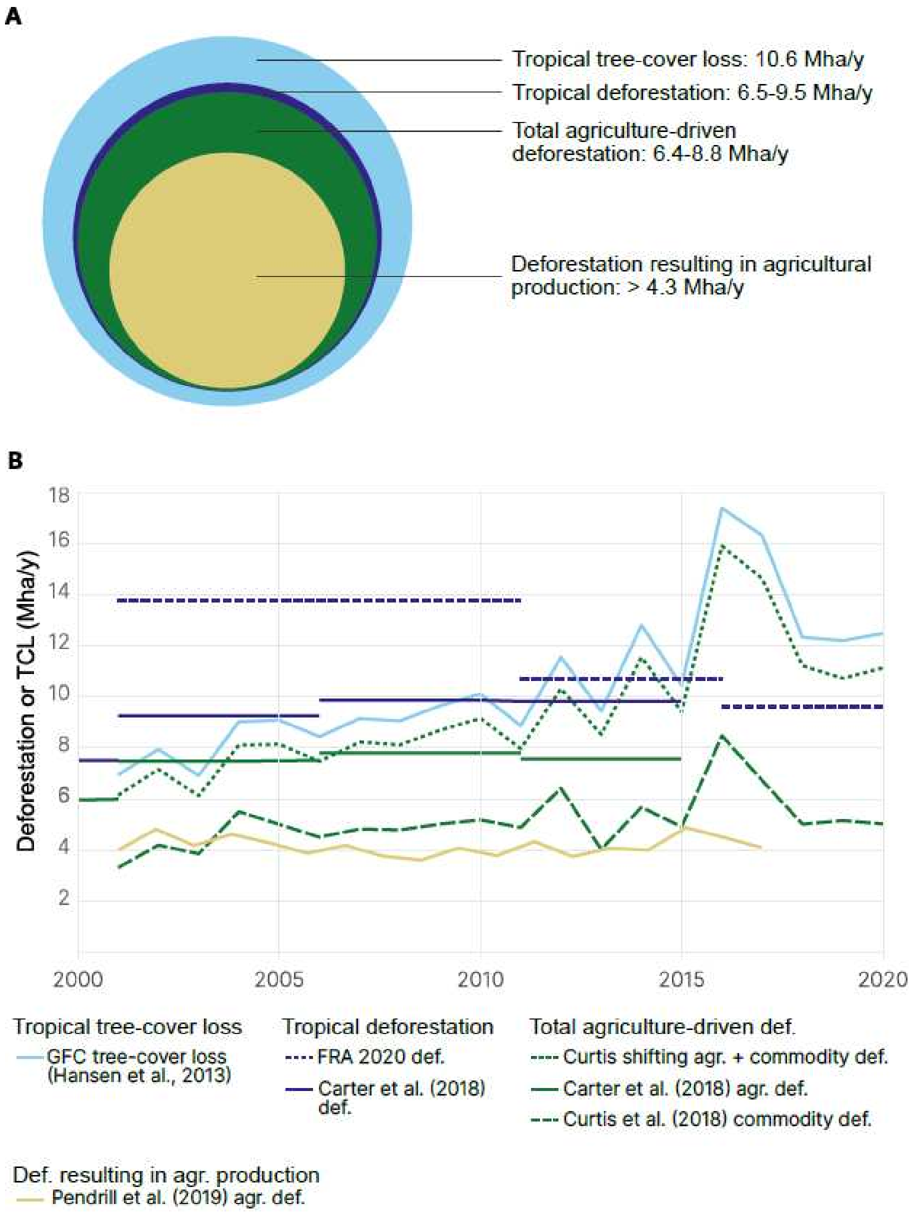

Fig. 1. Tree-cover loss, deforestation and agriculture-driven deforestation. (A) A conceptual diagram visualizing the concepts of tropical tree-cover loss, deforestation, agriculture-driven deforestation, and deforestation resulting in agricultural production, nested from the broadest to the narrowest concept. The area of each circle is scaled by the estimated extent, though the ranges are not represented, so for deforestation and agriculture-driven deforestation the extent is approximated. **(B)** Studies vary considerably in their estimated extents (millions of hectares per year) and trends, reflecting uncertainties and conceptual differences. The data on tree-cover loss (TCL) are from GFC (updated from Hansen *et al.* (*1*)); on deforestation from the FAO FRA (*3*) and Carter *et al.* (*32*); on agriculture-driven deforestation updated from Curtis *et al.* (*7*), Carter *et al.* (*32*), and on deforestation resulting in agricultural production updated from Pendrill *et al.* (*37*). Abbreviations used: "def" = deforestation, "agr." = agriculture. In all figures, the data have been aligned to the same set of 87 (sub-)tropical countries.

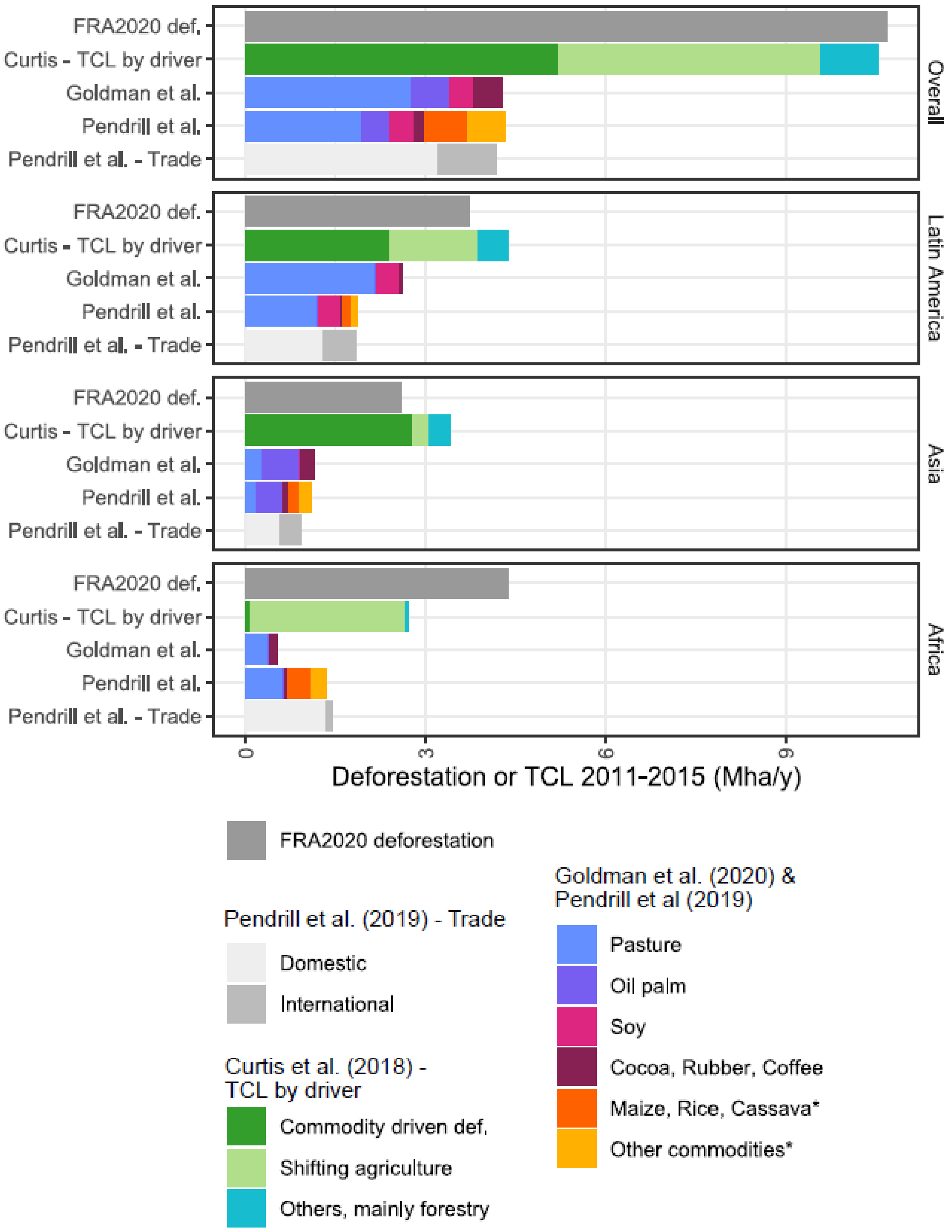

Fig. 2. Estimates of tropical deforestation and its agricultural drivers. The average extents (2011–2015) of TCL by driver (data from Hansen *et al.* (*1*) and Curtis *et al.* (*7*), where TCL driven by agriculture falls under Shifting agriculture and Commodity-driven deforestation) and of deforestation attributed to agricultural commodities (data from Goldman *et al.* (*36*), Pendrill *et al.* (*37*)) and international trade (data from Pendrill *et al.* (*37*)). Commodities followed by "*" are not quantified by Goldman *et al.* (*36*). FAO FRA (*3*) deforestation rates are included for comparison. Abbreviations used: "TCL" = tree-cover loss, "def" = deforestation, "agr." = agriculture, "prod." = production.

Fig. 3. The ways in which agriculture contributes to deforestation differ between regions. Agriculture-driven deforestation (based on Curtis *et al.* (*7*)) includes deforestation resulting in agricultural production (based on Pendrill *et al.* (*37*)) as well as agriculture-driven deforestation without expansion of agricultural production, which can occur through several potential mechanisms. Incomplete records of agricultural area and production might also explain a share of that deforestation, which should thus be attributed to certain land uses and commodities if monitoring systems improve. Deforestation resulting in agricultural production can, in turn, be attributed further to certain land uses and commodities (based on Pendrill *et al.* (*37*) and Goldman *et al.* (*36*)), and to export or domestic demand (based on Pendrill *et al.* (*37*)).

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Table 1. Data availability for assessing deforestation resulting in agricultural production. Deforestation rates (total and for major post-forest loss land-uses, in Mha/y) for the eleven countries with the highest rates of deforestation in the period 2011–2015, and quality of the underlying driver data (cell shading). Estimates are from Pendrill *et al.* (*37*) (P), Goldman *et al.* (*36*), or other studies (O) identified in the literature review and where national-level estimates for the time-period 2011–2015 could be extracted from the source (*28*).

	Defore-station rate	Cropland		Pasture			Soybeans			Oil palm			Rubber		Cocoa		Coffee		Maize, rice, cassava		
		P	O[a]	P	G	O[b]	P	G	O[c]	P	G	O[d]	P	G	P	G	P	G	P	P	P
Latin America																					
Brazil	1.5–2.2	0.46	0.19	0.75	1.1	0.49	0.27	0.22	0.06-0.16	0.00	0.00		0.00	0.00	0.00	0.02	0.00	0.02	0.11	0.01	0.01
Paraguay	0.36–0.38	0.11		0.14	0.14		0.08	0.02		0.00	0.00						0.00	0.00	0.01	0.01	0.00
Argentina	0.28–0.33	0.00		0.00	0.13		0.00	0.08			0.00							0.00	0.00	0.00	0.00
Bolivia	0.20–0.24	0.02		0.04	0.34		0.00	0.04			0.00				0.00	0.00	0.00	0.00	0.00	0.00	0.00
Africa:																					
DR Congo	0.37–0.84	0.36		0.02	0.01		0.00	0.00		0.01	0.00		0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.08	0.12
Angola	0.18	0.02		0.18	0.02		0.00	0.00		0.00	0.00				0.00	0.00	0.00	0.00	0.01	0.00	0.01
Madagascar	0.07–0.26	0.00		0.01	0.04		0.00	0.00		0.00	0.00				0.00	0.00	0.00	0.02	0.00	0.00	0.00
Mozambique	0.17	0.00		0.18	0.03			0.00			0.00							0.00	0.00	0.00	0.00
Asia:																					
Indonesia	1.2–1.3	0.64	0.3-0.8	0.09	0.03		0.00	0.01		0.39	0.45	0.14-0.24	0.04	0.06	0.01	0.05	0.00	0.03	0.03	0.07	0.00
Malaysia	0.25–0.26	0.07		0.00	0.01		0.00	0.00		0.05	0.16	0.08	0.01	0.05	0.00		0.00	0.00	0.00	0.01	0.00
Myanmar	0.14–0.24	0.06		0.01	0.06		0.00	0.00			0.00		0.01				0.00	0.00	0.01	0.00	0.00

[a] Brazil (*130*), Indonesia (*55, 114*)
[b] Brazil (*131*)
[c] Brazil (*80, 132, 133*)
[d] Indonesia (*55, 114, 134, 135*); Malaysia (*136, 137*)

Def. rate (Mha/y)
0 0.1 0.3 ∞

Data quality classification:
- Recent multitemporal extent maps of high resolution (<=30 m or vector) and/or accuracy.
- Recent (>2012), single year extent maps of high spatial resolution (<=30 m or vector).
- Official subnational agricultural statistics (recent & multitemporal, but not spatially explicit).
- Official national-level agricultural statistics (recent & multitemporal, but not spatially explicit).
- Based on unofficial national-level agricultural statistics (e.g., imputed by the FAO) or on older, coarse-resolution maps.

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Supplementary Materials

Materials and Methods

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Supplementary Materials for

Disentangling the numbers behind agriculture-driven tropical deforestation

Florence Pendrill, Toby A. Gardner, Patrick Meyfroidt, U. Martin Persson, Justin Adams, Tasso Azevedo, Mairon G. Bastos Lima, Matthias Baumann, Philip G. Curtis, Veronique De Sy, Rachael Garrett, Javier Godar, Elizabeth Dow Goldman, Matthew C. Hansen, Robert Heilmayr, Martin Herold, Tobias Kuemmerle, Michael J. Lathuillière, Vivian Ribeiro, Alexandra Tyukavina, Mikaela J. Weisse, Chris West.

Correspondence to: florence.pendrill@chalmers.se and toby.gardner@sei.org

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Materials and Methods

S1 Geographic and temporal scope of the study

This paper focuses on (sub-)tropical deforestation, as this is where almost all of the deforestation for agriculture, or farming, here including cropland, pastures and tree crops, occurs (*7*). The set of 87 included countries, to which all numbers have been aligned, account for 98% (10.6 Mha/y out of 10.8 Mha/y) of the total (sub-)tropical tree-cover loss and 51% (10.6 Mha/y out of 21.0 Mha/y) of total global tree-cover loss (TCL) (*1*). Some of the studies do not cover the complete 87-country set (table S2), but the exclusion of these countries is not expected to have any significant impact for comparing the results between the studies, as the missing countries all have very low (or zero) rates of GFC tree-cover loss or FAO Forest Resources Assessment (FRA) deforestation. For the multiple-region input-output (MRIO) trade model results from Pendrill *et al.* (*37*), (*138*), it was not possible to provide results only for the harmonized set of 87 countries, because of its regional aggregation. The differences resulting from this are expected to have a negligible impact on the overall results.

S2 Deforestation rates and trends—datasets and challenges

In the analyses presented here, we define *tropical deforestation* as the deforestation of both humid and dry natural forests, across the subtropics and tropics (pan-tropics), constrained to a set of 87 countries.

The two main global data sources on deforestation and forest loss assessed are the FAO Forest Resources Assessment (*3*) and the Global Forest Change (GFC) tree-cover loss dataset (*1*) (available for download from https://fra-data.fao.org/ and https://earthenginepartners.appspot.com/science-2013-global-forest respectively). These datasets differ in method, update frequency, and crucially also on the type of loss they portray, resulting in considerable differences in estimates of both the magnitude of loss and trends (fig. S2)[1].

Both the FRA and the GFC dataset definitions of forest and loss diverge somewhat from the definition of deforestation used in this synthesis (Box 1). The FRA focuses on *land-use change*, i.e., deforestation is only recorded if the tree-cover loss results in a change of land use from forestry towards agriculture or other land-uses (urban, etc.), but not if tree cover is expected to regenerate or if the land is replanted so that the land remains under forestry use (*139*). Therefore, conversion from a natural forest to a tree plantation, including for timber, pulp and rubber, is not considered deforestation by the FRA.

In contrast, the GFC tree-cover loss dataset focuses on *land-cover change* (where forests are defined primarily by their biophysical characteristics, such as tree height and canopy cover, measured by satellite remote sensing), which includes disturbances within existing forest stands. That is, the GFC dataset identifies tree-cover loss, defined as: "a stand-replacement disturbance or the complete removal of tree cover canopy [within pixels of 30-m resolution]" (*1*). This implies that 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 (*1*). These do not—at least in the initial stages—constitute deforestation. However, forest degradation is frequently a precursor of deforestation (*2*) and, e.g., if a forest has been burned and does not recover, we consider this de facto deforestation, despite an absence of a conversion to a formal land use (this is consistent with the deforestation definition in the Accountability Framework (*33*)). By contrast, forest

[1] For an accessible overview of these differences, see https://www.wri.org/insights/insider-global-forest-watch-and-forest-resources-assessment-explained-5-graphics.

degradation typically refers to disturbances within a natural forest that reduce its capacity to deliver ecosystem services, while the area remains as forest, with such disturbances including logging, fire, fragmentation, and the unsustainable collection of fuelwood and other forest products. The boundaries between forest degradation and deforestation are not clear cut, as severe degradation may impede regeneration even absent any other formal land use, resulting in de facto deforestation.

We would thus expect the total amount of deforestation to be lower than the amount of tree-cover loss and in the main paper, we also distinguish *tree-cover loss* (TCL) from *deforestation* (Box 1), with the GFC data providing estimated extents of tree-cover loss rates. We focus primarily on GFC tree-cover loss data (and its trends) as this is the main source used for agriculture-driven deforestation assessments. Many recent estimates of agriculture-driven deforestation use the GFC tree-cover loss dataset, as it provides annual maps at a 30-m resolution that can be summarized at different scales (rather than just national or coarser). This allows for clearer connections to the tree-cover loss drivers and more accurate assessments of the impacts of loss (on, e.g., carbon emissions and biodiversity loss).

There are also a few additional large-scale assessments of recent deforestation rates, which deviate somewhat from the definition of deforestation used in this synthesis. Carter *et al.* (*32*) estimate country-level deforestation rates by creating a weighted average of four sources (the FAO FRA 2015; GFC tree-cover loss (*1*); Kim *et al.* (*140*), and a 2012 Remote Sensing Survey from FAO and JRC), depending on their estimated uncertainty for each country (for five year time periods between 1990 and 2015). At the time of writing (March 2022), a new Remote Sensing Survey complementing the FRA 2020 is under preparation (*4*). Vancutsem *et al.* (*2*) provide comprehensive maps of tropical moist forest extents and deforestation rates (as well as forest degradation and recovery/regrowth, and dynamics over time; 1990–2019). As this is a recently released dataset, it has not yet been used in assessments of agriculture-driven deforestation. However, it will undoubtedly be a valuable source for future assessments of deforestation drivers because it has high spatial and temporal detail and distinguishes deforestation and forest degradation. Unlike the GFC tree-cover loss data, it does not, however, cover tropical dry forests.

The uncertainties in the GFC tree-cover loss data, and the disagreement between the deforestation datasets, are largest in Africa (*1, 2, 35*). These uncertainties propagate to Curtis *et al.* (*7*); Pendrill *et al.* (*37*) and Goldman *et al.* (*36*), which are all based on GFC tree-cover loss data.

For remotely-sensed estimates of tree-cover loss, such as the GFC tree-cover loss data, the conceptual challenges of defining forest loss include selecting appropriate thresholds on canopy cover (*30*) and patch size forests prior to loss (*29, 141*), as well as how much these need to be reduced to count as a loss (*31, 142*).

The minimum canopy-cover thresholds used to define forests prior to loss by the pan-tropical assessments of agriculture-driven deforestation (*7, 8, 32, 36, 37*) vary somewhat: between 10% and 30% (similar to the FAO minimum canopy cover threshold of 10% (*139*) and the range of 10%–30% allowed in UNFCCC's REDD+ process (*143*)). This is not expected to be a big source of discord between these sources; 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/y with a >10% threshold compared with 20.6 Mha/y with a >30% threshold (2001–2020) (*1*). (A >50% threshold gives an average global tree-cover loss rate of just under 18 Mha/y (*1*).)

The minimum forest patch size also varies between the pan-tropical assessments of agriculture-driven deforestation: from a single Landsat pixel (30 m by 30 m—around 0.1 ha) in Curtis *et al.* (*7*), Pendrill *et al.* (*37*) and Goldman *et al.* (*36*), between >0.1 and >0.5 ha in Carter *et al.* (*32*), and up to >5 ha in De Sy *et al.* (*8*). This can have a non-negligible impact on measures of deforested area (*141, 144*).

Most of the studies used in this analysis thus use a minimum canopy-cover threshold between 10% and 30% and a minimum span between 0.1 and 5 hectares. Some other ecosystems, not typically referred to as "forests", such as varyingly wooded savannas, can be partially included in this definition.

The FAO FRA 2020 deforestation rates presented throughout this paper for the 87 countries were calculated by using the FRA deforestation rate (*3*) where available. Otherwise, the FAO FRA (*3*) "Forest area net change" value was used if this was negative (i.e., net deforestation) or set to zero if this was positive (i.e., net afforestation). For the 2011–2015 time period, the FAO FRA 2020 total deforestation is estimated to be 10.7 Mha/yr. This exceeds the total estimated extent of GFC tree-cover loss, despite the FAO FRA 2020 applying a more restrictive definition of deforestation and only reporting net (not gross) deforestation for some countries. The uncertainty-weighted deforestation rates found by Carter *et al.* (*32*) of 9.8 Mha/y are also high; this partly reflects the fact that the FAO FRA (2015) is one of the major data inputs to the analysis by Carter *et al.* (*32*).

Additionally, the datasets show diverging trends, with an increase from 9 to 12 Mha/y in GFC tree-cover loss (*1*), compared to a decrease from 14 to 10 Mha/y between the 2001–2010 and 2011–2020 in FRA deforestation rates (FRA 2020) (*3*). The diverging trends may in part relate to an increased contribution of forest degradation detected in the GFC tree-cover loss data, but also points to considerable uncertainties in the trends, discussed further in the next section. This mirrors discrepancies in both rates and trends of tropical deforestation between the FAO FRA and remote sensing studies (*145*). The range of estimates of tropical deforestation rates for the 1980-90s (*145, 146*) also implies that it is hard to ascertain a long-term trend in tropical forest loss.

For a more limited subset of countries and forests (specifically, disturbances within tropical moist forests, for the 33 countries within our set that had at least 4 Mha of tropical moist forest cover), Vancutsem *et al.* (*2*) found around 4 Mha/y of deforestation (in their approach, "*direct* deforestation", defined as "*full removal of trees within a few months*") and 5 Mha/y of forest degradation (there defined as "*a disturbance in the tree cover canopy that is visible from space over a short time period (less than 2.5 years).*") The deforestation rates in tropical moist forest from Vancutsem *et al.* (*2*) generally declined 2000–2010, before increasing again between 2010 and 2016, and subsequently declining overall (fig. S2).

Consistent pan-tropical data on deforestation trends is lacking due to several methodological and conceptual challenges. First, at a more general level, the GFC tree-cover loss (*1*), the FRA deforestation (*3*) and Vancutsem *et al.* (*2*) 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. Second, these approaches may therefore capture differently distinct trends in different kinds for forest loss over time. While it is beyond the scope of this study to fully assess the reasons for why the GFC tree-cover loss data and the FRA deforestation rates show diverging trends, in addition to the increased sensitivity of GFC tree-cover loss to forest degradation and inconsistencies in the FRA deforestation rates over time, their diverging trends are likely in part related to changes in the relative proportions of different kinds of tree-cover 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, such as:

a) **Expansion of tree plantations at the expense of natural forests**. Accelerating trends of tree plantations would show up in GFC as tree-cover loss when plantations expand over natural forests. Conversely, they would not appear as deforestation in FRA or would even appear as an increase in forest cover when plantations expand into non-forested areas (see more in (*147*)).
b) **Inconsistencies in assessing importance of shifting agriculture as a driver of forest loss.** Shifting agriculture systems would show up as tree-cover loss in GFC but not necessarily in FRA deforestation, depending on country methodologies and decisions. Moreover, the attribution of shifting agriculture to deforestation estimates depends on whether the shifting agricultural system is expanding or remaining in rotations.
c) Increases in the share of agriculture-driven deforestation without expansion of agricultural production.
d) Increased natural disturbances, such as forest loss from wildfires, floods or landslides.

S3 Agriculture-driven deforestation—pan-tropical datasets and uncertainties

Table S1 provides an overview of pan-tropical assessments of agriculture-driven deforestation, including the types of drivers they assess, a brief summary of their methods, scope and resolution, as well as details on key limitations and data access details where applicable, and kinds of questions each study helps address. Table S4 presents the extent of agriculture-driven deforestation from all of these sources, more or less harmonized to the same set of 87 countries (discrepancies are detailed in table S2). The main sources used to derive the estimated ranges in this paper are Curtis *et al.* (*7*). and Pendrill *et al.* (*37*)[2]. Additional details on these datasets and how the estimated ranges presented in the main paper were derived are described in the next section. De Sy *et al.* (*8*), Cuypers *et al.* (*45*) and Carter *et al.* (*32*) also provide useful estimates of agriculture-driven deforestation (fig. S3 and table S4), but were not used further to inform the estimated ranges of agriculture-driven deforestation in the main paper due to their limited temporal scope: De Sy *et al.* (*8*) is available only until 2005, Cuypers *et al.* (*45*) only until 2008, and Carter *et al.* (*32*) assume a constant fraction of agriculture-driven deforestation based on pre-2010 data from De Sy *et al.* (*8*) and Hosonuma *et al.* (*20*) (table S1).

The most commonly cited number in this context—that around 80% of deforestation is caused by expanding agriculture—is based on Hosonuma *et al.* (*20*) and also presented in Kissinger *et al.* (*21*). The 80% number is occasionally also attributed to FAO's State of the World's Forests (SOFO) 2016 (*148*), as it presents an adaptation of the Hosonuma *et al.* (*20*) data. Lawson (*149*) also builds partly on the approach and data from Hosonuma *et al.* (*20*).

Hosonuma *et al.* (*20*) provides a very coarse estimate of the share of deforestation attributed to drivers, based on quantitative data for only 12 countries (covering around half of the

[2]Updated versions of both datasets are used, see table S1 for details.

deforestation), combined with qualitative estimates for 34 countries and extrapolation to 46 countries lacking driver estimates.

There are also a few recent studies assessing drivers for large parts of the tropics. For South America, Zalles *et al.* (*24*) assess conversions from natural land to pasture, cropland and plantations. The conversions are assessed annually from 1985 to 2018 at 30-m resolution, based on Landsat remote sensing data. Also, for Latin America, Graesser *et al.* (*150*) mapped the sources (in 2001) of cropland and pasture (in 2013) across Latin America, based on coarser (MODIS) remote sensing data. For Brazil and of the Amazon, Chaco, Pampa and the Atlantic Forest, the MapBiomas initiative assesses land-cover changes every year between 1985 and 2020, distinguishing between pasture, temporary crops and permanent crops (*114*). There is also a MapBiomas product for Indonesia.

For seven countries in Southeast Asia, Tenneson *et al.* (*117*) assessed land cover (and use) in the years 2000 and 2015, using visual interpretation of a stratified random sample. While their year 2000 map distinguishes just natural forest, tree crops, or other land cover (based on 30-m resolution Landsat data), their year 2015 map provides highly detailed land use categories (distinguishing multiple crops). Their comparison between these two maps indicates that 9.4 Mha (60%) of the 15.8 Mha cleared between 2000 and 2015 supported some crops in 2020.

For six countries in the Congo Basin, Tyukavina *et al.* (*35*) assessed direct deforestation drivers, including small- and large-scale agriculture, for every year between 2000 and 2014. Their study was based primarily on 30-m resolution Landsat data, supplemented by very high (<1–2.5 m) resolution satellite imagery from Google Earth and SPOT (*35*).

For a more long-term perspective, Winkler *et al.* (*151*) combine agricultural statistics with multiple remotely-sensed land cover maps to reconstruct changes to forest, cropland and pasture/rangeland between 1960 and 2019 across the globe.

S4 Estimating the ranges of deforestation and agriculture-driven deforestation

Building on the critical examination of the pan-tropical assessments (summarized in table S1), we synthesize the best available evidence from these studies to derive estimates of recent (2011–2015) (*i*) total tropical deforestation, (*ii-a*) total tropical deforestation due to the expansion of agricultural production and (*ii-b*) total tropical agriculture-driven deforestation, and (*iii*) the share of tropical deforestation linked to agriculture.

S4a Main datasets used

Multiple datasets were used to narrow down likely estimated ranges of deforestation and agriculture-driven deforestation. The main sources used are Curtis *et al.* (*7*) and Pendrill *et al.* (*37*), both relying on the same GFC tree-cover loss data (*1*). Aside from that, however, the methods used by the two studies differ significantly and can be seen as describing different aspects of the role of agriculture in driving deforestation. This section thus provides some additional details primarily on Curtis *et al.* (*7*) and Pendrill *et al.* (*37*) focusing on their uncertainties and how their methods relate to the operationalization of the concepts of *agriculture-driven deforestation* (primarily Curtis *et al.* (*7*)) and the narrower *deforestation resulting in agricultural production* (Pendrill *et al.* (*37*)) (Box 1).

Pendrill *et al.* (*37*) can be seen as an estimate of deforestation resulting in agricultural production employing a land-balance model to attribute GFC tree-cover loss to expanding cropland and pastures. The net expansion of cropland and pastures is primarily based on national agricultural statistics (FAOSTAT (*46*), and subnational data for Brazil and Indonesia).

Additionally, their gross expansion is estimated by supplementing this with remotely-sensed data on gross changes in grassland (as a proxy for pastures) and cropland (*152*)(which is based on ESA Climate Change Initiative (CCI) land cover data).

There are two key sources of uncertainty inherent in the Pendrill *et al.* (*37*) approach. The first source of uncertainty is its assumption that the agricultural land uses expanding at the national (or subnational) level are the drivers of deforestation. However, the method does not unequivocally establish whether these land uses expanded directly on cleared forest land or if they, rather, indirectly "pushed" other land uses into the forest (*37*). This may lead to some overestimation of deforestation resulting in agricultural production, but—as most agricultural expansion comes at the expense of other agricultural land uses or of forests (*23, 24, 150, 153*)—this source of uncertainty is more likely to affect the relative attribution between different agricultural land uses (*37*). That is, this first source of uncertainty is more likely to apply to the attribution between cropland and pasture, and between different crops, than to the attribution between agriculture and other land uses (such as infrastructure) (*37*). The second key source of uncertainty comes from its reliance on attributing forest loss to the expansion of cropland and pastures (and subsequently crops) according to FAOSTAT-recorded agriculture. This can lead to underestimation in countries that are slower to update their statistics and where the self-reporting by countries incompletely captures some agricultural activities (e.g., shifting cultivation). The data quality can also vary considerably between countries, and, in many instances, the data are imputed or estimated rather than reported directly by the countries themselves (the overall accuracy of the FAOSTAT data has not been assessed, though it is described as "reasonably accurate" (*46*)). There have also been some indications of a discrepancy between cropland expansion and harvested area expansion reported in FAOSTAT. The global increase in harvested area is more than three times that of the increase in cropland area (2002–2016), which likely cannot be fully explained by increased double- or triple cropping or decreasing fallows (*154*). For the countries where cropland area expansion is underestimated in FAOSTAT, the Pendrill *et al.* (*37*) approach likely underestimates the deforestation resulting in agricultural production (particularly due to cropland expansion).

We then assess agriculture-driven deforestation as deforestation occurring in landscapes where agriculture is the dominant driver of forest loss using the Curtis *et al.* (*7*) data, which identifies the dominant driver of GFC tree-cover loss (at 10-km resolution, i.e., within 10 km by 10 km grid cells) based on five classes: commodity-driven deforestation, shifting agriculture, forestry, wildfire and urbanization. Commodity-driven deforestation primarily includes *"[...] conversion of forest and shrubland to a nonforest land use such as agriculture (including oil palm) [...]"* (*7*), although it also includes some conversion to mining and energy infrastructure (expected to be at low rates). Shifting agriculture is *"defined as small- to medium-scale forest and shrubland conversion for agriculture that is later abandoned and followed by subsequent forest regrowth"* (*7*).

S4b Estimating the total tropical deforestation rates

We constrain the likely range of total tropical deforestation primarily by using the Curtis *et al.* (*7*) and ancillary datasets to assess lower and higher estimates of where the GFC tree-cover loss is likely to be permanent deforestation versus temporary tree-cover loss (e.g., rotational clearings in shifting cultivation systems, or in plantations or managed forests).

For the main deforestation range estimate, the GFC tree-cover loss data were split into three categories: (*i*) deforestation, (*ii*) not deforestation, or (*iii*) unknown mix of persistent deforestation and temporary tree-cover loss. This gives a lower estimate on deforestation equal to category (*i*), and a higher estimate equal to categories (*i*) plus (*iii*). This split was done based largely on Curtis *et al.* (*7*) classification of the dominating drivers of GFC tree-cover loss, together with a few complementary data sources (fig. S4). First, any tree-cover loss occurring within primary forest extents (*54*) was categorized as deforestation (category (*i*)). Second, to help constrain the higher estimate and refine the ranges further, we used data on tree plantation extent (*53*) to identify additional tree-cover loss that is likely not deforestation (category (*ii*)), because it occurred within existing plantations. Third, the remaining tree-cover loss was split based on the Curtis *et al.* (*7*) tree-cover loss dominant drivers, based on the following assumptions: commodity-driven deforestation and urbanization typically constitute deforestation (corresponding to our category (*i*) above); (large) wildfire is not deforestation (category (*ii*) above); and tree-cover loss driven by forestry and shifting agriculture constitutes a mix of deforestation and temporary forest loss (category (*iii*) above). Finally, the lower estimate was adjusted to reflect the assumed minimum amount of agriculture-driven deforestation at the country level (detailed further in the next subsection). Put together, this analysis results in an estimated range of 6.5–9.5 Mha/y of total deforestation in our set of 87 tropical and subtropical countries for the period 2011–2015.

The second step above—identifying tree-cover loss within existing tree plantations—required a couple of steps, as the time period of interest here (2011–2015) pre-dates the tree plantation data (which best represent plantation extents 2013–2015). We, therefore, first calculate the average share of tree-cover loss occurring within tree plantations 2015–2020 for each country and Curtis *et al.* (*7*) driver class. We then assume that this share is the same for the 2011–2015 time period (in doing this, we are thus assuming that there is no major change in the relative rates of tree plantation expansion, harvesting or other drivers between the two time periods). This share is then multiplied with the tree-cover loss amounts (per country and driver class) for 2011–2015 to obtain an estimate of how much tree-cover loss occurred within already existing plantations, thus allowing us to assign those amounts to category (*ii*). For example, if in country X, 20% of 2015–2020 tree-cover loss driven by forestry (GFC/Curtis *et al.* (*7*)) occurred within already existing tree plantations (SDPT), and there was on average 1 000 ha/y of tree-cover loss driven by forestry (GFC/Curtis *et al.* (*7*)) between 2011 and 2015, then we would assume that—of those 1 000 ha/y—200 ha/y (20% of 1 000 ha/y) was not deforestation and 800 h/y would remain in the unknown/mix category (*iii*).

The definition of deforestation in the FAO FRA differs from the main definition used in this paper, primarily in that conversion from a natural forest to a tree plantation is not considered as deforestation in the FRA, as the land remains under forestry use and thus assumed to regrow (*139*). Applying this definition to the GFC tree-cover loss and Curtis *et al.* (*7*) above would mean that no tree-cover loss driven by forestry would count as deforestation, irrespective of whether it was originally primary forest. This would reduce the estimate of total deforestation by 0.1 Mha/y on the lower estimate and 0.7 Mha/y on the higher estimate.

S4c Estimating agriculture-driven deforestation and deforestation resulting in agricultural production

The likely range of agriculture-driven deforestation depends on the interpretation. We make a distinction between "deforestation resulting in agricultural production" and the overarching "agriculture-driven deforestation" (Box 1).

For our 87-country set, Pendrill *et al.* (*37*) find a total of 4.3 Mha/y of deforestation resulting in agricultural production in 2011–2015. This can be considered a conservative estimate due to uncertainties in the agricultural statistics used.

Agriculture-driven deforestation is primarily quantified as a higher and lower estimate based on Curtis *et al.* (*7*). This range is derived using the same approach as for the total deforestation rate range described above, but exclusively focusing on the agriculture-related tree-cover loss driver classes: commodity-driven deforestation and shifting agriculture. As a first step, a low estimate value is the amount of commodity-driven deforestation (excluding the amounts estimated to have occurred within existing plantations), as well as tree-cover loss dominated by shifting agriculture in what was previously primary forest. The higher estimate additionally includes all tree-cover loss occurring in areas where loss is dominated by shifting agriculture. This results in a range of 5.5–8.8 Mha/yr. In a second step, the low estimate based on Curtis *et al.* (*7*), Harris *et al.* (*53*), Turubanova *et al.* (*54*) is compared with the estimated rate of deforestation resulting in agricultural production in each country (based on Pendrill *et al.* (*37*)). The highest of these two values is used to gain an improved estimate of the overall lower estimate of agriculture-driven deforestation, though capped at the total of commodity-driven deforestation and shifting cultivation. That is, for each country, we used whichever value was largest of: (a) the low estimate value based on Curtis *et al.* (*7*); and (b) the value by Pendrill *et al.* (*37*), unless this exceeded the sum of commodity-driven and shifting agriculture forest loss from Curtis *et al.* (*7*) (which occurs in some instances due to the difference in canopy cover threshold in the underlying deforestation data employed by Curtis *et al.* (*7*) and Pendrill *et al.* (*37*)) in which case the latter estimate was used. For most countries, the low estimate value based on Curtis *et al.* (*7*) is used, although the Pendrill *et al.* (*37*) value is used for several countries, especially in Africa where most tree-cover loss is classified as driven by shifting agriculture by Curtis *et al.* (*7*). This results in an overall lower estimate of 6.4 Mha/y (including more than twice as much agriculture-driven deforestation in Africa, compared with the low estimate value based on Curtis *et al.* (*7*): 1.3 Mha/y compared with 0.6 Mha/y). As noted, this improved estimate is also used for deriving the lower estimate of the deforestation rate.

Put together, this analysis results in a range of 6.4–8.8 Mha/y of total agriculture-driven deforestation and a range of 6.5–9.5 Mha/y of total deforestation in our set of 87 tropical and subtropical countries for the period 2011–2015. Our synthesized estimate range of agriculture-driven deforestation is narrowest (2.2–2.3 Mha/y) in Asia and widest in Africa (1.3–2.7 Mha/y); Latin America lies in between, with the highest estimate of agriculture-driven deforestation (2.9–3.8 Mha/y). Table S4 compares these rates with different pan-tropical studies across different (5-year) time periods and continents. Results per country are presented in table S7.

Carter *et al.* (*32*) similarly estimate the amount of deforestation driven by agriculture to 7.6 Mha/y in 2011–2015, though this is based on an assumed constant fraction of agriculture-driven deforestation over time (out of the deforestation rates), based on data for an earlier time period (table S1).

S4d Estimating the share of agriculture-driven deforestation

To estimate the likely range of the share of deforestation driven by agriculture, we again distinguish between the share of "deforestation resulting in agricultural production" and the share of "agriculture-driven deforestation".

The share of deforestation resulting in agricultural production is estimated by dividing the Pendrill *et al.* (*37*) estimate (4.3 Mha/y) by the lower and higher estimates of total deforestation derived above (6.5 and 9.5 Mha/y, respectively), resulting in a range of ~45–65%. The share likely lies in the higher end of that range, as the lower value of 45% would require much of the tree-cover loss attributed to shifting agriculture by Curtis *et al.* (*7*) to be net-expansion (i.e., constitute deforestation, rather than rotational clearing) which was not captured by the Pendrill *et al.* (*37*) dataset. This, in turn, would require a massive underestimation (of up to 3 Mha/y) of cropland area expansion in FAO statistics, primarily in Africa (as this is where most tree-cover loss is classified as shifting agriculture).

For the share of deforestation linked with agriculture, both the numerator (total deforestation linked with agriculture) and the denominator (total deforestation) contain considerable uncertainties. These uncertainties, however, somewhat neutralize each other when calculating the ratio between these two quantities, as the amount of total deforestation depends greatly on the estimated amount of deforestation linked with agriculture. Indeed, it is not reasonable to arbitrarily compare the lower estimate of agriculture-driven deforestation by the higher estimate of total deforestation, or vice versa, as both estimates vary with the assumption of how much of the tree-cover loss dominated by shifting agriculture constitutes permanent deforestation (i.e., the numerator and denominator are not independent, but co-vary, and thus only estimates using the same assumption should be compared). To calculate the lower estimate share of agriculture-driven deforestation, we, therefore, use the overall/improved lower rate of agriculture-driven deforestation (6.4 Mha/y) as the numerator, and the denominator is the sum of this and high estimate of forestry deforestation (0.7 Mha/y) (i.e., 6.4 Mha/y agriculture-driven deforestation divided by 7.1 Mha/y of total deforestation). To calculate the higher estimate of the share, we conversely assume the higher rate of agriculture-driven deforestation (8.8 Mha/y) and the minimum estimate of forestry deforestation (0.1 Mha/y) (i.e., 8.8 Mha/y agriculture-driven deforestation divided by 8.9 Mha/y of total deforestation). Tree-cover loss driven by urbanization (0.02 Mha/y) is assumed to constitute deforestation in both estimates. This results in a range of between 90–99% of deforestation linked with agriculture.

S5 Assessing the broader role of agriculture in deforestation

Our analysis suggests a large discrepancy (2.0–4.5 Mha/y) between *deforestation occurring in landscapes where agriculture is a dominant driver* and the *deforestation resulting in agricultural production*. Part of this discrepancy is likely due to unrecorded agricultural areas, and additionally, a small part of this can be attributed to non-agricultural commodities, such as mining and oil operations, the effect of these on forest cover is largely indirect (see, e.g., (*108*)). This implies that a substantial share of deforestation occurring in landscapes where agriculture is the dominant driver does not result in productive agricultural land. This is consistent with both regional and pan-tropical remote-sensing studies examining land use following tree-cover loss and finding large tracts of unused land.

De Sy *et al.* (*8*), analyzing the follow-up land-use after deforestation in the period 1990–2000, find that other land (comprising bare land, grassland, shrubland or other wooded land) amounted to 10.8 Mha, with this land-class accounting for 6.8%, 15.5% and 30.1% of post-deforestation land-use in Latin America, Africa and Asia respectively. Zalles *et al.* (*24*) estimate land-use transitions across Latin America over three decades (1985–2018), finding that land without any sign of human land-use is the second most common post-deforestation land class (after pasture), amounting to about 20 Mha of former forest land. Similarly, for Indonesia, Austin *et al.* (*55*) find that conversion to grassland and shrubland without signs of agricultural activity was the second most common land-class following forest loss (after oil palm plantations), constituting a total of 1.8 Mha and a fifth of all forest loss in the study period. For the Chaco, Baumann *et al.* (*155*), found that around a quarter to a third of the deforestation resulted in land that was not used or abandoned for a while.

While clearly prevalent, unused deforested land is not included as a driver in the classification by Curtis *et al.* (*7*), which focuses on "dominant drivers" within a landscape, meaning that tree-cover loss without subsequent human land-use is included in another ("active"/not unused) tree-cover loss driver classes (e.g., commodity-driven deforestation and shifting agriculture). With agriculture being the dominant identified driver of tree-cover loss across the tropics, most of the unused deforested land is likely occurring in landscapes where agriculture is the dominant driver.

S6 Attributing deforestation to commodities

S6a Pan-tropical estimates of deforestation attributed to commodities

Currently, only four pan-tropical studies quantify the role of multiple individual agricultural land uses (e.g., pasture or crops, producing one or multiple commodities) in driving deforestation: Pendrill *et al.* (*37*), Goldman *et al.* (*36*), Nguyen and Kanemoto (*38*) and Cuypers *et al.* (*45*).

These studies use different perspectives to approach the challenge of attributing deforestation to specific agricultural land uses—e.g., individual crops or pasture—in the face of the considerable data limitations on the extent and temporal changes of specific agricultural land uses. The first two studies, Pendrill *et al.* (*37*) and Goldman *et al.* (*36*), are described briefly in the main text. Nguyen and Kanemoto (*38*) use a similar approach and underlying datasets as the Goldman *et al.* (*36*) coarse approach to attribute tree-cover loss to 42 crops for an earlier time period (2006–2010), and their results are thus subject to the same uncertainties and limitations. Cuypers *et al.* (*45*) use a national level land-use transition model (using FAO FRA 2010 deforestation data and agricultural statistics), though this only covers the time period 1990–2008 and is thus not discussed further.

There are also several studies covering specific commodities and regions. A few recent and prominent examples include Song *et al.* (*25*), Tenneson *et al.* (*117*), and Henders *et al.* (*156*). Song *et al.* (*25*) provide annual maps (2000–2019) of soybean expansion at 30-m resolution for all of South America (which was also used by Goldman *et al.* (*36*) for soy), a combination of sample field data and satellite data (Landsat and MODIS). Tenneson *et al.* (*117*) identify deforestation followed by a number of crops, including oil palm, rubber, coffee, tea and coconut, for seven countries in Southeast Asia. Henders *et al.* (*156*) attribute deforestation to beef, palm oil and soybeans in seven countries, based on a literature review of remote sensing studies, supplemented by agricultural statistics on area expansion of commodity production (using simple assumptions on the association between deforestation and agricultural expansion).

S6b National-level estimates of deforestation attributed to commodities

While the numbers presented here are primarily averages for the whole (sub-)tropics and by continent, the specific agricultural land uses driving deforestation vary considerably between countries and continents (*36, 37, 45*). What is a major driver at the pan-tropical scale can differ markedly from the drivers in a specific country.

To complement the pan-tropical datasets, we therefore conducted a literature search for national-level estimates of deforestation resulting in agricultural production in general, and specifically for the commodities identified as most important at the pan-tropical level by Goldman *et al.* (*36*) or Pendrill *et al.* (*37*): pasture, soybeans, oil palm, rubber, cocoa, coffee, corn, rice and cassava. We limited the search to eleven countries identified as having the highest absolute rates of deforestation in the 2011–2015 period: Brazil, Paraguay, Argentina, Bolivia in Latin America; DR Congo, Angola, Madagascar, Mozambique in Africa; and Indonesia, Malaysia, Myanmar in Asia. We also limited the search to studies in English published in 2015 or later, presenting data on agriculture-driven deforestation post-2010 (in concordance with the time period analyzed using the pan-tropical data). We searched Web of Science, using the following search string for title and abstract:

deforestation
AND
(*Brazil* OR *Paraguay* OR *Argentina* OR *Bolivia* OR *Congo* OR *Angola* OR *Madagascar* OR *Mozambique* OR *Indonesia* OR *Malaysia* OR *Myanmar*)
AND
(*agriculture* OR *pasture* OR *soy** OR *"oil palm"* OR *"palm oil"* OR *rubber* OR *cocoa* OR *coffee* OR *maize* OR *corn* OR *rice* OR *cassava*)

The search yielded 557 hits, which were screened in the title and abstract for studies that quantified deforestation due to agricultural (cropland and pasture) expansion. We further excluded studies (based on full text) that did not present original analyses (e.g., review studies) or that did not quantify actual deforestation areas due to the queried land-uses (e.g., scenario analyses or econometric studies of deforestation drivers). The list of included studies (n = 49) was then checked by the full author team and studies fulfilling the inclusion criteria missed by the search were added (n = 10). Table S5 displays the complete list of studies included.

The list displays a clear geographical concentration, with comparatively little evidence on agricultural-driven deforestation in Africa (n = 6), compared to the Asian (n = 26) and Latin American (n = 27) countries. In particular, evidence for Latin America seems markedly better, with the existence of a handful of biome-wide assessments, e.g., for the Gran Chaco, Cerrado and the Brazilian Amazon. In terms of commodities, oil palm plantations are covered by most studies (n = 25) concentrated (but not limited to) Indonesia and Malaysia, followed by pastures (n = 12) and soybeans (n = 9), all in Latin America. It is also worth to note that aside from Brazil and Indonesia, there are few comprehensive (wall-to-wall) studies of commodity-driven deforestation even for the countries with high deforestation rates included in this analysis, though the countries in Latin America are relatively well covered by continental or biome-wide (e.g., Gran Chaco) assessments.

Where presented in the studies, we also extracted country-level data on deforestation attributed to the different post-deforestation land-uses included in the review (cropland, pasture, and the eight individual crops) for the period 2011–2015, with results presented in Table 1. That is, data pertaining to a larger temporal (e.g., average over 2001–2015) or spatial (i.e., biome wide assessments, without results being broken down by country) scales were not included. This implies that the underlying data availability is somewhat better than what is depicted in Table 1, especially for some regions and biomes (e.g., the Gran Chaco of South America). For Brazilian soy and Malaysian oil palm we combined data from sub-national analyses (Amazon and Cerrado biomes for Brazil; peninsular and insular Malaysia) from different studies in order to provide a country-level estimate.

S6c Combined evidence on deforestation attributed to commodities

The pan-tropical datasets suggest that pasture expansion alone accounts for around half of the deforestation resulting in agricultural production (c.1.9–2.7 Mha/y out of at least 4.3 Mha/y; with the lower value from Pendrill *et al.* (*37*) and the higher from Goldman et al, henceforth).

While both datasets (Goldman *et al.* (*36*), Pendrill *et al.* (*37*)) agree on pasture being the single most important driver of tropical deforestation by far, they differ considerably in the estimated extent of deforestation attributed to the expansion of pastures. This can partly result from discrepancies in estimates of pasture area based on land use classification methods and definitions (*85*). For pasture, the largest differences between Pendrill *et al.* (*37*) and Goldman *et al.* (*36*) are found in Brazil (c.0.8 by Pendrill *et al.* (*37*) compared with c.1.1 Mha/y Goldman *et al.* (*36*)) and Paraguay (c.0.1 compared with 0.3 Mha/y, by Pendrill *et al.* (*37*) and Goldman *et al.* (*36*), respectively). For Brazil, the Goldman *et al.* (*36*) estimate is likely the more accurate, as it is based on overlapping the tree-cover loss data with 30-m maps of recent (2018) pasture extents (from Lapig) (*36*). They are both also similar to a sample-based approach by Tyukavina *et al.* (*157*) (using visual interpretation of Landat images and high-resolution GoogleEarth imagery), finding around 0.5–0.7 Mha/y (2011–2013), of human clearing for pasture in the Brazilian Legal Amazon (i.e., not all of Brazil). These rates are also similar to, albeit somewhat lower than, those found by zu Ermgassen *et al.* (*131*), which find less than 0.5 Mha/y between 2011 and 2015 (of which around half in the Amazon and half in the Cerrado), though this is based on the year of pasture expansion, rather than the year of deforestation, and estimates in the preceding years (2005–2010) are somewhat higher: between 0.5 and 1 Mha/y. The estimates by zu Ermgassen *et al.* (*131*) are found by crossing Lapig pasture maps with deforestation rates from INPE (i.e., the same pasture maps as used by Goldman *et al.* (*36*), but different deforestation data). The MapBiomas (collection 6.0; Souza *et al.* (*114*)) estimate of deforestation due to pasture expansion is considerably higher: 2.5 Mha/y for Brazil (of which 1.1 Mha/y in the Amazon). For Paraguay, both estimates are uncertain: the Goldman *et al.* (*36*) estimate is based on pasture extents in the year 2000, whereas the Pendrill *et al.* (*37*) approach is based on the expansion of pastures (at the national level) from FAOSTAT, which for Paraguay has been calculated or manually estimated by FAO since the last "*data reported on country official publications or web sites (Official) or trade country files*" in 2003 (*46*). Similar data quality caveats apply to, e.g., Argentina, Bolivia and Mozambique (*46*), which are also some of the countries with bigger differences (each around 0.1 Mha/y difference) between the two pan-tropical datasets.

Oil palm and soy are also important drivers of tropical deforestation: oil palm caused, on average, around (0.5–)0.7 Mha/y and soy (0.4–)0.4 Mha/y (Pendrill *et al.* (*37*) in parentheses; the main value is based on the Goldman *et al.* (*36*) detailed approach). For both these commodities, the estimate from Goldman *et al.* (*36*) is likely the best pan-tropical estimate, as it is based on their detailed approach for these commodities (for soy, using spatially and temporally explicit extents in South America (from Song *et al.* (*25*)), and for oil palm, using a pan-tropical plantation map put together from several datasets (*36*)). Differences between Pendrill *et al.* (*37*) and Goldman *et al.* (*36*) are larger for earlier (pre-2011) years (table S6).

For oil palm in Indonesia, the pan-tropical estimates are twice as high as those found by Indonesia-specific studies by Austin *et al.* (*55*), Noojipady *et al.* (*135*) and Gaveau *et al.* (*134*) (both around 0.2 Mha/y in the Indonesia-specific studies compared with 0.4 Mha/y in both the pan-tropical estimates). Austin *et al.* (*55*) used visual interpretation of high-resolution remote sensing imagery (complemented by Landsat) to determine the land cover following a stratified sample of GFC tree-cover loss events (within primary forests). For the period 2011–2015, Austin *et al.* (*55*) found 0.14 Mha/y in oil palm plantations, though oil palm is likely also part of small-scale mixed plantations and large-scale plantations (where the species could not be determined), which amount to an additional 0.12 Mha/y together (*55*). Noojipady *et al.* (*135*) mapped oil palm plantations combining a number of different sources and overlaid with GFC tree-cover loss data, arriving at an estimate of annual deforestation for oil palm expansion of 0.24 Mha/y in the period 2010–2015. Gaveau *et al.* (*134*) found 0.17 Mha/y of deforestation for industrial oil palm plantations and 0.04 Mha/y in smallholder oil palm plantations (average 2011–2015), based on GFC tree-cover loss (*1*) within natural forests and oil palm maps based visual interpretation of high-resolution (<2 m resolution) and Landsat (30-m resolution) remote sensing.

Despite both the Pendrill *et al.* (*37*) and Goldman *et al.* (*36*) datasets indicating that oil palm expansion is also a key driver of recent deforestation in Malaysia, we find no national-level estimates of this in our literature review (see table S5). However, by combining the estimates of oil palm-driven deforestation in Peninsular Malaysia by (*158*) and in the Malaysia Borneo by (*137*), we estimate that just over 0.05 Mh/y of forests were converted to oil palm plantations in the 2010–2015 period. This estimate is similar to that of Pendrill *et al.* (*37*) (0.05 Mha/y), but only a third of that of Goldman *et al.* (*36*) (0.16 Mha/y) for the same time period.

Rubber, as well as some less commonly discussed forest-risk commodities—maize, rice, and cassava—that are staples in many parts of the world where they are grown also contribute significantly to deforestation in the tropics (*138, 159*). The limited available data indicate that they together account for at least 0.9 Mha/y, or an additional fifth of the deforestation resulting in agricultural production (Pendrill *et al.* (*37*) indicate for maize (0.3 Mha/y), rice (0.2 Mha/y) and cassava (0.2 Mha/y); Goldman *et al.* (*36*) for rubber, 0.2 Mha/yr). Hurni and Fox (*160*) estimated deforestation for rubber in Mainland Southeast Asia, the major hotspot of rubber expansion, at ~0.4 Mha/y over 2001–2014, while Tenneson *et al.* (*117*) suggest a lower estimate of ~0.05 Mha/y. For an earlier time period (2006–2010), Nguyen and Kanemoto (*38*)—which is based on a similar approach as the Goldman *et al.* (*36*) coarse approach—ascribe twice as much deforestation to maize, rice and cassava as Pendrill *et al.* (*37*). The Nguyen and Kanemoto (*38*) data are likely an overestimate as it counts all GFC tree-cover loss within existing shifting agriculture as deforestation. However, Pendrill *et al.* (*37*) may underestimate the deforestation due to the expansion of these crops, especially where they are produced for subsistence or in small agricultural holdings: some countries apply minimum criteria, e.g., on crop harvested area, to include them in the FAOSTAT agricultural statistics (*90*), which are used by Pendrill *et al.* (*37*) to assess their expansion.

Cocoa and coffee account for between 0.1 and 0.3 Mha/y together in the pan-tropical assessments (Pendrill *et al.* (*37*), Goldman *et al.* (*36*)). They typically receive a high level of attention as key forest-risk commodities, likely due to the commercial and international demand for these commodities compared to staple crops like maize, rice and cassava. The approach from Pendrill *et al.* (*37*) is likely to underestimate deforestation driven by cocoa and coffee, as these crops are known to have a stable net area in some countries while still having gross area changes (expansion in some places and contraction in others), which would not show up in the national-level agricultural statistics used. For coffee, some deforestation occurs as a result of coffee areas relocating in adaptation to climate change (going higher in altitudes) or in response to new demands such as high-quality or sustainability-certified coffee (*161*). For cocoa, especially in West Africa, but also in Southeast Asia, important dynamics involve smallholders leaving behind exhausted cocoa plantations to establish fresh plantations in forests as well as in-migration of prospective cocoa farmers into remaining forest areas (*162-164*). Some of the disused plantations might revert to forest, while some are reutilized for other crops and tree crops (*162, 163*). In contrast, the (coarse) approach from Goldman *et al.* (*36*) potentially overestimates cocoa and coffee-driven deforestation, due to the assumption that all GFC tree-cover loss driven by shifting agriculture (or commodity-driven deforestation) is deforestation and subsequently assuming that this deforestation is proportionally distributed to a commodity based on its prevalence within a grid cell. (For example, if a 10 km by 10 cell had 1000 ha of GFC tree-cover loss driven by shifting agriculture or commodity-driven deforestation, and 50% of the cell's agricultural land was cocoa in the year 2010, then Goldman *et al.* (*36*) attributes 500 ha of tree-cover loss to cocoa.) This can lead to overestimates where tree-cover loss driven by shifting agriculture reflects recurring rotations within stable shifting agriculture systems rather than deforestation. Conversely, in new frontiers (e.g., expansion into 10 km by 10 km cells which were not estimated to have any cocoa or coffee in 2010), Goldman *et al.* (*36*) might underestimate their role.

For cocoa and coffee, both pan-tropical estimates (Pendrill *et al.* (*37*), Goldman *et al.* (*36*)) rely heavily on agricultural statistics (Goldman *et al.* (*36*) do this indirectly via the use of MapSPAM (*165*)), which unreliably record cocoa and coffee (*86*). For instance, compared to a recent remote sensing estimate of 2019 cocoa extent in Côte d'Ivoire and Ghana (*166*), FAOSTAT overestimates harvested area by 30% (4.8 Mha in FAOSTAT compared with 3.7 Mha in Abu *et al.* (*166*)) in the former, but underestimates the area by 30% in the latter (1.5 Mha in FAOSTAT compared with 2.2 Mha in Abu *et al.* (*166*)), though it should be noted that the user's accuracy of the remote-sensing estimate was only 62% so this remote-sensing based area estimates should not be considered a fully adequate comparison.

For the remainder of commodities, the evidence is sparse at the pan-tropical scale. Pendrill *et al.* (*138*) provide estimates for all commodities within FAOSTAT, primarily based on national-level data. This can lead to misattribution where the crops expanding at the national level are not the same as what is expanding where deforestation occurs Pendrill *et al.* (*37*). Comprehensively identifying which crops are expanding into forests requires maps of crop extents and their changes (at least for the areas where deforestation has occurred) (e.g., as is done for soy across South America by Song *et al.* (*25*)), though subnational statistics on extents could also help.

S6d Uncertainties: data, mapping challenges, and concurrent drivers

In terms of drivers, the largest—pasture expansion—also contributes most to the uncertainty. Pasture expansion is one of the more difficult deforestation drivers to quantify for two key reasons: it is difficult to map and has complex dynamics with other deforestation drivers.

Mapping pastures is difficult for a couple of reasons, making global pasture extents and their changes are highly uncertain (*84, 85*). These reasons affect both agricultural statistics and spatially explicit maps of pasture extents. First, pasture mapping is complicated, conceptually, because the term pasture can encompass a diverse range of systems (*84, 85*). Some studies (e.g., *167*) distinguish between pastures (typically with higher densities and periodically cultivated vegetation) and rangelands (typically with lower livestock densities and more native vegetation), though this distinction is not consistently used, e.g., in remotely-sensed datasets on land cover (*85*). In HYDE 3.2, for example, Klein Goldewijk *et al.* (*167*) estimate that there are around 3.2 billion hectares of grazing land, of which around 0.8 billion hectares constitute pasture. How pasture is defined and measured can thus have a large impact on the resulting numbers (*85*). Second, pasture mapping is challenging because pastures in some biomes, such as savannahs, can be indistinguishable from cropland or natural vegetation in mainstream remote sensing approaches (due to spectral similarities between classes)(*82, 83*). These difficulties are likely part of the explanation for why the data availability is particularly dire for global pasture extents: most global land cover and use datasets do not specifically distinguish pasture (at best, providing separate classes for grassland and agriculture) (*85, 152, 168*) and the only dedicated global pasture map (*119*) is available only for the year 2000. (Livestock population densities for the year 2010 are available at 10-km resolution in the Gridded Livestock of the World (*169*) but would require additional assumptions to be converted into a pasture map.)

Pasture also interacts with other drivers of deforestation. Whilst clear that pasture expansion is the single most common land use following deforestation, the conversion of forest into pasture is in many places often not driven explicitly and exclusively by the demand for cattle products. Pasture clearing is sometimes associated with capital investments, land speculation or land claims, rather than the need to expand pasture, per se; so, although the post-deforestation land use may be pasture (not rarely of low intensity, in these cases), the demand for cattle may not be the main driver (*58, 79*). Additionally, conversion for pastures is often coupled to the demand for other commodities: In South America, soy frequently expands into previous pasture areas, which (a) are often low in intensity and productivity and (b) have often been deforested at an earlier stage (*24, 25, 130*), reflecting a more complex set of causality. This includes so-called “indirect land-use change”, where the expansion of a land use (e.g., soy) into pasture, indirectly increasing pressure to convert forest to pasture elsewhere (*51, 79, 170*), some of which may be occurring as a form of leakage in response to Brazil’s Soy Moratorium (*80, 171*). However, there is also increasing evidence that pasture and soy are interconnected through capital and actors, indicating that deforestation for soy and pasture may not be inherently separable; thus, understanding the interactions between these often-connected drivers can be crucial to designing effective policies (*81, 172*). This common joint causality between pasture and soy makes it challenging to put neat numbers on one or the other, especially in cases where both soy and cattle meat from pasture have been produced on a piece of recently deforested land. This can cause attribution challenges when estimates of deforestation need to avoid double-counting, though in some contexts it might be relevant to attribute deforestation jointly to both soy and pasture (as both sectors can have a part to play if the aim is to reduce deforestation).

For crops, establishing the links between deforestation, agricultural land uses and specific crops at the pan-tropical level is severely hampered by the lack of maps on their extents and changes over time. Although large progress is being made for some crops, such as soy in South America (*25*), crop types are also particularly difficult to validate without (often costly) ground-based assessments (*173, 174*).

Instead, the pan-tropical studies (Goldman *et al.* (*36*), Pendrill *et al.* (*37*), Nguyen and Kanemoto (*38*)) rely directly on agricultural statistics (mostly at the national level) or on already old maps of crop extents from the MapSPAM initiative, which also rely on agricultural statistics (*165*). The MapSPAM initiative collects and disaggregates agricultural statistics into maps (currently available globally for 2000, 2005 and 2010). The maps are available at 10-km resolution (in contrast, tree-cover loss is assessed at 30-m resolution); however, the input crop statistics are generally only available at the national level (*165*). This means that the quality of the attribution of deforestation to different crops is currently hampered also by the limited quality of agricultural statistics for many countries, especially in Africa (*46, 90, 119*). This applies to all approaches using agricultural statistics (primarily FAOSTAT) either through direct use (e.g., Pendrill *et al.* (*37*)) or indirectly, e.g., via the MapSPAM crop maps (e.g., the Goldman *et al.* (*36*) coarse approach and Nguyen and Kanemoto (*38*)).

To capture the sequences of land uses and commodities following deforestation, and better distinguish the direct and indirect land-use changes, requires consistent time-series data covering major crops (accounting also for multiple harvests) and pasture area. Both wall-to-wall and sample-based approaches, as well as combinations thereof, can be useful for this. Sample-based approaches can be valuable for several reasons including: (i) when relying on very-high resolution imagery (e.g., from Planet and in GoogleEarth), they can help to monitor aspects that are hard to detect in medium-scale imagery (such as pastures and small-scale land use) (*115, 175*) (ii) they can be done with local teams and know-how, bottom-up, helping capacity building and legitimacy of the data (*4, 115*), and (iii) they allow, at aggregated geographic scales, for validating temporal trends of land-cover transitions derived from spatially explicit maps as well as producing unbiased estimators of area of land-cover classes with known uncertainty, provided a suitable sampling design is used (*176*). However, sample-based approaches rely a lot on manual labor, making them costly, potentially more difficult to update (*174, 177*). In many cases, the sampling schemes are typically dense enough for allowing statistics at global, continental, and often national scales, but not necessarily subnational scales (*4, 23-25*). This limits their use for, e.g., for understanding internal land use dynamics within a country; for linking with subnational trade data (as is done by Trase.earth); and for detecting (emerging) hotspots. Therefore, and for transparency and many policy- and land-management purposes, people often prefer wall-to-wall maps (*7, 178*). Wall-to-wall approaches also use samples for training, testing and accuracy assessments used (*176, 179*), and it is also common to combine wall-to-wall and more pronounced sample-based approaches, e.g., (*23-25*). The choice of approach is therefore less a discussion of one or the other, but rather an issue of efficiently using the available data and expertise in a way that is suitable for the intended use. Machine-learning advances can mobilize data with higher spatial and temporal resolutions to enable easier creation of wall-to-wall maps of land uses, including specific crop types (*22*).

Another set of uncertainties lies in the methods for establishing which crops were responsible for the deforestation. The pan-tropical estimates discussed here focus primarily on the agricultural land uses following deforestation (sometimes called post-deforestation land use, e.g., (*8*)). This entails an assumption that the land use following deforestation is the main cause of interest (for other purposes, other parts of the causal chain may be more interesting, such as more indirect/underlying drivers) (*6, 27*). However, it is not always unequivocal which crop (or pasture) caused the deforestation (even if the data were perfect), as several successive land uses may follow on a single piece of land during the years after a forest was cleared. This means that there are many potential ways of attributing deforestation to crops; for example to: (*i*) the land use immediately after deforestation (e.g., if there is no crop the year after deforestation, no crop will be considered as driving deforestation); (*ii*) the first agricultural land use after deforestation (e.g., rice or pasture, even if it is just done with the intention of transitioning the land for later soy cultivation, as is common in South America (*25, 170*); or to oil palm after several years of degraded land following deforestation, which is common in Indonesia (*137*); (*iii*) the agricultural land use after a chosen time period (sometimes called lag time, allocation period, etc.), often aimed at allowing sufficient time for the "intended" land use to be established and identified (e.g., if in the first 2 years the land use is pasture, which is then followed by soy for the foreseeable long-term, then the time frame might be chosen so that soy will be identified as the driver); or (*iv*), to each of the successive land uses (e.g., to both pasture and soy in the previous example), either by splitting the "responsibility" or counting them both as responsible for the deforestation (i.e., double-counting). The resulting numbers can thus reveal different drivers, each potentially reflecting different parts of the causality. Similar challenges arise for crops that are double- or triple-cropped (as is increasingly common, especially in Brazil (*180*)).

Most scientific pan-tropical and continental-level studies attributing deforestation to crops (and pasture) use some version of (*iii*) above. That is, they identify the subsequent land use based on what expands or is established in previously forested areas within a fixed number of years, usually at least two to four years, e.g., Goldman *et al.* (*36*), Pendrill *et al.* (*37*) and Song *et al.* (*25*). Accounting for successive land uses is often hampered by lack of time-series data or maps (though Song *et al.* (*25*) are able to distinguish between "direct" and "latent" soy gain deforestation, based on whether gain occurred within or after three years). The choice of time lag is thus adapted to the data availability and typically based on general crop dynamics (either for crops in general, as done by Pendrill *et al.* (*37*), or adapted to specific crops, as done by Goldman *et al.* (*36*) in their detailed approach). These "fixed" time lags introduce some additional uncertainty: although they are chosen based on observed typical time lags, the time lags still vary between crops, pastures and places, and potentially also from case to case and over time (*25, 80, 137*).

The crop attribution should, in general, be considered as higher uncertainty than the estimates of agriculture-driven deforestation because these uncertainties compound. (The pan-tropical crop attribution approaches all rely on some estimate of agriculture-driven deforestation, except for the commodities covered by the Goldman *et al.* (*36*) detailed approach). Additionally, concurrent and interacting drivers of deforestation are generally poorly considered in current pan-tropical/continental scale assessments of deforestation drivers (*47*).

Fig. S1. Map of the 87 countries included in the harmonized country set (indicated in dark gray).

Not all the included studies cover the complete 87-country set (table S2). The complete set was used for GFC/Hansen *et al.* (*1*), Curtis *et al.* (*7*) and Hosonuma *et al.* (*20*). The Pendrill *et al.* (*37*) estimate is missing data for Cape Verde. The Carter *et al.* (*32*) estimate is missing six countries: Cape Verde, Lesotho, Solomon Islands, Eswatini, Trinidad and Tobago, and Vanuatu. The De Sy *et al.* (*8*) estimate misses 17 countries: Cuba, Dominica, Dominican Republic, Haiti, Jamaica, Saint Lucia, Saint Vincent and the Grenadines, Trinidad and Tobago, Pakistan, Singapore, Solomon Islands, Vanuatu, Burundi, Cape Verde, Gambia, Guinea-Bissau and Rwanda. For Goldman *et al.* (*36*), the country availability varies by commodity. The Nguyen and Kanemoto (*38*) data miss Cape Verde, Lesotho, Pakistan and Singapore.

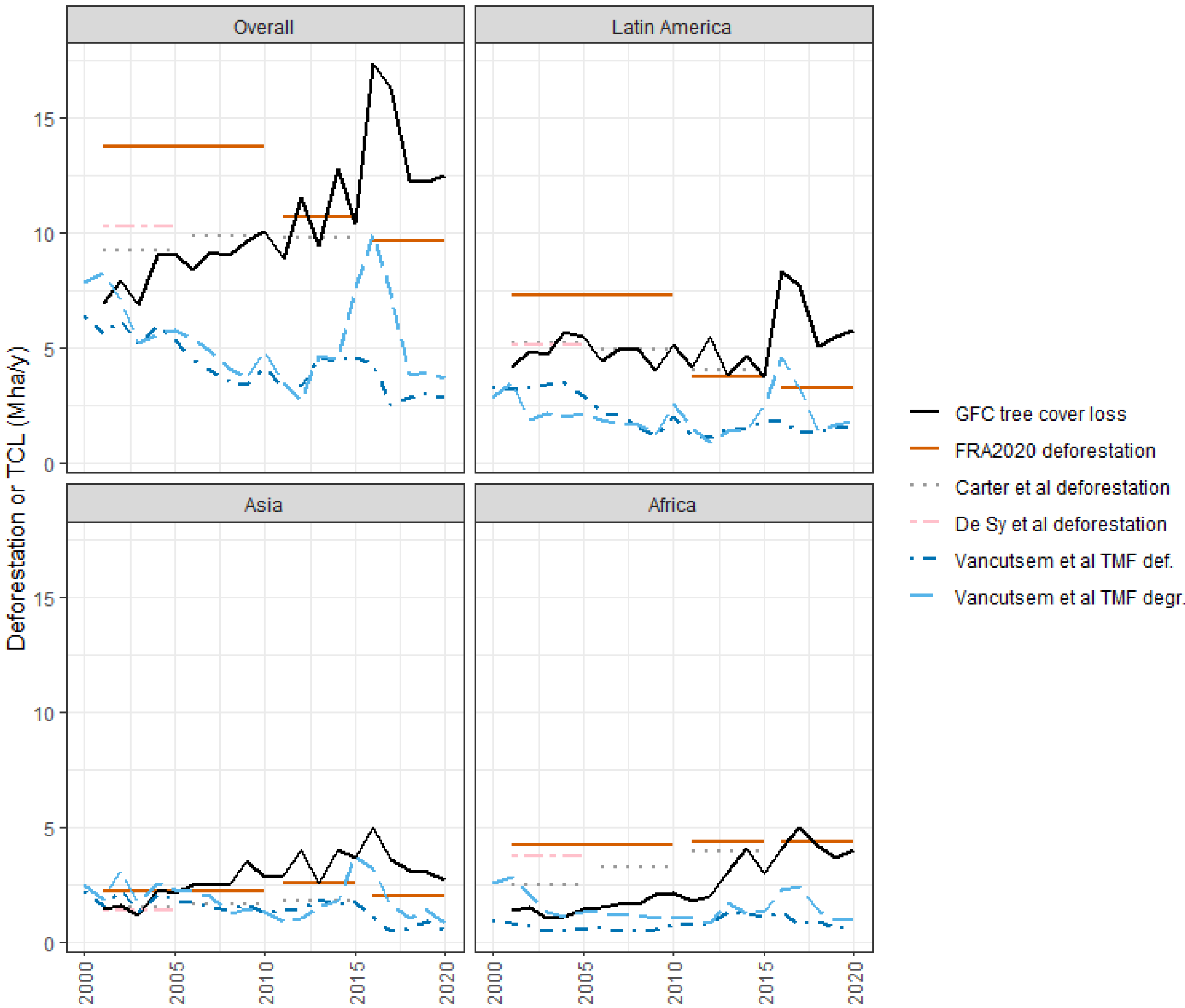

Fig. S2. Pan-tropical estimates of tree-cover loss and deforestation.
Estimated extents and trends of (sub-)tropical tree-cover loss and deforestation (in millions of hectares per year) vary between studies. This reflects uncertainties as well as conceptual differences. The data on tree-cover loss (TCL) are from global forest change (GFC) (Hansen *et al.* (*1*)); on deforestation from the FAO FRA 2020 (*3*), Carter *et al.* (*32*); De Sy *et al.* (*8*) and Vancutsem *et al.* (*2*). The FRA deforestation and the Carter *et al.* (*32*) 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), except for the data from Vancutsem *et al.* (*2*) data. The Vancutsem *et al.* (*2*) 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.

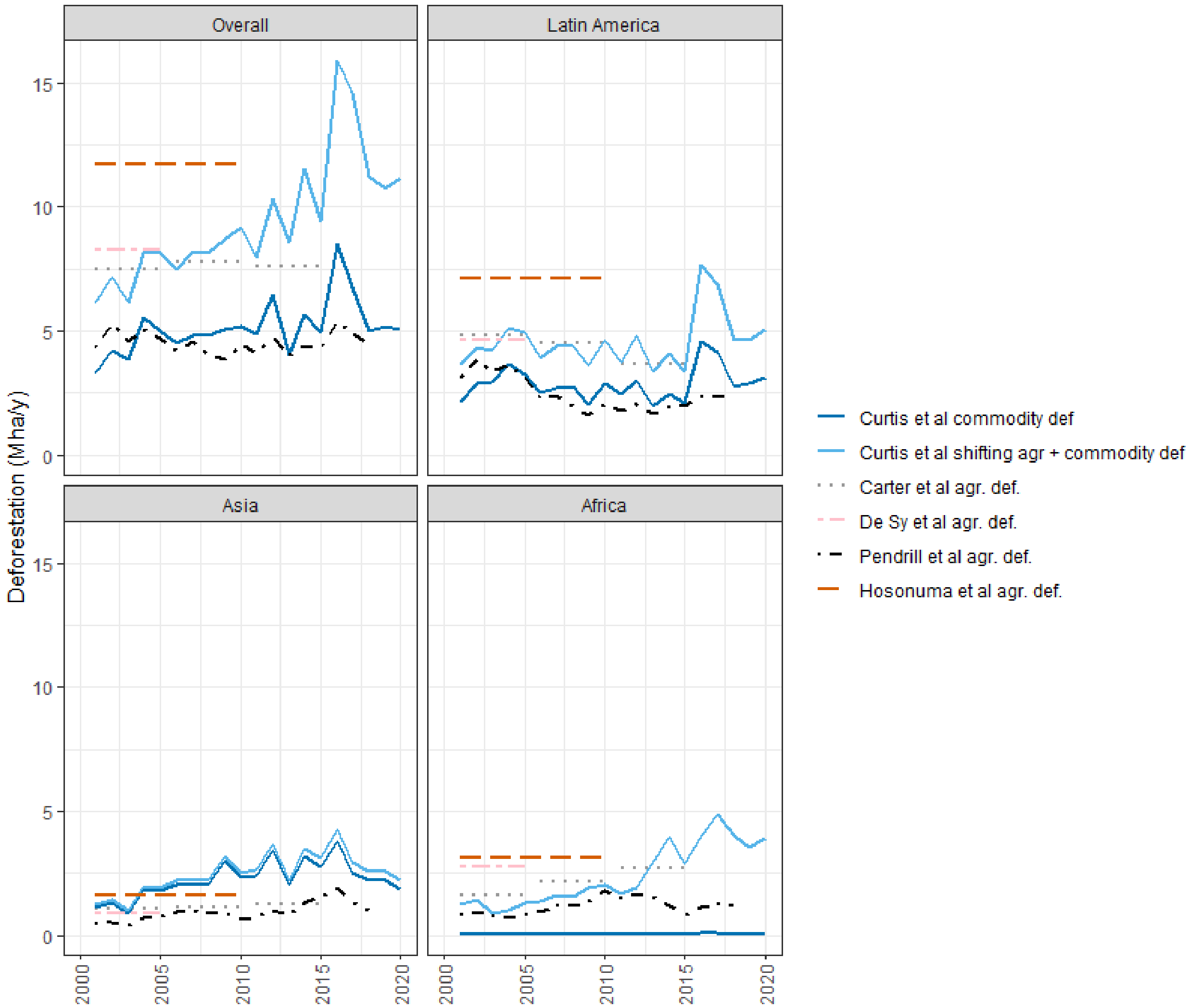

Fig. S3. Pan-tropical estimates of agriculture-driven deforestation.

Estimated extents and trends of agriculture-driven deforestation (in millions of hectares per year), assessed and defined in somewhat ways (table S1). The data *on agriculture-driven deforestation are* from Curtis *et al.* (*7*), Carter *et al.* (*32*), De Sy *et al.* (*8*) and Hosonuma *et al.* (*20*), and on *deforestation resulting in agricultural production* from Pendrill *et al.* (*37*). The Carter *et al.* (*32*), De Sy *et al.* (*8*) and Hosonuma *et al.* (*20*) data are averages over 5–10-year time periods. Abbreviations used: “agr” = agriculture, “def” = deforestation.

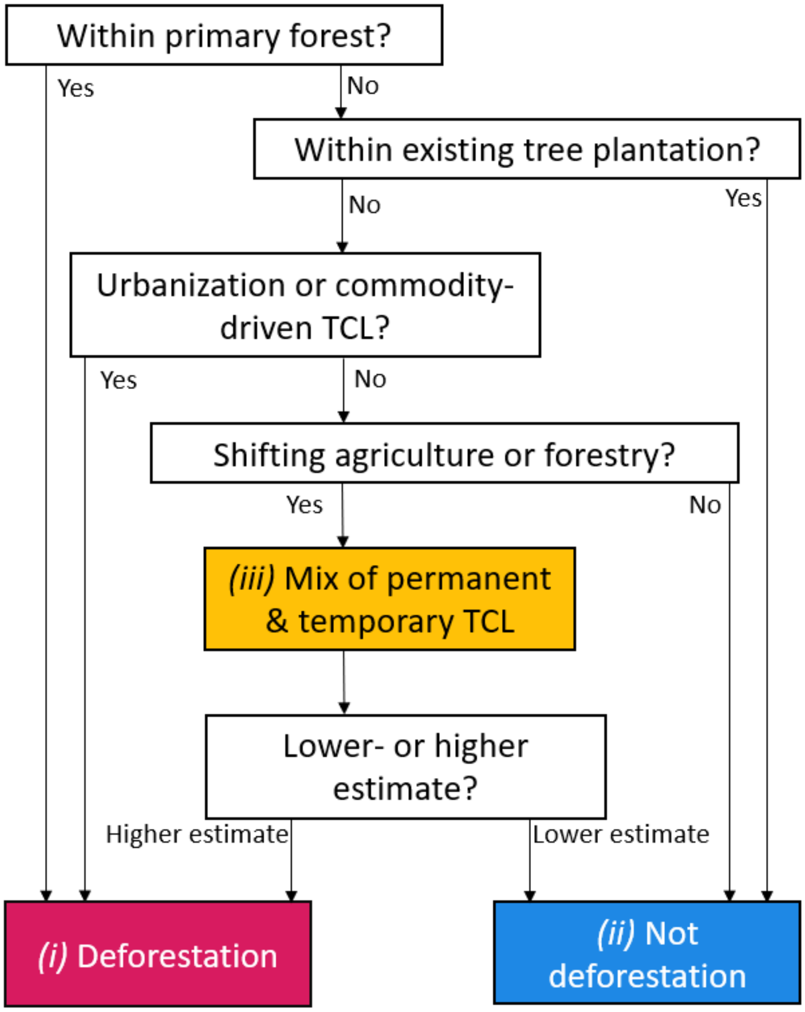

Fig. S4. Estimating the likely range of deforestation.

Schematic visualization of how we estimated the likely range of deforestation from the GFC tree-cover loss data. The GFC tree-cover loss data were split into three categories: (i) deforestation, (ii) not deforestation, or (iii) a mix of persistent deforestation and temporary tree-cover loss. These splits were based on maps of primary forest extents (*54*), existing tree plantations (*53*) and the Curtis *et al.* (*7*) dominant drivers of tree-cover loss (urbanization, commodity-driven, shifting agriculture and forestry). Finally (not shown), the lower estimate was adjusted to reflect the assumed minimum amount of agriculture-driven deforestation at the country level.

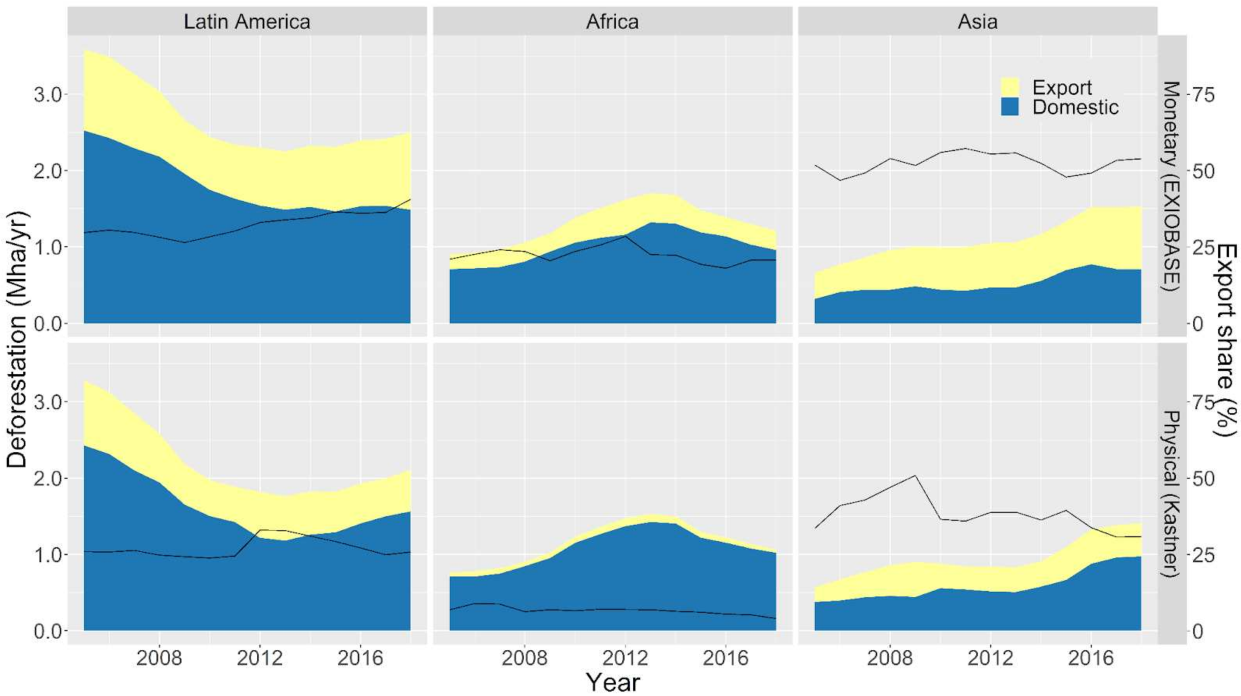

Fig. S5. Deforestation embodied in commodity production.

Amount of deforestation embodied in commodity production that is consumed in the country or region of production (Domestic) versus in other countries (Export), for major tropical regions (left-hand side y-axis), as well as the average share of embodied deforestation that is linked to international demand (black line; right-hand side y-axis), over the period 2005–2018. Data is Pendrill *et al.* (*138*) (which presents updated estimates of deforestation embodied in trade using the same approach as (*37*)) and results are shown for the two trade models used: the monetary multiregional input-output model (EXIOBASE (*181*), top) and the physical trade model (Kastner (*182*), bottom) (both using a five-year amortization period for this analysis). Note that the results from the models are not directly comparable, due to methodological choices: The physical trade model considers the place of consumption roughly to be where products are physically consumed as food or as intermediate inputs in, for example, industrial processes (*182*), whereas the MRIO additionally includes embodied deforestation initially utilized domestically and subsequently exported in different forms, such as protein, biodiesel, as well as more indirectly, e.g., in services (*181*). This implies that the higher export share estimated by EXIOBASE does not reflect a higher trade share of agricultural commodities. Additionally, EXIOBASE has a much coarser regional resolution, implying that intra-regional trade for much of the tropics (e.g., between countries in tropical Asia) is not accounted for. Hence, the shares would likely be somewhat different with a different choice of MRIO (such as GTAP or Eora, which have higher regional resolution) or with different methodological (and conceptual) choices in the physical trade model. These differences in methodological approaches imply that the results will be suitable for different purposes and reflect different understanding of how international trade drives deforestation (*94*).

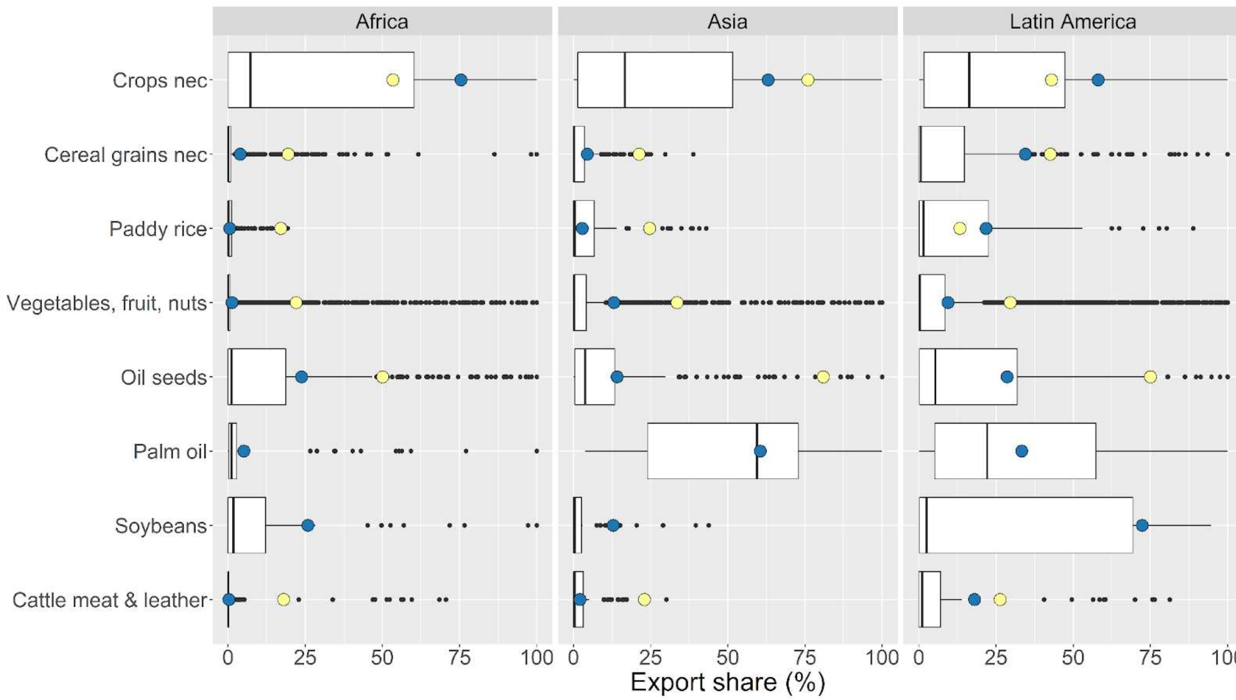

Fig. S6. Country-level distribution of the exported share of deforestation embodied in commodity production.

By commodity groups and major tropical regions for the period 2011–2015, based on a physical trade model (*182*). Data is taken from Pendrill *et al.* (*138*). 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 colored circles show the weighted average export share for the physical trade model (*182*)), and the yellow circles show the average export share for the multiregional input-output model EXIOBASE (no boxplots for this model, as its 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. As noted above (fig. S5), the results from the two models are not directly comparable, due to differences in system boundaries and model structure.

Table S1. An overview of the main pan-tropical datasets on agriculture-driven deforestation.

<table>
<tr><th>Source</th><th>Scope & resolution</th><th>Summary of method and key limitations</th></tr>
<tr><td>Original source: Curtis et al. (7)

Updated data access: Global Forest Watch</td><td>2001–2020
Annual

Global

Spatial resolution: gridded (10-km)</td><td>Drivers assessed: commodity-driven deforestation, shifting agriculture, forestry, wildfire and urbanization.

Method summary: Estimates the dominant driver of tree -cover loss in each 10 km by 10 km grid cell. Uses regional decision tree models trained on high-resolution imagery in Google Earth to classify drivers based on input data on tree-cover loss and regrowth, forest type (pre-2006), fires, and population.

Overall accuracy: 89%.

Limitations: The shifting agriculture and forestry classes primarily contain non-deforestation tree-cover loss but may in certain cases contain deforestation. The shifting agriculture class does not distinguish net deforestation over time (when clearing outweighs regrowth), and the forestry class cannot determine when forestry activity is expanding into areas not previously used for forestry. Assesses only a single, main (>50%) driver in each 10 km by 10 km grid cell for the whole time period, so may underestimate especially small, fragmented and varying causes of forest loss (e.g., “natural” wildfire losses in tropics may be missed because fires in the tropics are often a precursor to agricultural expansion). The wildfire class does not distinguish between wildfires started naturally (e.g., lighting) versus an anthropogenic source (e.g., spark from utility, campfires).

“Shifting agriculture” (covering essentially all Africa) obviously includes some marketed production, so the classification mixes type of production (commodity/not), scale, and land-use systems (permanent / shifting). The class is primarily defined by the presence of significant regrowth following loss.

Example of questions that particularly useful for:
• How much tree-cover loss occurs in landscapes where agriculture is the dominant driver of loss?
• Where is agriculture the dominant driver of tree-cover loss?
• Where is tree-cover loss likely to be permanent deforestation versus temporary loss?</td></tr>
</table>

Source	Scope & resolution	Summary of method and key limitations
Original source: Carter *et al.* (*32*)	1990–2015 5-year averages Pan-tropical (91 countries) Spatial resolution: National	*Drivers assessed:* Agriculture-driven deforestation. *Method summary:* National deforested area (A), derived from a weighted average of harmonized deforestation datasets, was multiplied with an agriculture-driven deforestation fraction taken from Hosonuma *et al.* (*20*) and De Sy *et al.* (*8*). This paper also further derived emissions from agriculture-driven deforestation and associated uncertainties. *Limitations:* The fraction of agriculture-driven deforestation was assumed constant over the time period (only deforested area was variable). Additionally, the limitations of the original fraction data sources apply (*8, 20*). The weighted average of deforested area might not reflect the actual trend. *Example of questions that particularly useful for:* • (Method for) best estimate of emissions from national agriculture-driven deforestation to compare trends in space and time. • Quantification of uncertainty associated with best estimate, and with variety of input datasets. • Recommendations for use/selection of data and further improvements on the estimation of emissions from agriculture-driven deforestation.

Source	**Scope & resolution**	**Summary of method and key limitations**
Original source: De Sy *et al.* (*8*)	1990–2000 & 2000–2005 10- and 5-year averages Pan-tropical *Spatial resolution:* Systematic sampling design of 10 by 10 km squares. Square sampling unit subdivided in similar LUC areas (polygons) of at least 5 ha	*Drivers assessed*: Mixed agriculture, large-scale crop, small-scale crop, tree crops, pasture, infrastructure, other land use, water (land use following deforestation used as a proxy for direct drivers). *Method summary*: Visual interpretation of high-resolution imagery of land use following deforestation. The Remote Sensing Survey of the Global Forest Resources Assessment 2010 of FAO (FAO FRA-2010 RSS) (FAO and JRC 2012) was used as input to identify deforestation areas. The FAO FRA-2010 RSS used a systematic sampling design with sample units (SU) of 10 by 10 km. Each SU was segmented into delineated areas (polygons) with a target minimum mapping area (MMU) of 5 ha. *Limitations*: Limited temporal availability (1990–2005) that will not be extended because of the labor-intensive method for driver assessment (visual interpretation) and underlying deforestation dataset (FAO FRA 2010) that will likely not be updated systematically. The rather coarse systematic sampling design only allows aggregation to larger regional scales (e.g., continental). Extensive land uses (e.g., rangelands) are difficult to assess so are often categorized as “other land use”. *Example of questions that particularly useful for:* • Assessment of land *use* following deforestation with high thematic detail (e.g., large-scale versus small-scale cropland). • Comparative analysis of spatial and temporal dynamics of direct deforestation drivers on a regional and continental scale.

Source	**Scope & resolution**	**Summary of method and key limitations**
Original source: Pendrill *et al.* (*37*) Updated data access: (*138*) Version used here: v.1.1	2001–2017 Annual Tropics & subtropics *Spatial resolution*: National (sub-national Brazil & Indonesia)	*Drivers assessed:* Pasture (cattle meat, leather), 100+ crops and wood products from tree plantations (land use following deforestation used as a proxy for direct drivers) Separates domestic and international trade, countries of consumption. *Method summary*: Estimates how much tree-cover loss (Hansen *et al.* (*1*)) is followed by expanding cropland (and crops), pasture and tree plantations, using primarily agricultural statistics in a land balance model. The analysis is performed at the national level (except for Brazil and Indonesia) and depends on assumptions about predominant land-use transitions. *Limitations:* The (primarily) national scale of analysis implies that deforestation is attributed to the land uses and crops expanding at the national level and thus does not clearly separate direct and indirect drivers of deforestation, i.e., between the land uses (e.g., a crop) directly expanding on cleared forest land versus those expanding in other parts of the country (potentially indirectly "pushing" other land uses into the forest). Interacting commodity and land-use drivers, and successive land-use transitions over time are only cursorily dealt with. Relies largely on agricultural statistics (primarily FAOSTAT) for identifying which land uses and crops are expanding. It is thus sensitive especially to how well year-on-year variations are reported (e.g., in many cases, the data show constant numbers over consecutive recent years, especially for countries in Africa). *Example of questions that particularly useful for:* • Deforestation for agriculture: amount of deforestation driven by (primarily) net expansion of agriculture. • Key forest risk commodities (FRCs): the amount and share of agricultural-driven deforestation due to different FRCs. • Trade in embodied deforestation: e.g., the amount and share of deforestation related to domestic versus export demand; and the amount of embodied deforestation and key commodities "imported" by a country of consumption.

Source	Scope & resolution	Summary of method and key limitations
Original source: Hosonuma *et al.* (*20*), Kissinger *et al.* (*21*)	2000–2010 10-yr average Tropics & subtropics *Spatial resolution*: National	*Drivers assessed:* Agriculture (commercial), Agriculture (subsistence), Mining, Infrastructure, Urban expansion. *Method summary*: A coarse estimate of the share of deforestation attributed to drivers, based on a limited set of quantitative data, combined with qualitative estimates and extrapolation. *Limitations:* Largely based on data self-reported by countries as part of REDD+ readiness. Quantitative estimates were used only for 12 countries, covering just under half of the forest loss. The remaining deforestation driver estimates are based on qualitative estimates of drivers (e.g., if drivers A > B > C, then A= 1/2, B = 1/3, C= 1/6) for 34 countries, subsequently extrapolated to an additional 46 countries. *Example of questions that particularly useful for:* • Relative importance of deforestation drivers for different continents and forest transition phases. • National-level data availability on drivers.

Source	**Scope & resolution**	**Summary of method and key limitations**
Original source: Goldman *et al.* (*36*) Updated data access: [Global Forest Watch]()	2001–2015(+) Annual Global (mostly) *Spatial resolution*: subnational	*Drivers assessed:* Seven commodities (Palm oil, Soy, Cattle meat, Wood Fiber, Cocoa, Coffee, and Rubber). *Method summary*: Estimates where tree-cover loss (Hansen *et al.* (*1*)) is followed by seven key forest risk commodities, using the best available spatially explicit data. Uses two approaches—one detailed and one coarse—depending on whether detailed data are available for subnational estimates. Where available, the detailed approach is probably the best available estimate of deforestation driven by these commodities, using spatially explicit data on recent commodity extents. However, the detailed approach is limited to certain commodities and countries. The coarse approach allocates all tree-cover loss within the 10 km by 10 km grid cells identified by Curtis *et al.* (*7*) as commodity-driven deforestation or shifting agriculture to commodities based on their past area shares (of agricultural land) within each grid cell. *Limitations*: The coarse approach risks over-allocating deforestation to commodities where the coarse grid cells in the Curtis *et al.* (*7*) data might be hiding the contribution of other drivers or where shifting agriculture does not constitute deforestation. Additionally, it relies on the assumption that the commodity area shares did not change from the year 2000 (pasture) / 2010 (crops) and were equally likely to expand into forests, which may not always hold for forest risk commodities, especially in rapidly changing deforestation frontiers. Oil palm is based entirely on the detailed approach, while Coffee and Cocoa are based only on the coarse approach. Rubber and wood fiber are only assessed for a handful of countries (based exclusively on the detailed approach). The rest of the commodities are based on a mix of the two approaches: e.g., pasture uses the detailed approach only for Brazil, while soy uses a detailed approach for all of South America. Data post-2015 are currently only preliminary and likely underestimates. *Example of questions that particularly useful for:* • How much deforestation is linked to specific commodities? • Where are national and subnational hot spots of deforestation linked to specific commodities?

Source	Scope & resolution	Summary of method and key limitations
Original source: Cuypers *et al.* (*45*)	1990–2008 In two time periods: 1990–2000 and 2000–2008 Global Spatial resolution: National	*Drivers assessed:* Primary sectors and commodities, separates domestic and international trade, countries of consumption. *Method summary*: Uses a national-level land-use transition model, applying constraints to attribute forest conversion (net deforestation and afforestation) from the FAO FRA 2010 to changes in agriculture (and subsequently crops), built-up land and other land (according to FAOSTAT) in proportion to their increased land demand. Depends on assumptions about land-use transitions. *Limitations:* Limited temporal availability (only up to 2008) and resolution (as the deforestation data is only available as averages over 5–10 year time periods). Like for the Pendrill *et al.* (*37*) approach, the national level of the model does not allow for separating the direct and indirect drivers of deforestation. It also relies largely on FAOSTAT agricultural statistics for identifying which land uses and crops are expanding. It is thus sensitive to how well year-on-year variations are reported. *Example of questions that particularly useful for:* • Key forest risk commodities (FRCs): the amount and share of agricultural-driven deforestation due to livestock and different crops. • Trade in embodied deforestation, especially to the EU.

Table S2. The 87 countries included in the harmonized country set in this analysis. List includes the continent division used, as well as deviations from this set, i.e., on which countries are missing from De Sy *et al.* (*8*) and Carter *et al.* (*32*) and on which countries were included from Vancutsem *et al.* (*2*). The complete 87-country set was available in and used for GFC/Hansen *et al.* (*1*), the FAO FRA 2020 deforestation rates (*3*) (after complementing reported deforestation rates with “Forest area net change” rates), Curtis *et al.* (*7*) and Hosonuma *et al.* (*20*). Only Cape Verde was missing from Pendrill *et al.* (*37*). Nguyen and Kanemoto (*38*) missed only Cape Verde, Lesotho, Pakistan, and Singapore. For Goldman *et al.* (*36*), the country availability varies by commodity.

ISO	Country name	Continent	De Sy *et al.* (*8*)	Carter *et al.* (*32*)	Vancutsem *et al.* (*2*)
AGO	Angola	Africa			Included
ARG	Argentina	Latin America			
BGD	Bangladesh	Asia			
BLZ	Belize	Latin America			
BEN	Benin	Africa			
BTN	Bhutan	Asia			
BOL	Bolivia	Latin America			Included
BWA	Botswana	Africa			
BRA	Brazil	Latin America			Included
BFA	Burkina Faso	Africa			
BDI	Burundi	Africa	Missing		
KHM	Cambodia	Asia			Included
CMR	Cameroon	Africa			Included
CPV	Cape Verde	Africa	Missing	Missing	
CAF	Central African Republic	Africa			Included
TCD	Chad	Africa			
CHL	Chile	Latin America			
COL	Colombia	Latin America			Included
COG	Congo	Africa			Included
CRI	Costa Rica	Latin America			
CIV	Cote d’Ivoire	Africa			Included
CUB	Cuba	Latin America	Missing		
COD	DR Congo	Africa			Included
DMA	Dominica	Latin America	Missing		
DOM	Dominican Republic	Latin America	Missing		
ECU	Ecuador	Latin America			Included
SLV	El Salvador	Latin America			
GNQ	Equatorial Guinea	Africa			
ETH	Ethiopia	Africa			

ISO	Country name	Continent	De Sy *et al.* (*8*)	Carter *et al.* (*32*)	Vancutsem *et al.* (*2*)
GAB	Gabon	Africa			Included
GMB	Gambia	Africa	Missing		
GHA	Ghana	Africa			Included
GTM	Guatemala	Latin America			Included
GIN	Guinea	Africa			
GNB	Guinea-Bissau	Africa	Missing		
GUY	Guyana	Latin America			Included
HTI	Haiti	Latin America	Missing		
HND	Honduras	Latin America			
IND	India	Asia			Included
IDN	Indonesia	Asia			Included
JAM	Jamaica	Latin America	Missing		
KEN	Kenya	Africa			
LAO	Laos	Asia			Included
LSO	Lesotho	Africa		Missing	
LBR	Liberia	Africa			Included
MDG	Madagascar	Africa			Included
MWI	Malawi	Africa			
MYS	Malaysia	Asia			Included
MLI	Mali	Africa			
MEX	Mexico	Latin America			Included
MOZ	Mozambique	Africa			
MMR	Myanmar	Asia			Included
NAM	Namibia	Africa			
NPL	Nepal	Asia			
NIC	Nicaragua	Latin America			Included
NGA	Nigeria	Africa			Included
PAK	Pakistan	Asia	Missing		
PAN	Panama	Latin America			Included
PNG	Papua New Guinea	Asia			Included
PRY	Paraguay	Latin America			
PER	Peru	Latin America			Included
PHL	Philippines	Asia			Included
RWA	Rwanda	Africa	Missing		
LCA	Saint Lucia	Latin America	Missing		
VCT	Saint Vincent and the Grenadines	Latin America	Missing		
SEN	Senegal	Africa			
SLE	Sierra Leone	Africa			

ISO	Country name	Continent	De Sy *et al.* (*8*)	Carter *et al.* (*32*)	Vancutsem *et al.* (*2*)
SGP	Singapore	Asia	Missing		
SLB	Solomon Islands	Asia	Missing	Missing	
SOM	Somalia	Africa			
ZAF	South Africa	Africa			
LKA	Sri Lanka	Asia			
SDN	Sudan	Africa			
SUR	Suriname	Latin America			Included
SWZ	Eswatini	Africa		Missing	
TZA	Tanzania	Africa			
THA	Thailand	Asia			Included
TLS	Timor-Leste	Asia			
TGO	Togo	Africa			
TTO	Trinidad and Tobago	Latin America	Missing	Missing	
UGA	Uganda	Africa			
URY	Uruguay	Latin America			
VUT	Vanuatu	Asia	Missing	Missing	
VEN	Venezuela	Latin America			Included
VNM	Viet Nam	Asia			Included
ZMB	Zambia	Africa			
ZWE	Zimbabwe	Africa			

Table S3. Estimated extents of tree-cover loss (TCL) and deforestation.

The estimates are from several large-scale assessments (in millions of hectares per year; 5-year averages). The data are from this synthesis (where L = lower estimate and H = higher estimate) and from (*1-3, 8, 32*) and have been harmonized to the same set of 87 countries (minor discrepancies are detailed in table S2). The data from Vancutsem *et al.* (*2*) are for a more limited subset of forests (only TMF = tropical moist forests) and only 33 of the 87 countries. Abbreviations used: D+D = Deforestation plus degradation, Def = Deforestation and Deg = Degradation. (Note that the definitions vary).

		Deforestation (various definitions)					**TCL**	**Disturbances of TMF**		
		This synthesis		**FAO FRA 2020**	**Carter *et al.* (*32*)**	**De Sy *et al.* (*8*)**	**Hansen *et al.* (*1*)**	**Vancutsem *et al.* (*2*) (only 33 of the 87 countries)**		
	Year	**L**	**H**					**D+D**	**Def**	**Deg**
Overall	2000–2005			13.8	9.3	10.3	8.0	12.1	5.7	6.4
	2006–2010			13.8	9.9		9.3	8.5	3.9	4.6
	2011–2015	6.5	9.5	10.7	9.8		10.6	8.7	4.1	4.6
	2016–2020			9.6			14.1	8.9	3.1	5.8
Africa	2001–2005			4.2	2.5	3.7	1.3	2.3	0.6	1.7
	2006–2010			4.2	3.2		1.8	1.7	0.6	1.1
	2011–2015	1.3	2.7	4.4	4.0		2.8	2.3	1.0	1.2
	2016–2020			4.3			4.2	2.4	0.8	1.6
Asia	2001–2005			2.2	1.5	1.4	1.7	4.1	1.8	2.3
	2006–2010			2.2	1.7		2.8	3.2	1.5	1.6
	2011–2015	2.2	2.7	2.6	1.8		3.4	3.4	1.6	1.8
	2016–2020			2.0			3.5	2.3	0.7	1.6
Latin America	2001–2005			7.3	5.3	5.2	5.0	5.6	3.3	2.4
	2006–2010			7.3	5.0		4.7	3.7	1.8	1.8
	2011–2015	2.9	4.2	3.7	4.1		4.4	3.0	1.4	1.6
	2016–2020			3.3			6.5	4.1	1.6	2.6

Table S4. Estimated rates of agriculture-driven deforestation from pan-tropical studies. Rates are summarized across different time periods and continents (in millions of hectares per year; 5-year averages). The data are from this synthesis (where L = lower estimate and H = higher estimate) and (*7, 8, 20, 32, 37*). Abbreviations used: "agr." = Agriculture, "def." = deforestation, "prod" = production, TCL = tree-cover loss, "com. def." = commodity-driven deforestation.

		Agr.-driven def.		Def. resulting in agr. prod.	Other estimates of agriculture-driven deforestation				
		This synthesis		Pendrill *et al.* (*37*)	Curtis *et al.* (*7*) (TCL driven by agriculture)		Carter *et al.* (*32*)	De Sy *et al.* (*8*)	Hosonuma *et al.* (*20*)
	Year	L	H		Com. def.	Shifting agr. + com. def.			
Overall	2001-2005			4.8	4.4	7.1	7.5	8.2	11.7
	2006-2010			4.2	4.9	8.3	7.8		11.7
	2011-2015	6.4	8.8	4.3	5.2	9.6	7.6		
Africa	2001-2005			0.8	0.0	1.2	1.6	2.8	3.1
	2006-2010			1.3	0.0	1.7	2.2		3.1
	2011-2015	1.3	2.7	1.3	0.0	2.7	2.7		
Asia	2001-2005			0.6	1.4	1.5	1.1	0.9	1.6
	2006-2010			0.9	2.3	2.5	1.1		1.6
	2011-2015	2.2	2.3	1.1	2.8	3.0	1.2		
Latin America	2001-2005			3.4	3.0	4.5	4.8	4.6	7.1
	2006-2010			2.0	2.6	4.2	4.5		7.1
	2011-2015	2.9	3.8	1.9	2.4	3.9	3.7		

Table S5. Studies quantifying agriculture resulting in agricultural production at the national level.

Comprehensive list of studies identified by the literature review. The review covered the eleven countries with the highest identified rates of deforestation and searched for estimates of deforestation due to expanding cropland, pastures, or key commodities.

Reference	Countries	Geographical scope	Post-forest land-use	Time period
Latin America:				
(*183*)	Argentina	Formosa	Agricultural land	2001-2008, 2010-2015
(*184*)	Argentina, Bolivia & Paraguay	Gran Chaco biome	Cropland, pasture	2010-2017
(*185*)		Gran Chaco biome	Soybeans	2000-2012
(*186*)		Gran Chaco biome	Cropland, pasture	1976-2012
(*187*)*	Argentina, Bolivia, Brazil & Paraguay	Sub-Andean South America	Cropland	1990-2014
(*188*)		National (wall-to-wall)	Cropland, pasture	2001-2011
(*25*)		National (wall-to-wall)	Soybeans	2000-2019
(*24*)*		National (sample-based)	Cropland, pasture	1985-2018
(*189*)	Bolivia	Chapare region	Cropland	1986-2018
(*190*)	Brazil	Para state	Oil palm	2006-2014
(*191*)		Para state	Oil palm	2010-2018
(*192*)		Apuí, Amazonas state	Agriculture	1982-2016
(*193*)		Paraíba Valley, Sao Paulo state	Cropland, pasture	1985-2011
(*194*)		Mato Grosso state	Soybeans	2009-2016
(*195*)		National (sample-based)	Oil palm	<2014
(*80*)		Amazon & Cerrado biomes	Soybeans	2006-2013
(*196*)		Mato Grosso state	Cropland, pasture, soybeans	2001-2014
(*197*)		Mato Grosso state	Pasture, soybeans	2001-2016
(*198*)		MATOPIBA region	Cropland, pasture, soybeans	1990-2017
(*132*)*		Cerrado biome	Soybeans	2003-2015
(*199*)		Novo Progresso, Para state	Pasture	1985-2012
(*200*)		Mato Grosso state	Pasture, soybeans	2001-2017
(*114*)*		National (wall-to-wall)	Cropland, pasture	1985-2017
(*157*)		Legal Amazon	Cropland, pasture	2001-2013
(*130*)*		National (wall-to-wall)	Cropland	2000-2014
(*133*)		Amazon & Cerrado biomes	Soybeans	2006-2017
(*131*)		National (wall-to-wall)	Pasture	2000-2017
Africa:				
(*201*)	Angola	South-central Angola	Cropland	1989-2013
(*202*)		South-central Angola	Cropland	1989-2014
(*35*)*	DR Congo	National (sample-based)	Agriculture	2001-2014
(*203*)	Madagascar	North-eastern region	Rice	1995-2011
(*204*)*	Mozambique	Northern Mozambique	Cropland	2001-2017
(*205*)*		National (wall-to-wall)	Cropland	2000-2016
Asia:				
(*206*)	Indonesia	Sumatra, Kalimantan, Papua	Oil palm	1995-2015
(*55*)		National (sample-based)	Cropland, oil palm	2001-2016

* Additional studies, not identified through the systematic literature review.

(*207*)		Lubuk Kertang mangrove forest, North Sumatra	Oil palm	1996-2016
(*208*)		North Sumatra	Oil palm	1990-2015
(*134*)		National (wall-to-wall)	Oil Palm	2001-2019
(*209*)		North Central Timor	Cropland, rice	2000-2015
(*210*)		Sambas regency, West Kalimantan	Oil palm	1990-2013
(*135*)		National (wall-to-wall)	Oil palm	2002-2014
(*211*)		Deforestation hotspot sample	Cropland	2018
(*49*)		Bungo & Merangin, Jambi province	Oil palm	1988-2013
(*212*)		National (wall-to-wall)	Cropland, oil palm	1990-2012
(*137*)	Indonesia, Malaysia	Borneo	Oil palm	2000-2015
(*213*)		Borneo	Oil palm	2000-2017
(*214*)		Peatlands in Malaysia, Sumatra & Kalimantan	Cropland, oil palm	1990-2015
(*215*)		Peninsular Malaysia & Sumatra	Cropland, oil palm	2000-2015
(*216*)		Malaysia, Sumatra & Kalimantan (sample-based)	Oil palm	2001-2016
(*117*)*	Indonesia, Myanmar	National (sample-based)	Oil palm, rubber, coffee, rice	2000-2015
(*217*)	Indonesia, Malaysia, Myanmar	Mangrove forests (wall-to-wall)	Oil palm, rice	2000-2012
(*218*)	Malaysia	North Selangor Peat Swamp Forest	Oil palm, rice	1989-2016
(*158*)		Peninsular Malaysia	Cropland, oil palm, rubber	2010-2015
(*219*)		Peninsular Malaysia	Oil palm, rubber	1988-2012
(*220*)		Peninsular Malaysia	Oil palm	1988-2012
(*221*)		District of Beaufort, Sabah	Oil palm, rubber	1985-2012
(*222*)	Myanmar	Mangrove forests	Oil palm, rubber, rice	1996-2016
(*223*)		Shan state	Corn	2001-2019
(*160*)		Shan state	Cropland, rubber, coffee	2001-2014

* Additional studies, not identified through the systematic literature review.

Table S6. Pan-tropical estimates of deforestation due to specific agricultural land uses. Commodities marked with an asterisk (*) are not included in the Goldman *et al.* (*36*) dataset. "Other commodities" include all other agricultural commodity land uses assessed by the respective studies (these differ between the studies). Achieving precise estimates of the importance of different agricultural land uses for total agricultural-driven deforestation remains fraught with uncertainty.

Continent	Driver	Years	Pendrill *et al.* (*37*)	Goldman *et al.* (*36*)	Nguyen and Kanemoto (*38*)
Overall	Pasture	2001–2005	2.9	3.1	
		2006–2010	1.9	3.0	
		2011–2015	1.9	2.7	
Overall	Oil palm	2001–2005	0.2	0.5	0.8
		2006–2010	0.5	0.9	
		2011–2015	0.5	0.7	
Overall	Soy	2001–2005	0.6	0.7	0.4
		2006–2010	0.2	0.5	
		2011–2015	0.4	0.4	
Overall	Maize*	2001–2005	0.2		0.7
		2006–2010	0.3		
		2011–2015	0.3		
Overall	Rice*	2001–2005	0.2		0.4
		2006–2010	0.2		
		2011–2015	0.2		
Overall	Cassava*	2001–2005	0.1		0.4
		2006–2010	0.2		
		2011–2015	0.2		
Overall	Cocoa	2001–2005	0.1	0.1	

Continent	Driver	Years	Pendrill *et al.* (*37*)	Goldman *et al.* (*36*)	Nguyen and Kanemoto (*38*)
		2006–2010	0.1	0.1	0.2
		2011–2015	0.0	0.2	
Overall	Rubber	2001–2005	0.0	0.1	
		2006–2010	0.0	0.2	
		2011–2015	0.1	0.2	
Overall	Coffee	2001–2005	0.0	0.1	0.1
		2006–2010	0.0	0.1	
		2011–2015	0.0	0.1	
Overall	Other commodities*	2001–2005	0.6		3.1
		2006–2010	0.8		
		2011–2015	0.6		
Latin America	Pasture	2001–2005	2.4	2.8	
		2006–2010	1.5	2.5	
		2011–2015	1.2	2.1	
Latin America	Oil palm	2001–2005	0.0	0.0	0.1
		2006–2010	0.0	0.0	
		2011–2015	0.0	0.0	
Latin America	Soy	2001–2005	0.6	0.7	0.3
		2006–2010	0.2	0.5	
		2011–2015	0.4	0.4	
Latin America	Maize*	2001–2005	0.1		0.4
		2006–2010	0.1		
		2011–2015	0.1		

Continent	Driver	Years	**Pendrill *et al.* (*37*)**	**Goldman *et al.* (*36*)**	**Nguyen and Kanemoto (*38*)**
Latin America	Rice*	2001–2005	0.1		0.1
		2006–2010	0.0		
		2011–2015	0.0		
Latin America	Cassava*	2001–2005	0.0		0.1
		2006–2010	0.0		
		2011–2015	0.0		
Latin America	Cocoa	2001–2005	0.0	0.0	0.1
		2006–2010	0.0	0.0	
		2011–2015	0.0	0.0	
Latin America	Rubber	2001–2005	0.0	0.0	
		2006–2010	0.0	0.0	
		2011–2015	0.0	0.0	
Latin America	Coffee	2001–2005	0.0	0.1	0.1
		2006–2010	0.0	0.1	
		2011–2015	0.0	0.0	
Latin America	Other commodities*	2001–2005	0.2		1.4
		2006–2010	0.2		
		2011–2015	0.1		
Asia	Pasture	2001–2005	0.1	0.1	
		2006–2010	0.1	0.1	
		2011–2015	0.1	0.2	
Asia	Oil palm	2001–2005	0.2	0.5	0.7
		2006–2010	0.4	0.9	

Continent	Driver	Years	Pendrill *et al.* (*37*)	Goldman *et al.* (*36*)	Nguyen and Kanemoto (*38*)
		2011–2015	0.4	0.6	
		2001–2005	0.0	0.0	
Asia	Soy	2006–2010	0.0	0.0	0.0
		2011–2015	0.0	0.0	
		2001–2005	0.0		
Asia	Maize*	2006–2010	0.0		0.1
		2011–2015	0.1		
		2001–2005	0.1		
Asia	Rice*	2006–2010	0.1		0.2
		2011–2015	0.1		
		2001–2005	0.0		
Asia	Cassava*	2006–2010	0.0		0.0
		2011–2015	0.0		
		2001–2005	0.0	0.0	
Asia	Cocoa	2006–2010	0.0	0.0	0.0
		2011–2015	0.0	0.1	
		2001–2005	0.0	0.1	
Asia	Rubber	2006–2010	0.0	0.2	
		2011–2015	0.1	0.1	
		2001–2005	0.0	0.0	
Asia	Coffee	2006–2010	0.0	0.0	0.0
		2011–2015	0.0	0.0	
Asia	Other commodities*	2001–2005	0.1		

Continent	Driver	Years	Pendrill *et al.* (*37*)	Goldman *et al.* (*36*)	Nguyen and Kanemoto (*38*)
		2006–2010	0.1		0.8
		2011–2015	0.2		
Africa	Pasture	2001–2005	0.4	0.2	
		2006–2010	0.4	0.3	
		2011–2015	0.6	0.4	
Africa	Oil palm	2001–2005	0.0	0.0	
		2006–2010	0.0	0.0	0.0
		2011–2015	0.0	0.0	
Africa	Soy	2001–2005	0.0	0.0	
		2006–2010	0.0	0.0	0.0
		2011–2015	0.0	0.0	
Africa	Maize*	2001–2005	0.1		
		2006–2010	0.2		0.2
		2011–2015	0.1		
Africa	Rice*	2001–2005	0.0		
		2006–2010	0.1		0.1
		2011–2015	0.1		
Africa	Cassava*	2001–2005	0.0		
		2006–2010	0.1		0.2
		2011–2015	0.2		
Africa	Cocoa	2001–2005	0.0	0.1	
		2006–2010	0.0	0.1	0.1
		2011–2015	0.0	0.1	

Continent	Driver	Years	Pendrill *et al.* (*37*)	Goldman *et al.* (*36*)	Nguyen and Kanemoto (*38*)
Africa	Rubber	2001–2005	0.0	0.0	
		2006–2010	0.0	0.0	
		2011–2015	0.0	0.0	
Africa	Coffee	2001–2005	0.0	0.0	
		2006–2010	0.0	0.0	0.0
		2011–2015	0.0	0.0	
Africa	Other commodities*	2001–2005	0.2		
		2006–2010	0.5		0.9
		2011–2015	0.3		

Table S7. Country-level estimates of total deforestation rates and agriculture-driven deforestation.

Expressed as annual averages over the period 2011–2015. For an explanation for how the ranges (low/high) are calculated, see the Materials and Methods above.

		Total deforestation (Mha/y)		Agriculture-driven deforestation (Mha/y)	
Continent	**Country**	Low	High	Low	High
Latin America	Argentina	0.28	0.33	0.27	0.31
	Belize	0.01	0.02	0.01	0.02
	Bolivia	0.20	0.24	0.20	0.24
	Brazil	1.55	2.22	1.54	2.01
	Chile	0.01	0.10	0.01	0.01
	Colombia	0.14	0.17	0.14	0.17
	Costa Rica	0.00	0.01	0.00	0.01
	Cuba	0.00	0.01	0.00	0.00
	Dominica	0.00	0.00	0.00	0.00
	Dominican Republic	0.01	0.01	0.01	0.01
	Ecuador	0.01	0.04	0.01	0.04
	El Salvador	0.00	0.00	0.00	0.00
	Guatemala	0.02	0.06	0.02	0.05
	Guyana	0.01	0.01	0.01	0.01
	Haiti	0.00	0.00	0.00	0.00
	Honduras	0.03	0.04	0.03	0.04
	Jamaica	0.00	0.00	0.00	0.00
	Mexico	0.06	0.18	0.05	0.17
	Nicaragua	0.01	0.04	0.01	0.04
	Panama	0.00	0.02	0.00	0.02
	Paraguay	0.36	0.38	0.36	0.38
	Peru	0.14	0.19	0.14	0.19
	Saint Lucia	0.00	0.00	0.00	0.00
	Saint Vincent and the Grenadines	0.00	0.00	0.00	0.00
	Suriname	0.01	0.01	0.01	0.01
	Trinidad and Tobago	0.00	0.00	0.00	0.00
	Uruguay	0.00	0.00	0.00	0.00
	Venezuela	0.04	0.08	0.04	0.07

Continent	Country	Total deforestation (Mha/y) Low	Total deforestation (Mha/y) High	Agriculture-driven deforestation (Mha/y) Low	Agriculture-driven deforestation (Mha/y) High
Africa	Angola	0.18	0.18	0.18	0.18
	Benin	0.00	0.00	0.00	0.00
	Botswana	0.00	0.00	0.00	0.00
	Burkina Faso	0.00	0.00	0.00	0.00
	Burundi	0.00	0.00	0.00	0.00
	Cameroon	0.04	0.08	0.04	0.08
	Cape Verde	0.00	0.00	0.00	0.00
	Central African Republic	0.01	0.04	0.01	0.04
	Chad	0.00	0.00	0.00	0.00
	Congo	0.02	0.05	0.02	0.05
	Cote d'Ivoire	0.09	0.18	0.09	0.18
	DR Congo	0.37	0.84	0.37	0.84
	Equatorial Guinea	0.00	0.01	0.00	0.01
	Eswatini	0.00	0.00	0.00	0.00
	Ethiopia	0.02	0.03	0.02	0.03
	Gabon	0.02	0.03	0.02	0.03
	Gambia	0.00	0.00	0.00	0.00
	Ghana	0.01	0.07	0.01	0.06
	Guinea	0.02	0.10	0.02	0.10
	Guinea-Bissau	0.01	0.01	0.01	0.01
	Kenya	0.01	0.01	0.01	0.01
	Lesotho	0.00	0.00	0.00	0.00
	Liberia	0.04	0.12	0.03	0.12
	Madagascar	0.07	0.26	0.07	0.26
	Malawi	0.01	0.01	0.01	0.01
	Mali	0.00	0.00	0.00	0.00
	Mozambique	0.17	0.17	0.17	0.17
	Namibia	0.00	0.00	0.00	0.00
	Nigeria	0.05	0.05	0.04	0.04
	Rwanda	0.00	0.00	0.00	0.00
	Senegal	0.00	0.00	0.00	0.00
	Sierra Leone	0.01	0.12	0.01	0.12
	Somalia	0.00	0.00	0.00	0.00
	South Africa	0.01	0.02	0.01	0.01
	Sudan	0.00	0.00	0.00	0.00
	Tanzania	0.12	0.16	0.11	0.15
	Togo	0.00	0.00	0.00	0.00
	Uganda	0.02	0.05	0.02	0.05
	Zambia	0.04	0.09	0.04	0.09
	Zimbabwe	0.01	0.01	0.01	0.01

Continent	Country	Total deforestation (Mha/y) Low	Total deforestation (Mha/y) High	Agriculture-driven deforestation (Mha/y) Low	Agriculture-driven deforestation (Mha/y) High
Asia	Bangladesh	0.00	0.01	0.00	0.00
	Bhutan	0.00	0.00	0.00	0.00
	Cambodia	0.16	0.17	0.16	0.16
	India	0.03	0.10	0.02	0.02
	Indonesia	1.25	1.31	1.23	1.25
	Laos	0.15	0.20	0.14	0.16
	Malaysia	0.25	0.26	0.24	0.24
	Myanmar	0.14	0.24	0.13	0.18
	Nepal	0.00	0.00	0.00	0.00
	Pakistan	0.00	0.00	0.00	0.00
	Papua New Guinea	0.04	0.08	0.04	0.08
	Philippines	0.04	0.05	0.04	0.04
	Singapore	0.00	0.00	0.00	0.00
	Solomon Islands	0.01	0.01	0.01	0.01
	Sri Lanka	0.00	0.01	0.00	0.00
	Thailand	0.05	0.11	0.04	0.05
	Timor-Leste	0.00	0.00	0.00	0.00
	Vanuatu	0.00	0.00	0.00	0.00
	Viet Nam	0.09	0.12	0.09	0.11