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Review article

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The global deforestation footprint of agriculture and forestry

Chris West [1] ✉, **Gabriela Rabeschini** [2,3], **Chandrakant Singh** [4], **Thomas Kastner** [2], **Mairon Bastos Lima** [5], **Ahmad Dermawan** [6], **Simon Croft** [1] & **U. Martin Persson** [4]

Abstract

Global forest loss impacts climate, biodiversity and sustainable development goals. Deforestation footprinting attributes forest loss to commodity production and consumption, identifying global trends, drivers and hot spots to inform zero-deforestation policies. In this Review, we provide an overview of global deforestation footprinting approaches and their trends. Major economies, including Brazil, Indonesia, China, the United States and Europe, are responsible for most commodity-linked deforestation, with agriculture-linked deforestation in Brazil alone reaching over 12.8 million hectares between 2005 and 2015. Agriculture is a dominant driver of deforestation. For example, 86% of global deforestation occurring between 2001 and 2022 can be attributed to crop and cattle production. Footprinting of commodity-linked deforestation has contributed to the scope and implementation of supply chain regulation to mitigate forest loss. For example, footprint estimates have been used in risk assessments for EU and UK due diligence regulations. Although forest loss to agriculture is relatively well documented, a lack of data on non-agricultural drivers – such as mining and mangrove clearance for aquaculture – limits the scope of footprints in fully attributing total global forest loss to human activities. Future research should focus on methodological and data harmonization, transparency and sharing to enable footprinting approaches to cover a wider range of deforestation drivers.

Sections

[1]Stockholm Environment Institute York, University of York, York, UK. [2]Senckenberg Biodiversity and Climate Research Centre, Frankfurt, Germany. [3]Department of Biological Sciences, Goethe University Frankfurt, Frankfurt, Germany. [4]Department of Space, Earth and Environment, Chalmers University of Technology, Gothenburg, Sweden. [5]Stockholm Environment Institute, Stockholm, Sweden. [6]Norwegian University of Life Sciences, Ås, Norway. ✉e-mail: chris.west@york.ac.uk

Introduction

Global deforestation is a primary driver of climate change. Globally, deforestation and other disturbances are linked with global greenhouse gas emissions of approximately 8.1 ± 2.5 $GtCO_2e\ yr^{-1}$ (ref. 1). Deforestation is also a primary driver of biodiversity loss[2,3] and is closely linked to broader sustainable development issues, including the human rights[4,5] and livelihoods of rural[6] and indigenous communities[7,8], and the emergence of zoonotic disease[9,10]. In turn, commodity production for domestic consumption and international trade is identified as a primary driver of global forest loss[11,12]. However, despite recognition of deforestation as a pressing concern, and the associated attention by private sector and governmental actors, depletion of forests has continued past planetary limits[13].

Environmental footprinting can provide an overview of global responsibility, hot spots of concern, and trends in the links between consumption and its environmental consequences. Examples of environmental footprints include those covering greenhouse gases[14,15], water consumption and scarcity[16,17], and biodiversity[18,19], among others[20–22]. A deforestation footprint can provide a specific assessment of a national or sectoral linkage to, or responsibility for, forest loss. Although multiple kinds of information are required to support mitigation actions across scales and supply chain stages, footprinting approaches have supported private sector[23], government[24,25] and civil society actors[26]. Such support includes identifying and monitoring supply chain exposure, improving national accounts of environmental risks and dependencies, and supporting impact-reduction targets.

In recognition of the role of forests as critical in fighting climate change[27], many demand-side actors, such as major agricultural traders and retailers, financial institutions and governments, have stepped up policy action to remove deforestation from commodity supply chains. Building upon voluntary action by the private sector, these policy actions have – so far – had mixed success[28]. Central to both voluntary and regulatory schemes are the data required to monitor supply chain exposure to deforestation and evaluate the progress or consequences of interventions[29]. In this context, deforestation footprinting can be an important tool. Yet there is no universally accepted standard for conducting footprint assessments[30]. Furthermore, with advances in computational and remote-sensing technologies[31,32], information availability has developed quickly. Thus, the evidence base has rapidly shifted and will continue to do so[12]. Interpretation of the results of deforestation footprinting exercises therefore requires an appreciation of their varying methods, underpinning data and assumptions.

In this Review, we synthesize existing estimates of national level deforestation footprints, drawing on evidence linking forest loss through to commodity production and consumption via domestic, regional and international trade. We focus on agricultural commodities as a key driver but also discuss other commodities influencing deforestation. Presenting a historical timeline of methodological development in the context of an advancing data landscape, we summarize points of commonality and differences between footprinting approaches. We compare data originating from methods with varying scope and purpose, focusing particularly on approaches that provide global-level analyses, but also contrast these with a selection of finer-resolution commodity-specific or nation-to-nation-specific analyses. Finally, we reflect on the role of the research landscape in supporting governance efforts and recommend areas of future improvement and attention.

Quantifying deforestation and its drivers

Deforestation footprint estimates rely on definition and quantification of the extent of deforestation, attribute forest loss to human productive activities, and distribute attribution of deforestation through associated supply chains and consumption systems (Fig. 1). Each step involves data collection, modelling and applies assumptions, which influence the resulting estimates. Quantifying deforestation area and attribution to production and consumption, and how agriculture and forestry, aquaculture and mining, and urbanization and infrastructure influence deforestation are now discussed.

Quantifying deforestation area

Global forest loss is inextricably linked to human activities, but quantifying and attributing of forest loss to its drivers is not trivial. Firstly, there is no universal definition of a forest or deforestation. Legislators in the EU[33] and UK[34] have adopted the United Nations Food and Agriculture Organization (FAO) forest definition[35]: “Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ”. However, this definition can differ from those used in many remote-sensing products, such as Global Forest Watch (GFW), which defines forest as “woody vegetation with a height of at least 5 meters and a canopy density of at least 30 percent at 30 m resolution”[36].

The FAO also does not consider conversion of natural forest to managed forest plantations as deforestation. This omission contrasts with standard-setting attempts by civil society, such as the Accountability Framework initiative, that do consider conversion of natural forests to plantations as deforestation[37]. Similarly, the extent of forests and deforestation captured by deforestation footprint estimates commonly vary (Fig. 1). Such differences can greatly impact deforestation estimates[12]. For example, deforestation in Africa between 2011 and 2015 is estimated at 4.8 $Mha\ yr^{-1}$ by the FAO, with GFW estimating only 2.8 $Mha\ yr^{-1}$ of forest loss in the same time period[12].

Attributing deforestation to production

Furthermore, when forest is cleared, capturing the dynamics of what replaces it is not straightforward. For example, if forest plantations used for timber production replace primary forest then these can be periodically cut and replaced, but remote-sensing products can still record this as forest loss[11]. Whether footprinting approaches account for this periodic clearing in their deforestation measure varies. However, this issue can be particularly problematic in temperate and boreal regions, where clearing in managed forests accounts for a large share of total forest loss[11].

A highly influential global assessment[11] geospatially attributed tree cover loss to five categories of dominant drivers (Fig. 1). The assessment defined a single, dominant disturbance type within each 10 km^2 pixel across the globe over the 2001–2015 time period. Overall, up to 76% of global tree cover loss is attributed to agriculture and forestry[38]. Only urbanization (estimated as a minor contributor to forest loss of <1% globally) and commodity-driven loss (25%) are classified as permanent drivers of loss (areas where no short-term tree regrowth is likely). However, when applied to derived deforestation footprints, the broader classes of forestry (31%) and shifting agriculture (21%) are also linked to economic activities within footprint quantifications[39].

A complication in deforestation attribution is the potential lag time between deforestation and emergent land-use change. Several years can elapse between forest loss and productive land outputs owing to crop maturation time or other land-use dynamics, such as

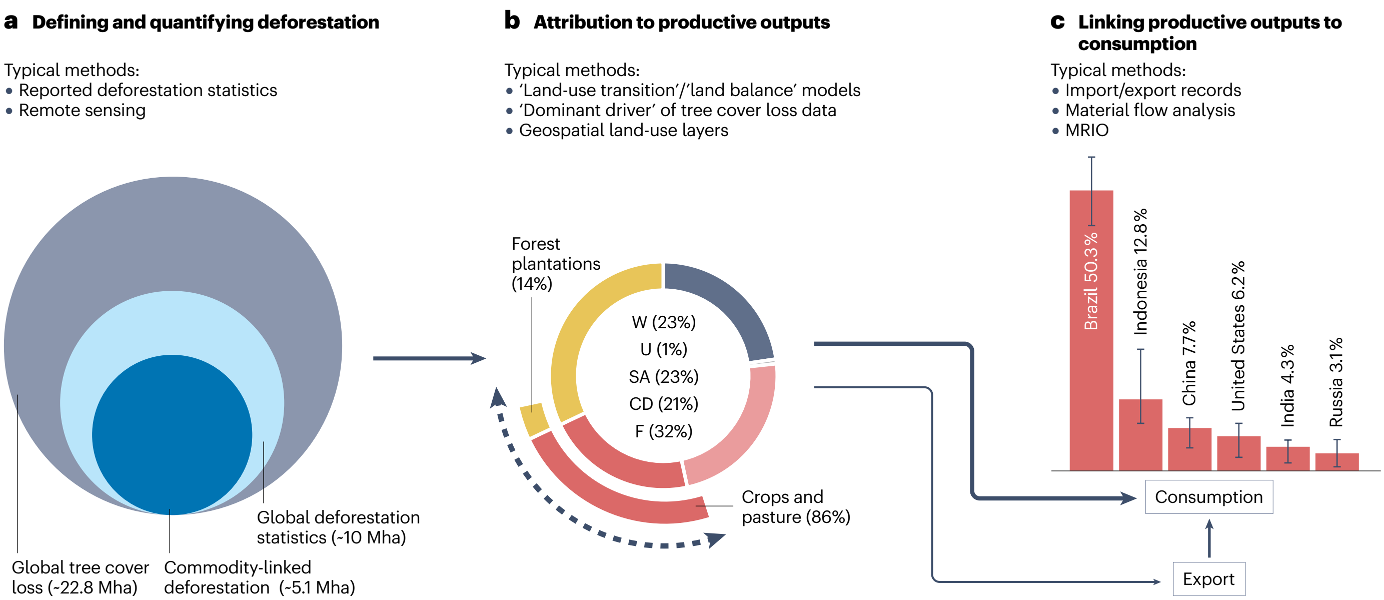

Fig. 1 | Overview of the construction of deforestation footprints. a, Defining and quantifying deforestation. The grey outer circle represents a 2022 global tree cover loss estimate based on Global Forest Watch remote sensing[103]. The light blue circle represents global deforestation estimate based on reported statistics from the United Nations Food and Agriculture Organization's 2020 Forest Resources Assessment[114]. The blue inner circle represents an estimate of deforestation explicitly linked to agriculture and forestry 2022[104]. **b**, Attribution of deforestation to productive outputs. The relative contributions to deforestation based on direct links of dominant drivers to productive-output (inner circle) or commodity-specific land-use change (outer circle). The dominant drivers shown include wildfire (W), urbanization (U), shifting agriculture (SA), commodity deforestation (CD) and forestry (F). Yellow represents forest plantations and/or forestry, dark pink represents cropland and/or commodity deforestation, pale pink represents shifting agriculture, grey represents urbanization and dark blue represents wildfire. The dashed black arrow indicates estimates that are not directly comparable owing to the adoption of alternative classifications. Data from refs. 11,104. **c**, Linking productive outputs to consumption. The top five national deforestation footprints (based on a comparative hybridized full consumption-based approach) are shown, error bars represent distributions across comparative estimates (data from Table 1 and Supplementary Note 1). Deforestation footprints can help understand deforestation drivers, hotspot locations and commodities of concern, and monitor the progress of zero-deforestation commitments over time. MRIO, multiregional input–output.

short-term use as pasture, before use for crops[40]. Whether such lags are accounted for in footprint assessments varies.

Amortization assumptions are also variably used[41]. These assumptions seek to spread out the initial deforestation event to attribute impacts to production over subsequent years, to account for the fact that the same parcel of land can generate economic outputs for an indefinite period. Furthermore, deforestation can be linked to agricultural activities that do not necessarily lead to productive output and therefore might not appear within footprint accounts[12]. For example, deforestation associated with land speculation[42], economic boom-and-bust cycles[43], land conflicts[44] or fires spreading from agricultural land[45].

Linking deforestation to consumption

Once deforestation has been linked to economic drivers, a final step in footprinting is allocation to human consumption activities. Bilateral trade information can provide a direct deforestation footprint associated with trade in focal products[46]. However, direct use of trade data can mask true origins. For example, the Netherlands is a key trade hub for Europe, but many materials are not produced there[47]. Therefore, methods need to be able to account for re-export (imports followed by export to another nation), and the processing and trade of intermediate products. These methods typically use mass-based data and are considered estimates of apparent consumption[48]. However, insufficient supply chain transparency[49] means that it is not always possible to fully track commodities downstream, and more complex processing stages and paths can be missed.

Full consumption approaches, where economy-wide models are used, provide a solution. Monetary multiregional input–output (MRIO) models[50,51], representing global intersectoral and international transactions, are commonly applied. Hybrid models combining physical and monetary approaches are also capable of resolving downstream commodity trading and processing[46,52].

Agriculture and forestry

Although agricultural commodities are the largest driver of tropical forest loss[12], forestry is identified as a primary concern in temperate or boreal regions[11]. Forestry has been included in several global footprint analyses[38,39,48,53,54], but estimates are complicated by uncertainties in measuring permanent, natural forest loss as opposed to rotational clearing[11]. Aside from plantation forestry, selective logging of primary forest for timber is also an important driver of deforestation and forest degradation[55,56] that is also variably captured by footprinting methods. Clearcutting is captured by tree-cover loss datasets, but several footprinting approaches[38,48,53] depend on FAO data for forest plantation expansion or contraction, which will not cover selective logging activities[57].

As much as 69% of global forest loss driven by commercial agriculture is illegal deforestation[58]. Illegal deforestation activity can be missed or misattributed if not included in datasets used in footprint analysis (such as the commonly used FAO records)[59]. Furthermore, illicit unreported activities, such as the production of narcotics, can be important contributors to deforestation. For example, coca cultivation increased by 43% (from ~150,000 ha to over 200,000 ha) in Colombia between 2020 and 2021[60] and, along with wider trafficking activities[61], increased the probability of deforestation[62]. Quantifying the connection between illegal activities and deforestation is difficult because illegal production will rarely be captured within the (often officially reported) datasets on which footprinting studies rely, but such evidence is nonetheless of great relevance to forest governance[61].

Aquaculture and mining

Aquaculture and mining are two important sectors associated with deforestation[63–66]. In footprinting assessments so far, these drivers can be subsumed, without specificity, under commodity-driven categories of forest loss[39] or not quantified at all. However, aquaculture is a key driver of mangrove conversion[67], with global losses of mangroves estimated to be approximately 860,000 ha between 1990 and 2020[68]. Rates of mangrove loss in South and Southeast Asia are particularly high[69,70]. However, although historically dominant, loss of mangroves appears to have become a less important component of forest loss in these regions[70].

Estimates indicate that 326,400 ha of tropical forest were directly lost to mining between 2000 and 2019, with these impacts heavily concentrated in Indonesia, Brazil, Ghana and Suriname[71]. Assessments are hampered by a lack of transparency on mine location and throughput[71]. However, emerging datasets combining remote imagery and corporate disclosure information are closing this gap[72–76]. Data coverage for artesanal and small-scale mining is limited and uncertain[71,75], yet can account for a relatively large fraction of mining production[75]. Mining can also be linked indirectly to deforestation (for example, via energy infrastructure, in-migration and transport infrastructure)[71], but attributing values to such indirect impacts is challenging[12,77]. The dynamic nature of mining lifecycles, along with varying inclusions of mine features or mining areas in datasets, imparts further complexity in estimates of the extent and impact of mining as a deforestation driver[75].

Urbanization and infrastructure

Urbanization also drives deforestation. However, the coarse resolution of data on the dominant drivers[11] of deforestation does not detect the impacts of urbanization outside of major urban areas[39]. Another analysis indicates that the relative impacts of urbanization and infrastructure have been more substantial (explaining around 30% of deforestation) earlier in forest transitions in African and Asian regions, where rates of deforestation were low but accelerating[78].

Drivers of deforestation also interact with one another[79]. For example, increased road connectivity opens corridors for expansion of other industries that can drive land-use change. Similarly, roads can follow prior agricultural or mining expansion[71,80,81].

Ultimately, estimating deforestation footprints requires the collation of deforested area estimates, evidence of attribution to productive sectors and data to map deforestation impacts through to consumption. The science estimating agricultural- or forestry-linked footprints has evolved rapidly and captures the main drivers of deforestation. However, it is worth noting that even for these systems, uncertainties can be high and data quality poor. In comparison, although drivers beyond agricultural and forestry are clearly important, attribution science remains relatively nascent compared with data sources and approaches that allow agricultural or forestry footprints to be established.

Estimating deforestation footprints

Estimates of deforestation footprints have evolved rapidly, from initial explorations and general attempts to correlate deforestation activities to trade, to approaches that use a variety of methods to estimate commodity-specific footprints of specific trade and consumption activities at ever-higher resolution and accuracy. Agriculture and forestry account for most deforestation, thus the following discussion of estimating footprints focuses on these sectors as those estimates are most widespread.

Early developments

The term deforestation footprint started to appear in the literature around 2007, in relation to the management of deforestation-linked emissions[82,83]. The term was introduced (in the context that it still applies) to conceptualize the connection between consumption activities within a nation that can displace impacts overseas to production or source regions. Although the wider drivers of deforestation – and the linkage between agriculture and forest loss – were well-established before this time[84–86], the introduction of the term also coincided with increased interest in quantifying connections among consumption, trade and global forest loss[87,88].

Initially, regression-model-based analyses explored interfaces between generalized export activity and agricultural land expansion[89], then deforestation[90,91]. Analyses of forestry products[92,93], beef[94], coffee[95] and soy[96] then emerged, which all concluded that trade is a key explanatory variable in deforestation activity. Concurrently, material balance sheets emerged for commodities to explore the influence of import and exports on local and overseas deforestation[97]. For example, a relatively simple analysis of consumptive demand (production plus imports, minus exports) used associated timber requirements as a proxy for extraction to infer deforestation[98]. Another example for Vietnam demonstrates that net reforestation was achieved from 1992, partly via the displacement of forest extraction to other nations, which resulted in overseas deforestation equating to 39% of the total forest regrowth within Vietnam itself[97] (Fig. 2).

Collectively, these early analyses laid the foundations for deforestation footprinting as it is now considered. Importantly, most of these approaches include a mechanism – and associated data – to quantify deforestation activity, which serves as a key component of deforestation footprinting. These early estimates[90,92–96] typically used national, non-spatial, forest cover and deforestation statistics from the FAO's Forest Resources Assessment (FRA) (although some used remote-sensing data[91,99]), which are collated by the FAO based on estimates of forest cover submitted via national reporting processes[100].

Global deforestation footprinting

An early example of deforestation footprinting conducted at global scale[48] also made use of 2010 FRA data[101] (Fig. 1). These deforestation statistics were explicitly attributed and quantitatively linked to a range of associated production systems (including crops, livestock production, logging, natural hazards and an unexplained category) via a stepwise land-use transition model, which apportioned responsibility for forest loss. Since the early 2010s, geospatial data influenced the trajectory of deforestation footprinting. Of particular importance is the global tree cover loss data from GFW[102,103]. This dataset underpins two seminal global deforestation-footprint estimates[39,53] that – despite

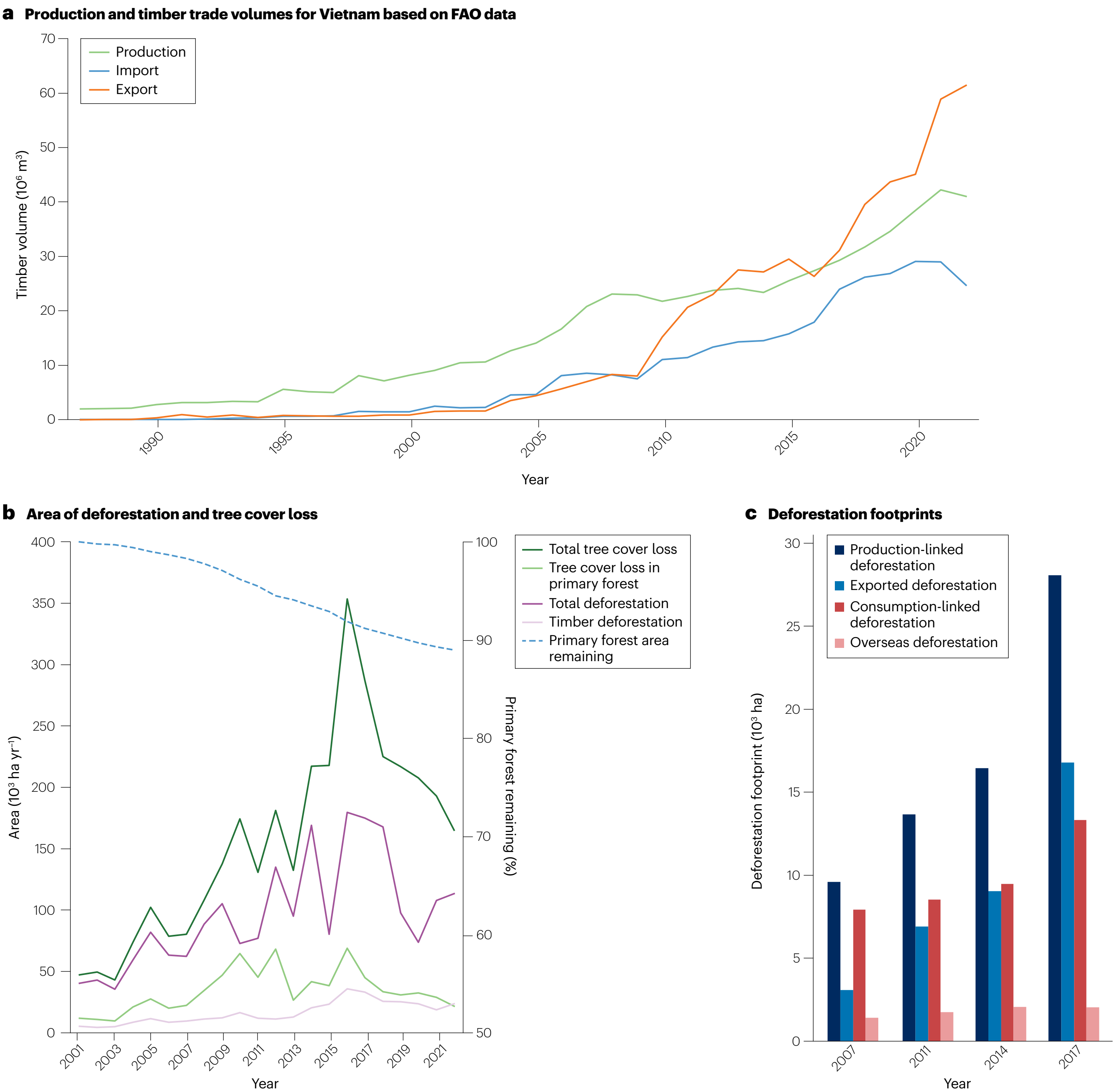

Fig. 2 | The deforestation linked to timber production in Vietnam. a, Timber production, export and import between 1987 and 2022. Data from the Global Food and Agriculture Statistics of the United Nations Food and Agriculture Organization (FAO)[228]. **b**, Tree cover loss and deforestation data between 2001 and 2022. Data from refs. 104,229. **c**, Deforestation footprints. Data from ref. 126 (see Supplementary Note 2 for further details). Despite reforestation efforts, Vietnam has a notable and growing deforestation footprint linked to domestic and overseas timber demand.

sharing a common forest-loss dataset — offer diverging methods of attributing deforestation to productive outputs from land.

The land balance approach. One global analysis[53] uses the GFW data together with a land balance model[48]. This analysis excluded GFW data for non-tropical regions because of the challenges in separating permanent forest loss from temporary managed-forest rotation, as well as excluding forest loss in existing plantations in Indonesia and Malaysia[104]. The land balance model is conceptually similar to the land-use transition model discussed above[48]. The land balance approach applies statistical (non-geospatial) estimation of gross expansion of permanent pastures, croplands and forest plantations, based on Global Food and Agriculture Statistics of FAO (FAOSTAT)[105] national-scale data (aside from Brazil and Indonesia where subnational records are used) and remote-sensing data on cropland and grassland loss[106]. Forest loss is proportionally attributed to pasture, cropland (and then further to individual crops) and forest plantations based on relative expansion. This approach attempts to capture lags between deforestation activities and productive use of land, assuming a period of 3 years (ref. 53).

The dominant driver approach. A second global analysis based on the GFW dataset takes an alternative approach to attribution[39]. Similar to the land balance analysis[53], forest loss data are first combined with bespoke oil palm and rubber plantation masks to account for areas that would otherwise be included within deforestation estimates. Calculated forest loss is then allocated according to the geospatial dominant drivers dataset[11]. These data are used to assign forest loss to forestry, urbanization, agriculture and other commodities, which includes energy and mining in addition to crops. Compared with the land balance model[53], this analysis provides estimates of non-tropical, in addition to tropical, forest loss linked to all productive economic output (not just agriculture)[39]. However, it also includes forest loss that is not deforestation, particularly in the non-tropics where non-permanent loss from forest management dominates. Another difference is the absence of accounting for a lag between deforestation and productive outputs, with annual forest loss simply being linked to the equivalent year's data for productive output[39].

The DeDuCE method. Latterly, an improved global attribution dataset combines aspects of these methods and introduces additional geospatial data[38]. In the Deforestation Driver and Carbon Emission (DeDuCE) model[38], tree cover loss data (GFW[102,103]) is overlaid with other datasets, providing spatio-temporal land-use (change) information. Although the model aims to include a wide range of available commodity extents, most existing crop commodity datasets are focused on the tropics, including, for instance, soybeans across South America[107], cocoa in Côte d'Ivoire and Ghana[108], and oil palm across the tropics[109–111]. Spatial datasets[112,113] for forestry and tree crops and forest management status are also used to distinguish natural forest loss from rotational clearing.

Within DeDuCE, a staged approach to attribution is adopted. Where available, spatial and crop-specific information is used, otherwise a land balance-equivalent approach[53] (with FAO statistics on crop expansion) is applied. The inclusion of dominant-driver[11] data for non-tropical areas also allows for inclusion of temperate and boreal regions, though limited to forest loss identified as forest plantation or agricommodity driven (to not include forest loss that is not deforestation). Finally, forest plantation attribution is capped based on Global Forest Resources Assessment 2020[114] statistics. An important distinction with the dominant drivers approach is that, owing to data gaps, forestry-linked deforestation overall captures just the expansion of dedicated tree plantations and not the broader phenomenon of logging of natural forests for timber. Mixing both spatial and non-spatial data within DeDuCE introduces additional uncertainties and potential inconsistencies, and therefore the approach also provides a quality score for each of its attribution estimates[38]. Further advances have utilized subnational production statistics across the Amazon to improve attribution of deforestation to commodities[115].

Linking deforestation to trade and consumption

Following attribution of deforestation to productive sectors, the final component of deforestation footprinting entails linking attribution through global (and domestic) supply chains to points of consumptive use. Although trade information can be used directly[46], it is more common for global footprint estimates to use modelling to account for either apparent or full consumption, with the latter providing a more comprehensive assessment of the role of economies in driving deforestation.

In the early land-use transition model[116], both apparent and full consumption methods were used via a physical material flow model (LANDFLOW[117]) and a monetary MRIO (Global Trade Analysis Project; GTAP[118]), respectively. The former used time series data on crop and livestock production, supply and utilization from FAOSTAT[105], integrated into trade matrices to track physical quantities (and associated deforestation estimates) through to apparent consumption (excluding more processed products downstream and those categorized as other utilization outputs). The MRIO method attributed estimates of deforestation to the appropriate economic sectors of the input–output tables. A follow-on approach[119,120] used equivalent deforestation attribution methods but adopted a hybrid-trade model for downstream attribution, with other utilization outputs from LANDFLOW being adjoined to non-food-linked sectors within the EXIOBASE MRIO[121,122].

Similarly, both the land balance and DeDuCE methodologies have been linked to models of apparent and full consumption, applying physical trade methods[123,124] that use different assumptions to LANDFLOW, and the EXIOBASE MRIO[122,125]. Linkage to consumption models includes the application of an amortization approach to reflect the fact that productive output can reasonably be attributed back to earlier deforestation (a 5-year amortization period is commonly adopted). Latterly, these datasets have also been integrated into a hybridized MRIO modelling framework as the basis of the Global Environmental Impacts of Consumption (GEIC) indicator[52,126], which uses physical trade information combined with monetary MRIO data from either EXIOBASE or GTAP.

In the dominant drivers[39] and another conceptually similar approach[127], linkage is made to the appropriate industrial sectors within Eora[128], a monetary MRIO, with deforestation distributions mapped according to the gross economic output of the sector. A further contemporary example that also uses Eora combines this model with estimates of deforestation derived from FAO FRA deforestation statistics[129].

Advances via regional and sectoral analyses

The examples above have global coverage in terms of locations of production, trade flows, commodities and/or economic sectors. However, this small number of truly global estimates are complemented by national-scale estimates, often focusing on single or a handful of commodities. For example, a regional-scale analysis[130] provides an apparent consumption-based approach for pastures, soybean, palm oil and wood plantations in Argentina, Bolivia, Brazil, Paraguay, Indonesia, Malaysia and Papua New Guinea. This approach uses attribution methods[131] derived from remote-sensing information with physical trade methods[123] used for attribution downstream, and showed that the production of the four commodities across the seven focal countries accounted for 40% of total tropical deforestation – an impact increasingly driven by international trade. Another analysis[116] focuses on emissions from deforestation in Brazil (rather than quantifying deforested area), using remotely sensed deforestation estimates from Brazil's

PRODES system[132], which are linked to land-use and carbon-cycle models before the GTAP MRIO model is used to distribute emissions through to regions of final consumption. This analysis highlighted that 30% of emissions linked to deforestation in Brazil were exported, with export markets such as Russia and China increasingly responsible.

An advantage of regional or commodity-specific analyses is that they can focus more explicitly on the characteristics of associated supply chains. For example, employing sectoral material-flow accounting and network analysis provides an apparent consumption footprint of four EU nations for palm oil from three producing regions[133], demonstrating a trend in palm oil consumption away from food and towards biofuel. Focusing on a single commodity and regional production also facilitates the integration of three distinct deforestation-attribution estimates, reflecting different methods for deforestation attribution and different temporal perspectives (Supplementary Note 3).

Global analyses tend to operate at national scales; however, the potential to derive more detailed connections between points of production and consumption has become apparent. For example, Trase – a data-led non-profit research programme promoting supply chain transparency for deforestation-linked commodities[134] – and its high-resolution supply chain mapping approach[135] can provide deforestation estimates for selected commodities at subnational scales. Trase combines trade, shipment and tax records, industry information on storage and processing facilities, and optimization modelling based on the costs or time of transport[135,136]. An advantage of such a fine-scale analysis is that it can highlight discrete differences between the deforestation footprints of consumers and actors, within a region of production, that would otherwise be unapparent[135,137]. For example, exports of Brazilian beef to China in 2020 – of which proportionally more originates from the higher-risk Amazon biome – have a deforestation risk per tonne that is almost double (0.28 ha t^{-1} versus 0.15 ha t^{-1}) that of exports to the EU[40,138].

The conceptually similar TRAcking Corporations Across Space and Time (TRACAST) method[139] has also been applied for detailed local exploration of deforestation embedded in traded supply chains, such as US imports of rubber from Sri Lanka[140] and avocados from Mexico[141]. Such estimates depend on relatively intensive data collection and processing activities that, coupled with a lack of global availability of the data on which they depend[49], means that they are often limited in scope and coverage. These approaches tend to focus on direct trade, but they have also been coupled to apparent and full consumption-footprint assessments[46,142]. Localization of footprints has also been explored at the demand end, with the derivation of city-scale deforestation footprints based on the land balance deforestation attribution approach[143].

Footprinting methods have developed rapidly since the early 2010s. Although statistical data for attribution (either alone[129] or in combination with spatial data[38]) are still used, approaches now make much more extensive use of remote-sensing data. Methods encompassing trade and consumption linkages have also developed, with the introduction of hybrid models and advanced material flow accounts, and the advent of subnationally specific datasets providing more granular interrogation of the links among impact, supply and demand.

Comparing footprint estimates

Varying methods provide contrasting results, which is now discussed through comparison of selected deforestation footprint estimates (see Supplementary Data 1 for an overview of the compared methods). Global footprinting analyses are the primary focus, as they allow for comprehensive comparison of drivers and trends. However, a selection of regional analyses is also explored. Methodological differences complicate comparisons as there are different time series, different commodity and national scopes and granularity, different assumptions adopted, and the scope of published information varies. For example, there is a 2005–2018 time series available for footprint results derived from the land balance footprint approach[53], a 2001–2015 time series for data derived from the use of dominant drivers attribution[39], and a 2005–2022 time series available from the DeDuCE model[104].

Time series of deforestation footprint estimates are compared for selected analyses and consumption-model variants for a set of nations common across assessments (Fig. 3 and see Supplementary Note 4 for additional comparison for EU nations). This comparison excludes deforestation linked to forestry as these are not included across all variants (see Supplementary Note 5 for an additional comparison for forestry). Land balance-based estimates exclude temperate and boreal forest. The dominant drivers-based estimates, by contrast, include temperate and boreal deforestation, but also include forest loss in managed forested land, which is therefore not in alignment with FAO or Accountability Framework initiative definitions. Estimates derived from DeDuCE include global deforestation (including in temperate and boreal regions), but are limited to permanent deforestation only[38].

The disparity between these estimates highlights the strong influence the deforestation definition has on quantified footprints. For the latest common year in the time series (2015), the full consumption footprint derived from the dominant drivers approach is 5,767,064 ha, which is much higher than the 2,652,253 ha estimate derived from DeDuCE hybridized full consumption data[104] (Fig. 3a). Although the dominant drivers attribution methods allow for inclusion of the potential for non-agricultural commodities (such as those from mining), and use an alternative MRIO model, most of this difference is explained by a lack of control for temporary forest loss[39]. The lowest estimates are derived from the land balance dataset, which is restricted to tropical deforestation, and are around 81% of DeDuCE results over the time series for common years, reflecting relatively limited agriculture-driven deforestation outside the tropics[11].

Forestry-linked footprints derived using the DeDuCE method equate to only 12% of the dominant drivers approach across common years (Supplementary Note 5). For example, in the dominant drivers approach, the 2015 domestic deforestation footprint of Sweden (associated with domestic forestry) was approximately 107,000 ha. However, the DeDuCE method did not allocate any deforestation footprint to domestic forestry as the approach does not capture conversion of natural to managed forests[38]. Thus, defining what constitutes deforestation and having sufficient data to identify such deforestation has important implications for estimating footprints and identifying deforestation hot spots.

Consumption-model estimates sharing common deforestation-attribution methods provide more consistent results. Results derived from apparent consumption models are typically slightly lower than those derived from MRIOs. For example, the apparent consumption version of DeDuCE averages ~92% of the hybridized full consumption estimates for consumer nations (Fig. 3a). A larger full consumption footprint is unsurprising for common nations with developed economies, as such economies – by virtue of high gross domestic product – generally display larger footprints when all consumption activities are fully accounted for (Fig. 3a). Differences between models are more variable for individual national footprints than when the footprints of countries are aggregated (Fig. 3b,c).

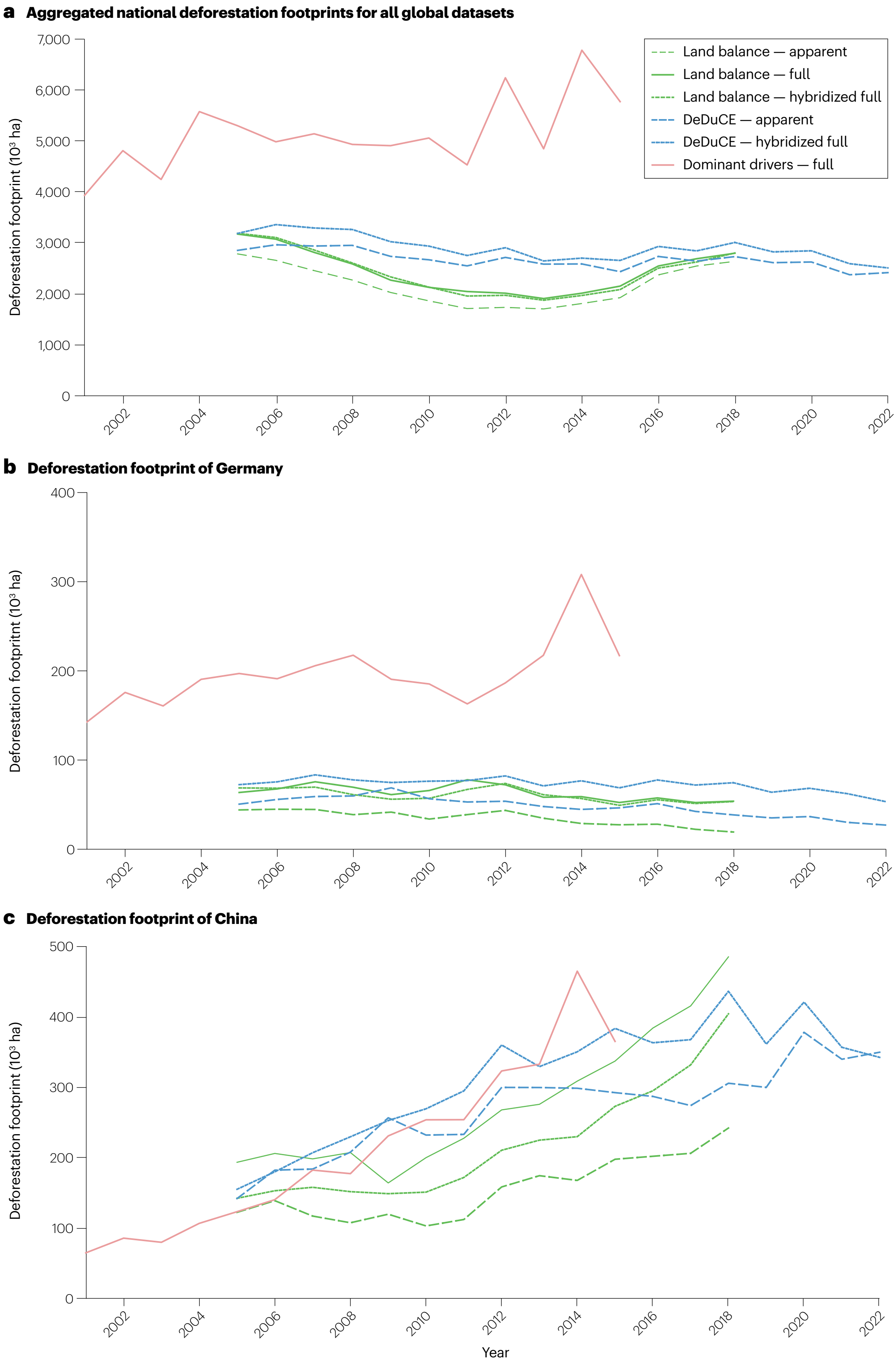
a Aggregated national deforestation footprints for all global datasets
Deforestation footprint (10³ ha)
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
Land balance — apparent
Land balance — full
Land balance — hybridized full
DeDuCE — apparent
DeDuCE — hybridized full
Dominant drivers — full
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022
b Deforestation footprint of Germany
Deforestation footprint (10³ ha)
400
300
200
100
0
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022
c Deforestation footprint of China
Deforestation footprint (10³ ha)
500
400
300
200
100
0
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022
Year

Fig. 3 | Comparison of national deforestation footprints between global analyses. a, Aggregated national deforestation footprints for nations common to all global datasets: Brazil, Indonesia, China, Russia, India, USA, South Africa, Germany, Japan, Australia, Italy, Turkey, France, South Korea, Mexico, Canada, Sweden and Norway. **b**, The deforestation footprint for Germany (in hectares). **c**, The deforestation footprint for China (hectares). Data from refs. 39,104,125,126 (see Supplementary Note 1 for additional details). Methodologies underpinning footprint assessments can lead to markedly different quantifications of impact and responsibility and complicate making comparisons of trends over time. DeDuCE, Deforestation Driver and Carbon Emission.

For example, differences between full and apparent consumption for Germany (Fig. 3b) are larger than for China (Fig. 3c). Overall, however, the choice of consumption approach appears to have a smaller impact on estimates than the assumptions used for deforestation estimation and attribution (Fig. 3).

Comparison across footprint time series to identify common trends is tempting but complicated. Increasing trends might indicate increasing deforestation linked to consumption, which could be concluded from the time series derived from the dominant drivers approach (Fig. 3a–c). At face value, estimates derived using the land balance and DeDuCE data conclude differently, suggesting slight decreases in deforestation rates after 2005 followed by increases between 2013 and 2018, and then further decline (Fig. 3a). However, such comparisons are complicated by attribution differences. In particular, the dominant driver approach has no lags between conversion and attribution, whereas the land balance and DeDuCE approaches factor in both lags and amortization periods[38,39,53]. The latter has a smoothing effect and helps explain contrasts with the comparatively variable and spiky results derived from the dominant drivers approach (Fig. 3a). Despite these methodological differences, these methods appear to agree in suggesting that deforestation footprints in China have continued to increase since 2001 (Fig. 3c).

A common theme in environmental footprinting is the important role of Europe and North America as key drivers of impact[14,18], which also holds true for deforestation footprints to a degree. For example, the United States and Germany appear relatively high in the total deforestation footprint rankings during the 2005–2015 time frame (Table 1). The different estimation approaches are in relative agreement on the positioning of common nations in terms of their ranking. An example of inconsistent ranking is Russia, which ranks lower in the land balance and DeDuCE full-consumption and dominant drivers approaches than for apparent consumption approaches. Mexico is also ranked notably higher by the dominant drivers approach than for land balance and DeDuCE approaches.

Importantly, the various approaches show strong agreement that domestic markets and consumption have an important role in national deforestation footprints, and thus should not be overlooked[12,144]. Indeed, all comparison estimates (Table 1) indicate that Brazil – the nation with highest deforestation rates – has a substantial consumption footprint (around half of the total cumulative national footprints shown). In Indonesia too, domestic consumption has an important role.

However, absolute estimates of the footprint share linked to domestic versus overseas consumption can be heavily influenced by the applied consumption model. For example, contrasting the DeDuCE hybridized full consumption model with a global footprint estimate based on a combination of Eora26 monetary MRIO[145] and FRA-based deforestation estimates (Supplementary Note 6) demonstrates the considerable variation in estimates of exported consumption (Table 2). For instance, the Democratic Republic of Congo exports 30.1% of its footprint based on Eora–FRA-derived methods or 3.4% based on DeDuCe hybridized methods. Although the Eora–FRA approach includes estimates of deforestation attributed to sectors beyond agriculture and forestry, it is the alternative consumption models applied that can explain the difference in export-share estimates (Table 2).

Regulation is increasingly focused on reducing deforestation associated with key forest-risk commodities, such as soy, beef or palm oil[146]. Therefore, comparing and contrasting estimates of individual commodity-level detail is useful. Such detail can support regulatory decisions to reduce deforestation through helping assess policy efficacy via the direct influence of changing practises linked to commodities, and also identifying influential commodities and regions to guide regulations. The land balance and DeDuCE approaches are currently the only global estimates that provide commodity-specific deforestation footprints. However, these estimates are in general agreement that meat (cattle and buffalo), followed by oil palm and soybeans are the top three agricultural drivers of global deforestation. That said, the relative importance of other commodities differs between models (Supplementary Note 7 and Supplementary Table 4).

Commodity-specific footprints from global estimates can also be compared to local and regional estimates. For example, Trase[134] estimates the total Brazilian beef-linked deforestation exported to China in 2020 was 370,407 ha compared with the DeDuCE apparent consumption estimate of 144,497 ha (ref. 104). Trase uses Lapig and PRODES deforestation data[132,147], alternative attribution assumptions and truncates supply chain mapping to the point of first import. Conversely, DeDuCE uses GFW deforestation data and accounts for re-exports beyond point of first import, which contributes to the contrast in estimates. In another example, the TRACAST method[139,141] suggests that of the 14,614 ha of Mexican deforestation between 2001 and 2017 linked to avocado production, 261 ha can be linked each year to annual avocado imports in the USA, whereas DeDuCE estimates the US apparent consumption at 637 ha per year (Supplementary Note 8).

Footprint analyses can be used to explore both direct and indirect links between consumer and producer regions. For example, a footprint analysis of palm oil originating from Indonesia, Malaysia and Papua New Guinea that was distributed in Europe between 2000 and 2020 indicates that Spain and Italy had more direct links with producing regions (for example, ~57% of their palm oil equivalent imports were directly from Indonesia) than Germany and France, which were associated with deforestation via more indirect supply chains (with only 16% and 25%, respectively, of imports directly from Indonesia)[133]. This analysis adopts an apparent consumption approach and employs alternative deforestation estimates. Thus, based on estimates specific to palm oil plantation concessions, a long-time series estimation for national forest loss, and short-time series estimate derived from remote sensing, three annualized palm oil deforestation footprint estimates for France of 318 ha, 7,450 ha and 1,527 ha are provided (Supplementary Table 2). By comparison, the DeDuCE apparent consumption approach estimates that the annualized palm oil-linked deforestation footprint of France was 4,723 ha (estimated across 2005–2020) (Supplementary Table 2). Comparison with a regional analysis of the deforestation emissions footprint of beef and soy production in Brazil[116] also indicates that differing assumptions influence results regarding attribution (Fig. 4).

Table 1 | Ranked comparative contributions to global deforestation footprints

Nation/region	Land balance — apparent consumption		Land balance — full consumption		Land balance — hybridized full consumption		DeDuCE — apparent consumption		DeDuCE — hybridized full consumption		Dominant drivers — full consumption	
	Rank	%	Rank	%	Rank	%	Rank	%	Rank	%	Rank	%
Brazil	1	56.3	1	47.4	1	51.7	1	52.5	1	49.9	1	44.0
Indonesia	2	13.8	3	10.2	2	8.5	2	13.4	3	9.0	2	21.8
China	3	6.6	2	9.5	3	7.8	3	8.8	2	9.2	4	4.1
Russia	4	4.5	6	3.0	10	2.0	4	5.6	6	2.8	14	0.7
India	5	3.9	5	5.5	5	4.9	5	4.8	5	5.3	10	1.4
USA	6	2.4	4	6.8	4	7.1	6	4.2	4	8.2	3	8.5
South Africa	7	2.0	12	1.3	12	1.5	13	0.7	16	0.6	11	1.1
Germany	8	1.8	8	2.5	6	2.6	7	2.0	7	2.5	5	3.8
Japan	9	1.4	7	2.7	7	2.5	9	1.4	8	2.4	6	3.5
Australia	10	1.4	11	2.8	11	1.9	16	0.3	14	0.9	15	0.7
Italy	11	1.3	10	1.7	8	2.3	8	1.4	9	2.2	9	1.8
Turkey	12	1.3	13	1.4	13	1.3	15	0.6	14	0.9	16	0.3
France	13	1.1	9	1.8	9	2.1	10	1.2	10	1.8	8	2.8
South Korea	14	1.0	14	1.2	15	1.2	12	1.0	12	1.1	13	0.8
Mexico	15	0.8	15	1.1	14	1.2	11	1.1	11	1.3	7	3.4
Canada	16	0.2	16	0.7	16	0.8	14	0.7	13	1.1	12	0.9
Sweden	17	0.2	17	0.3	17	0.3	17	0.2	17	0.3	17	0.2
Norway	18	0.1	18	0.2	18	0.3	18	0.1	18	0.3	18	0.2
Total hectares	22,909,373		26,128,642		26,043,245		29,939,538		32,751,226		76,987,296	

The values relate to 2005–2015. Percentages are comparative contributions within, and total footprints for, the regions shown and not the total global deforestation footprint estimated. DeDuCE, Deforestation Driver and Carbon Emission model. Dominant drivers full consumption values are based on tree cover loss data that do not control for permanent deforestation. See Supplementary Note 1 for additional details.

Across deforestation approaches, the methods used to attribute impacts to production and to distribute the impacts downstream to consumption contribute to contrasting footprint results. The influence of deforestation quantification steps appears to be particularly influential in determining absolute footprint values. Differing approaches — although complicating intercomparisons — could offer alternative insights into the complex interplay between consumption and impacts on forests.

Supporting land-use governance

Overall, deforestation footprinting can help improve understanding of deforestation dynamics and responsibilities to support the complex task of effective land-use governance in a global context. Besides commodity producers, a multitude of supply chain actors, financiers, consumers, indigenous peoples, local communities and civil society organizations influence production activity protocols and the mitigation of environmental impacts[148]. Relevant parties geographically far from producer regions, who are under increasing pressure to respond to sustainability and human rights issues[28], take measures that then become intertwined with domestic land-use governance[149,150]. Despite progress in some areas, there has been mixed success of these commitments[28]. For example, deforestation rates in the Amazon dropped from historic highs in 2004 in response to improved law enforcement[151]. However, policy changes between 2012 and 2022 led to increases in deforestation rates, revealing substantial volatility in response to changes in domestic policies[8,151]. Likewise in Indonesia, palm oil-linked deforestation decreased between 2012 and 2020[152] — potentially in response to corporate and public zero-deforestation commitments, commodity prices, civil society pressure and forest scarcity[153] — but observations in 2023 indicate it is rising again[154].

Given the recognized role of forests in mitigating climate change[27], many demand-side actors have enhanced policy action to remove deforestation from their commodity supply chains[155]. For example, the EU has approved a Regulation on Deforestation-Free Products (EUDR)[156], whereby supply chain operators must demonstrate due diligence to ensure that their sourcing remains deforestation free. Similar legislation is being adopted in the UK[157], and might potentially be adopted by the USA[158]. Such policies have, at times, been accused of being discriminatory[159], poorly conceived[160] or invading producer national sovereignty[161]. However, these policies are unlikely to disappear and will remain an important component of the policy mix[162], making governance efforts for sustainable land use inherently complex.

Footprinting estimates and the underpinning datasets have informed and influenced the introduction and scope of environmental policies. For example, knowledge of the key drivers of deforestation and their link to the EU based on the land balance method[53] supported the inclusion of key commodities within the EUDR impact assessment[163]. Similarly, the GEIC indicator has been cited by the UK Government and non-government organizations responding to public consultation[164,165] during scoping of the UK's regulation[34]. The indicator itself emerged from recommendations from the UK's Global Resource Initiative[166,167], indicating that governance processes can guide and by guided by environmental footprinting. From the producer side, deforestation footprinting might help inform negotiations linked to compensation for biodiversity loss and damage[168,169] by identifying consumer nations who benefit from habitat destruction[168]. Identifying specific connections between places of production and consumption can also promote opportunities for multilateral dialogue[170], such as those linked to Target 16 of the Convention on Biological Diversity[171].

The EUDR has committed to a benchmarking process where the due diligence reporting requirements imposed on supply chain actors vary according to levels of perceived risk of deforestation occurring in countries of supply chain origin[172]. Authorities enforcing regulations nationally are also required to undertake risk-based checks[173]. Identification of commodity-linked deforestation hot spots, and potentially the specific commodity and derived-product supply chains involved[174], via footprinting can support such risk assessments. Introducing demand-side policy is coincident with commitments to monitor and review policy scope and effectiveness over time and, if necessary, adjust accordingly[175]. Changes in deforestation risk and downstream exposure can be captured within footprinting, allowing this information to support such monitoring. Information nested within footprint results can also shed light on direct and indirect of supply chain responsibilities[133] and the extent to which existing policy mechanisms are effective (Supplementary Note 7).

As footprinting has already informed policy development and review, it has been demonstrated as fit for purpose in providing an evidence base for identifying deforestation responsibility and guiding policy prioritization processes. Footprint methods scale from macroeconomic analyses, providing a global view of impacts, through to fine-scale footprinting (for example, Trase and TRACAST), which provide insight into specific supply chains, further illustrating their value to governance, as well as public and private sector actors. For example, global analyses can form the basis of indicator development for national-scale monitoring linked to policy[176], whereas finer-scale information can support assessments of national and regional exposure to specific deforestation frontiers[177].

Similarly, for companies trading materials with uncertain provenance[137], tools such as Trase have proven effective in informing deforestation risk profiles[178]. Global-scale deforestation footprint data can also guide investment. For example, global footprints have been applied in tools for financial institutions, who invest in activities that can be several steps removed from points of production[179].

Given that footprint estimates can be complicated by the varying and non-standardized methodologies involved, it is important that users of such datasets be aware of the associated uncertainties to ensure successful policy implementation[180]. Data availability problems dictate the use of limiting assumptions within footprint assessments, and geographic coverage of finer-resolution datasets remains constrained by the lack of detailed publicly accessible supply chain information[49,181]. Efforts to increase the availability and quality of information for use within trade-linked impact assessments need to ramp up both in production landscapes, such as global crop maps[38,182], and on the demand side, for example, filling gaps in trade data[183]. International programmes also provide important avenues for improvement. For example, the Forest, Agriculture and Commodity Trade Dialogue has a workstream promoting traceability and transparency in supply chains[184], as do activities such as the Forest Data Partnership[185].

Footprinting analyses are not without limitations, however. For example, data derived from trade modelling cannot replace geolocated traceability, as mandated as part of the EUDR's company-disclosure processes[186], which can identify supply chain connections to deforestation with higher granularity and confidence than model data[187–189]. Additionally, a consumption-based perspective is limited as not all deforestation results in productive output[12]. Speculative land clearing in response to market prices[42,190] can complicate attribution, as production might only be realized several years after initial market demand signals, or not at all[12]. Even where footprint methods partly

Table 2 | Attribution of deforestation impacts to domestic or overseas consumers

Nation/region of deforestation impact	FRA-based full consumption–Eora26 model (average 2010–2015)[a]			DeDuCE hybridized full consumption–GTAP-derived hybrid model (for 2014)[b]		
	Total annual deforestation estimate (kha^{-1})	Total exported deforestation (kha^{-1})	Percentage exported	Total annual deforestation estimate (kha^{-1})	Total exported deforestation (kha^{-1})	Percentage exported
Brazil	1,538	135	8.8%	1,405	340	24.2%
DR Congo	1,100	331	30.1%	542	18	3.4%
Indonesia	926	110	11.9%	772	437	56.6%
Angola	555	115	20.8%	69	12	17.9%
Paraguay	414	79	19.1%	303	80	26.4%
Tanzania	373	160	43.0%	67	20	30.4%
Cambodia	348	99	28.5%	63	22	34.3%
Myanmar	290	139	47.8%	110	64	57.7%
Argentina	223	65	29.0%	236	129	54.6%
Bolivia	212	41	19.5%	170	71	41.7%

[a]An approach[129] using United Nations Food and Agriculture Organization (FAO) Forest Resources Assessment (FRA) 2020 data combined with a monetary multiregional input–output, Eora26. [b]An approach using Deforestation Driver and Carbon Emission (DeDuCE) data combined with a hybrid physical–financial multiregional input–output based on the Global Trade Analysis Project data (GTAP)[126]. DR Congo, Democratic Republic of Congo. Only the ten top ranking nations/regions in terms of footprint according to approach[a] are shown. For additional details, see Supplementary Note 6.

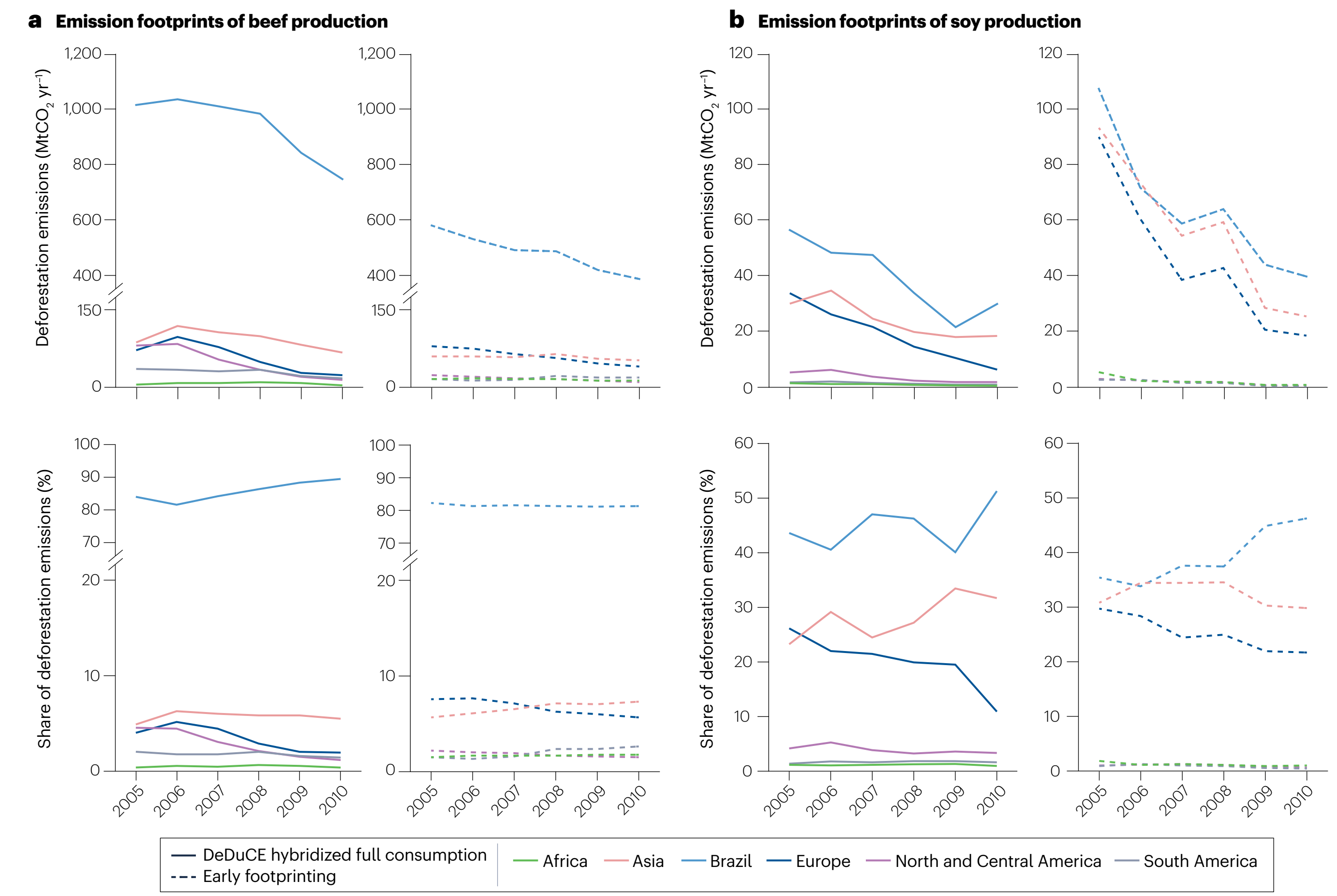

Fig. 4 | Emissions from deforestation attributed to soy and beef production in Brazil. a,**b**, Deforestation emissions from beef production (**a**) and soy production (**b**), each showing a comparison of results from the Deforestation Driver and Carbon Emission (DeDuCE) hybridized full consumption approach[104] (left) and an early footprinting approach[116] (right). The top row shows the distribution of the total deforestation emissions footprint across consumer regions and the bottom row shows the share of deforestation emissions across consumer regions. See Supplementary Note 3 for additional details. This comparison illustrates that differences between land-use models and how deforestation is allocated between commodity drivers can drive contrasting interpretations of deforestation drivers.

account for such effects by applying lags, such dynamics are highly simplified. Moreover, certain commodities can drive indirect land-use change, such as with soy and cattle production in Brazil. Domestically consumed beef places Brazil at the top in deforestation footprint rankings from 2005 onwards (Table 1), yet export-oriented soy expansion has contributed in driving pastures further into native ecosystems since the early 2000s[191,192].

Footprinting attributes forest loss specifically to economic sectors or products that operate as proximate drivers. Therefore, footprinting provides restricted insight into broader dynamics of land-use change or the appropriateness of land-use governance in deforestation hot spots[193–195]. Despite commodity-specific intervention being part of the broader governance challenge[196], failing to acknowledge the broader dynamics and solely focusing on a commodity can prevent progress beyond specific supply chains[197]. Relatedly, a nation or supply chain actor making changes to its sourcing regions to lower footprints might do little to affect overall rates of global deforestation as other consumers – including domestic markets – or other production systems may just be substituted. Ultimately, an over-focus on nation-specific commodity drivers is unlikely to achieve objectives to reduce deforestation across landscapes[198] owing to issues such as supply chain leakage[199,200].

Supply chain actors and policymakers have shown an appetite for footprint information and the associated insights on exposure and attribution that it can provide to inform and to help monitor zero-deforestation commitments. Alongside other datasets and information, and in a context where deforestation rates continue to be a critical barrier to sustainable development, there remains high potential for deforestation footprinting to promote and help deliver improved policy and practice.

Summary and future perspectives

Global analyses of deforestation footprints linking global forest loss to production, international trade and consumption are few in number.

Yet commodity-driven deforestation is a key driver of climate change and biodiversity loss. Despite methodological differences complicating comparisons and leading to variation in estimates, available footprints collectively highlight deforestation impacts driven by consumption. In some cases, for example, in Vietnam and China, growing footprints suggest a worsening challenge for global deforestation commitments[201] (Figs. 1 and 3c). Advances in deforestation footprinting owing to the use of near-time and high-resolution remote-sensing products[31,32] provide opportunities to more robustly and accurately identify deforestation drivers and hot spots, as well as to monitor landscape-scale changes and the impact of policy and regulatory shifts designed to reduce deforestation.

A fundamental limitation with deforestation footprints is data availability. Therefore, making additional data and the full underpinning datasets available would allow for more comprehensive comparison of approaches. Conducting deep intercomparisons of methods and results will enable better communications of their differences, enhance method development and increase confidence in the robustness of estimates. Such intercomparisons would enable the community to consolidate around methods and develop harmonized best practices that can help support and inform policy decisions. However, full methodological alignment is unwarranted as divergence in footprinting methods can shed light on different dynamics if methods are understood and communicated clearly.

Another priority is to reduce data gaps in forest management and commodity maps. Existing divergence in deforestation footprints partly results from varying assumptions driven by data gaps. For example, global maps of specific crops distributions are lacking[182], and footprinting efforts depend on coarse analyses of deforestation drivers, particularly in temperate regions[11]. Improved statistical methods to promote a finer-scale understanding of where crops are grown, as well as improved remote-sensing resources, are resource intensive. Therefore, improvements require substantial investment in data collection capacity and associated research methods.

Existing deforestation footprinting methods generally omit non-agricultural land-use dynamics, such as the impacts of selective logging, mining or aquaculture on forest loss. In addition, footprinting provides a relatively narrow commodity view, thus it is important to account for displacement of direct deforestation risk of a specific commodity that results from expansion of another production system elsewhere[202,203] or from land tenure issues[204,205]. For comprehensive deforestation footprints better able to guide policy, these impacts will need to be integrated and accounted for within agriculture-based footprint datasets. Increasing the geographic and commodity scope of subnational footprint estimates – which can capture the dynamics of deforestation and commodity expansion more granularly – can contribute to advanced understanding of the role of trade and consumption in shifting deforestation frontiers.

Another major priority relates to the social dimensions of land use. Emerging policies often include commitments to preserving the livelihoods of those supporting commodity supply chains[33] and whose marginalization would undermine sustainable development[206,207]. Frameworks to prevent deforestation also commonly include provisions for protecting human rights[208,209]. Yet analysis of social footprints remains a relatively underdeveloped area of research, with data availability constraints owing to their dependence on primary information that pertains to specific socioeconomic, governance and cultural circumstances in regions of production[210,211]. To overcome this gap, collaboration between researchers and potential data holders – such as public agencies or non-governmental organizations (NGOs) in high-deforestation-risk production regions – should be promoted to consolidate and integrate regional information on human rights grievances and other social impacts (positive or negative), with artificial intelligence providing potential opportunities to streamline complex data collection and analysis[212].

Clearly, data sharing and transparency across a range of datasets is core to multiple priorities in deforestation footprinting. Regulation to mandate transparency and data sharing (from public and private sectors) could be a valuable mechanism to further improve data quality and overcome persistent gaps. Policies such as the EU's Corporate Sustainability Due Diligence Directive require companies to report on how their operations impact human rights and the environment. If extended globally, such policies could transform the availability of global supply chain data suitable for integration into footprint assessments. As the role of footprinting in shaping or monitoring policy is limited by decision-maker confidence in the estimates, such regulatory data policies could provide a positive feedback loop boosting policymaker confidence in footprints.

Similarly, clearly communicating the results and methodological differences of different footprinting approaches is key to optimizing their role in supporting deforestation policy. Data analysis capacity within decision-making bodies can be low[186,213], therefore effective and targeted communication of footprint data is critical. For example, the dominant driver analysis[39] achieved strong uptake in the media[214,215], facilitated by translation of data into the accessible number of trees lost metric. Interactive dashboards (such as those of the GEIC indicator[126] or for city-scale footprints[216]) can also enhance accessibility and facilitate public and policy engagement. Likewise, data platforms and accompanying insights from Trase have helped NGO organizations hold governments and supply chain actors to account over their connection to deforestation activities[217,218]. Enhanced attention on knowledge translation is fundamental to ensure that footprinting supports global policies to tackle deforestation through identifying the drivers, challenges and solutions to deforestation.

Deforestation footprinting should also aim to co-evolve with relevant environmental policies. For example, broadened definitions of deforestation would allow for inclusion of other wooded lands, such as more sparsely wooded landscapes in the Brazilian Cerrado[219], as proposed in the EUDR review process[175] and advocated by NGOs[220], entailing broader land-use classification data[221]. Similarly, accounting for ecological qualities of varying habitat types[222] could further support development and application of biodiversity footprint metrics[223,224]. Ultimately, if policy adapts to apply broadened definitions of vegetation coverage (or by putting more emphasis on forest degradation[225] or forest ecosystem services[226], such as the water cycle[227]), then metrics based on forest loss alone might become insufficient, and further developments in footprinting methods will be needed to support such improved actions.

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