Amazon deforestation footprint across global food and financial systems

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Abstract

Agriculture-driven deforestation in the Amazon remains a major threat to ecosystem stability, biodiversity, and climate regulation[1,2]. Yet the role of global commodity consumption and finance in driving deforestation in the Amazon remains poorly understood and inadequately addressed[3]. We provide the first comprehensive assessment of the Amazon deforestation footprint embedded in global supply chains and commercial financial systems. Considering direct drivers, between 2001 and 2022, pasture expansion accounted for 83% of Amazon deforestation; however, crop-driven deforestation dominates in Bolivia, Ecuador, and Peru. While domestic consumption is indirectly linked to most deforestation, international demand remains an important driver, with China, the European Union, and the United States being major consumer markets. We also identify financial institutions that channelled at least US$1.9 trillion in financing to commodity exporters exposed to Amazon deforestation between 2010 and 2022. Most of these financial flows were attributed to institutions headquartered in Asia, Europe, and North America, while specific countries show disproportionately large financial exposure relative to their deforestation footprints. Our findings strengthen the case for a more coordinated strategy to reduce Amazon deforestation at scale by removing perverse incentives and incentivising and rewarding a shift towards sustainable agriculture.

Main

The alarming rate of agriculture-driven deforestation in the Amazon risks triggering ecological tipping points[1,4]–pushing the ecosystem to a more degraded state. Such a shift will have profound consequences for local and regional communities, global climate stability and food security[5]. Yet our understanding of drivers of deforestation in the Amazon is limited in at least three ways.

First, existing land-use-based assessments of deforestation in the Amazon (comprising eight countries and one overseas territory) have typically been conducted at a national scale[6,7]. When assessments are conducted at finer scales, they usually link deforestation only to broad land-use categories (e.g., agriculture, pasture, mining)[8,9]; however, most studies focus on Brazil[10–13]. Such limitations overlook or mask regional hotspots and trends in both deforestation and commodity-specific drivers, limiting the policy responses that are urgently needed. For example, while cattle ranching is widely recognised as the dominant direct driver of deforestation[14]—particularly due to its scale in Brazil[15,16]—this emphasis obscures other crop commodities that might play major roles in specific subregions[17].

Second, few attempts have been made to link Amazon-wide deforestation to broader systemic drivers—particularly regional and global consumption and trade dynamics[10]. Understanding these connections is essential given the incentives for land-based investments in areas of weak environmental governance[18,19], and the impact of domestic, regional, and international markets in incentivising agricultural expansion[14]—a trend that may be further reinforced by prospective trade liberalisation agreements[20] (e.g., the EU-Mercosur agreement). As a result, commodities that are currently seen as minor contributors to deforestation might considerably shape future trajectories in response to global market demand and trade.

Third, the indirect role of financial institutions—including banks, pension funds, and asset managers—in shaping the global market dynamics that influence deforestation in the Amazon, remains even less well understood than the role of consumption and trade. However, many financial actors, often headquartered far from the Amazon, profit from transactions linked to the production and trade of commodities produced on these deforested land[21]. This distance creates a structural accountability gap[22,23]. Capital accrues returns from financing forest-risk commodities, whereas the environmental and social costs are externalised. Identifying how financial institutions are connected to deforestation, therefore, broadens the set of intervention points for improved governance along value chains, be it through conditional lending[24], shareholder engagement, portfolio alignment, or transition finance[25].

Here, we provide the first comprehensive assessment of the deforestation footprint embedded in agricultural and financial systems of the entire Amazon region (Extended Data Fig. 1). Using spatially explicit commodity and land-use datasets combined with national and sub-national agricultural statistics, we attribute deforestation to specific agricultural and forestry commodities across the entire region[26] (Box 1). These estimates are then linked to domestic, regional, and international consumption using a hybrid physical–monetary trade model[27]. Finally, by linking attributed deforestation estimates to exporter-groups[28] (corporate groups responsible for exporting commodities) and financing information[29], where available, we provide a partial assessment of financial institutions exposed to deforestation[30], focusing on commercial financial flows (Extended Data Fig. 1).

Box 1 | Direct, statistical, and indirect land-use change

Direct land-use change (dLUC) refers to the observable conversion of land from one use to another—for example, clearing forest to establish pasture or cropland (or specific crop commodities such as soy or sugarcane). dLUC is measured explicitly in space and quantifies land-use change resulting directly from a specific land-use activity (e.g., cropland or commodity expansion). However, not all commodities that drive deforestation in the Amazon have spatially explicit land-use data. These data gaps necessitate the use of statistical land-use change (sLUC) approaches to provide a more complete picture of commodity-linked deforestation.

Statistical land-use change (sLUC) refers to deforestation attributed to commodities using national or subnational agricultural production statistics rather than direct spatially explicit evidence. In this approach, land-use change is allocated based on a statistical correlation between commodity expansion and deforestation. Where spatially explicit information is unavailable, the deforestation attribution model used in this study—DeDuCE—assigns deforestation proportionally to each crop commodity according to its relative expansion in area. sLUC therefore identifies the *potential* land-use change based on aggregate land-use change statistics. To provide a comprehensive assessment of deforestation in the Amazon based on the best data available for different regions, the deforestation estimates used in this study combine both dLUC (using spatial data for pasture, soy, and sugarcane; see Supplementary Table 3) and sLUC approaches (for other crops).

Indirect land-use change (iLUC) refers to land-use change that occurs spatially or temporally removed from the original production area as a consequence of market-mediated, behavioural, or displacement effects[31]. For example, expanding soy production onto existing pasture may displace cattle ranching into forested areas elsewhere, thereby *indirectly* linking deforestation to soy. However, this study does not quantitatively assess indirect drivers of deforestation, as they cannot be accurately inferred at scale from spatial or statistical data.

Results

Our results demonstrate that Amazon deforestation is embedded in both local and global markets. Between 2020 and 2022, Amazon deforestation accounted for approximately 38% of all agriculture-driven deforestation worldwide (i.e., 1.7 Mha yr^{-1} of Amazon deforestation footprint compared with 4.5 Mha yr^{-1} of global deforestation footprint embedded in global supply chains; Extended Data Fig. 2). Furthermore, the Amazon accounts for 59% of the global deforestation footprint linked to cattle products and 33% to soy, underscoring the region's disproportionate contribution to agriculture-driven deforestation worldwide (Extended Data Fig. 2).

Regional heterogeneity in agriculture-driven deforestation

Between 2001 and 2022, Brazil accounted for 81% (31 million hectares; Mha) of Amazon-wide deforestation, followed by Bolivia (9.6%), Peru (4.6%), and Colombia (3.9%), with the remaining Amazonian countries contributing much smaller shares (Fig. 1a). Pasture expansion accounted for 83% (or 32 Mha) of direct pan-Amazon deforestation, with 28 Mha in the Brazilian Amazon alone (Fig. 1b and Box 1). However, this overall picture conceals important patterns of spatial-temporal variability in direct deforestation drivers. We find that deforestation associated with cropland expansion is roughly comparable to that linked with pasture expansion in Guyana and Venezuela, whereas crop-driven deforestation is linked to 60% of deforestation in Bolivia, 52% in Peru, and as much as 81% in Ecuador (Fig. 1b). Moreover, crop-driven deforestation has been increasing in recent years—most notably in Colombia, Peru, and Venezuela (Extended Data Fig. 3).

Between 2001-2022, soy stands out as the single largest crop directly driving deforestation in the Amazon, accounting for approximately 2.9 Mha of deforestation (or 44.6% of crop-related deforestation and 7.8% of total deforestation in the region) (Fig. 1b). Notably, however, some food and feed crops—including maize (542 kha), rice (441 kha) and sorghum (405 kha)—are linked to much more deforestation than some of the major export-oriented crops such as oil palm (229 kha), cocoa (173 kha) and coffee (125 kha) (Fig. 1b).

During the same period, deforestation directly associated with pasture expansion in the Amazon has declined substantially from 5 Mha in 2001–2003 to 4.1 Mha in 2020–2022 (18% decrease), with soy-driven deforestation declining even further (from 748 kha to 185 kha; a 75% decrease) (Extended Data Fig. 4 and Supplementary Fig. 1). This decline is likely due to a combination of factors including the influence of sustained civil-society and international pressure that led to voluntary zero-deforestation commitments (such as the Amazon Soy Moratorium), alongside strengthened public monitoring and property-registry systems that complemented these private supply-chain agreements[32]. In contrast, deforestation linked to other crops increased between the same two periods (2001-2003 and 2020-2022), including for oil palm (+63 kha or +1,201%), cocoa (+51 kha or +6,030%), coffee (+21 kha or +309%) and rubber (+5 kha or +302%), with the strongest increases for these commodities occurring in Colombia, Ecuador and Peru (Extended Data Fig. 4 and Supplementary Fig. 1). Growth in deforestation linked to maize (+137 kha or +486%) and sorghum (+112 kha or +406%) surpassed deforestation linked to coffee and rubber, crops with much stronger connections to global markets (Extended Data Fig. 4 and Supplementary Fig. 2).

Our results also reveal clear regional patterns in direct deforestation drivers. Pasture expansion into forest is the dominant driver in the central parts of the Amazon—linked, in part, to cropland displacement onto existing pastures, pushing cattle ranching deeper into forest frontiers[33]—whereas cropland expansion is the dominant deforestation driver in western, southern and northeastern subregions of Amazon (2017-2021; Fig. 1c and Supplementary Fig. 3). Deforestation associated with cropland expansion also exhibits clear patterns: while deforestation linked to maize and rice are widespread across the Amazon region, soy-driven deforestation remains concentrated along the eastern and south-eastern Brazilian and Bolivian corridor (Extended Data Fig. 5). By contrast, deforestation linked to export-oriented crops such as oil palm, cocoa and coffee is more pronounced along the western parts of the Amazon (Extended Data Fig. 5). Transitional zones—extending across eastern Brazilian, southeastern Bolivian and northwestern Colombian Amazon—that are dominated by mixed crop–pasture land-uses, exhibited a simultaneous expansion of soy and other food and feed crops (Fig. 1c and Supplementary Figs. 3-4).

Comparing regional patterns of deforestation and agricultural production also exposes stark variability in agricultural productivity. Regions of the Amazonas state, Brazil, show high pasture-driven deforestation and low cattle stocking rates, whereas parts of Pará state with high pasture-driven deforestation have much higher stocking rates (Supplementary Figs. 5–6). While the pattern in Amazonas is more suggestive of speculative forest clearing, where low-productivity pasture systems are used to claim land ownership[34,35], speculation for longer-term capital gains may still underpin even the most efficient cattle-production systems. This underscores the difficulty of inferring causality from land-use data alone (Box 1), especially when several drivers interact (Box 2). Parallel mismatches in productivity—whether due to financial, technical or other factors—also exist for soy, maize, and rice, where some subregions of Bolivia and Colombia show extensive deforestation and low production volumes, while other regions in the Amazon exhibit comparatively higher production levels (Supplementary Figs. 5–6).

Box 2 | Deforestation associated with pasture expansion is not always linked to cattle production

Pasture expansion remains the most important direct driver of deforestation in the Amazon. Large areas of forest are cleared to establish grazing land for cattle, often through rapid, low-cost conversion methods such as *large-scale burning*[36]. Across much of the Brazilian Amazon, pasture is the dominant land use immediately following clearing, making cattle ranching the most visible and extensive land use linked to deforestation (Fig. 1b). However, many areas of pasture on recently cleared land do not always translate into productive and economically viable cattle systems. Rather, many pastures are maintained in very low-intensity systems, reflecting limited investment, weak enforcement, and the speculative nature of frontier land-use change[35].

Indirectly, pasture plays a strategic role in *land control and market positioning*. Clearing forest for pasture is frequently used to signal “productive use”, helping actors strengthen tenure claims in contexts of weak governance. This makes pasture central to *land grabbing and speculative clearing*, in which forests are cut not only for livestock production but also to consolidate control over land, increase its market value, and enable resale[37].

Pasture expansion is often closely linked to agricultural expansion, particularly soy, which plays a key role in driving up land prices and incentivising land speculation. Most soy expansion in the Amazon occurs on already-cleared land, including unproductive pastures, effectively *displacing* pasture expansion and cattle production further into the remaining forest[33]. This represents a form of indirect land-use change as ranching shifts towards less-regulated frontier areas, where land is cheaper, and governance is weaker, thereby sustaining pressure for new forest clearing even when crops are not directly expanding into primary forests.

Taken together, pasture expansion is not only the dominant direct driver of deforestation but also a key structural driver of wider land-use change embedded in broader economic and governance systems that, in cases, may only be weakly connected to cattle farming. This has been highlighted in previous studies, which show that although cattle ranching is profitable across much of the Amazon, this profitability often hinges on access to cheap land[34].

While both productive uses and speculation contribute to the persistence of pasture deforestation in the Amazon, given the difficulty of disentangling these linked drivers, this study assigns all deforestation linked to pasture expansion to cattle-derived commodities—cattle meat (95%) and leather (5%)—and uses these estimates in the subsequent supply-chain assessments (Figs. 2 and 3).

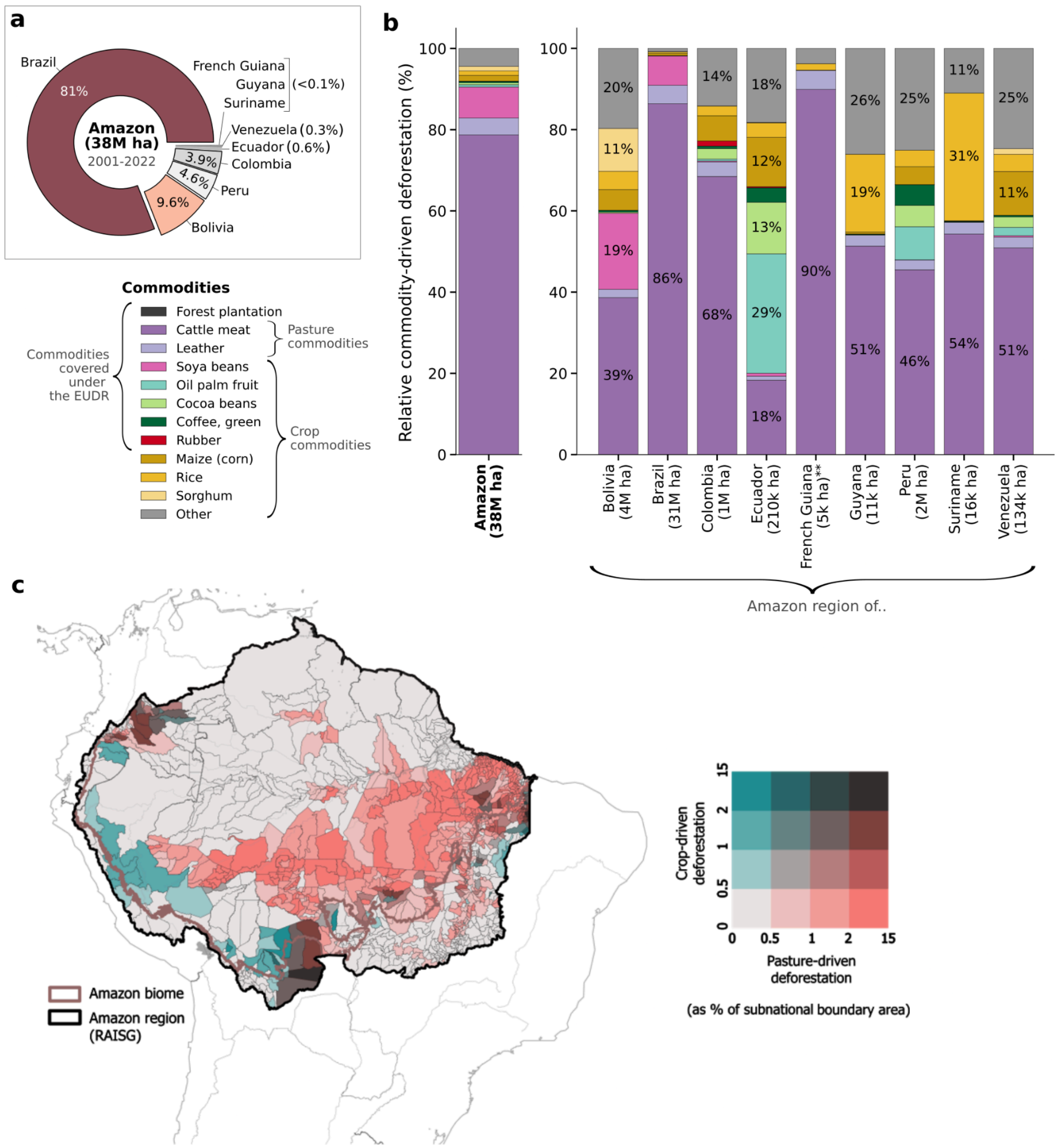

Fig. 1 | Deforestation attributed to agricultural and forestry commodities in the Amazon. (a) Total deforestation associated with agriculture and forestry commodities across the Amazon and (b) its distribution among individual Amazonian countries from 2001–2022 (as % of total deforestation). **Deforestation attribution for French Guiana is limited to 2001–2006 due to the non-availability of national or subnational agricultural statistics thereafter. In panel (b) legend, 'EUDR commodities' refers to commodities regulated under the European Union Deforestation Regulation. (c) Spatial distribution of dominant agricultural drivers of deforestation across the Amazon region, as delimited by Amazon Network of Georeferenced Socio-Environmental Information (RAISG), for the period 2017–2021. Mapping of the dominant deforestation driver is based on the availability of agricultural statistics at the sub-national level. The year 2022 is excluded from this mapping because subnational data are unavailable for Amazonian countries other than Brazil. For the period 2017-2021, subnational estimates are available only for Bolivia, Brazil, Colombia, Ecuador, and Peru, while national-level estimates are used for Guyana, Suriname, and Venezuela. Note that all analyses presented in this study refer exclusively to deforestation within the Amazon region of the respective countries (boundary shown in panel (c)). This includes subregions whose boundaries intersect with the Amazon region; however, only deforestation occurring within the Amazon region is attributed to agriculture and forestry commodities, keeping our deforestation estimates exclusive to the Amazon region.

Deforestation embedded in domestic, regional and international markets

To better understand how Amazon deforestation is embedded in local and global markets, we distinguish between deforestation embedded in both direct physical trade and final consumption of end products, capturing both first-order exports and downstream re-exports across supply chains. Between 2020 and 2022, deforestation associated with direct international trade (i.e., excluding domestic trade) represents only a small fraction of total deforestation (4.3% or 76 kha yr^{-1}), whereas consumption-based attribution increases this share to 15% (260 kha yr^{-1}; Extended Data Fig. 6), with the majority of deforestation linked to domestic consumption (i.e., within the producing country; 1.5 Mha yr^{-1}) (Fig. 2a).

This dominance of domestic consumption as a deforestation driver is especially evident for Brazil (87% of deforestation linked to domestic consumption between 2020-2022), Bolivia (87%) and Colombia (79%) (Fig. 2a). The deforestation footprint of domestic consumption is dominated by beef, with 1.3 Mha yr^{-1} of deforestation linked to domestic beef markets—92% of the total Amazon deforestation footprint linked to cattle production (Fig. 2a). Similarly, sorghum (41 kha yr^{-1}; or 90% of the total Amazon deforestation footprint) and rice (28 kha yr^{-1}; 86%) show deforestation footprints overwhelmingly tied to domestic demand (Fig. 2b). Note that this disproportionately large share of cattle-driven deforestation includes speculative clearing and expansion of low-productivity pasture systems (Box 2), meaning that the attribution of deforestation to beef consumption per se is necessarily an overestimate.

Brazil has the largest area of deforestation linked to international consumption—148 kha yr^{-1} (11% of the total Amazon deforestation footprint between 2020-2022)—with deforestation in Peru (39 kha yr^{-1}; 41%) and Colombia (17 kha yr^{-1}; 17%) also having strong connections to international markets (Fig. 2a). Demand for beef is the largest international driver of Amazon deforestation (95 kha yr^{-1}; 7% of deforestation linked to cattle production), with soy (34 kha yr^{-1}; 56%), maize (25 kha yr^{-1}; 46%), cocoa (14 kha yr^{-1}; 80%), coffee (8 kha yr^{-1}; 83%) and bananas (8 kha yr^{-1}; 67%) all standing out as key drivers of deforestation linked to international consumption (Fig. 2a-c). Among international consumer markets, China (51 kha yr^{-1}; accounting for 23% of the total Amazon's international deforestation footprint), the European Union (EU-27) (39 kha yr^{-1}; 17%), and the United States (36 kha yr^{-1}; 16%) rank among the top international markets linked to consumption of Amazon's deforestation-risk commodities (Fig. 2a). Comparing the deforestation footprint of different crops, soy has a much larger contribution to the deforestation footprint of China, whereas the EU-27 and the United States exhibit a broader distribution of deforestation risk across multiple commodities, including from maize, cocoa and coffee (Fig. 2c).

Consumption patterns linked to Amazon deforestation have changed significantly over time. In particular, we found that deforestation linked to domestic and regional consumption of cattle meat and soybeans declined in relative terms by 19–69% between 2005–2007 and 2020–2022 (Fig. 3a,c). In contrast, China's consumption footprint for the same commodities increased by 53–99% during the same period. Meanwhile, the international consumption footprints for soy and beef declined by 42–52% for the United States, 70-71% for the EU-27, and 38–47% for the rest of the international market (Fig. 3b,c). International deforestation footprints also rose substantially for other key commodities such as cocoa (+668%), coffee (+210%), and oil palm fruit (+299%), as well as for staple food and feed crops including maize, rice, and sorghum, with notable increases observed for China, the EU-27, and the United States (Fig. 3c).

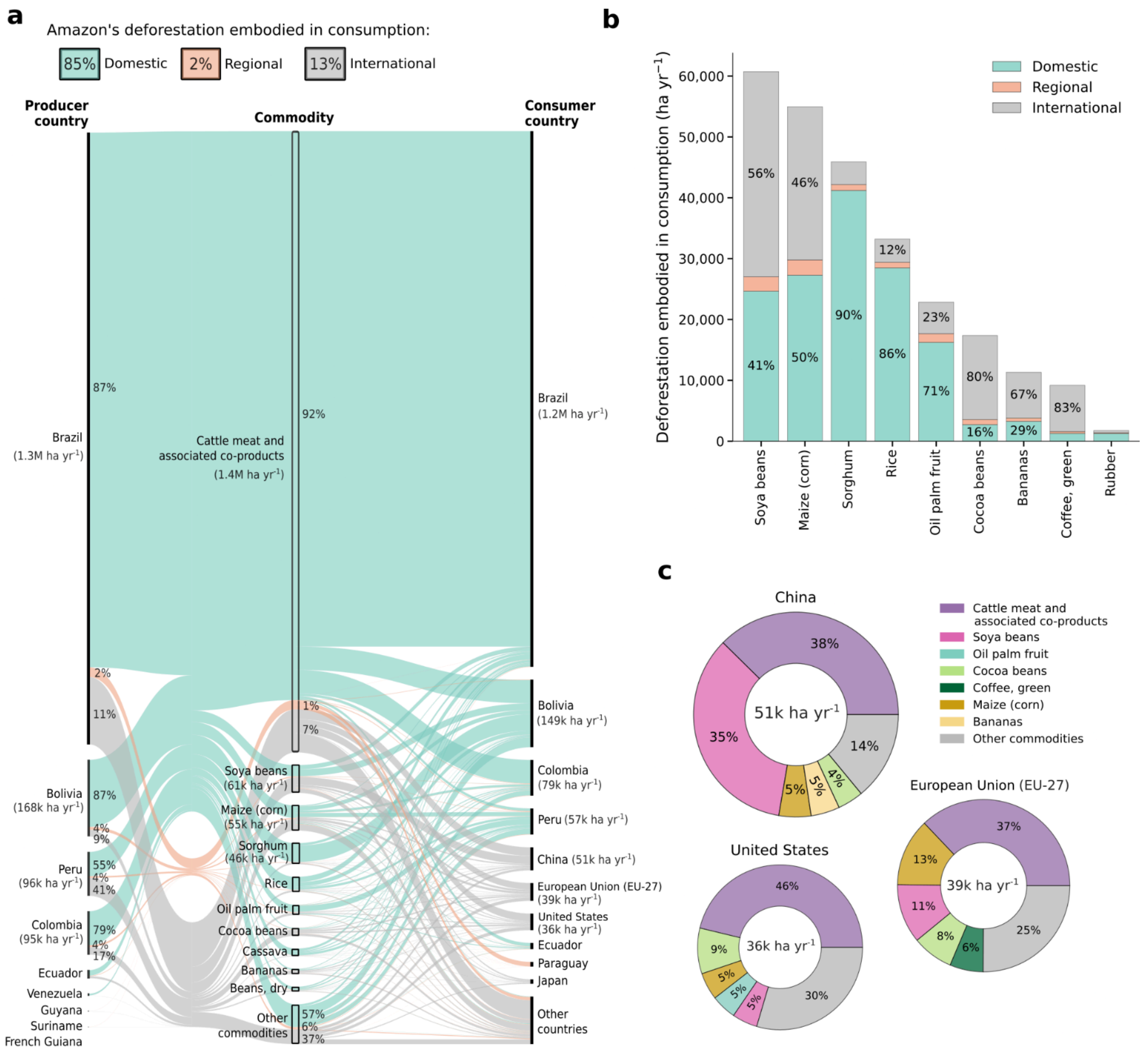

Fig. 2 | Amazon's deforestation embedded in domestic, regional, and international consumption. (a) Average annual Amazon deforestation (ha yr^{-1}; 2020–2022) embedded in domestic (within the producing country), regional (within South America but outside the country of production), and international (all other regions) consumption, aggregated across the top-10 deforestation-risk commodities and consumer countries. The category 'Other countries/commodities' includes remaining contributions. Percentage labels indicate the share of deforestation attributed to each consumption type. Note that since this attribution incorporates analysis dependent on the GLORIA multi-regional input–output (MRIO) dataset, several countries not individually represented are grouped under the broader category 'Rest of America' (Supplementary Fig. 7). In this study, individually represented non-Amazonian South American countries and the 'Rest of America' category are classified as regional consumers. (b) Breakdown of deforestation embedded in domestic, regional, and international consumption footprints for top deforestation-risk crop commodities in the Amazon. (c) Deforestation footprints of the top-5 commodities attributed to international consumption linked to China, the European Union (EU-27), and the United States. The deforestation footprint for individual EU-27 member countries is shown separately in Supplementary Fig. 8.

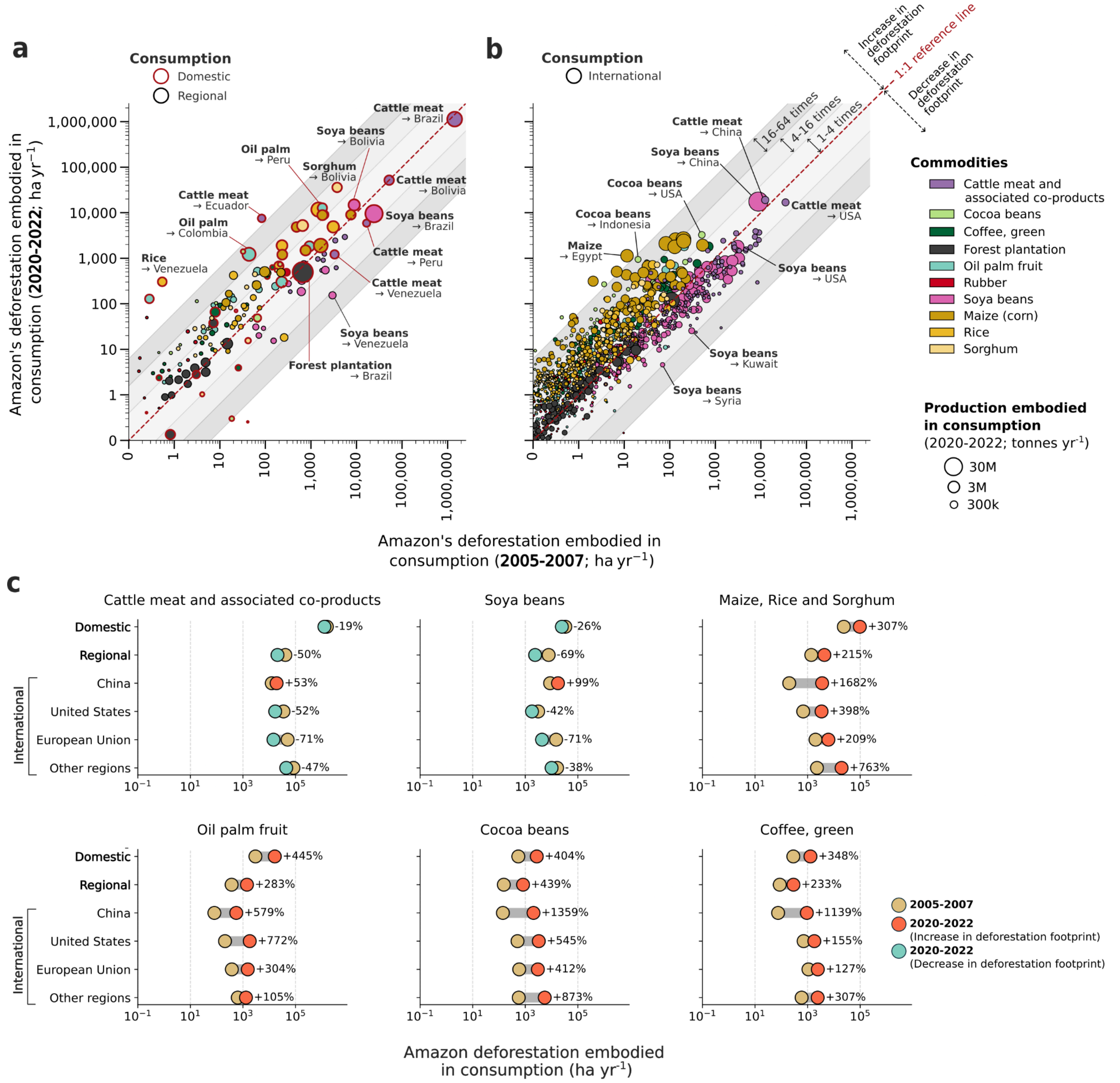

Fig. 3 | Changes in Amazon deforestation footprint linked to domestic, regional and international consumption. The scatter plot shows average annual deforestation (ha yr^{-1}) associated with key agricultural commodities in 2005–2007 (x-axis) and 2020–2022 (y-axis), based on consumption-linked attribution. Results are shown separately for (a) domestic and regional consumption, and (b) international consumption. Point size reflects the average production volumes in 2020–2022 (tonnes yr^{-1}). Grey bands along the 1:1 line indicate proportional changes in deforestation footprint: points above the line represent increases relative to 2005–2007, whereas points below indicate reductions by the corresponding factor shown in the insets. (c) Aggregated changes in deforestation footprints across domestic, regional, and international consumption (shown separately for China, the European Union and the United States) for selected commodities.

Financial institutions linked to deforestation

For a subset of countries and commodities (see Methods), we resolve Amazon deforestation embedded in corporations responsible for exporting commodities (or exporter groups) and examine commercial financial flows to these exporter groups—specifically bank loans, corporate bond issuances, and equity issuances—facilitated by financial institutions (Fig. 4). We identified 515 individual institutions that, when including unknown and self-arranged flows, collectively channelled US$1.9 trillion (adjusted to 2024 US$) to identified commodity exporters exposed to Amazon deforestation over 2010-2022 (sensitivity range: US$1.4–2.3 trillion; Fig. 4a,b and Supplementary Fig. 10). Of this US$1.9 trillion, 90% were facilitated by privately owned or publicly listed actors, 7% from state-owned actors, and the last 3% could not be attributed to individual actors or were self-arranged by the companies.

To assess the proximity of these flows to deforestation-risk activities, we applied a rules-based classification (see Methods). We find that only ~5% of all financial flows (US$84 billion) were classified under 'high-proximity' (Fig. 4a), meaning they were provided to entities headquartered in Amazon or Latin America and the Caribbean and operating in sectors closely linked to Amazon deforestation (e.g., production or transportation; see full criteria in Supplementary Table 1). By contrast, 58% of flows were classified as 'low-proximity' (US$1.1 trillion; Fig. 4a), reflecting finance directed to entities within the same corporate groups as deforestation-linked exporters but headquartered in more distant geographies and operating in sectors with minimal direct relation to deforestation. Across all financial flows, bank loans accounted for 68% (or US$1.3 trillion), followed by corporate bond issuances (28%) and equity issuances (4%) (Fig. 4b). Latin America and the Caribbean accounted for only 3% of these identified financial flows (US$59 billion; Fig. 4b). By comparison, Europe was the largest region linked to financial flows (36% or US$663 billion), followed by Asia (29%; US$564 billion) and North America (25%; US$466 billion) (Fig. 4b).

The distribution of financial flows across institutions differed markedly depending on this proximity classification. For example, Mitsubishi UFJ (responsible for channelling a total of US$145 billion) and Mizuho Financial Group (US$118 billion) ranked highest in total flows to exporter groups, yet only ~1% of their finance was classified as high-proximity (Fig. 4a), suggesting they primarily finance diversified trading conglomerates exposed to Amazon deforestation. In contrast, some Brazilian banks, such as Banco Bradesco (US$18 billion) and Banco do Brasil (US$11 billion) rank lower in total flows, but have 49% and 55% of their financial flows classified as high-proximity finance, respectively (Fig. 4a).

Proximity patterns also varied across the commodities associated with exporter groups. Exporter groups exposed to cattle- and soy-driven deforestation in Brazil received similar absolute volumes of high-proximity finance, but differed starkly in relative terms (US$33 billion; 32% of flows linked to cattle, versus US$32 billion; 3% of flows linked to soy) (Extended Data Fig. 7). This likely reflects supply-chain structure: soy-linked finance is distributed across a wider set of downstream actors (notably traders and processors) with more diffuse exposure[38], whereas cattle-linked exposure is more concentrated around upstream production and slaughter/processing nodes[16], increasing the share classified as high-proximity. Finally, at the asset level, bond deals represented the largest share of high-proximity finance (US$35 billion) despite ranking below loan deals overall (Fig. 4b).

Comparing the geography of financial flows with the consumption-driven deforestation footprints (2010–2022) reveals distinct global hubs of financing and demand. The United States, China and Japan emerge as major centres linked to both financial investment in, and consumption of, deforestation-risk commodities from the Amazon (Fig. 4c). By contrast, countries such as the United Kingdom (UK) and France exhibit disproportionately high levels of financial flows relative to their consumption. Similar asymmetries—high overall financial flows relative to consumption—are also evident for other major economies, including Canada, Russia, Australia and Italy (Fig. 4c). For the EU-27 and the UK, this highlights a regulatory mismatch where trade policies are designed to exclude deforestation-linked commodities from supply chains[39,40], but they do not cover financial institutions headquartered in these jurisdictions that continue to support exporter groups exposed todeforestation[41] (Fig. 4c).

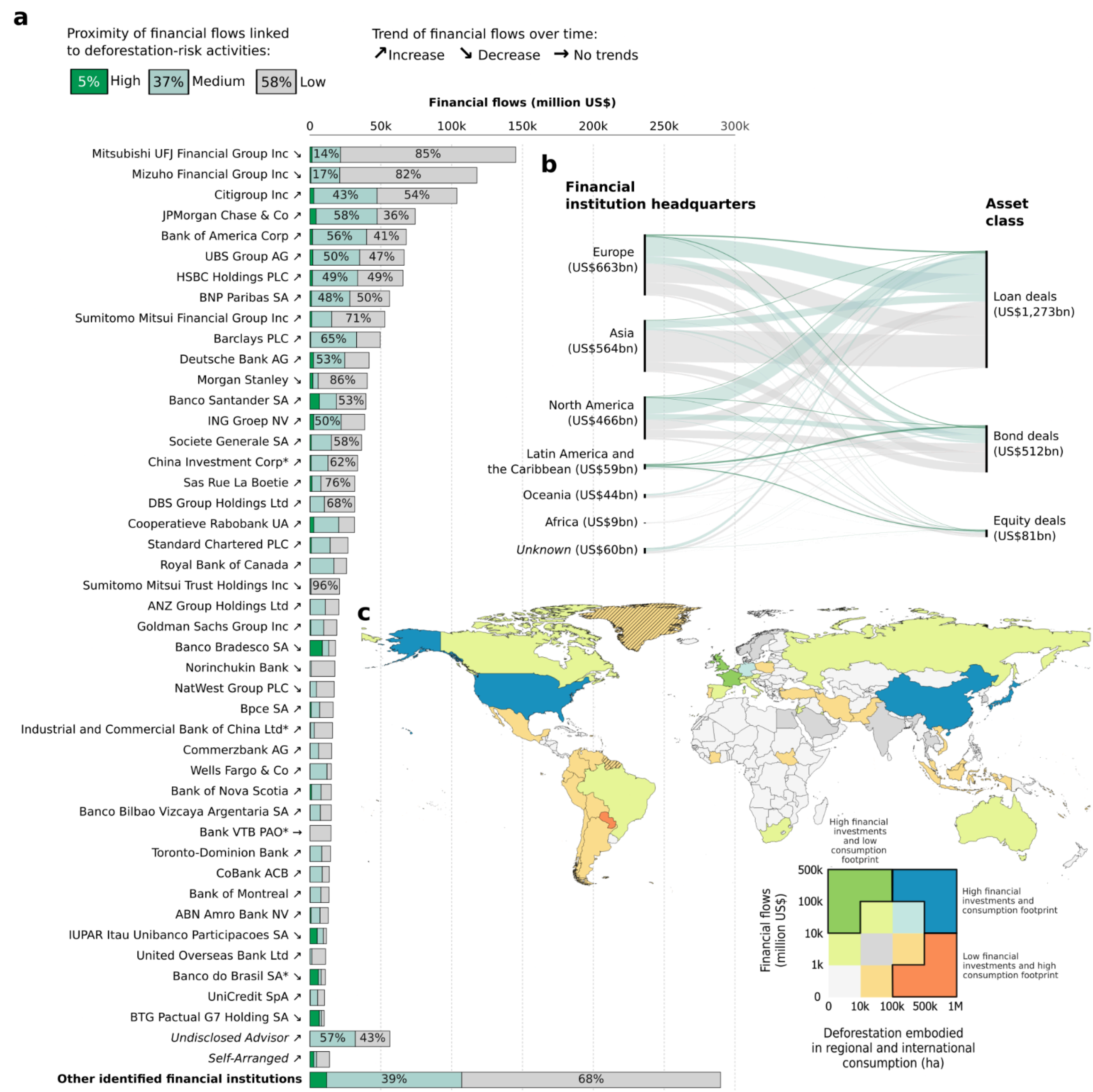

Fig. 4 | Financial flows linked to a subset of the Amazon's deforestation-risk commodities. Financial flows (in million US$, all adjusted to 2024 US$) to exporter groups exposed to Amazon deforestation over 2010-2022 (see methods), disaggregated by (a) individual financial institution exposure, (b) region of financial institution headquarters and the asset class through which flows were channelled. To account for lags between financing and deforestation-risk activities, financial flows are included within ±2 years of the years in which exporter group-level data were available (Supplementary Table 2). Furthermore, to account for diversified exporter groups' operations extending beyond the Amazon, financial flows are classified as 'high', 'medium', and 'low' based on the proximity of the directly financed entity to Amazon deforestation in terms of activity and location (see Supplementary Methods and Supplementary Table 1 for detailed criteria). In (a), arrows indicate the trend in financial flows per institution over the period, * indicates state-owned financial institutions, and 'Self-Arranged' refers to deals arranged directly by the company without financial institutions. Here, the country is allocated based on where the deal was issued. Note that limited coverage of exporter groups linked to deforestation-risk commodities means these flows represent only a subset of total potential financing exposed to Amazon deforestation (Supplementary Table 2 and Supplementary Fig. 9), and thus the results should be interpreted with caution. Our intention is not to single out individual companies or financial institutions, but to use available data to highlight broader gaps in financial disclosure and coverage.

(c) Spatial pattern of overall financial flows by country of financial institution headquarters, and regional and international consumption associated with Amazon's deforestation-risk commodities (2010–2022). Here, hatched areas indicate aggregated countries classified as 'Rest of the World' in the MRIO dataset used to estimate deforestation embedded in consumption (Supplementary Fig. 7).

Discussion

Our results show that while the main proximate driver of Amazon deforestation is domestic demand, especially for beef, deforestation is deeply embedded in regional and international supply chains and commercial finance that are critical indirect drivers[10,42] (Figs. 2-4). A clear understanding of these direct (or proximate; Fig. 1) and indirect (or systemic) drivers is important because it helps identify a much broader set of potential interventions and beneficiaries of deforestation that share both the risks associated with deforestation exposure and the responsibility for addressing it[17,32]. It also highlights that reducing deforestation in the Amazon cannot—and should not—rely solely on domestic market actions or a narrow set of export commodities. Successfully reducing deforestation in the Amazon requires much more coordinated action across producing regions, intermediaries (e.g., traders and exporters), consumer markets, and investors[42,43]. Greater coordination can strengthen enforcement and incentives to tackle deforestation, including by aligning standards, policies and monitoring requirements[44–46]. A step-change in action in at least three areas is needed to deliver the change that is needed.

First, domestic governance within Amazonian countries must be strengthened. The dominance of domestic consumption as a direct driver of deforestation (Fig. 2), together with spatially concentrated commodity frontiers (Fig. 1 and Extended Data Fig. 5), indicates that national policy—implemented through subnational monitoring, enforcement, and economic incentives—remains a critically important lever for near-term mitigation of deforestation in the Amazon[10]. Priorities include consolidating land-tenure security (Box 2), expanding transparent property registries[47], and robust monitoring systems (supported by high-resolution commodity mapping[48]) and enforcement in frontier municipalities[45] (Fig. 1). Policies that increase the opportunity cost of forest clearing and reduce the perverse distortions in the land market that incentivize clearing—such as conditioning rural credit and support on legal compliance (as previously demonstrated by its success in Brazil[24,49]), strengthening penalties for illegal conversion[50,51] and land grabbing (especially regarding pasture expansion; Box 2), and scaling support for forest restoration and sustainable agricultural intensification[52]—are likely to yield outsized benefits[53].

Importantly, domestic market interventions should not be treated as secondary to international policies. A priority for Amazonian countries is to embed deforestation-free criteria into public procurement, domestic slaughterhouse standards, grain-trader sourcing policies, and national agricultural development programmes, so that 'deforestation-free' becomes a default market expectation that levels the playing field for all supply chain actors rather than an incentive limited to niche export markets. Ongoing regional initiatives, including the Amazon Cooperation Treaty Organisation (ACTO) and the Belém Declaration, could help consolidate these efforts across the basin by providing a platform for shared intelligence—including interoperable subnational monitoring and data infrastructures that enable mutual recognition and reduce duplication of compliance costs[54,55]—harmonised standards, and joint action across the Amazon[44].

Second, trade and supply-chain regulations must be harmonised and interoperable, include robust traceability and due diligence requirements, and incentivise collective action to tackle systemic risks shared across the supply bases of many companies. Consumption-based attribution shows that direct trade of primary commodities from the Amazon substantially understates the deforestation footprint transmitted through global markets (Extended Data Fig. 6), because downstream processing, re-exports, and sale of goods and services can shift responsibility away from immediate importers[56,57]. This creates an accountability gap, and thus due-diligence regimes must be designed to cover indirect trade, and especially downstream (processed) products, not only first-order imports of unprocessed commodities[58].

While the EU Deforestation Regulation (EUDR)[39] and the UK's Forest Risk Commodity (UKFRC) regulation[40] are a significant step in this direction, their effectiveness will depend on how rigorously and consistently the mechanisms are implemented and enforced[26]. Complementary measures that incentivise deforestation-free production in other major consumer markets (Fig. 2) are essential for achieving the scale needed and reducing the risk of leakage into non-EU/UK markets[59–61]. Crucially, integrating subnational supply-chain and trade data (e.g., municipality-level sourcing, trader/exporter linkages, and port-to-destination flows[28]) into monitoring systems in producer countries would enable earlier identification of high-risk frontiers, improve targeting of enforcement and credit conditionality, and help detect displacement of high-risk or non-compliant commodities to domestic or less regulated international markets. Regulators must also ensure that trade-policy instruments—including environmental provisions in agreements such as the EU-Mercosur[20]—include enforceable safeguards and cooperation mechanisms (data-sharing, technical assistance, and verification protocols) that support compliance rather than merely shifting burdens along the supply chain[62] (e.g., compliance costs or liability to upstream producers).

Third, deforestation risk linked to financial flows warrants distinct policy attention, as it cannot be addressed by supply-chain traceability and producer- or consumer-facing policies alone[63]. Our findings on the links between commercial financial flows and deforestation—predominantly channelled through indirect, low-proximity pathways—illustrate the highly diffuse nature of accountability for Amazon deforestation for many financial institutions (Fig. 4). Because most exposure is mediated through corporate lending and capital-market finance, where proceeds are fungible and rarely traceable to specific farms or shipments[64], transaction-level exclusions modelled on the EUDR's consignment-level due-diligence logic are unlikely to shift on-the-ground production practices. Effective oversight of this segment of finance, which is predominantly associated with larger companies[65], therefore requires mandatory disclosure of total exposure to deforestation-linked companies across lending, underwriting, and investment portfolios, under harmonised definitions and auditable metrics[66]. Beyond transparency, stricter financing restrictions—paired with targeted transition finance conditional on verifiable gains in traceability, land-use compliance and deforestation-free production—could shift incentives away from deforestation-linked exposure and towards forest restoration and sustainable production on already-cleared land[67,68].

Taken together, these strategies define a coordinated approach to reduce Amazon deforestation at scale by removing perverse incentives and incentivising and rewarding a shift towards sustainable agriculture.

Methods

Our methodology for assessing Amazon's deforestation footprint across global supply chains and financial systems involves the following steps:

Attributing commodity-driven drivers of deforestation in the Amazon

We adapted the methodology of the DeDuCE model by Singh and Persson[26], which utilises remote sensing and agricultural statistics to link deforestation and carbon emissions to agricultural and forestry commodities (Extended Data Fig. 1a and Supplementary Table 3). This approach overlays global spatio-temporal data on tree cover loss with datasets on specific crop commodities (such as soy, oil palm, cocoa), land use maps (croplands, forest plantations, and pastures), and other drivers of forest loss (e.g., forest fire, excluding tree cover losses over existing plantations and managed forests). The model prioritises high-quality data where available, characterised by their spatio-temporal resolution and clarity of mapped information (e.g., whether the data are a broader land-use or a specific commodity map), to associate deforestation with its direct land-use change (dLUC) drivers (Box 1)[26]. For regions where deforestation cannot be directly attributed to specific agricultural or forestry commodities using the spatial attribution approach described above, we apply a statistical land-use change method (sLUC; Box 1), allocating deforestation proportionally to individual crop commodities based on their relative expansion in planted or harvested area[26].

In this study, we use the Global Subnational Agricultural Production (GSAP)[69] statistics for all Amazonian countries (Supplementary Table 4) except Brazil, where we utilised subnational-level statistics from the Brazilian Institute for Geography and Statistics (IBGE)[70], to attribute deforestation to individual crop commodities at a fine (municipal) scale. For countries without subnational agricultural statistics from GSAP or IBGE, we rely on national-scale estimates from FAOSTAT[71]. Processing sub-national agricultural statistics for GSAP starts by obtaining official production and crop area data from national statistical offices, ministries of agriculture, and agricultural surveys. This data is then converted to tabular format through multiple methods, including web data scraping and AI-based optical character recognition (OCR), depending on the format in which the data became available. We ensure data uniformity by standardising geographical units, crops, and measurement units according to Global Administrative Areas (GADM), FAO codes, and metric units, respectively. A rigorous quality assurance process follows, involving the identification of duplicates and the verification of internal and external data consistency with FAOSTAT data, thereby assuring the reliability of the agricultural statistics. Despite rigorous efforts to find and collate data for as many areas and years as possible, some countries or ministries have not made their agricultural statistics publicly available throughout the whole period, limiting our ability to attribute deforestation sub-nationally using these statistics consistently between 2001-2022 (spatio-temporal coverage of subnational agricultural statistics from GSAP is provided in Supplementary Table 4). In such cases, deforestation attribution is conducted at the national level. Deforestation attributed directly to pasture expansion is allocated between cattle meat (95%) and leather (5%)[26]. Deforestation associated with forest plantations is not attributed to specific commodities unless spatially explicit data are available. The framework yields annual deforestation estimates attributed to individual agriculture and forestry commodities at the subnational or national level from 2001 to 2022.

Since this study focuses specifically on Amazon's deforestation footprint, we limit the analysis to the Amazon region as defined by the Amazonian Network of Georeferenced Socio-Environmental Information (RAISG)[72] (Fig. 1c). To assess this, we exclude tree cover loss occurring outside this boundary from the DeDuCE deforestation attribution framework. This exclusion also applies to subnational administrative units that straddle the Amazon region boundary—deforestation is only attributed to the portions falling within the boundary, and portions outside are excluded from attribution. However, the trade model (see next section: 'Evaluating deforestation embedded in trade and consumption') requires country-level deforestation estimates to align with national production data and to enable mass-balancing with exports for analysing deforestation embedded in trade. As a result, this analysis generates two sets of deforestation estimates: (i) total deforestation across Amazonian countries, and (ii) deforestation occurring only within the Amazon region of those countries (Fig. 1c).

A comparison of deforestation attribution at the national scale (using FAOSTAT) and the subnational scale (using GSAP and IBGE) for Amazonian countries is provided in Supplementary Table 5.

Evaluating deforestation embedded in trade and consumption

The aim of this analysis is to examine how trade and consumption of agricultural and forestry commodities drive deforestation in producer countries. To achieve this, we use direct-trade statistics from FAOSTAT[71] and UN Comtrade[73] along with the Input-Output Trade Analysis (IOTA) framework[27]—a hybrid physical-monetary multi-regional input-output (MRIO) model that combines commodity-level data in physical units with sectoral monetary expenditure data (derived in the latest version from the GLORIA MRIO[74])—to map the complete supply chain from producers to consumers for each commodity (Extended Data Fig. 1b). IOTA[27] has been successfully applied—using national-level production and deforestation data[75]—in the development of the 'Global Environmental Impacts of Consumption' (GEIC) indicator, which is used as an official statistic in the United Kingdom to support deforestation-monitoring efforts[76].

In addition to compiling results at the national scale for crop commodities, cattle meat and associated products, and timber using the DeDuCE data described above, we extend the traditional IOTA framework—which typically resolves commodity flows only at the national level—by integrating subnational production data for crop products where available (from GSAP and IBGE). Cattle and forestry products are excluded from this subnational analysis owing to the lack of corresponding subnational production data in GSAP and IBGE. In the absence of detailed information linking subnational production hotspots to specific trade destinations, we apply a proportional downscaling approach based on relative production volumes in the main analysis. Although simple, this extension enables the mapping of global trade flows from individual municipalities or provinces within the Amazon to consuming countries, thereby improving the spatial resolution of deforestation-risk attribution along supply chains. This results in two complementary deforestation footprints:

(a) Direct trade in primary commodities – based on physical trade flow data from FAO and UN Comtrade, showing the initial importing country (excluding re-exports), and
(b) Final consumption – which takes direct trade information as an input, processes it to account for re-export activities, and inserts the resultant data into an MRIO model to trace deforestation through intermediate transactions to the final consumer (which can include allocation to the country of raw material production in addition to international markets), using the monetary MRIO data to account for inter- and intra-sectoral flows (such as consumption through sales of goods and services).

Comparing these two perspectives is important because while direct trade highlights immediate trade relationships and provides granular commodity details on local as well as international export markets for forest-risk commodities, the final consumption approach inherently incorporates downstream processing of materials and subsequent trade, which is often overlooked when considering the ultimate drivers of deforestation (Extended Data Fig. 6). To provide trade and consumption deforestation data specifically for the Amazon, deforestation embedded in trade at the national level is adjusted using a scaling factor that accounts for the proportional difference between national and Amazon-specific deforestation within each producer country/subregion, commodity, and the year of deforestation.

Linking commodity-driven deforestation to financial institutions

This analysis links Amazon deforestation to financial institutions, focusing on the provision of commercial financial flows (defined as bank loans, equity and bond issuances) facilitated primarily by banks to exporter groups exposed to deforestation. This scope thus presents a partial picture of the Amazon deforestation footprint in financial systems, as other parts of the supply chain (e.g., producers that do not export) and sources of financial flows (notably rural credit and supply chain finance[77]) are not captured here. It also does not include other types of financial exposure that result from financial flows (e.g., equity ownership by institutional investors or insurance[78]). Our analysis focuses explicitly on exporter groups because company-level resolution of deforestation exposure across the supply chain is currently only available through datasets such as Trase[28]. However, they are key actors to focus on since exporters occupy a central position between producers and international markets, aggregating supply from multiple production sites and interfacing with global markets[44]; they also provide financing and support to other parts of the agricultural supply chain[79].

We identified companies involved in the export of deforestation-risk commodities at national or subnational levels (Extended Data Fig. 1c). To achieve this, we linked Amazon deforestation estimates from this study with commodity production and exporter group data from the Trase database (see Supplementary Method 1). Our analysis therefore covers only those country–commodity settings for which Trase[28] provides spatial and temporal coverage (countries, commodities and years; Supplementary Table 2), which varies across settings and does not fully overlap with the DeDuCE dataset.

We then link these companies to financial institutions, building on the methodology in Marsden et al.[30,80]. First, we map the identified exporter groups in each country-commodity pair to specific legal entities and their identifiers (including their ultimate parent entities) in the London Stock Exchange Group (LSEG) PermID dataset[81], applying adjustments for ownership changes and duplicates (Supplementary Methods 2). Second, we use LSEG's SDC Deals Business Intelligence Data[29] to gather commercial financial flows—lending, equity issuances and bond issuances, in US dollars (US$) based on LSEG conversion factors at the time of close—issued over 2008-2024 where the identifier relates to the entity, entity intermediate parent, or entity ultimate parent receiving finance. Third, the name-based matching and allocation methodology in Marsden et al.[80] is used to collect the identity, ownership, and headquarters of actors (primarily commercial banks) named on financial flows where available, and to distribute financial amounts between them based on disclosed data or an allocation rule conditional on their role in the transaction. These data were all collected via the LSEG API in August 2025. Fourth, financial flows are sorted to each country-commodity setting based on the identifiers associated with exporter groups in each year and cleaned for duplicates and incomplete transactions. Finally, we construct an overall Amazon-wide dataset using an allocation rule for cases where exporter groups operated across multiple country-commodity settings, which would lead to double-counted financial flows (Supplementary Methods 2). Legal entities were only available for a subset of exporter groups, and financial flows for a subset of these, which are likely to represent larger actors and larger financial transactions[82,83].

Since the causality between financial flows and environmental impacts is not well established in both time[84,85] and space[64], we conduct two sensitivity analyses. First, we use varying time windows centred on the years for which the Trase data are available for each country-commodity setting, thereby deriving upper and lower bounds for estimated total financial flows (Supplementary Methods 2, Supplementary Fig. 10). Second, we develop a rules-based classification to categorise the likely proximity of each financial flow to Amazon deforestation based on the location and industry classification of the entity directly receiving finance, from 'low' to 'high' proximity. This accounts for financing to some exporter groups that are exposed to the Amazon via a subsidiary of their activities, but also operate globally across a much wider range of industries (Fig. 4, Supplementary Methods 3 and Supplementary Table 1).

Data availability: All data associated with this publication will be made openly available on Zenodo before publication. The insights from the DeDuCE model can be viewed at: https://www.deforestationfootprint.earth/Amazon.

Code availability: All codes associated with this publication will be made openly available on GitHub before publication. The original codes for the DeDuCE model are available here: https://github.com/chandrakant6492/DeDuCE.

Competing interests: The authors declare no competing interests.

Author contributions: C.S., V.R., U.M.P. and P.P. conceived the study with support from T.G., C.W., S.C. and L.M. Together with R.F. and V.G., they contributed to the overall analytical framework. C.S. led the deforestation attribution, performed the data analysis and visualisations. S.C. and C.W. led the global supply-chain and consumption analysis, with analytical support from J.C. L.M. led the financial-flow analysis and associated visualisations. R.F. led the development of the Global Subnational Agricultural Production (GSAP) dataset. C.S., U.M.P. and C.W. wrote the first draft of the manuscript with support from S.C., L.M., P.P., V.G., T.G. and R.F. All authors reviewed and edited subsequent drafts and approved the final manuscript.

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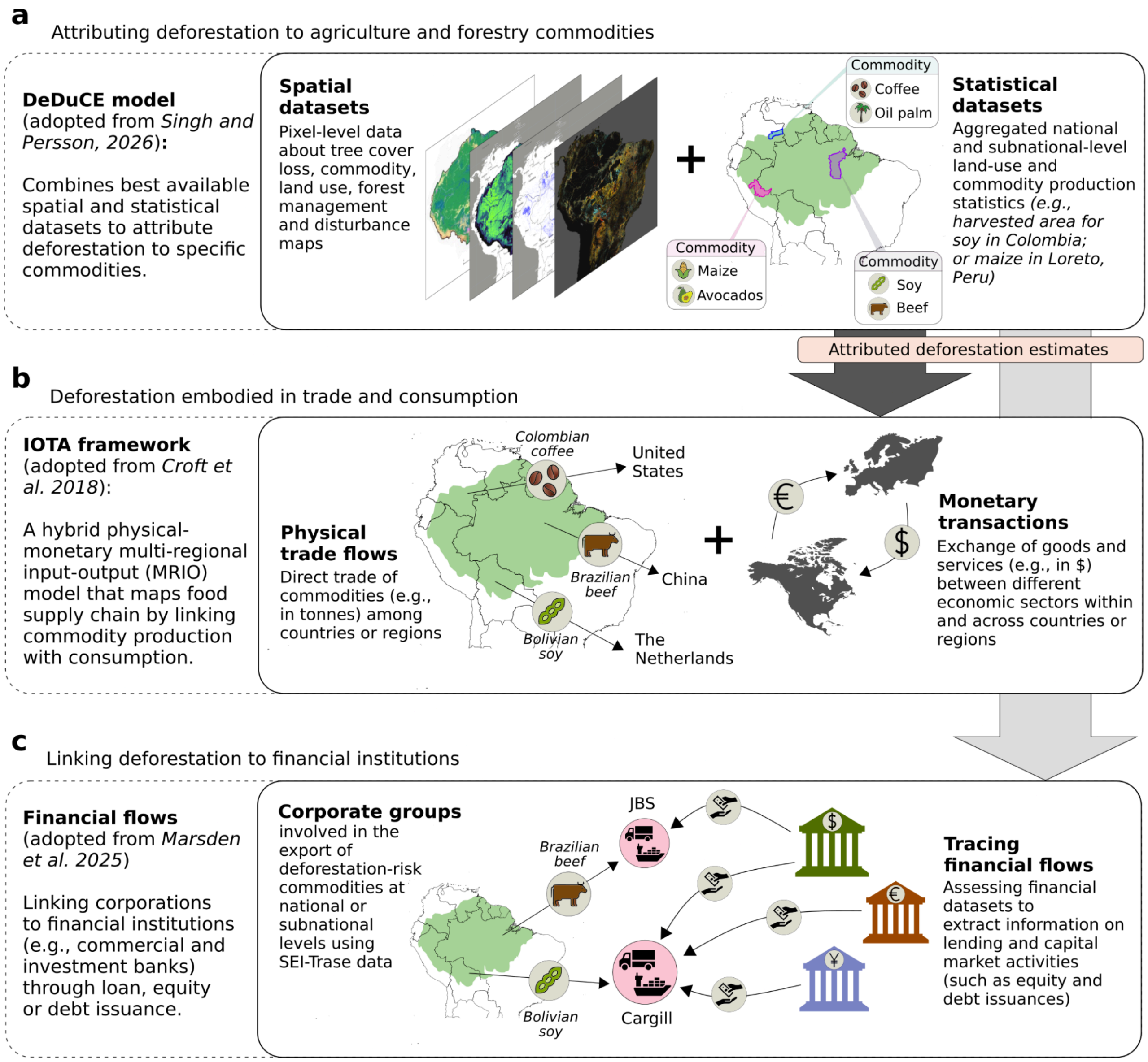
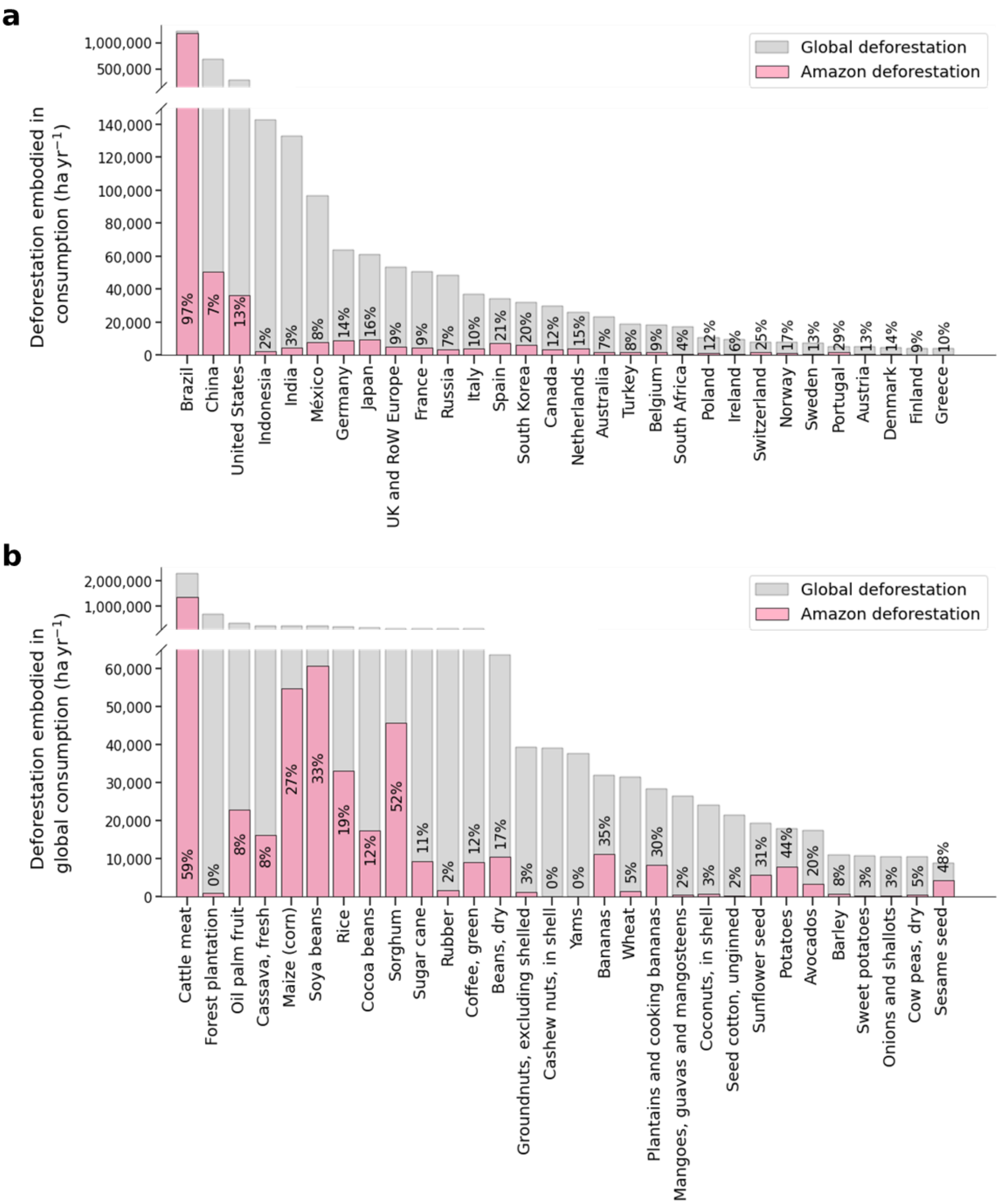
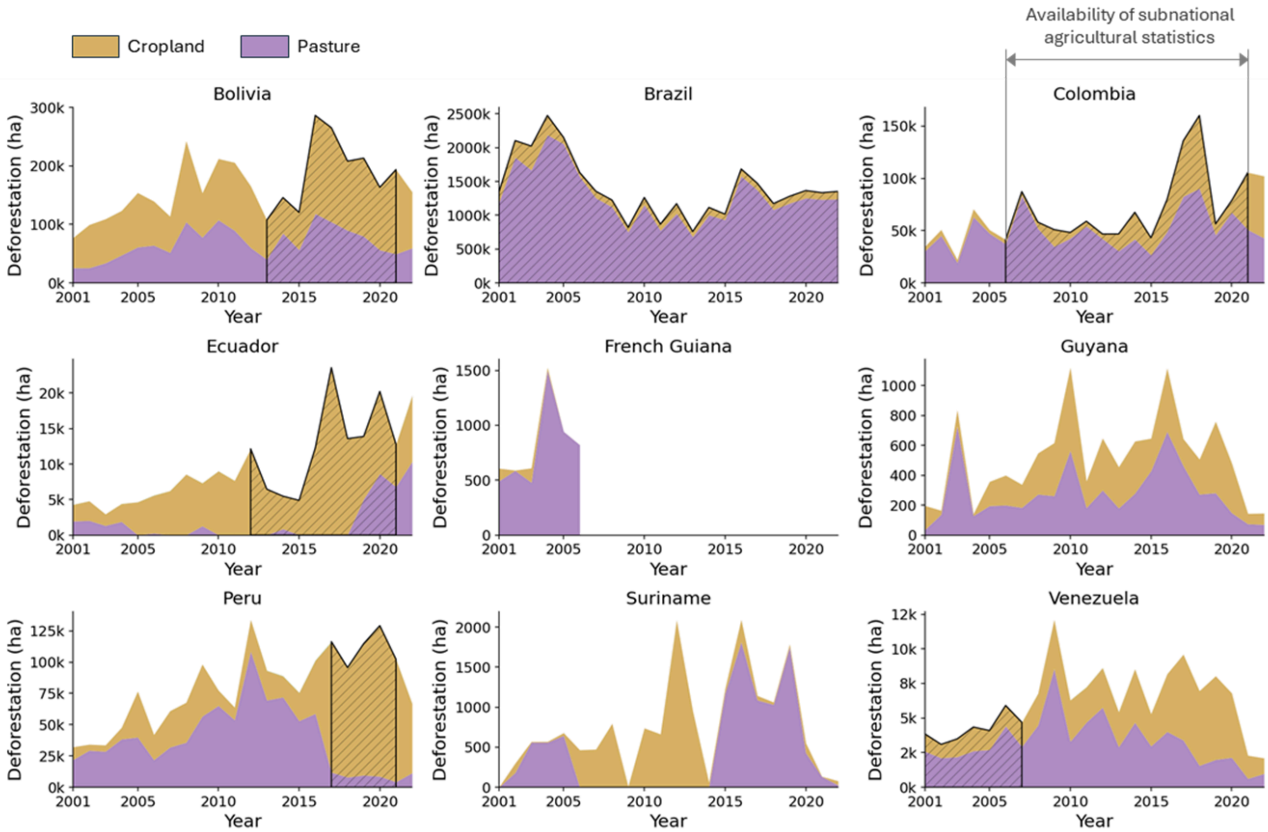
Extended Data Figures



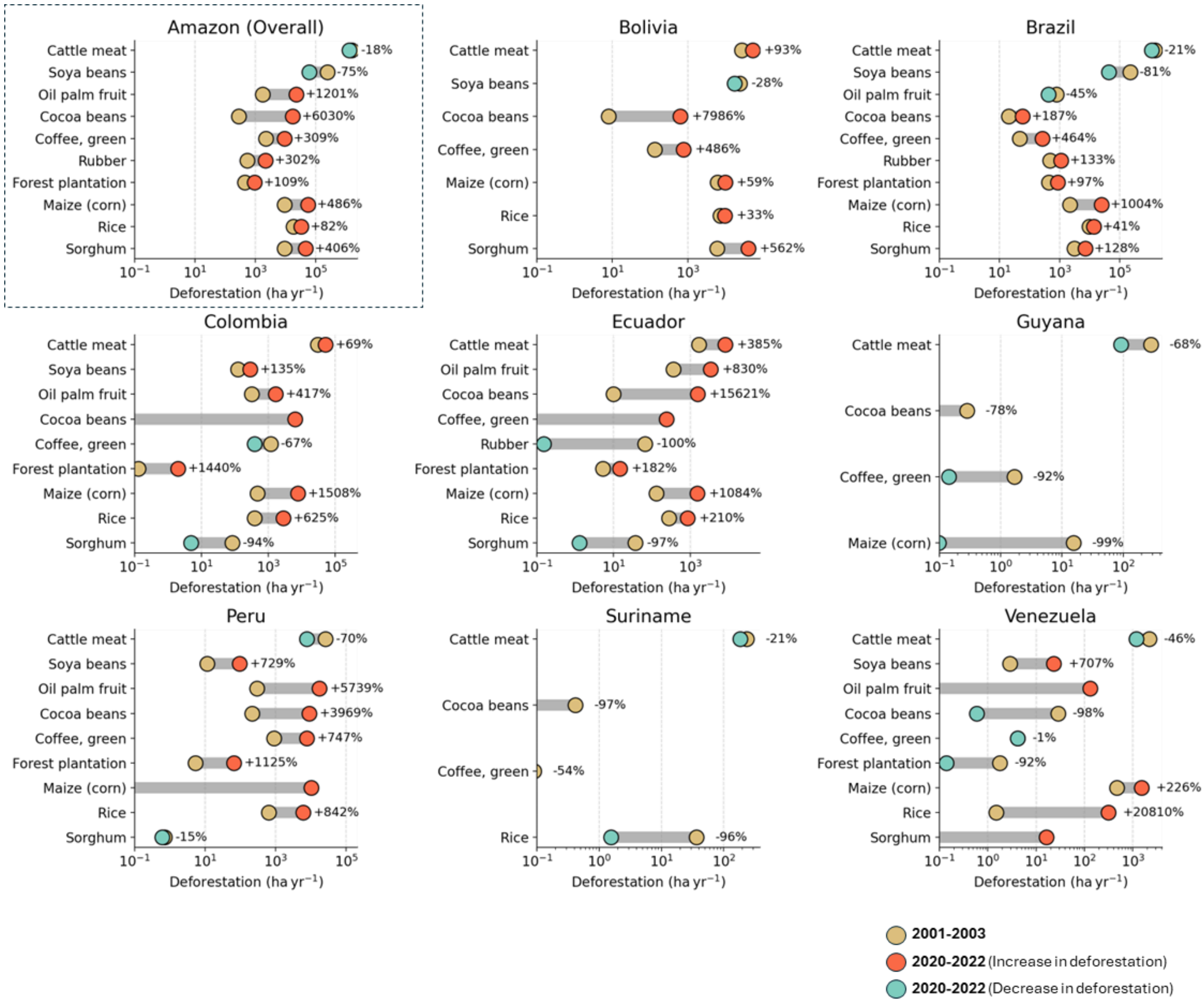
Extended Data Fig. 1 | Methodological framework for assessing Amazon's deforestation footprint across global food and financial systems. (a) The framework attributes deforestation to individual agriculture and forestry commodities using spatial and statistical datasets. (b) These attributed estimates are used to assess deforestation embedded in direct trade and consumption using a hybrid physical-monetary trade model. (c) Lastly, by linking exporter groups exposed to deforestation-risk activities to financial institutions, we identify financial flows exposed to deforestation.



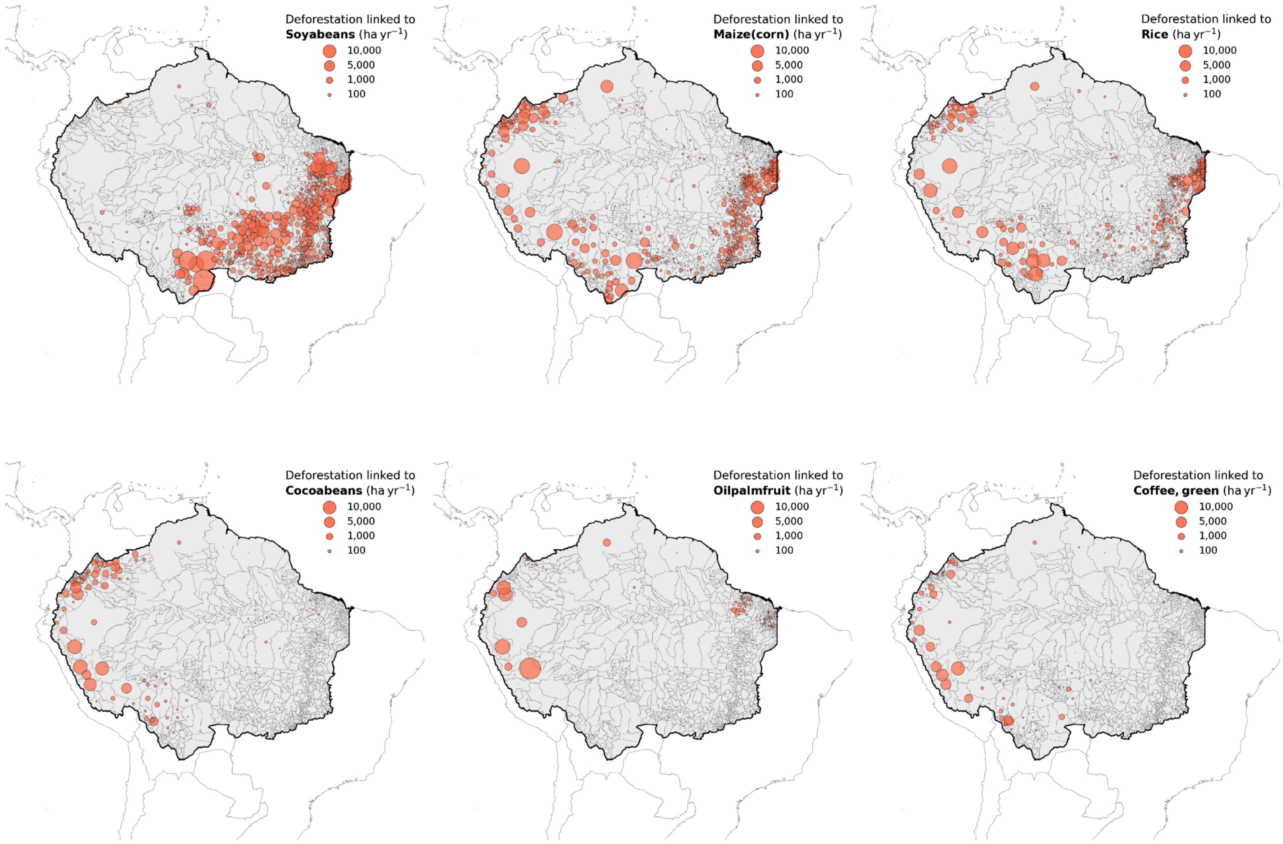
Extended Data Fig. 2 | Amazon deforestation linked to agricultural and forestry commodities embedded in global supply chains. Share of Amazon deforestation relative to global deforestation embedded in supply chains for individual (a) consumer countries and (b) commodities (average 2020–2022). Percentages above bars indicate the proportion of each country's or commodity's global deforestation footprint that occurs within the Amazon. Global deforestation embedded in the consumption of agricultural and forestry commodities is based on data from ref[86].



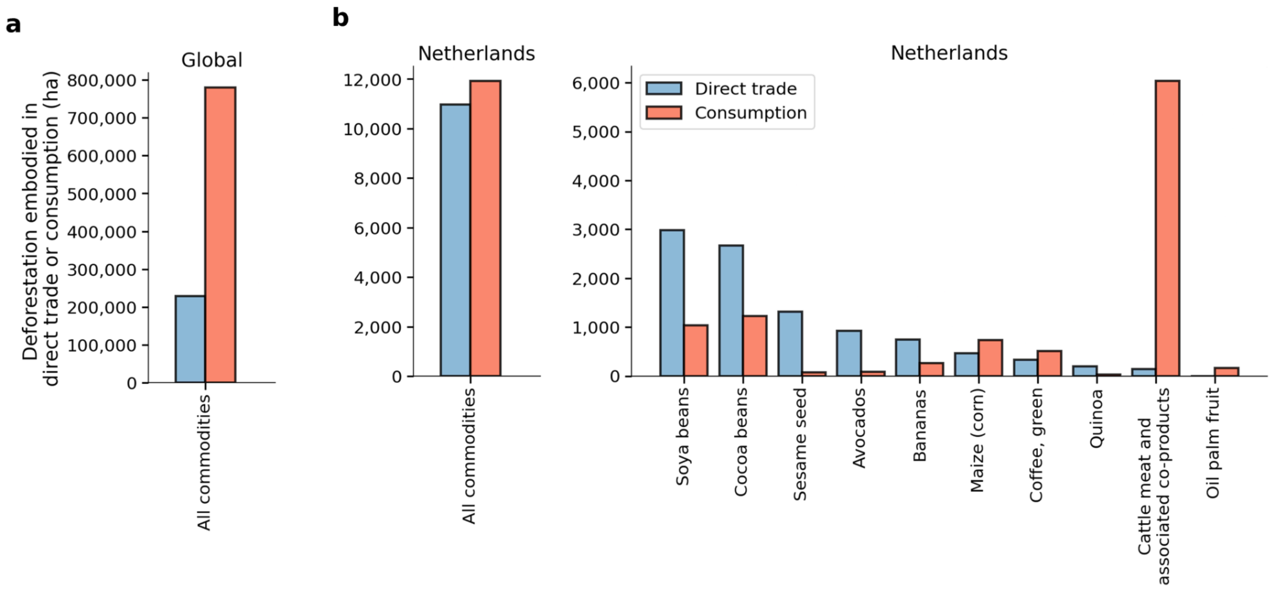
Extended Data Fig. 3 | Temporal trends of deforestation across the Amazon region, disaggregated by land use and individual Amazonian countries. While deforestation associated with forest plantation expansion is included, its contribution remains relatively minor compared to deforestation driven by cropland and pasture expansion. The hatched area indicates the time period during which sub-national agricultural statistics were available and used for sub-national deforestation attribution in the DeDuCE model.



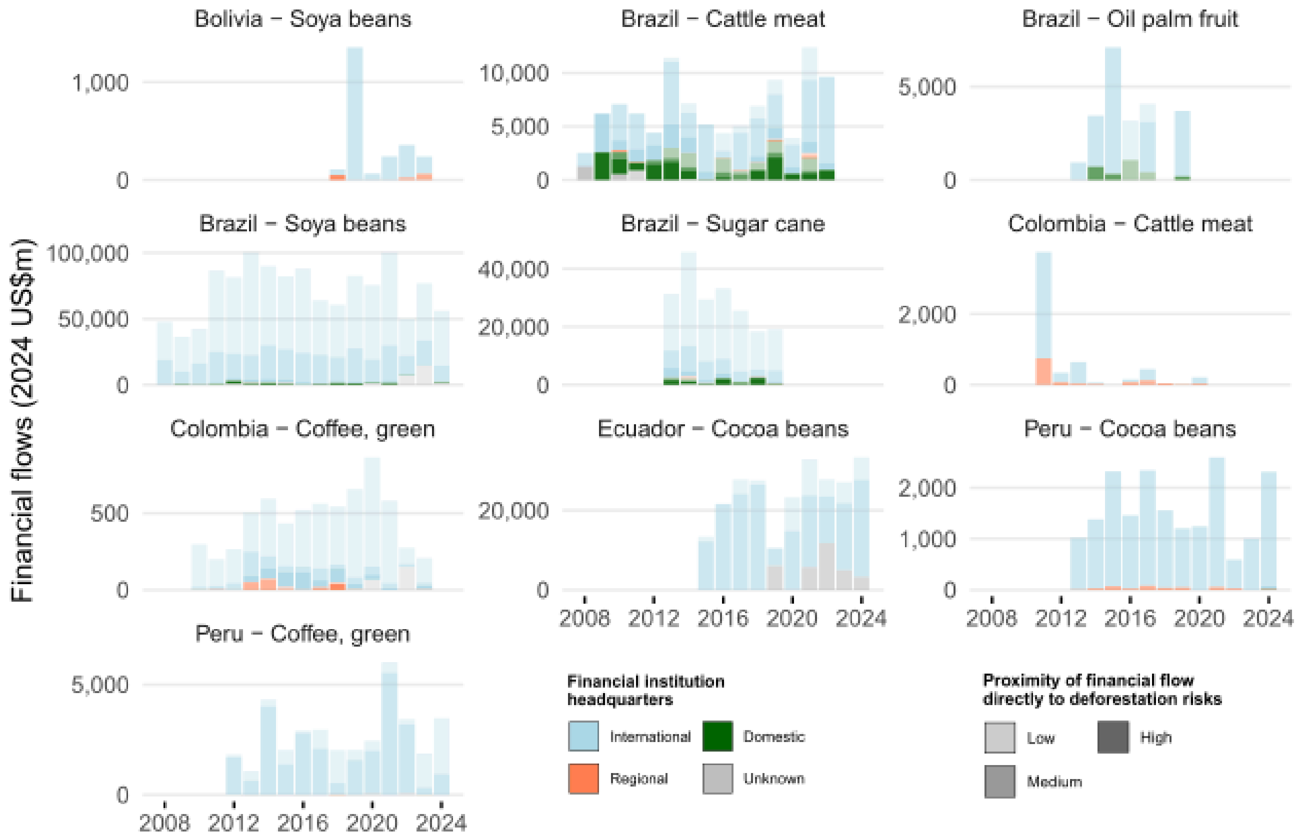
Extended Data Fig. 4 | Trends of agriculture-linked deforestation across the Amazon. The plots show average annual deforestation (ha yr^{-1}) linked to major agricultural and forestry commodities (as highlighted in Fig. 1b) for the period 2001–2003 (yellow circles) and 2020–2022 (red and green circles) across the Amazon, and distributed among individual Amazonian countries. Percentage labels denote the relative change between the two periods. Positive values indicate an increase in deforestation, while negative values indicate a decline in deforestation. Annual trends for these commodities are shown in Supplementary Figs. 1 and 2.



Extended Data Fig. 5 | Mapping major deforestation-risk commodities across the Amazon. The estimates represent cumulative deforestation from 2017-2021 (ha). For this period, subnational estimates are available only for Bolivia, Brazil, Colombia, Ecuador, and Peru, while national-level estimates are used for Guyana, Suriname, and Venezuela.



Extended Data Fig. 6 | Amazon deforestation embedded in direct trade and final consumption at the global scale and for the Netherlands. Bars compare deforestation embedded in direct trade (immediate exports from producing countries) and in final consumption (including downstream re-exports and through the sales of goods and services within global supply chains). Panel (a) shows the global aggregate across all commodities, while panel (b) shows the total and some of the major commodity-specific footprints for the Netherlands.



Extended Data Fig. 7 | Trends in financial flows to exporter groups exposed to Amazon deforestation across a subset of commodities and countries between 2010 and 2022. Note that limited coverage of exporter groups linked to deforestation-risk commodities means these flows likely represent only a subset of total financing exposed to Amazon deforestation in each case. Where exporter groups operate across multiple cases, flows were distributed between cases based on relative commodity production values from FAOSTAT (see Supplementary Methods). To account for the leads and lags between financing and deforestation-risk activities, and for the limited range of some cases (e.g., 2015-207 for Brazilian sugar cane), financial flows are included within ±2 years of the years in which deforestation was attributed to exporter groups. For example, the 2015–2017 Brazilian sugarcane coverage is evaluated over a wider assessment window (2013–2019). Fill indicates the country of headquarters of financial institutions relative to the country-commodity case – for 'Self Arranged' deals. Here, the country is allocated based on where the deal was issued. 'Domestic' refers to the same country, 'Regional' refers to Latin America and the Caribbean, and 'International' refers to all other regions. 'Unknown' refers to undisclosed financial institutions or a small portion of institutions with no headquarters information available. Opacity indicates the proximity of financial flows to Amazon deforestation based on the location and activity of the entity directly receiving finance (see Methods and Supplementary Methods).

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Supplementary Information

Amazon deforestation footprint across global food and financial systems

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Supplementary Methods

1. Analysing exporter groups' exposure to deforestation

The Trase dataset provides information on global supply chains for selected country–commodity pairs (Supplementary Table 4), linking production regions to global markets. From the Trase data, we utilise information on the country of production (i.e., name of the country where commodity was produced), subnational boundaries (where available; e.g., municipality level for Brazil), biome (i.e., name of the biome according to the IBGE classification where the production subregion is located; available only for Brazil and Bolivia), exporter groups (i.e., corporate group responsible for exporting the commodity), and production area (i.e., area of land being used to produce the commodity; in hectares). When subnational boundaries are not available for a given country, deforestation exposure is assessed at the national level (Supplementary Eq. 1-2).

For Brazil and Bolivia, where regions can be filtered by biome, we restrict the analysis to exporter groups operating within the Amazonia, Chiquitano Dry Forests, and Southwest Amazon Moist Forests biomes, respectively. Furthermore, for some commodities, Trase does not report production area but instead provides trade volumes (in tonnes). In these cases, we convert trade volumes to production area using country-level yield data from FAOSTAT (kg ha^{-1}). For converting the production volume of cattle meat to area, we use a conversion factor of 0.227[1].

Trase also provides deforestation exposure estimates for a limited subset of commodities from the pool of countries and commodities it covers. However, to enable coverage of a broader set of commodities, we calculate exporter-group-level deforestation exposure ($Deforestation\ exposure_{\ i,t,k}$) using the production area estimates associated with exporter groups from Trase ($Production\ area\ {}^{Trase}_{i,t}$) and deforestation estimates produced in this study ($Deforestation\ {}^{DeDuCE}_{i,t}$) (Supplementary Eq. 1-2).

For regions where $Production\ area\ {}^{Trase}_{i,t} \leq Deforestation\ {}^{DeDuCE}_{i,t}$

$$Deforestation\ exposure_{\ i,t,k} = Production\ area\ {}^{Trase}_{i,t,k} \tag{1}$$

Where $Production\ area\ {}^{Trase}_{i,t} > Deforestation\ {}^{DeDuCE}_{i,t}$

$$Deforestation\ exposure_{\ i,t,k} = Deforestation\ {}^{DeDuCE}_{i,t} \times \frac{Production\ area\ {}^{Trase}_{i,t,k}}{Production\ area\ {}^{Trase}_{i,t}} \tag{2}$$

Here, *i* denotes the country–commodity pair (with data reported at either the national or subnational scale for each country; e.g., soy for Brazil; Supplementary Table 4), *t* denotes the year of deforestation, and k denotes individual exporter groups. $Production\ area\ ^{Trase}_{i,t,k}$ refers to the production area associated with exports by a specific exporter group k in year t.

Given the large number of companies exposed to deforestation risk in the Amazon identified in our analysis above, we apply a significance threshold to define the scope of the financial flow analysis. We focus on companies with >50 ha of deforestation from 2010 onwards (considering unique combinations of producer country, year of deforestation, commodity associated with deforestation, and company associated with the trade of deforestation-risk commodities). Two key reasons behind this threshold are: (i) the timeframe of 2010-onwards enables us to link ~30% of deforestation in the Amazon to specific exporter groups—the highest coverage across all tested combinations in the time series, and (ii) the deforestation threshold of >50 ha effectively filters out companies with a deforestation intensity of less than 1 ha per 1,000 tonnes of production.

2. Matching exporter groups to legal entities and allocating financial flows between country-commodity pairs

Mapping financial flows requires unique identifiers for the companies involved in deforestation. To achieve this, we matched the Trase data – which is compiled from export records that do not contain these identifiers – into LSEG's entity dataset, PermID, to identify the legal entity associated with the exporter group and its ultimate parent and their identifiers (PermIDs), manually reviewing each match. When exporter groups are state-owned, we treat the last corporate entity below the state as the ultimate parent.

As we explore financial flows between 2008-2024, we reconstruct the historical ownership structure of each exporter group to account for mergers and acquisitions over this period. For example, several major exporter groups in the Brazilian sugar cane sector were owned by BP Plc in 2025. However, from 2019 until 2024, they were owned as part of a joint entity between BP Plc and Bunge Global SA, and from 2008 to 2019, they were owned separately by either BP Plc or Bunge Global SA. This results in a set of PermIDs (legal entity, parent, and ultimate parent) associated with each exporter group, in each year. Financial flows were retrieved for all unique PermIDs appearing in any year of the dataset across the whole study period (2008–2024) and subsequently filtered to reflect the contemporaneous ownership structure in each year.

Some exporter groups are treated as distinct in Trase, even though they are ultimately owned by the same legal entity. For example, *Agroindustrial Santa Juliana* and *Usina Itapagipe Açúcar e Álcool* are listed as separate exporter groups in Trase's Brazil sugarcane dataset. Since 2024, both are ultimately owned by BP Plc (previously BP-Bunge Bioenergia SA until 2023). In such cases, we grouped exporter groups sharing the same PermID within a given year to avoid duplicating financial flows when constructing country–commodity datasets. As a final step, within each country–commodity dataset, we deduplicated financial transactions using LSEG's unique tranche identifier to ensure that each transaction appeared only once. Because each Trase dataset is constructed separately for individual country–commodity settings, there is no built-in harmonisation for exporter groups that operate across multiple Amazon countries and commodities.

Financial flows to these legal entities appear in each individual country-commodity dataset, and simply summing them would result in double-counting. To resolve this, we apportioned the across country–commodity cases based on the relative monetary value of total production for each relevant commodity and country, using country-level data from FAOSTAT[2]. We use production value to approximate the relative economic scale of commodity exposure across countries, since firm-level revenue data are not consistently available for all subsidiaries involved in financial flows. For instance, if an exporter group is exposed to Amazon deforestation through both Brazilian beef and Colombian beef, financial flows to its associated legal entities are split between these two settings according to the ratio of the monetary value of beef production in Brazil to that of beef production in Colombia in the corresponding year to the financial flow. This ensures that in the final Amazon-wide dataset, the sum of apportioned flows equals the original transaction values, and that in the final Amazon-wide aggregate, each financial flow is counted only once. Financial flows attributed to 'unknown' institutions or country of headquarters (~3% of central total) primarily reflect LSEG's classification of deals as facilitated by 'Undisclosed Advisor' or other explicitly unknown labels. A small volume of flows (<0.01% of the central estimate total) had named financial institutions but missing parent PermIDs or headquarters country. These transactions were retained in the final analysis to preserve overall transaction totals and highlight gaps in financial disclosure.

3. Sensitivity analysis and assessing the proximity of financial flows to deforestation

Our original dataset encompassed all financial flows over 2008-2024 to identified exporter groups' legal entities; however, Trase data is not available across this time period for all country-commodity pairs (Supplementary Table 2). Financial flows outside the period covered by the Trase data may still indirectly enable deforestation and be exposed to deforestation risks. Financial flows prior to deforestation exposure remain relevant, while speculative land clearing can itself attract investment (i.e., reverse causation)[3]. Exporter groups' deforestation exposure outside the Trase coverage window cannot be directly observed. This is particularly relevant for commodities with short Trase coverage windows, such as Brazilian sugarcane, for which exporter group data are available only for 2015–2017 (Supplementary Table 2). To balance these factors, we conducted sensitivity analyses across a range of boundary periods and used these results to report a range of total financial flows exposed to Amazon deforestation, centred on a central estimate defined by a ±2-year window around the years in which deforestation was attributed to exporter groups (Fig. 4 and Supplementary Figure 10). Variation in the boundary period results in only minor changes in the relative ranking of the top financing countries and financial institutions identified in our analysis (Supplementary Figure 11).

A scale mismatch exists between the resolution at which deforestation can be attributed—down to specific commodities at subnational levels—and the scale at which financial flows are typically provided, which is most often at the level of firms' overall operations rather than specific regions or products[4]. As a result, not all finance provided to exporter groups operating across multiple jurisdictions and sectors will be closely associated with deforestation. At the same time, since finance is fungible, capital provided to subsidiaries located far from the Amazon may still be internally reallocated to support deforestation-risk activities[5,6]. This is particularly the case for multinational companies that tend to separate operational and financial entities, the latter of which manages the financial wealth of the company and its financial flows[7]. On an individual transaction basis, available data does not allow us to distinguish between these cases due to limited transparency regarding the end use of proceeds from financing, which is typically provided as a general corporate purpose[8,9]. To address this, we develop a rules-based classification to assess the likely proximity of each financial flow to Amazon deforestation(Supplementary Table 1). Though simple, our approach is transparent and easily applied across large financial flows datasets.

The approach uses information available at the flow-level on the headquarters location and primary business activity—classified using the Refinitiv Business Classification (TRBC)—of the entity directly receiving finance in each transaction (the issuer). Each issuer belongs to the same legal hierarchy as an exporter group exposed to deforestation in the Trase data (i.e., shares the same ultimate parent). In each country-commodity dataset, the issuance location is classified as domestic, regional, or international relative to its proximity to the producer country in focus. The primary business activity is classified as direct, indirect, or minimally related, with a minority of transactions manually classified where the business activity was not available.

Supplementary Notes

1. Comparison of the financial flow methodology of this study with the Forests & Finance's approach

The approach used in this study offers a distinct perspective compared to the most widely used methodology in the grey literature, which was developed by a consortium of civil society organisations[10] and underpins regular assessments of financial flows to forest-risk activities[11]. For example, the Forests & Finance methodology applies an "adjuster" approach, whereby financial flows are scaled down using manually researched calibration factors that estimate the share of a financed entity's activities that are directly linked to forest-risk supply chains—such as the proportion of a company's revenues derived from soy production and trading relative to its total reported revenues[12].

While the Forests & Finance approach provides a more precise estimate of financing directly linked to agricultural and forestry supply chains, the 'unadjusted' portion of financing is important for overall financial support of exporter groups, particularly those that are diversified across activities and geographies.

We conducted a high-level comparison between our results and the Forests & Finance dataset for Brazilian soy over the period 2010–2022 and found notable differences in total financing volumes, key financial hubs, and the institutions associated with deforestation risk (Supplementary Fig. 12; Supplementary Tables 6 and 7). Because our approach does not apply adjusters, as expected, we estimate a considerably larger volume of financial flows than Forests & Finance. Nevertheless, when excluding Brazil's non-commercial rural credit scheme (ex-SNCR), financial flows to "high-proximity" activities in our dataset are of similar magnitude to those reported by Forests & Finance (US$32 billion versus US$11 billion, respectively). Several institutions—including Rabobank, ING, and Bradesco—feature prominently in both approaches, while others differ markedly (Supplementary Table 6).

Differences in the prominence of financing hubs further highlight the implications of our classification scheme versus adjusters. China features more prominently in the Forests & Finance dataset, whereas Japan plays a larger role in our results. This reflects differences in the treatment of COFCO and Mitsubishi Corp. Adjusters applied to COFCO for Brazilian soy are substantially higher (2–10%, and occasionally up to 50%) than those applied to Mitsubishi Corp (<0.2%), reflecting their contrasting business models as a specialised food processor and a highly diversified conglomerate, respectively. As a result, our classification scheme captures a larger share of financing to Mitsubishi Corp that would be excluded under the Forests & Finance methodology.

Supplementary Tables

Supplementary Table 1 | Assessment criteria for the proximity of financial flows to deforestation risk.

Classification of the headquarters location of the entity directly receiving financial flows by its proximity to Amazon countries.		
Domestic	**Regional**	**International**
The entity directly receiving financial flows (the issuer) is in the same country as the producer country for the country-commodity setting in focus. For example, the entity is headquartered in Brazil for the financial dataset on Brazil (cattle meat).	The entity directly receiving financial flows (the issuer) is in the same world region as the producer country for the country-commodity setting in focus. For example, the entity is headquartered in Latin America and the Caribbean (e.g., Colombia) for the financial dataset on Brazil (cattle meat).	The entity directly receiving financial flows (the issuer) is in a different world region than the producer country for the country-commodity setting in focus. For example, the entity is headquartered in Europe (e.g., Liechtenstein) for the financial dataset on Brazil (cattle meat).

Classification of primary business activity of the entity directly receiving financial flows by their proximity to deforestation-risk activities.		
Direct	**Indirect**	**Minimally related sectors**
- Agricultural production (e.g., crop production, biofuels) - Agricultural processing (e.g., meat processing) - Related land-use intensive sectors (e.g., logging)	- Agricultural midstream (e.g., food markets) - Agricultural downstream (e.g., supermarkets) - Agricultural inputs (e.g., fertilisers) - Transport (e.g., ports, freight) - Enabling services (e.g., financial intermediaries)	- Extractive activities not related to soft commodity-driven deforestation (e.g., oil & gas, coal) - Non-related sectors (e.g., biosciences, engineering) - Utilities (e.g., lighting, water)

Overall classification of the proximity of financial flows by combining the region and sector of the entity directly receiving financial flows.		
High	**Medium**	**Low**
- Domestic issuance + direct sector - Domestic issuance + indirect sector - Regional issuance + direct sector	- Domestic issuance + minimally related sector - Regional issuance + indirect sector - International issuance + direct sector	- Regional issuance + minimally related sector - International issuance + indirect sector - International issuance + minimally related sector

Supplementary Table 2 | Countries and commodities covered by the Trase dataset and their respective time periods.

Country	Commodity	Year	Administrative level
Bolivia	Soya beans	2020-2021	2 (i.e., Province)
Brazil	Cattle meat	2010-2017 & 2019-2020	2 (i.e., Municipality)
	Cocoa beans	2015-2017	2
	Coffee, green	2016-2017	2
	Maize (corn)	2015-2017	2
	Seed cotton, unginned	2015-2017	2
	Soya beans	2004-2022	2
	Oil palm fruit	2015-2017	0 (i.e., National)
	Sugar cane	2015-2017	0
Colombia	Cattle meat	2013-2018	0
	Cocoa beans	2017-2022	0
	Coffee, green	2012-2021	0
	Oil palm fruit	2013-2018	0
Ecuador	Cocoa beans	2017-2022	0
Peru	Cocoa beans	2013-2022	0
	Coffee, green	2013-2022	0

Supplementary Table 3 | Spatial datasets used in this study and their description.
Pre-processing information for these datasets is described in Supplementary Table 7 of Singh and Persson[13].

Datasets	Spatial extent	Spatial resolution	Temporal resolution	Additional remarks
Global forest change-v1.10[14]	Global	30 m	2001-2022	Tree cover (2000) and tree cover loss (2001-2022)
Global plantation dataset[15]	Brazil, Colombia, Ecuador, Peru, Venezuela	30 m	1982-2020	
MapBiomas Collection[16]	Bolivia, Brazil, Colombia, Ecuador, French Guiana, Guyana, Peru, Suriname, Venezuela	30 m	1985-2022 (for all Amazonian countries, except Bolivia); 1985-2021 (for Bolivia)	Besides broader land use, MapBiomas also provides pixel-level data for sugarcane, soya beans, rice, seed cotton, coffee, oil palm fruit, and citrus fruit across different collections
Croplands[17]	Global	30 m	Aggregated temporally at every 4-year intervals between 2000-2019	
Sugarcane[18]	Brazil	30 m	Aggregated temporally using data for the years 2016-2019	
Soya beans[19]	Bolivia and Brazil	30 m	2001-2022	
Coconut[20]	Pan-tropical	20 m	2020	
Oil palm fruit[21]	Pan-tropical	10 m	2019	
Forest loss due to fire[22]	Global	30 m	2001-2022	
Forest management[23]	Global	100 m	Aggregated temporally using data for the years 2014-2016	Used to extract deforestation from tree cover loss for countries for which the Global Plantation dataset doesn't have coverage
Dominant drivers of forest loss[24]	Global	10 km	Aggregated temporally using data for the years 2001-2022	
Database of Global Administrative Areas-v4.1 (GADM)[25]	Global	Vector	–	Demarcates country boundaries at national (administrative level 0) and subnational

				levels (administrative levels 1 and 2).

Supplementary Table 4 | Spatio-temporal scale of Global Subnational Agricultural Production (GSAP) statistics for the Amazonian countries.
Municipality-level (Admin. level-2) agricultural statistics for Brazil are obtained from the Brazilian Institute of Geography and Statistics (IBGE). For countries where subnational agricultural statistics are not available, deforestation is attributed at the national level.

Countries	Spatial scale (Administrative level)	Temporal scale
Bolivia	Province (Admin. level-2)	2013 – 2021
Colombia	Department (Admin. level-2)	2006 – 2021
Ecuador	Province (Admin. level-1)	2012 – 2021
Peru	Region (Admin. level-1)	2007 - 2021
Venezuela	Federal entities (Admin. level-1)	2001 – 2007

Supplementary Table 5 | Comparison of deforestation attribution estimates at the national and subnational scales.
National-level deforestation attribution is based on agricultural statistics from FAOSTAT, while subnational attribution uses agricultural statistics from GSAP and IBGE.

Country	Year	Deforestation (using national-level agricultural statistics-FAOSTAT; in ha)	Deforestation (using subnational-level agricultural statistics; in ha)	% Difference (w.r.t. to national level estimates)
Bolivia	2013-2021	1,735,621	1,886,868	8.71%
Brazil	2001-2022	38,375,103	38,329,216	-0.12%
Colombia	2006-2021	1,848,581	1,767,542	-4.38%
Ecuador	2012-2021	159,751	159,730	-0.01%
Peru	2017-2021	559,414	559,414	0.00%
Venezuela	2001-2007	144,848	144,846	0.00%

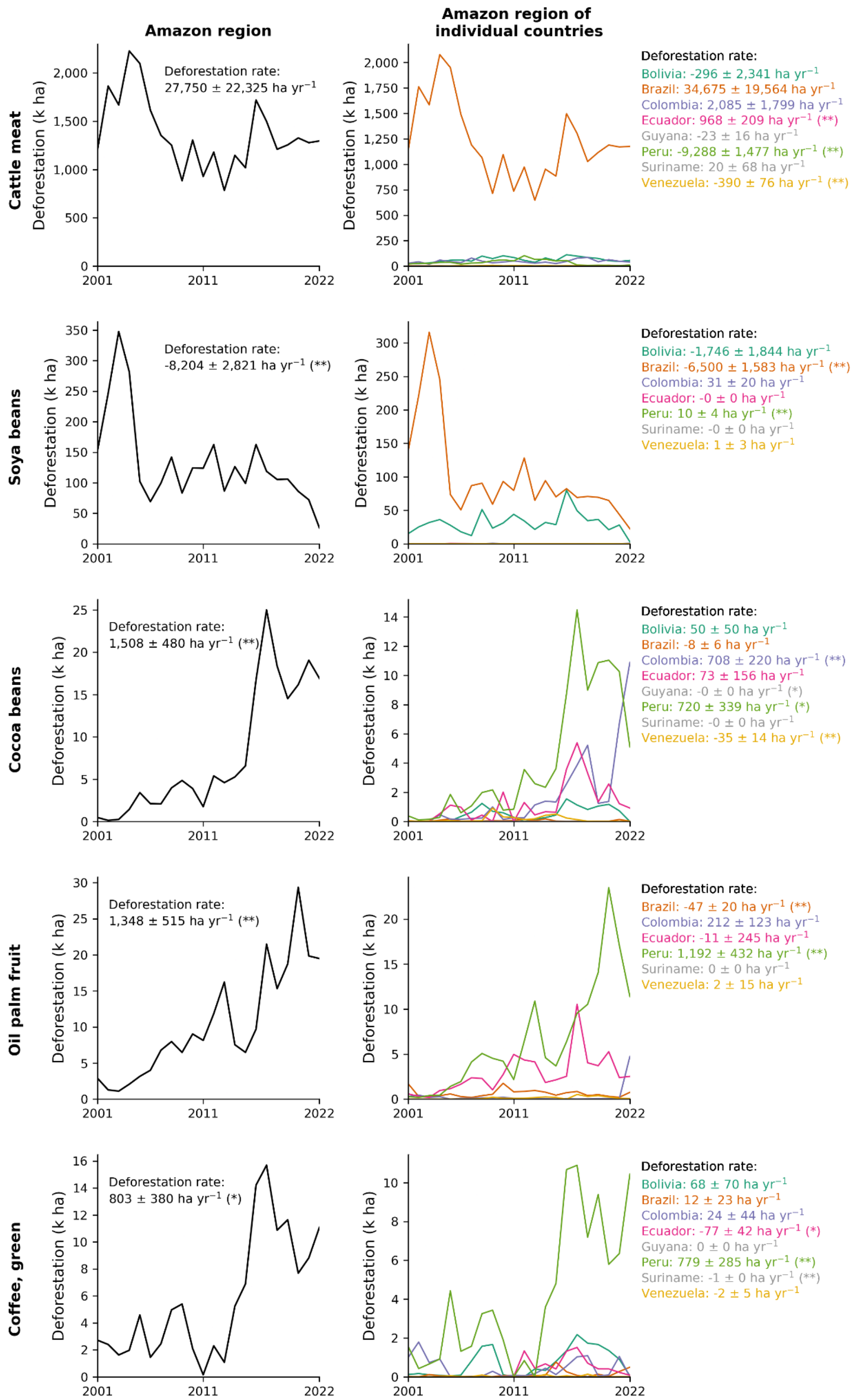
Supplementary Table 6 | Top ten financial institutions identified in this study (from high- to low-proximity flows) and in Forests & Finance for Brazilian soy between 2010–2022.
'SNCR' refers to the *Sistema Nacional de Crédito Rural*, Brazil's rural credit scheme managed by the Central Bank of Brazil, which plays a major role in financing agricultural producers. Our analysis is complementary to, and does not include, the Brazilian rural credit scheme. The *Forests & Finance* category 'Other' is most comparable to the 'High' proximity category used in this study.

Rank	This study			Forests & Finance	
	High	Medium	Low	SNCR	Other
1	BTG Pactual G7 Holding SA	JPMorgan Chase & Co	Mitsubishi UFJ Financial Group Inc	Banco do Brasil	Industrial and Commercial Bank of China
2	Banco Bradesco SA	Citigroup Inc	Mizuho Financial Group Inc	Bradesco	Bank of China
3	ING Groep NV	Bank of America Corp	Citigroup Inc	Itau Unibanco	Rabobank
4	Citigroup Inc	Barclays PLC	Sumitomo Mitsui Financial Group Inc	Banco do Nordeste do Brasil	SMBC Group
5	Self-Arranged	BNP Paribas SA	Morgan Stanley	Santander	China Construction Bank
6	Banco Santander SA	HSBC Holdings PLC	Undisclosed Advisor	Rabobank	China Merchants Bank
7	Cooperatieve Rabobank UA	Mizuho Financial Group Inc	UBS Group AG	Banco da Amazonia	Itau Unibanco
8	Banco do Brasil SA	Deutsche Bank AG	Sumitomo Mitsui Trust Holdings Inc	Banco do Estado do Rio Grande do Sul (Banrisul)	Agricultural Bank of China
9	Sumitomo Mitsui Financial Group Inc	Mitsubishi UFJ Financial Group Inc	JPMorgan Chase & Co	Sicredi	Bradesco
10	Deutsche Bank AG	Sumitomo Mitsui Financial Group Inc	Bank of America Corp	John Deere Bank	ING Group

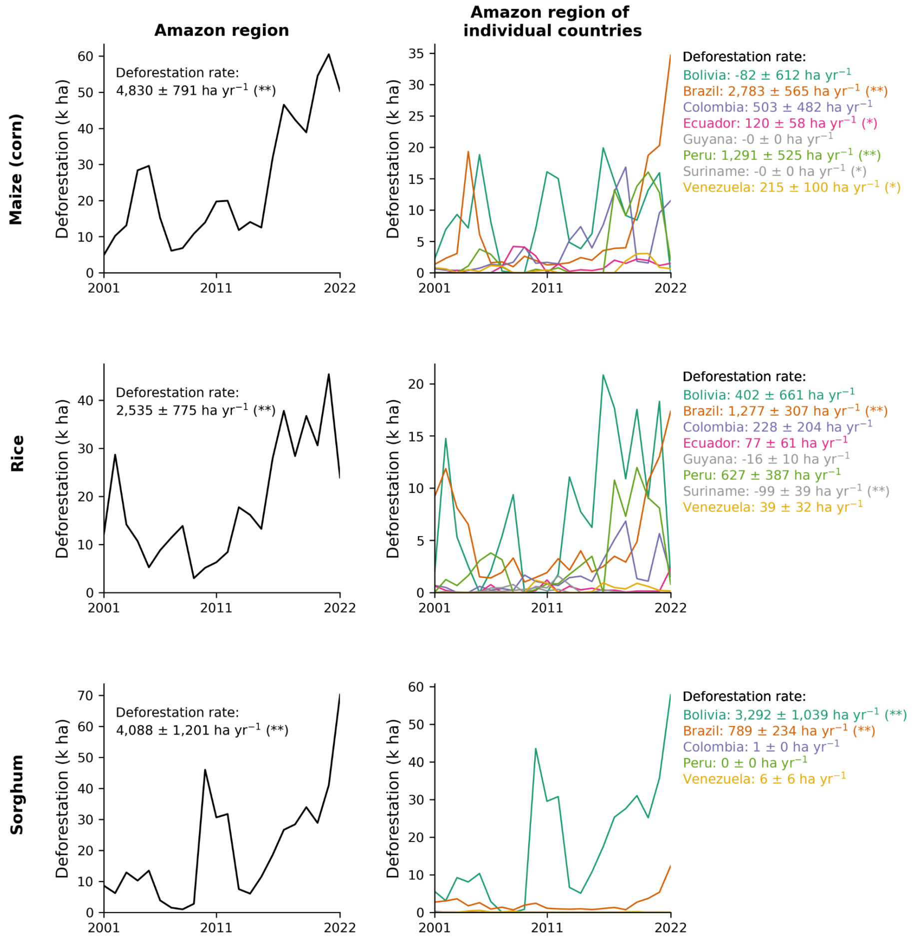
Supplementary Table 7 | Top ten financial hubs identified in this study (from high- to low-proximity flows) and in Forests & Finance for Brazilian soy between 2010–2022.
'SNCR' refers to the *Sistema Nacional de Crédito Rural*, Brazil's rural credit scheme managed by the Central Bank of Brazil, which plays a major role in financing agricultural producers. Our analysis is complementary to, and does not include, the Brazilian rural credit scheme. The *Forests & Finance* category 'Other' is most comparable to the 'High' proximity category used in this study.

Rank	This study			Forests & Finance	
	High	Medium	Low	SNCR	Other
1	Brazil	United States of America	Japan	Brazil	China
2	United States of America	United Kingdom	United States of America	Spain	United States
3	Netherlands	Japan	France	Netherlands	Brazil
4	Japan	France	United Kingdom	United States	Netherlands
5	France	Netherlands	Singapore	Bahrain	Japan
6	Germany	Germany	China	China	United Kingdom
7	United Kingdom	China	Canada	France	France
8	Canada	Canada	Germany	Japan	Spain
9	Spain	Australia	Netherlands	Germany	Australia
10	Switzerland	Spain	Switzerland	Nigeria	Singapore

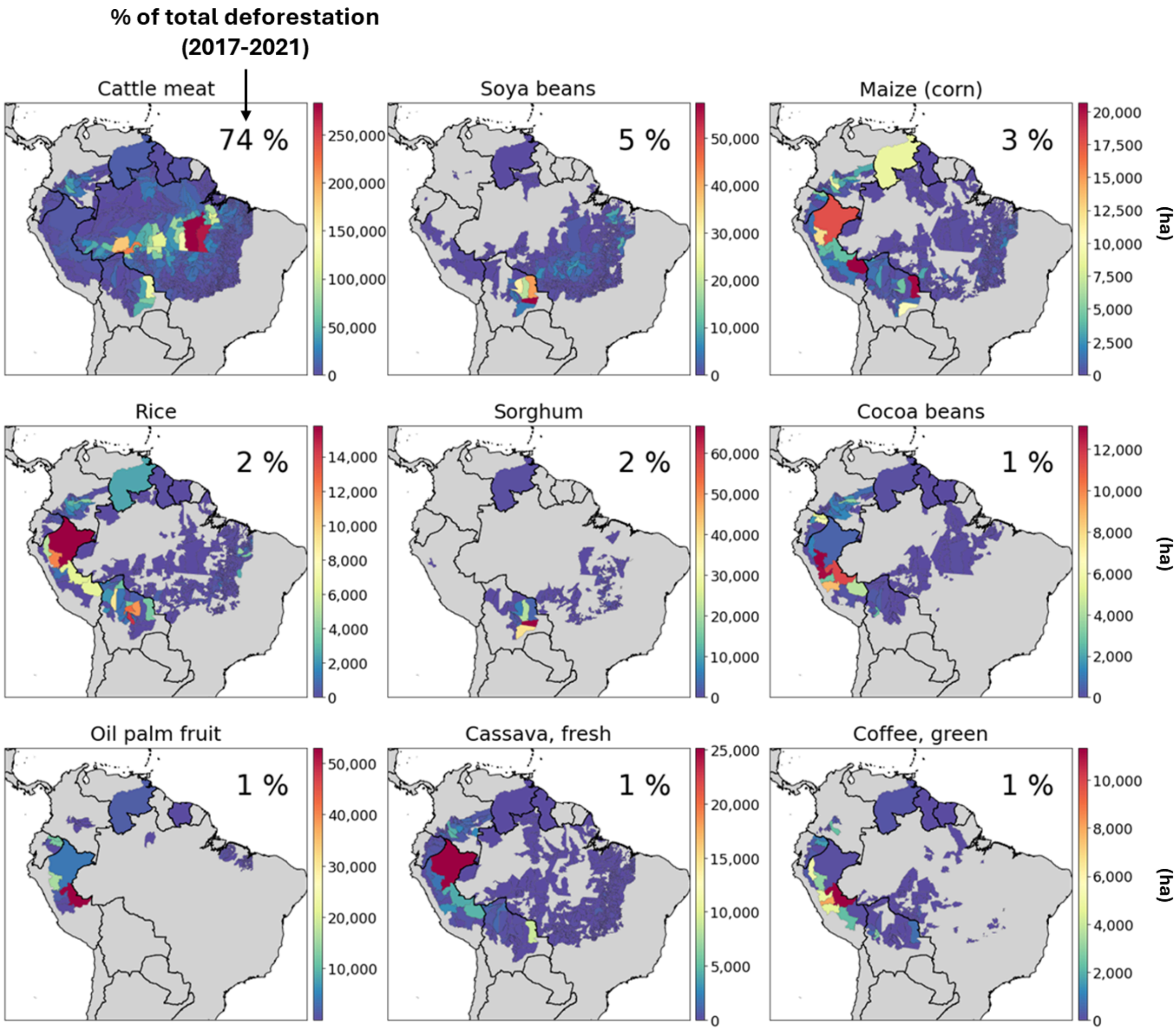
Supplementary Figures



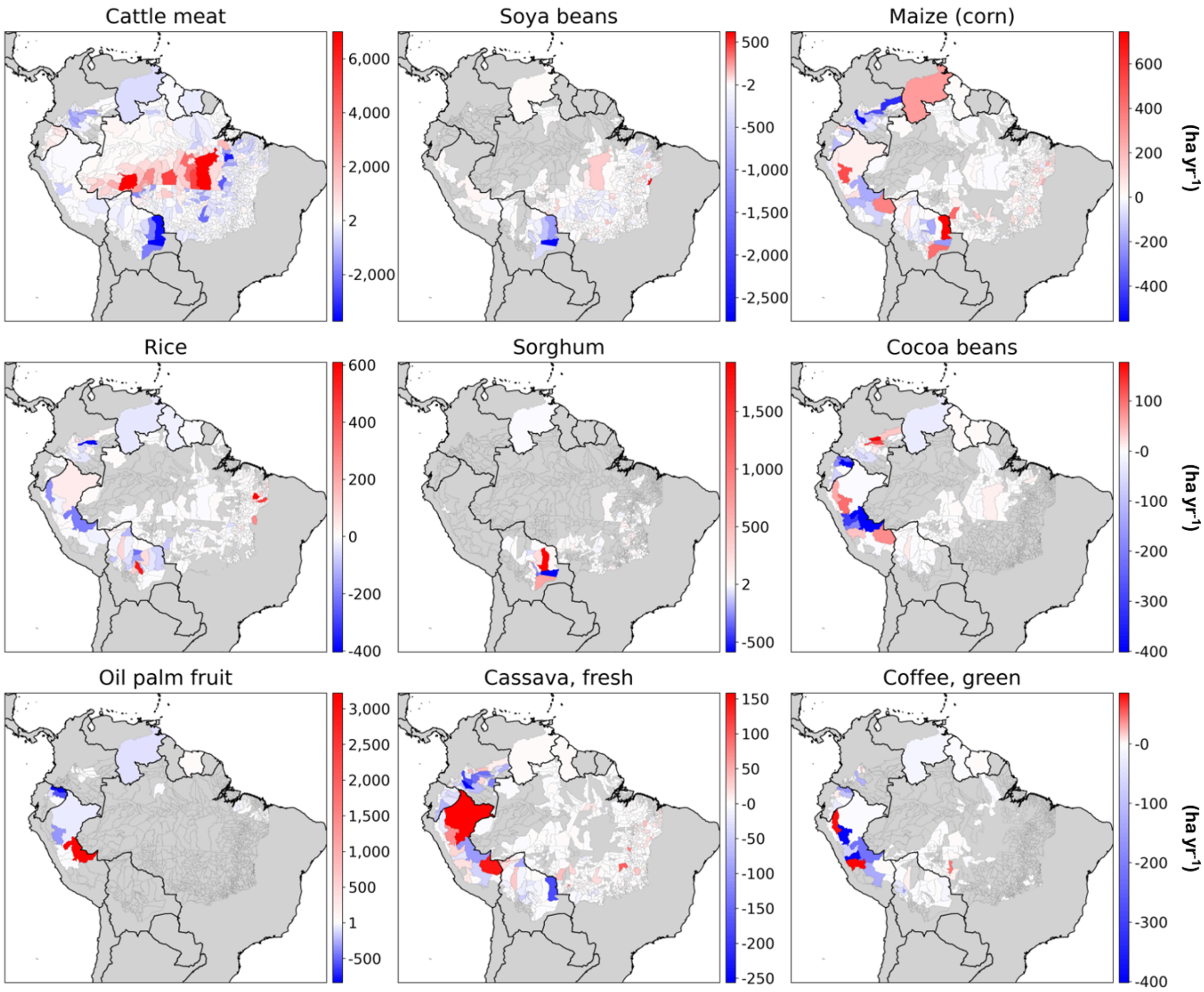
Supplementary Fig. 1 | Deforestation trends of selected EUDR commodities in and across the Amazon region.
This figure presents deforestation trends across the Amazon region from 2001 to 2022 for selected EUDR-relevant commodities, along with a disaggregated breakdown for key Amazonian countries with considerable deforestation. However, the deforestation rate is only calculated between 2012-2022. The statistical significance of these trends is indicated as (**) for *p-value* ≤ 0.05 and (*) for *p-value* ≤ 0.10.



Supplementary Fig. 2 | Deforestation trends of selected staple commodities across the Amazon region. This figure presents deforestation trends across the Amazon region from 2001 to 2022 for selected staple commodities, along with a disaggregated breakdown for key Amazonian countries with considerable deforestation. However, the deforestation rate is only calculated between 2012-2022. The statistical significance of these trends is indicated as (**) for p-value ≤ 0.05 and (*) for *p-value* ≤ 0.10.

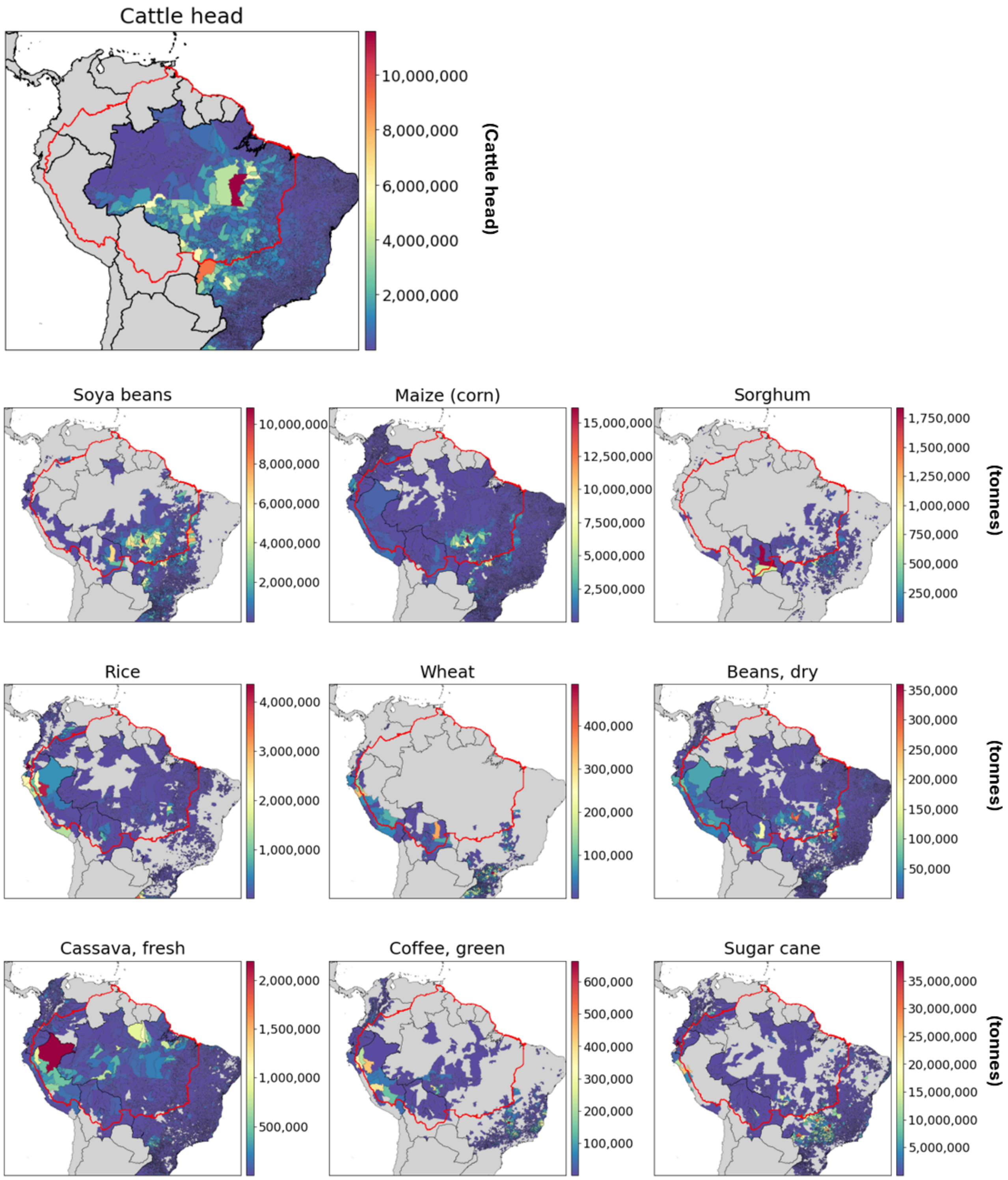


Supplementary Fig. 3 | Spatial patterns of deforestation (in ha) for major deforestation-risk commodities in the Amazon (2017–2021).
For this period, subnational estimates are available only for Bolivia, Brazil, Colombia, Ecuador, and Peru, while national-level estimates are used for Guyana, Suriname, and Venezuela.

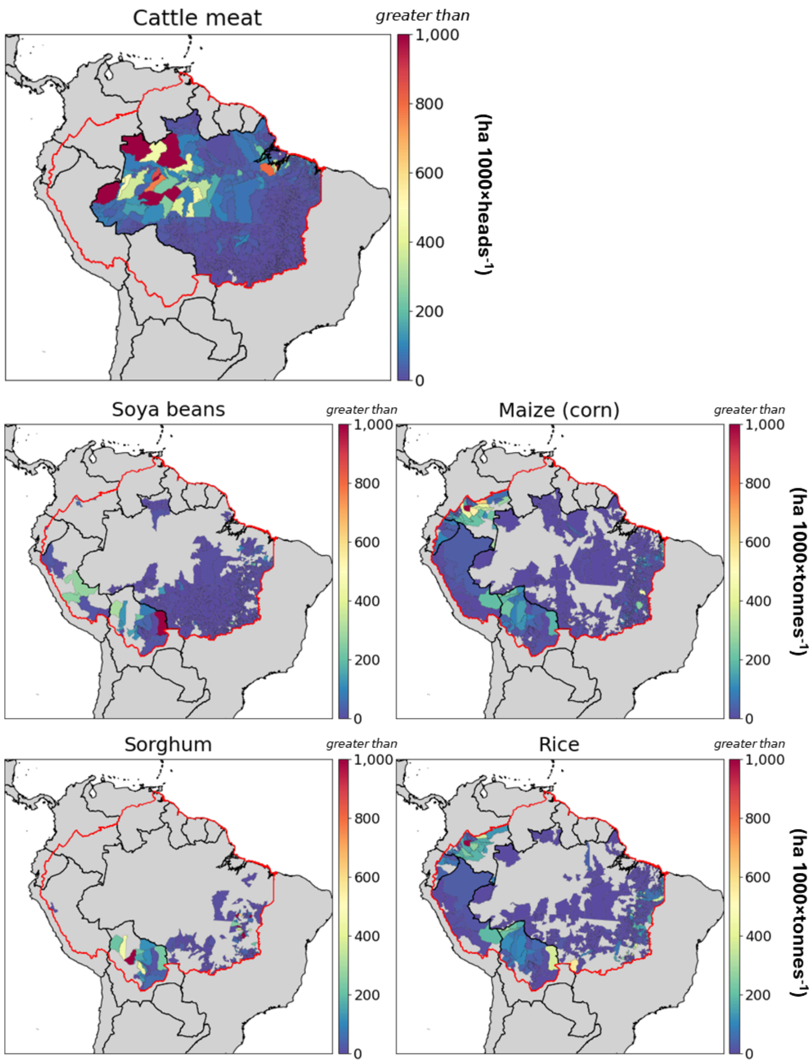


Supplementary Fig. 4 | Spatial patterns of the rate of deforestation (in ha yr^{-1}) for major deforestation-risk commodities in the Amazon (2017–2021).

For this period, subnational estimates are available only for Bolivia, Brazil, Colombia, Ecuador, and Peru, while national-level estimates are used for Guyana, Suriname, and Venezuela.

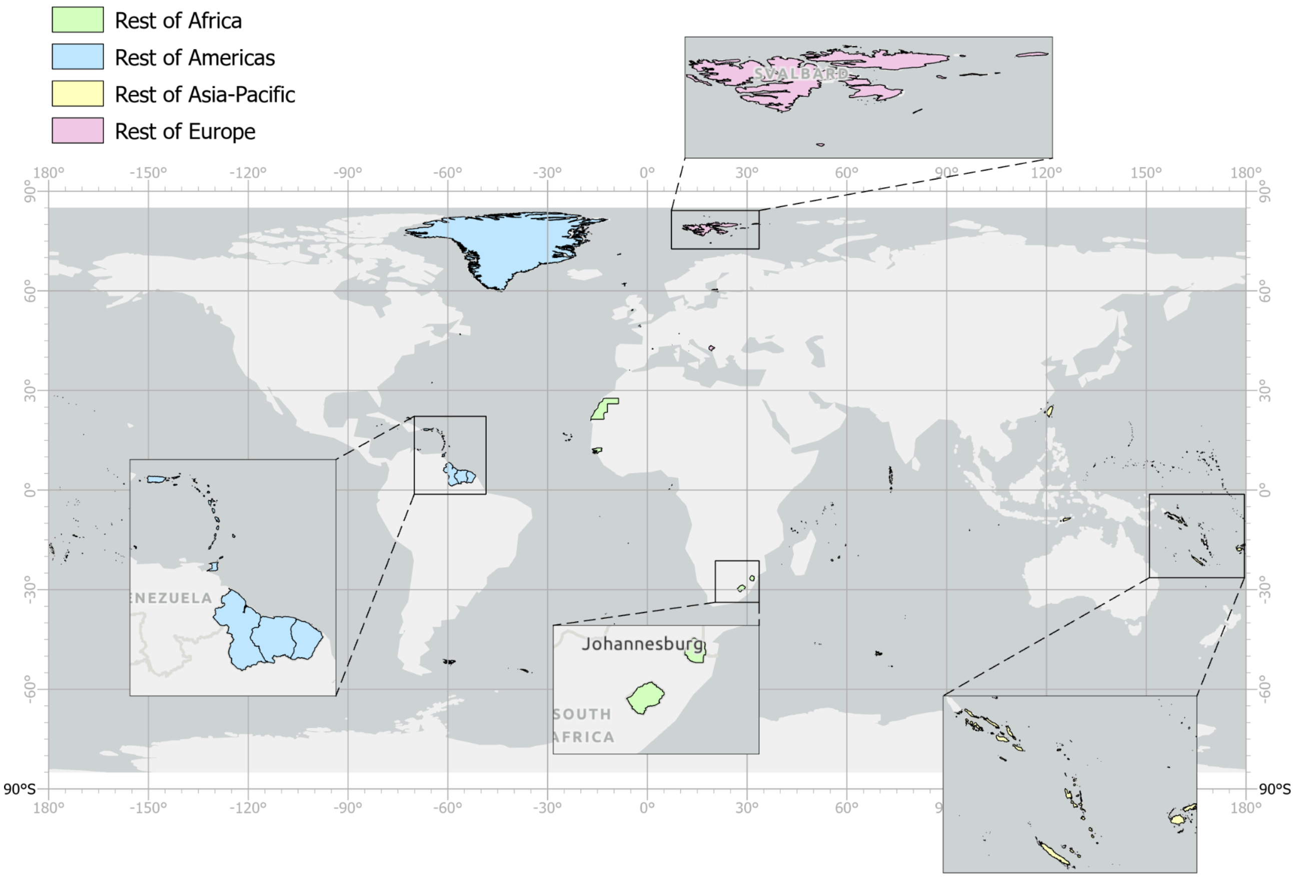


Supplementary Fig. 5 | Spatial patterns of production (in cattle head and tonnes) for major deforestation-risk commodities for Amazonian countries (2017–2021).
The spatial plots only show subnational estimates for Bolivia, Brazil, Colombia, Ecuador, and Peru. Cattle head data is only available for Brazil. The boundary of the Amazon region is highlighted in red.

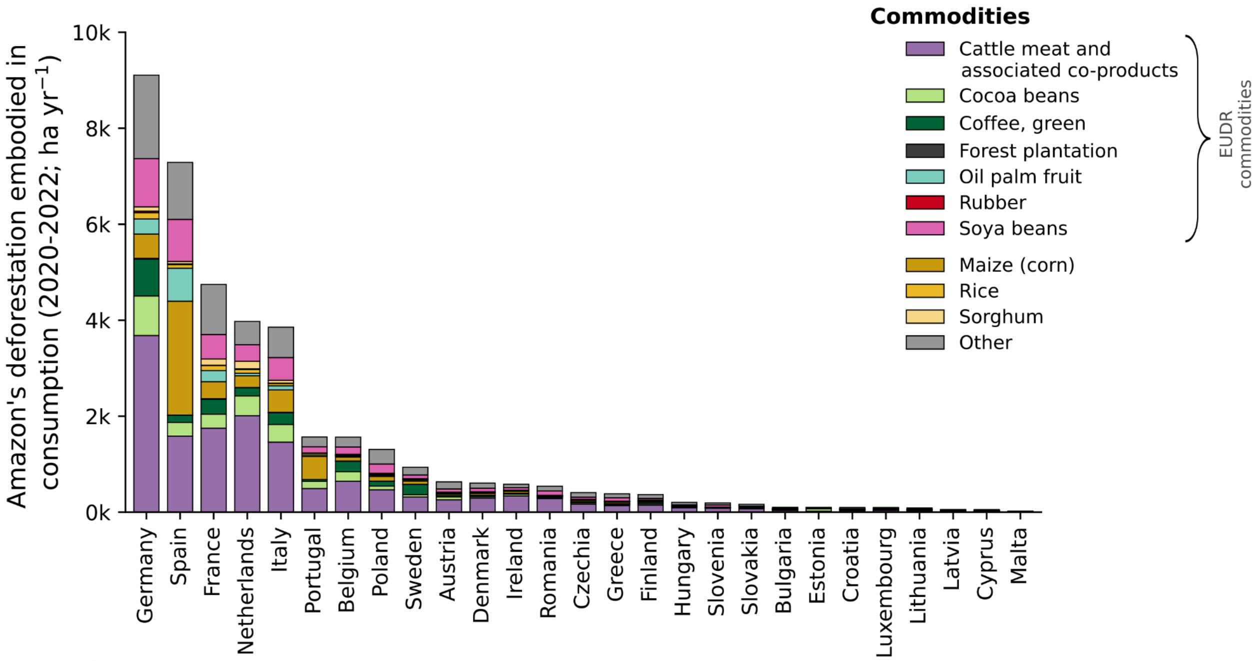


Supplementary Fig. 6 | Deforestation intensity of cattle meat (in ha 1000×cattle heads^{-1}) and key crop commodities (in ha 1000×tonnes^{-1}) in the Amazon (2017–2021).

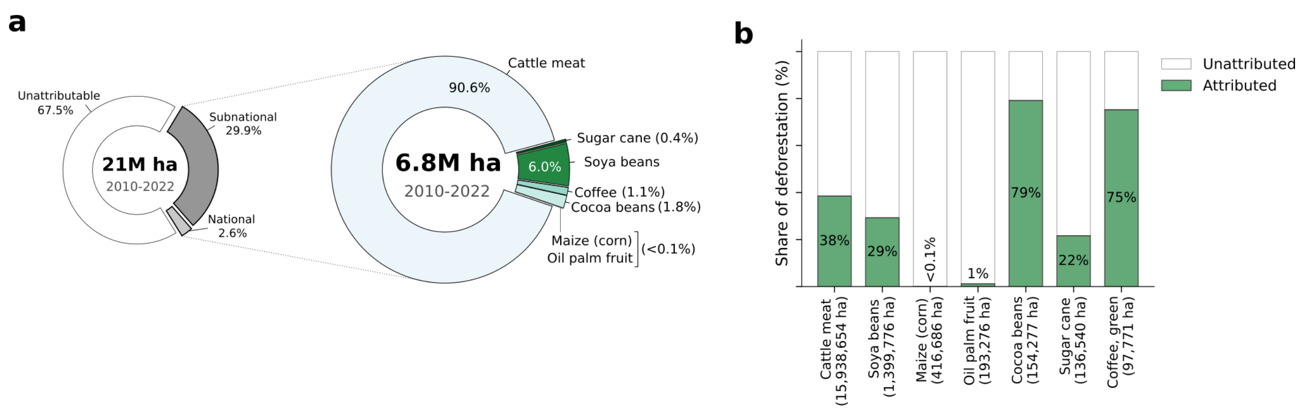
The spatial plots only show subnational estimates for Bolivia, Brazil, Colombia, Ecuador, and Peru. Cattle head data is only available for Brazil. The boundary of the Amazon region is highlighted in red.



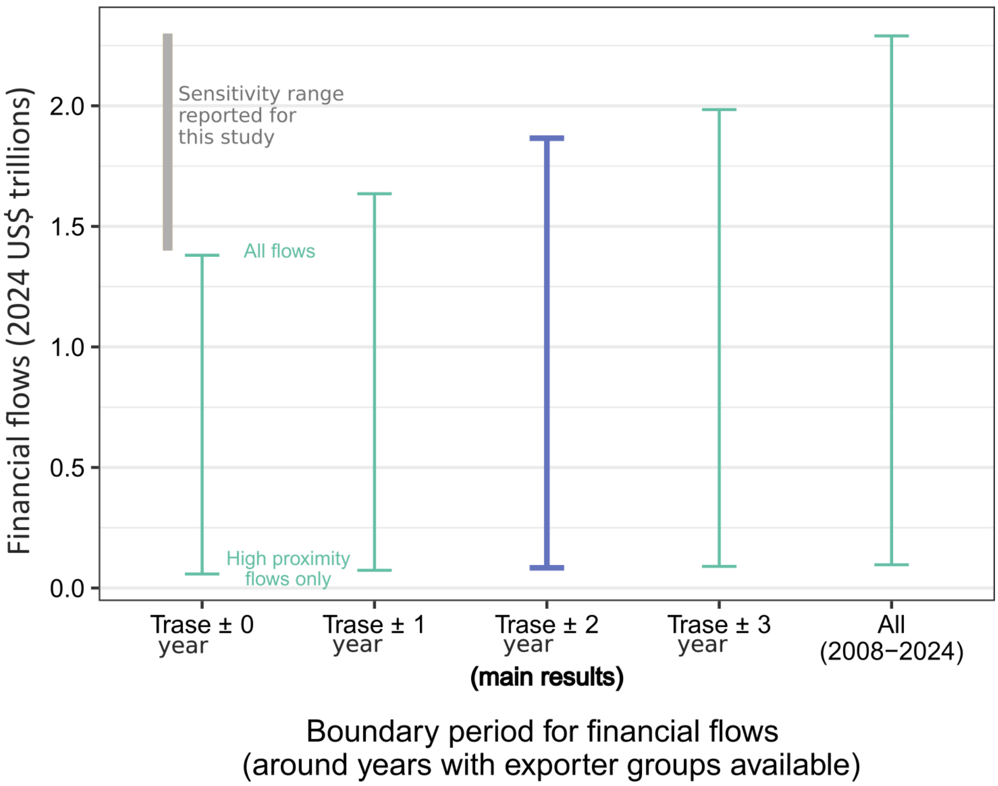
Supplementary Fig. 7 | Countries aggregated in the multi-regional Global Resource Input-Output Assessment (GLORIA) database.



Supplementary Fig. 8 | Amazon's deforestation footprint associated with European Union (EU-27) member countries.

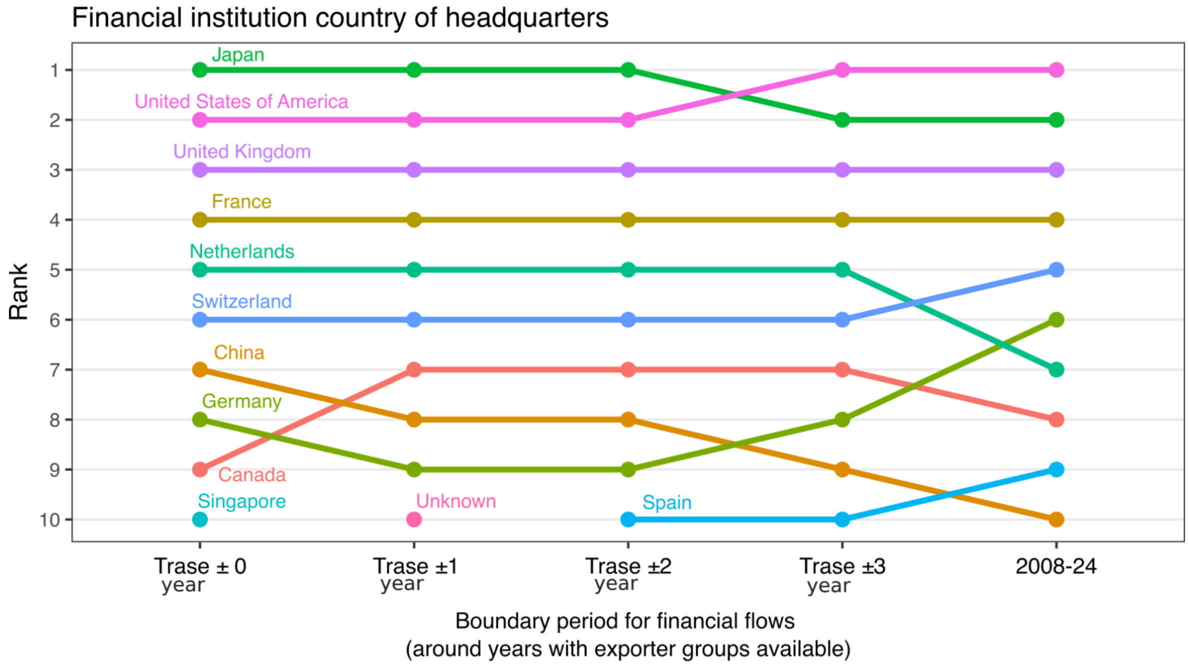


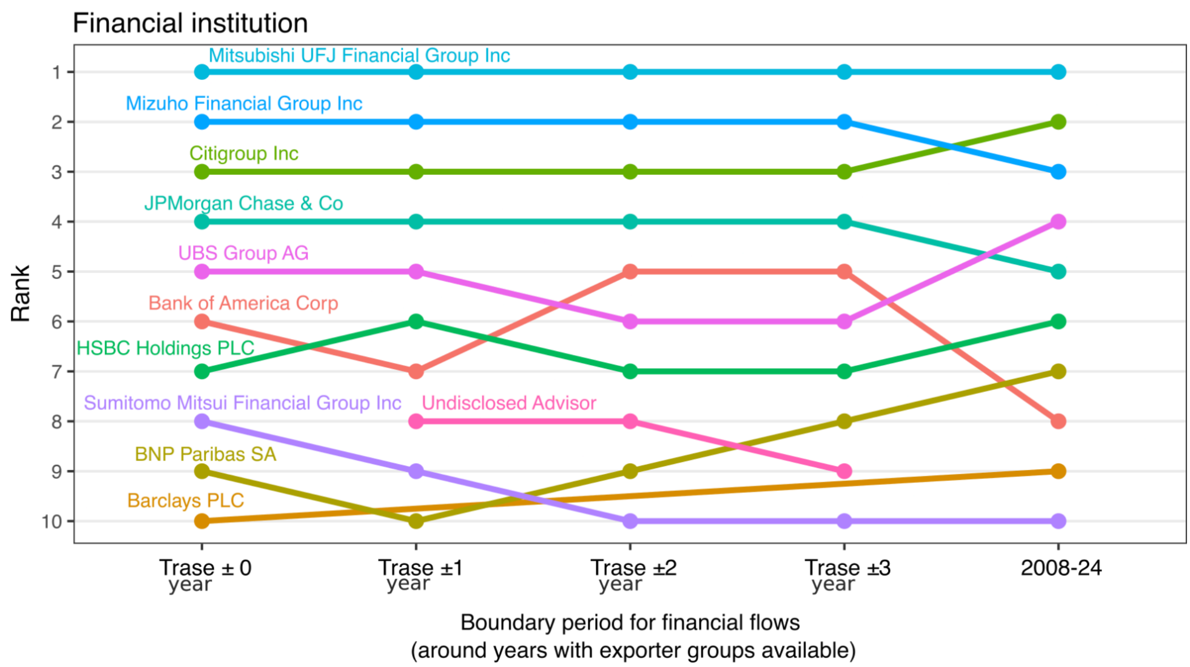
Supplementary Fig. 9 | Amazon deforestation linked to exporter groups.
(a) Amazon deforestation attributable to individual exporter groups during 2010–2022, based on national and subnational deforestation estimates from DeDuCE (this study) and supply chain data from Trase (see Methods). (b) Share of attributable deforestation relative to total deforestation over the same period, disaggregated by commodity.



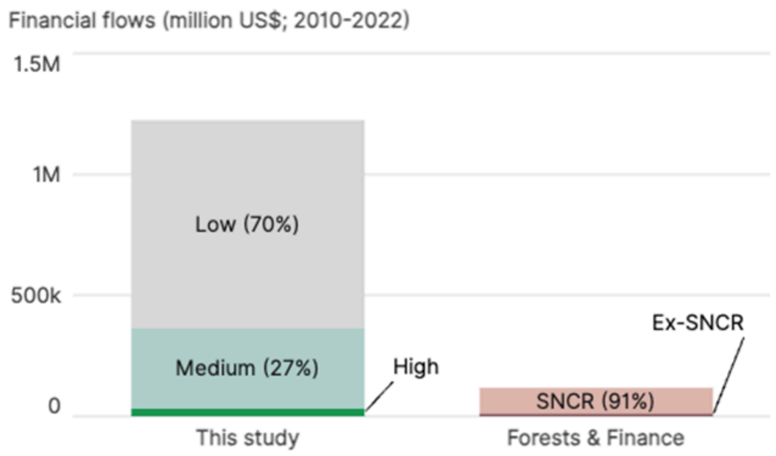
Supplementary Fig. 10 | Sensitivity analysis for the total financial flows exposed to Amazon deforestation for different boundary periods between 2010–2022.

The boundary period refers to the lag between financing and deforestation-risk activities (±2 years used in Fig. 4). Trase (data availability) years are mentioned in Supplementary Table 2. Lower whiskers represent high-proximity financial flows only (see Supplementary Methods), while upper whiskers include both direct and indirect flows. The lower-bound estimate reported in the main text corresponds to values including indirect flows for years with available Trase data only (i.e., upper whisker of boundary period '0'), whereas the upper-bound estimate includes all financial flows from 2008–2024 across all countries and commodities (i.e., upper whisker of boundary period 'all').





Supplementary Fig. 11 | Sensitivity analysis of key financing countries and financial institutions across alternative boundary periods around the Trase exporter group data.
The time period of the Trase exporter group data is mentioned in Supplementary Table 2.



Supplementary Fig. 12 | Comparison of financial flows linked to Brazilian soy between this study and Forests & Finance between 2010–2022.
'SNCR' refers to the *Sistema Nacional de Crédito Rural*, Brazil's rural credit scheme managed by the Central Bank of Brazil, which plays a major role in financing agricultural producers. Our analysis is complementary to, and does not include, the Brazilian rural credit scheme.

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