REVIEW SUMMARY

LAND USE CHANGE

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

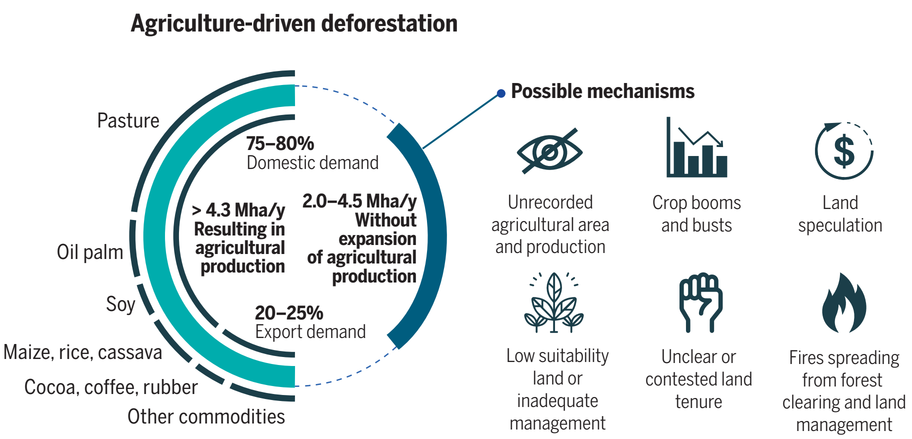
BACKGROUND: Agricultural expansion is a primary cause of tropical deforestation and therefore a key driver of greenhouse gas emissions, biodiversity loss, and the degradation of ecosystem services vital to the livelihoods of forest-dependent and rural people. However, agriculture-driven deforestation 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 pantropical 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. However, only a handful of studies estimate agriculture-driven deforestation across the entirety of the tropics. Although these studies agree that agriculture is the dominant land use following forest clearing, their estimates of pantropical rates of agriculture-driven deforestation during the period 2011 to 2015 vary greatly—between 4.3 and 9.6 million hectares (Mha) per year—with our synthesized estimate being 6.4 to 8.8 Mha per year. 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 to 99%) of tropical deforestation occurs in landscapes where agriculture is the dominant driver of tree cover loss, a smaller share (45 to 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 a result of 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 most 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 pantropical data on deforestation trends are lacking. This limits our ability to assess overall progress on reducing deforestation and account for leakage across regions. Second, with the exception of 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 although 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 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 and cereals, including 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 ways which often interact. Most tropical deforestation occurs in landscapes where agriculture is the dominant driver of forest loss. Part of this agriculture-driven deforestation results in agricultural production (left) meeting domestic and export demand for various agricultural commodities. However, agriculture-driven deforestation also occurs without expansion of managed agricultural land through several mechanisms (right), which may lead to the deforested area being abandoned or semi-abandoned. Incomplete agricultural records also explain a share of such deforestation.

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REVIEW

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Disentangling the numbers behind agriculture-driven tropical deforestation

Florence Pendrill[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[10,11], Javier Godar[2], Elizabeth Dow Goldman[12], Matthew C. Hansen[13], Robert Heilmayr[14,15], Martin Herold[16], Tobias Kuemmerle[7,17], Michael J. Lathuillière[2], Vivian Ribeiro[2], Alexandra Tyukavina[13], Mikaela J. Weisse[12], Chris West[18]

Tropical deforestation continues at alarming rates with profound impacts on ecosystems, climate, and livelihoods, prompting renewed commitments to halt its continuation. Although 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 pantropical evidence to provide clarity on how agriculture drives deforestation. Although most (90 to 99%) deforestation across the tropics 2011 to 2015 was driven by agriculture, only 45 to 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 tropical dry forests and forests across Africa.

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*). Although 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*).

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Currently there is considerable attention on curbing tropical deforestation, including 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 on eliminating deforestation from international supply chains of agrifood commodities such as palm oil, soybeans, and beef. With the adequacy of past pledges having received damning assessments (e.g., 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 have its basis in a clear understanding of the scale of the problem, its location, and the relative importance of different drivers.

However, 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 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 and to identify key data and knowledge gaps.

We aim to provide such a synthesis to disentangle the key rates and mechanisms of agriculture-driven deforestation, organized around three central questions regarding 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 the extent to which 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 there are often interactions between multiple drivers (*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). Notably, agriculture-driven deforestation is not limited to the direct expansion of commodity production into forests. We review recent pantropical 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 and Southeast Asia (*28*) (fig. S1), and focus on the time period of 2011 to 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 nonforests nor between deforestation and forest degradation and as a result different studies and monitoring systems rely on different definitions (29–31). Second, although 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; further, technical and practical constraints result in imperfect data (e.g., negative effects of 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 upon the definition presented by the Accountability Framework initiative (33). There is currently no pantropically consistent, spatially explicit dataset that quantifies deforestation as defined above, although 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 most 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- to 10-year intervals (3). Many recent pantropical assessments of deforestation drivers rely partly on GFC. A key challenge for assessing deforestation based on the GFC data is that although all deforestation is in principle captured by TCL, not all TCL (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, TCL 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 in which 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 the national level only and are collected from country reports based on a variety of methods including remote sensing and inventories (34).

For 2011 to 2015, GFC TCL rates averaged 10.6 million hectares (Mha) per year in the tropics while the FAO FRA 2020 estimated deforestation to be 10.7 Mha per year (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 per year, although TCL amounts to 2.8 Mha per year (Fig. 2 and table S3). For some countries these differences are also considerable: for India, the FRA (gross) deforestation rate (0.67 Mha per year; based on remote sensing) (3) far exceeds the GFC TCL (0.10 Mha per year).

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 pantropical 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, human settlements, or tree plantations.

Agriculture: Agriculture includes cropland, pastures, and tree crops but not forestry (agriculture thus excludes 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); further, indirect or underlying drivers always play a role (6, 27).

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

Agriculture-driven deforestation without expansion of agricultural production: This is defined as deforestation occurring in landscapes where agriculture is the dominant driver of forest loss but 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 TCL in the sense that the forest has been fully cleared and there are signs of other types of land use, though in practice the boundary can be hard to draw.

Additionally, the two main datasets show opposing pantropical trends between 2001 to 2010 and 2011 to 2020, with an increase from 9 to 12 Mha per year in GFC TCL (1), compared with a decrease from 14 to 10 Mha per year in FRA deforestation rates (3) (Fig. 1B). Although discrepancies in rates are expected as approaches differ in how they define forests and deforestation [for further discussion see (1, 2, 32, 35)], the observation that the GFC TCL and FRA deforestation data report a difference in the overall trend direction is more puzzling. Uncertainties in trends arise as a result of several methodological and conceptual challenges which must be taken into account for drawing conclusions about trends in TCL 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), and Nguyen and Kanemoto (38).

The increasing trend in GFC TCL 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—some of which could be more adequately characterized as forest degradation rather than deforestation—after 2011 and especially after 2015 (39, 40), due to both changes in the methodology and increased quality and volume of Landsat satellite data. Caution is thus needed when trying to compare TCL 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 as a result of 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 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 pantropical 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 pantropical estimates of the importance of agriculture in

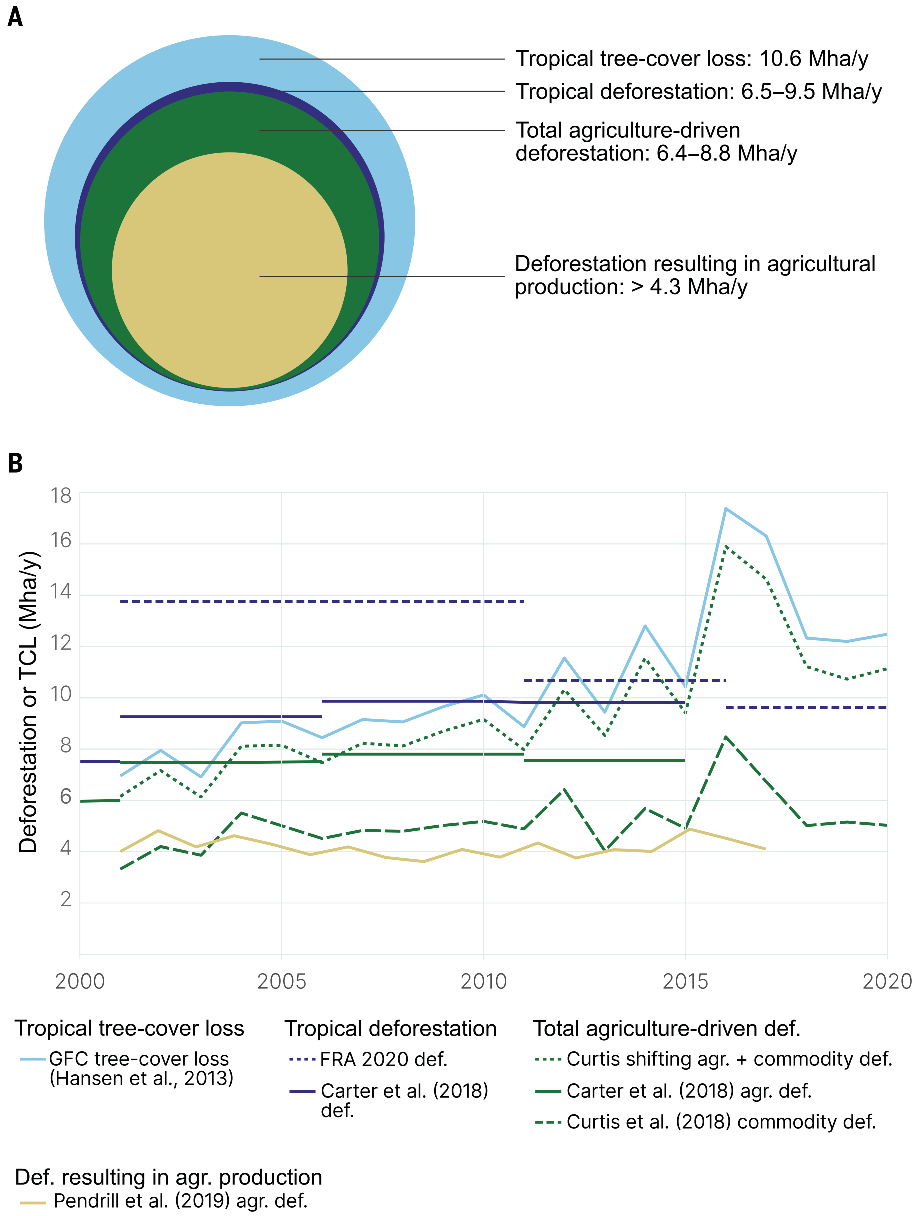

Fig. 1. TCL, deforestation, and agriculture-driven deforestation. (**A**) Conceptual diagram visualizing the concepts of tropical TCL, deforestation, agriculture-driven deforestation, and deforestation resulting in agricultural production, nested from the broadest to the narrowest concept. The area of each circle is scaled by the estimated extent although the ranges are not represented; consequently 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 TCL data are from GFC [updated from Hansen *et al.* (*1*)]; deforestation, from the FAO FRA (*3*) and Carter *et al.* (*32*); agriculture-driven deforestation, updated from Curtis *et al.* (*7*), Carter *et al.* (*32*), and deforestation resulting in agricultural production updated from Pendrill *et al.* (*37*). def, deforestation; agr, agriculture. In all figures, the data have been aligned to the same set of 87 (sub)tropical countries.

driving 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 use of the cleared land is assessed within at least two to four years after forest clearing although the precise number of years varies between studies (~1 to <20 years) depending on method and data availability (*28*). For these reasons we focus our analysis on the period 2011 to 2015.

For that period three studies provide pantropical estimates of agriculture-driven deforestation (fig. S3). One [Carter *et al.* (*32*)] assumes a constant fraction of deforestation being agriculture-driven on the basis of 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 TCL data (*1*)—provide notably different estimates of agriculture-driven deforestation ranging from 4.3 Mha per year [Pendrill *et al.* (*37*)] up to 9.6 Mha per year [Curtis *et al.* (*7*)] (Fig. 1B and table S4). This variation arises both as a result 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 to 8.8 Mha per year (Fig. 1A). As detailed below, this range reflects uncertainties in how much of the TCL attributable to shifting agriculture constitutes deforestation as opposed to cyclical crop-fallow rotations. With total deforestation ranging between 6.5 and 9.5 Mha per year (table S3), this implies that most (~90 to 99%) 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 of ~45 to 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 TCL to expanding cropland and pastures. They evaluate the expansion of cropland and pastures primarily on the basis of 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 per year of deforestation resulting in agricultural production should therefore be considered a conservative estimate (*28*).

By contrast, Curtis *et al.* (*7*) assess the dominant direct drivers of TCL in 10-by-10 km grid cells using decision tree models trained on high-resolution imagery in Google Earth. Dominant drivers of GFC TCL are divided into five classes: commodity-driven deforestation

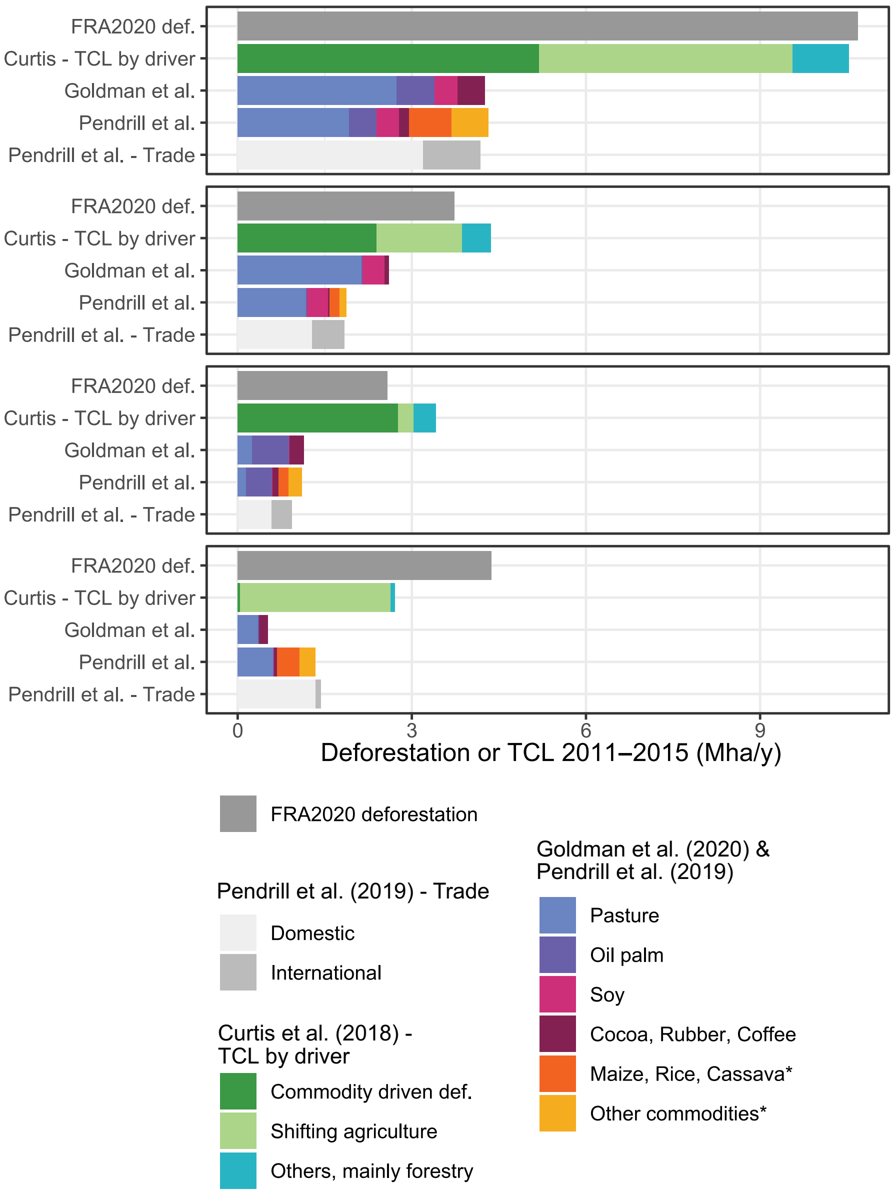

Fig. 2. Estimates of tropical deforestation and its agricultural drivers. The average extents (2011 to 2015) of TCL by driver [data from Hansen *et al.* (*1*) and Curtis *et al.* (*7*), where TCL driven by agriculture falls under shifting agriculture and commodity-driven deforestation] and of deforestation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

(5.19 Mha per year; primarily for agriculture), shifting agriculture (4.37 Mha per year), forestry (0.93 Mha per year), wildfire (0.02 Mha per year), and urbanization (0.02 Mha per year).

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 TCL is deforestation. Some of the dominant drivers of TCL correspond to deforestation (i.e., commodity-driven deforestation and urbanization) but 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) and regular rotations in stable shifting agriculture systems, plantations, or managed forests, which do not constitute deforestation under most definitions (including the one adopted here). Second, the Curtis *et al.* (*7*) approach allocates all TCL in each grid cell to a single dominant (defined as >50%) driver of TCL for the whole time period (2001 to 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 TCL, not all TCL is necessarily directly driven by agricultural expansion. 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 colocated but causally uncoupled. However, drivers of deforestation often interact (*6*, *9*, *47*) and so in landscapes where most deforestation is directly due to agriculture, evidence from multiple studies suggest that agriculture typically contributes indirectly to much of the deforestation 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; e.g., areas in which land is logged first but with prospects of conversion 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 per year (commodity-driven deforestation only) to 9.47 Mha per year (sum of commodity-driven deforestation and shifting agriculture) (Fig. 2). We narrowed this range down to 6.4 to 8.8 Mha per year (*28*) by excluding TCL 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 to 4.5 Mha per year) between the deforestation resulting in agricultural production (>4.3 Mha per year) and the overarching category of agriculture-driven deforestation (6.4 to 8.8 Mha per year) (Figs. 1A and 3). This discrepancy is present across all three continents in our country sample, totaling 1.0 to 2.0 Mha per year in Latin America, 0.0 to 1.3 Mha per year in Africa, and 1.1 to 1.2 Mha per year in Asia (Fig. 3), though uncertainties abound and part of the discrepancy is likely a result of unrecorded agricultural areas.

The discrepancy reflects the complex role of agriculture as a driver of tropical deforestation and indicates that 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 pantropical remote sensing studies finding large tracts of unused land following forest loss (*8*, *24*, *28*, *55*, *56*), including a pantropical estimate that 20 to 30% of agriculture-driven TCL in the period 2015 to 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 [see (*61*, *62*), for example] create crop booms and potential busts (*63*). This can lead to land being cleared anticipatively but not subsequently being taken into production because of deteriorating market conditions, 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 pantropically but is 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 expertise, 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 clearing forests for new agriculture and as a land management tool (e.g., 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 pantropical rates of deforestation attributed to cropland, pasture, and associated commodity production in more recent

Table 1. Data availability for assessing deforestation resulting in agricultural production. Deforestation rates (total and for major post–forest loss land uses, in millions of hectares per year) for the 11 countries with the highest rates of deforestation in the period 2011 to 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 to 2015 could be extracted from the source (*28*). Superscripts indicate the citations to other studies (O). Superscript a indicates citations for cropland deforestation in Brazil (*130*) and Indonesia (*55*, *114*); superscript b for pasture deforestation in Brazil (*131*); superscript c for soybean deforestation in Brazil (*80*, *132*, *133*); superscript d for oil palm deforestation in Indonesia (*55*, *114*, *134*, *135*) and Malaysia (*136*, *137*).

	Deforestation 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

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.

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 the national level. Given its lack of spatial detail this method does not unequivocally establish whether these land uses expanded directly on cleared forest land or indirectly displaced other land uses into the forest (*37*). Goldman *et al.* (*36*) attribute deforestation to commodities by overlaying GFC TCL 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 TCL classified as dominated by commodity-driven deforestation or shifting agriculture is assumed to constitute deforestation resulting in agricultural production, which risks over-allocating TCL as deforestation assigned to commodities. Second, it assumes that the relative shares of commodity area and thus share of deforestation in each grid cell have 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 pantropical datasets differ considerably in the estimated extent of deforestation attributed to the expansion of pastures [1.9 compared with 2.7 Mha per year 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 (~1.2 and 2.1 Mha per year) (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 cover types based on remote sensing as 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, notably in South America for soy and in Southeast Asia for oil palm (Fig. 2 and table S6), particularly in Indonesia. Pantropical 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., Indonesia (*28*)], underscoring the value of having multiple data sources.

The cultivation of rubber, cocoa, coffee, rice, maize, and cassava account for most of the

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*)].

remaining deforestation resulting in agricultural production (28, 36, 37). However, the evidence is currently lacking to confidently estimate their significance or changes in their significance over time (37) and country-level assessments are largely lacking (table S5). For these crops the data are limited or of poor quality (Table 1) and both pantropical 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 (87–89). Further, 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 as a result of 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 pantropical 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 the analysis extends in regards to international supply chains (94). A physical trade model—which traces deforestation embodied in raw or lightly processed agricultural commodities—suggests that 20 to 25% of all deforestation resulting in agricultural production is linked to exports (37) (fig. S5). This average, however, hides substantial variation across countries, regions, and commodities (fig. S6): soybeans, palm oil, and cash crops (e.g., rubber, coffee, and cocoa) are primarily destined for export markets whereas beef and cereals are typically consumed domestically. An economic, multiregional input-output model, which traces deforestation all the way to final consumption, raises the share of commodity-driven deforestation linked to international demand to ~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.

Although 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, in South America soy expansion in one location has been linked to pasture expansion in others (79, 81), and timber harvesting is often a precursor to deforestation, e.g., in case of 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 are largely lacking on the legality of deforestation and production (97), 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 nonagricultural deforestation drivers. Logging and demand for wood products (e.g., timber and pulp), charcoal, and fuelwood—alongside agricultural expansion—are key direct drivers of deforestation and even more so of degradation (6, 55, 101, 102). Although deforestation resulting from the expansion of tree plantations is estimated by Goldman *et al.* (36) and Pendrill *et al.* (37) (0.1 and 0.8 Mha per year, 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 pantropical level.

Urbanization, mining, and energy infrastructure such as hydropower dams are relatively minor direct drivers of deforestation from a pantropical perspective, together amounting to just 2% of land use 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). Further, 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 the extent of that of 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 pantropical 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: (i) to encompass both dry and wet tropics, (ii) to provide estimates of deforestation that go beyond TCL and satisfy the commonly held definition of a persistent conversion of natural forest to any other land use, and (iii) to 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 improvement of contextual data on tree plantations and shifting agriculture to systematically filter out temporary TCL from the GFC data (1), or by expanding the Vancutsem *et al.* (2) approach to the dry tropics, for example. Furthermore, deforestation area metrics alone are a crude proxy for multiple social-ecological impacts, which vary significantly between geographical locations (30). Improved quantification of these impacts is an ongoing need.

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 substantial deforestation occurs. In contrast to deforestation data, data on drivers need not be pantropical 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 most of a given commodity, e.g., soy across South America and oil palm in Southeast Asia, play a key role as they are built on regional knowledge and thus are typically not just more accurate but also more region- and policy-relevant, e.g., in terms of land use and management characterization (112). However, currently 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 building confidence in temporal trends in deforestation (4, 23–25, 116, 117). Future advances should include improving the collection and organization of subnational 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 with 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 vary, and where smallholder and shifting agriculture results in small, irregularly shaped, 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 with 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 active agricultural production. Although as much as 90 to 99% of deforestation occurs in landscapes where agriculture is the main driver of TCL, only 45 to 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, although 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 also 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.

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SUPPLEMENTARY MATERIALS

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Disentangling the numbers behind agriculture-driven tropical deforestation

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Forest loss for food
Agricultural expansion is recognized as a major driver of forest loss in the tropics. However, accurate data on the links between agriculture and tropical deforestation are lacking. Pendrill *et al*. synthesized existing research and datasets to quantify the extent to which tropical deforestation from 2011 to 2015 was associated with agriculture. They estimated that at least 90% of deforested land occurred in landscapes where agriculture drove forest loss, but only about half was converted into productive agricultural land. Data availability and trends vary across regions, suggesting complex links between agriculture and forest loss. —BEL

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