Agricultural and forestry trade drives large share of tropical deforestation emissions

Abstract

Deforestation, the second largest source of anthropogenic greenhouse gas emissions, is largely driven by expanding forestry and agriculture. However, despite agricultural expansion being increasingly driven by foreign demand, the links between deforestation and foreign demand for agricultural commodities have only been partially mapped. Here we present a pan-tropical quantification of carbon emissions from deforestation associated with the expansion of agriculture and forest plantations, and trace embodied emissions through global supply chains to consumers. We find that in the period 2010–2014, expansion of agriculture and tree plantations into forests across the tropics was associated with net emissions of approximately 2.6 gigatonnes carbon dioxide per year. Cattle and oilseed products account for over half of these emissions. Europe and China are major importers, and for many developed countries, deforestation emissions embodied in imports rival or exceed emissions from domestic agriculture. Depending on the trade model used, 29–39% of deforestation-related emissions were driven by international trade. This is substantially higher than the share of fossil carbon emissions embodied in trade, indicating that efforts to reduce greenhouse gas emissions from land-use change need to consider the role of international demand in driving deforestation. Additionally, we find that deforestation emissions are similar to, or larger than, other emissions in the carbon footprint of key forest-risk commodities. Similarly, deforestation emissions constitute a substantial share (~15%) of the total carbon footprint of food consumption in EU countries. This highlights the need for consumption-based accounts to include emissions from deforestation, and for the implementation of policy measures that cross these international supply-chains if deforestation emissions are to be effectively reduced.

Keywords: Deforestation, carbon emissions, international trade, agriculture, forestry, carbon footprints

1. Introduction

There is increasing recognition that to effectively reduce environmental impacts, pressure must be alleviated not only at the point where environmental impacts occur, but also by addressing the broader socio-economic drivers of those impacts, which are often distant (Liu et al., 2015, Geist and Lambin, 2002, Kanemoto et al., 2014). For instance, foreign demand has already been shown to be a major driver of carbon emissions from fossil fuel combustion (Davis and Caldeira, 2010, Peters et al., 2011, Peters et al., 2012) and air pollution (Kanemoto et al., 2014), particularly for the developing world, as well as a driver of land use (Weinzettel et al., 2013), forestry (Kastner et al., 2011a), water extraction (Hoekstra and Mekonnen, 2012), and biomass consumption (Erb et al., 2009).

However, despite the fact that tropical deforestation—the second largest source of anthropogenic greenhouse gas emissions (van der Werf et al., 2009, Smith et al., 2014) and a major driver of biodiversity loss (Maxwell et al., 2016, Tilman et al., 2017)—is increasingly driven by international demand for agricultural commodities (DeFries et al., 2010), up-to-date, comprehensive (pan-tropical) assessments of embodied emissions from deforestation are still lacking. Existing studies analysing deforestation emissions embodied in trade have either considered only a handful of countries (Saikku et al., 2012, Karstensen et al., 2013, Henders et al., 2015), or are based on outdated data on deforestation and carbon stocks (European Commission, 2013, Sandström et al., 2018) that do not draw on recent advances in remote sensing estimates of both forest loss and associated carbon emission (Baccini et al., 2017). A better understanding of the links between trade and deforestation could support recent efforts to rid supply chains from deforestation, as encompassed, for example, by the goals of the Tropical Forest Alliance 2020 and the New York Declaration on Forests (Lambin et al., 2018), as well as the UN Sustainable Development Goals (SDGs) which aspire to halt deforestation by 2020 (target 15.1).

Here we attribute emissions associated with forest loss to the primary drivers of deforestation (Geist and Lambin, 2002, Hosonuma et al., 2012) across the tropics: expanding cropland, pasture and plantation (henceforth we label this forest loss as deforestation, even if e.g. oil palm or short-rotation tree plantations may still technically be classified as forests). The analysis is based on state-of-the-art spatial datasets on tree cover loss (Hansen et al., 2013) and forest carbon stocks (Zarin et al., 2016). We exclude emissions associated with logging and other selective biomass extraction, but include those from peatland drainage. We allocate emissions to 10 commodity groups (including all crops covered by FAOSTAT (FAO, 2017), plus cattle meat, and forestry products), and go beyond most previous studies by covering 106 countries across the tropics and sub-tropics. Additionally, for Brazil and Indonesia—the two countries dominating tropical forest loss in 2001–2014 (together they account for 40% of total tropical forest loss) (Hansen et al., 2013)—the analysis is done at subnational level

(557 Brazilian micro-regions and 34 Indonesian provinces). We then trace those embodied emissions through international supply chains to countries of consumption using two different models: a physical-based bilateral trade-model (Kastner et al., 2011b) and an economic multi-regional input-output model (Stadler et al., 2018).

2. Methods

The analysis linking deforestation to agricultural and forestry production, trade and consumption is carried out in three steps: (1) attributing detected deforestation to expanding land uses (cropland, pastures and forest plantations) and associated commodity production, (2) quantifying the carbon emissions resulting from the land-cover changes by estimating net carbon stock changes in above-ground biomass, below-ground biomass and soil organic carbon, as well as emissions from peatland drainage, and finally, (3) using international trade models to assess the flows of embodied emissions to countries of consumption (Fig. A.1). The first two steps employ a methodology for calculating land-use change carbon footprints developed proposed by Persson et al. (2014b), using a simple land-balance model that attributes forest loss to major land uses and crop groups across the tropics (Pendrill et al., 2019). For the third step we use two complementary models: (a) a physical trade (PT) model based on bilateral trade data (Kastner et al., 2011b) that provides an understanding of the physical, country-to-country linkages between deforestation, production and trade in agricultural commodities, and (b) a new version of the environmentally-extended multi-regional input output model (MRIO) EXIOBASE3 (Stadler et al., 2018, Wood et al., 2015), that also accounts for indirect linkages between deforestation and consumption throughout the whole economy.

2.1. Attribution of deforestation

Ideally, attribution of forest loss and associated carbon emissions to agricultural and forestry production would be based on spatially explicit (e.g., remotely-sensed) data. However, existing spatial analyses of land cover and use following forest loss in the tropics are limited both geographically (continental-scale analyses only available for tropical Americas (De Sy et al., 2015, Graesser et al., 2015)) and temporally. Although pan-tropical data on forest loss (Hansen et al., 2013, Kim et al., 2014, Curtis et al., 2018) and land cover exist (Congalton et al., 2014, Gómez et al., 2016), quality and consistency of land classifications across datasets is still too poor for combining these to sufficiently assess post-forest land use with sufficient discrimination between pastures and cropland (Pendrill and Persson, 2017).

Here we therefore use a simple land balance model—encompassing cropland, pastures, forest plantations and other land uses—to attribute detected forest loss (Hansen et al., 2013) to agricultural and forestry commodities on national level. For Brazil and Indonesia, the same model is applied at the sub-national level. The model is based on the premises that where there is detected forest loss, (1) if cropland is expanding, it first expands into pastures (if there is a gross loss of pasture area) and then into forests, and (2) if pastures and forest plantation areas are expanding, they are replacing forest land. While these assumptions are simplifications that do not describe all possible land-use transitions, they reflect the predominant land-use transitions related to tropical deforestation: forests and other native vegetation (e.g., woodlands and shrublands) are the main sources of new agricultural land in the tropics (Gibbs et al., 2010), but cropland expansion also occurs on former pastureland (the latter is primarily evident in Latin America (Gibbs et al., 2010, Graesser et al., 2015); this is also evident in our data, and the results for tropical Africa and Asia are less affected by this assumption).

Formally, detected forest loss area (Hansen et al., 2013), ΔF_t, in a given year (t) is attributed to expanding cropland ($\Delta F_{CL,t}$), permanent pasture ($\Delta F_{PP,t}$), and forest plantations ($\Delta F_{FP,t}$) according to:

$$\Delta F_{CL,t} = \mathrm{MIN}\left[\mathrm{MAX}[CLE_t - GPL_t;0];\Delta F_t \cdot \frac{\mathrm{MAX}[CLE_{Lt}-GPL_t;0]}{\mathrm{MAX}[CLE_t-GPL_t;0]+PPE_t+FPE_t}\right], \quad (1)$$

$$\Delta F_{PP,t} = \mathrm{MIN}\left[PPE_t;\Delta F_t \cdot \frac{PPE_t}{\mathrm{MAX}[CLE_t-GPL_t;0]+PPE_t+FPE_t}\right], \quad (2)$$

$$\Delta F_{FP,t} = \mathrm{MIN}\left[FPE_t;\Delta F_t \cdot \frac{FPE_t}{\mathrm{MAX}[CLE_t-GPL_t;0]+PPE_t+FPE_t}\right], \quad (3)$$

where CLE_t, PPE_t, FPE_t denotes expansion of cropland, permanent pastures and forest plantations, respectively (i.e., where these land classes are shrinking, these variables are zero), and GPL_t denotes gross pasture loss (all expressed in hectares).

In words, Eq. 1–3 attributes forest loss to cropland, pasture and forest plantations in proportion to their relative area expansion, capped at total forest loss area. More specifically, if detected forest loss exceeds (or equals) the expansion of cropland, pastures and forest plantations, the deforestation attributed to each land use will be the full amount of their respective expansion, and any forest loss exceeding the expansion of these land uses is left "unattributed" (i.e. due to causes not identified here). If detected forest loss area is lower than the total expansion of cropland, pastures and forest plantations (the denominator in Eq. 1–3), the total area attributed to the expanding land uses is capped at total detected forest loss area, attributing all (but never more than) detected forest loss to cropland, pastures and forest plantations in proportion to their relative area expansion.

Forest loss attributed to cropland expansion ($\Delta F_{CL,t}$) is further allocated to the eight crop groups (paddy rice; wheat; other cereal grains; vegetables, fruits and nuts; oil seeds; sugar; plant-based fibres; other crops; following EXIOBASE sectors, see Table A.1) based on the expansion of each crop group i ($CGE_{i,t}$) (in ha) relative to the other crop groups according to

$$\Delta F_{CL,i,t} = \Delta F_{CL,t} \cdot CGE_{i,t} / \sum_i CGE_{i,t}. \quad (4)$$

Thus, land uses and associated commodities that are not expanding during the time period considered will not be attributed any forest loss nor any concomitant emissions.

Given that the attribution of forest loss estimated by Eq. 1–4 is non-spatial, with data aggregated at national level, it will mix direct and indirect drivers (i.e., direct expansion of a land use or crop onto previous forest land, or expansion onto another land use or crop that pushes that land use onto forest land, directly or through substitution of subsequent land uses). We reduce this problem for the common land-use transition (in tropical America) of cropland expanding into pastures, indirectly pushing cattle ranchers into forest frontiers (Barona et al., 2010, Graesser et al., 2015), by assuming cropland first expands on pastures.

The mixing of direct and indirect drivers is also likely to be more prevalent the larger the spatial unit at which Eq. 1–4 is evaluated. Therefore, conducting the analysis as sub-national instead of national level yields better results. While data availability makes this a challenge to accomplish globally, we perform subnational analyses for Brazil and Indonesia, as they are two of the largest countries in our sample and account for 40% of the forest loss in the period analysed. We carry out this analysis at micro-region (n=557) and province (n=34) level, respectively.

Because we focus on expanding land uses, this attribution method does not capture areas where forests were cleared for timber without subsequent establishment of cropland, pastures or plantations. As this can be an important driver of forest loss in some countries (especially in Southeast Asia (Henders et al., 2015)), it will lead to an underestimation of the emissions attributed to forestry products (here capturing only those resulting from expanding plantations), but the lack of a land use following forest loss makes logging in natural forests much harder to quantify, resulting in high uncertainties (Henders et al., 2015).

2.2. Forest loss and deforestation for cropland, pasture, plantations and crops: definitions & data

Here we use the term deforestation to refer to forest loss attributed to the expansion of cropland, pasture or plantations (i.e., $\Delta F_{CL,t}$, $\Delta F_{PP,t}$, and $\Delta F_{FP,t}$). Forest loss (ΔF_t), on the other hand, is defined as complete removal of tree cover exceeding 5 m height and 25% canopy cover (in year 2000), and ideally not within tree plantations. Forest loss data (2001–2014) were taken from updates of Hansen et al. (2013), which include not only loss of primary forests and secondary vegetation, but also harvesting of planted forests, so where tree plantations occupy large areas, this may overestimate carbon losses. For Indonesia and Malaysia, we therefore only consider forest loss outside tree plantations using spatial data on tree plantation extent (Petersen et al., 2016).

National level data on net changes in cropland and pasture areas in 2000–2014 are taken from FAOSTAT (FAO, 2017), using the categories 'Arable land and permanent crops' and 'Permanent meadows and pastures'. These net changes will not entirely capture where gross expansion caused forest loss (e.g., in shifting cultivation, or where loss in one place— e.g., due to urbanization or cropland degradation—is supplanted by expansion elsewhere). Hence, we estimate gross expansion of pasture (PPE_t) and cropland (CLE_t) area by adding estimates of gross losses of grasslands (assumed to approximate pasture loss; discussed further in A1. Supplementary Methods) and cropland from remote sensing data (Li et al., 2018) respectively to the net changes from the FAOSTAT data.

The sub-attribution of cropland deforestation to the eight aggregated crop groups ($\Delta F_{CL,i,t}$) is based on harvested area data from FAOSTAT (FAO, 2017). In line with the approach of Opio et al. (2013), we assume that pasture expansion into forests is primarily for extensive cattle grazing for meat production (and not dairy products), and hence allocate all associated carbon emissions to cattle meat.

National level data on forest plantations are also from FAO (2016). These data are only available in 5-year intervals (2000, 2005, 2010, and 2015) and thus interpolated to create an annual time-series. As there is no data on gross loss of forest plantation area, we only assess net area changes.

Sub-national agricultural and forest plantation statistics were taken from the Brazilian Institute of Geography and Statistics (IBGE, 2018, IBGE, 2015) and the Brazilian Tree Industry (IBA and ABRAF, 2015) for Brazil, and from the Ministry of Agriculture (Republic of Indonesia Ministry of Agriculture, 2017) and Ministry of Forestry (Dermawan, 2017) for Indonesia (see A1. Supplementary Methods for details).

All changes in cropland, crop group, pasture and forest plantation areas were averaged over the three years following the forest loss, implying that forest loss is attributed to an expanding land-use if expansion occurs within a maximum three years following deforestation (Gibbs et al., 2015). To account for this time-lag (and for an amortization time, see below), the input data on land-use change needs to pre-date (and cover) the study time period. The availability of the input data thus constrained to study time period to 2010–2014.

2.3. Carbon emissions

Carbon emissions were estimated by quantifying changes to carbon stocks as a result of forest loss and the subsequent land use, considering changes in three carbon reservoirs: above-ground biomass (AGB), below-ground biomass (BGB) and soil organic carbon (SOC). We also estimate carbon emissions resulting from peatland drainage (see section 2.4).

Loss of AGB carbon was estimated in a spatially-explicit manner, combing forest loss (2001–2014) data (Hansen et al., 2013) with a co-located dataset on AGB carbon stocks (Zarin et al., 2016) prior to forest loss (year 2000), both based on satellite remote sensing techniques. AGB carbon loss was evaluated for each 30-m pixel, and subsequently summarised per country (micro-region and province for Brazil and Indonesia, respectively). Note that this approach allocates the entire loss of carbon stock in each forest loss pixel to the forest loss event, implying that where there have been carbon losses due to forest degradation (e.g. through selective logging) after 2000, our approach may overestimate the carbon emissions attributed to agriculture and forest plantations.

Estimates of the impact of land-use change on BGB are uncertain, and most studies rely on assuming a ratio between BGB and AGB to estimate the total carbon stocks in BGB (Mokany et al., 2006). The ratio used here is vegetation-type specific, varying between 0.20 and 1.06 (depending on AGB and the FAO global ecological zone (FAO, 2012) of the forest land), following 2006 IPCC Guidelines (IPCC, 2006) and Mokany et al. (2006). The gross losses of AGB and BGB were attributed to commodity groups based on the share of total deforestation associated with each group (i.e., a commodity attributed 10% of total deforestation area is attributed 10% of total gross carbon losses).

Stocks of AGB and BGB for the land uses replacing forests were based on existing literature. We accounted for differences in carbon stocks between different crops in the EXIOBASE crop groups by splitting them into subcategories with similar carbon content, primarily distinguishing between annual and perennial (tree) crops (see Table A.7 for details and references).

Finally, to approximate SOC stock changes associated with the land-use transitions, we used estimate SOC loss values from a meta-analysis specific to the tropics (Don et al., 2011) (Table A.7).

2.4 Emissions from peatland drainage

For all countries but Indonesia (which accounts for nearly two-thirds of tropical peatland carbon (Page et al., 2011)), estimates of carbon emissions from peatland drainage are based on Joosten (Joosten, 2010), providing country-level data on carbon emission from peatlands drained for agriculture and forestry for the years 1990 and 2008. We use Joosten's emissions factors to convert emissions to area peatland drained, interpolating the data between 1990 and 2008. We extrapolate the area up to 2014 based on expansion of agricultural land and forest plantations (i.e., assuming that the share of cropland and forest plantations that are on drained peatlands is constant) and subdivide the cropland area on peat by the crop categories in proportion to their harvested area, all based on data from FAOSTAT (FAO, 2017). Finally, we estimate carbon emissions from drainage by commodity group using the IPCC emission factors (Drösler et al., 2014) for tropical 'long-rotation plantations' (forestry), 'paddy rice', 'oil palm', and 'cropland and fallow' (all other crops). The IPCC emission factors do not include the potentially high emissions from drainage in the first five years after forest clearing, so we estimate these separately, based on data from Hooijer et al. (2012).

Our estimates for Indonesia are primarily based on data from Miettinen et al. (2016), which provide province-level, time-series (1990, 2007, 2015) data on peatland area under smallholder-dominated cultivation and industrial plantations on Sumatra and Kalimantan. This is supplemented by data for Papua (accounting for ~40% of Indonesian peatland area) from Hooijer et al. (2010) for the year 2000. We adjust the smallholder area from Hooijer et al. (2010) downwards so that it matches with data from Miettinen et al. (2016) where they overlap, as Hooijer et al. (2010) label all land classified as mosaics of tree cover, other natural vegetation, and croplands as smallholder area. Data from Miettinen et al. (2016) are interpolated to yield an annual time-series, and for Papua (where expansion of cropland and plantations has been more limited than on Sumatra and Kalimantan) drained peatland area is conservatively estimated to be constant between 2000 and 2014. Again, cropland area is subdivided by crop group based on harvested area by province (Republic of Indonesia Ministry of Agriculture, 2017) and carbon emission are estimated using the same emission factors as for the pan-tropical analysis.

A comparison between carbon emissions from peatland drainage estimated here and in previous studies can be found in Table A.8.

2.5 Calculating land-use change carbon footprints

Given that land-use change is a one-time event (to which we here assign the AGB, BGB and SOC carbon-stock change emissions), but commodities flow from the cleared land over time, we amortized (uniformly distributed) the estimated carbon emissions over a period of 10 years, giving us a time-series of total carbon emissions attributed to each of the 10 commodity groups for the years 2010–2014. The amortization period is not intended to represent when the emissions to the atmosphere occur, but rather to distribute responsibility for the emissions based on an (highly simplified) assumption that expansion of the land use is done with an anticipation of 10 years of production. In practice, however, there is large variation and uncertainty in this and the deforested land may in theory be used indefinitely, so the choice of amortization period is ultimately arbitrary (Persson et al., 2014a, Ponsioen and Blonk, 2012, Cederberg et al., 2011, Hörtenhuber et al., 2014). However, results for 1 and 5 years amortization are similar (Table A.2).

To then trace the emissions through international trade to consumers and to estimate carbon footprints per commodity and consumer country, total emissions (AGB, BGB, SOC and peatland drainage emissions) attributed to each commodity group were averaged over the total production in that year (expressed in dollars for the MRIO, and in tonnes, taken from FAOSTAT (FAO, 2017), for the PT model and carbon footprints; i.e., assuming homogenous emissions for all products within the same commodity group and country). This implies that the results cannot be directly used to infer emissions resulting from changes in demand for a given commodity (i.e., are analysis follows an attributional life cycle assessment (LCA) approach, rather than a consequential LCA modelling approach).

2.6. Trade models

Building on recent discussions on model choice in assessments of environmental impacts embodied in trade for different applications (Hubacek and Feng, 2016, Kastner et al., 2014b, Bruckner et al., 2015), we use two conceptually different trade models that provide complementary perspectives: (1) a physical trade model of country-to-country trade flows in the agriculture and forestry sectors, and (2) a global multi-regional input-output (MRIO) model that covers all sectors of the economy, albeit with more coarser regional and commodity resolution.

The two models differ both in what is tracked (physical quantities versus monetary flows) and in what they consider as the end-user. The physical trade model used here traces products to where they are physically consumed, either as food or in industrial processes (except for livestock feed, which is further followed indirectly through traded animal products) (Kastner et al., 2014a). The MRIO further follows indirect monetary trade flows through multi-stage supply chains and economic sectors all the way to final consumption, including further food processing, manufacturing and services (Stadler et al., 2018, Wood et al., 2015).

The trade approaches were both used to provide annual data on trade flows 2010–2014, and the same 10 commodity groups were traced with both approaches. The PT model encompasses trade between 191 countries, and the MRIO between 44 countries and 5 rest-of-the-world regions. Results from both trade approaches are presented below, typically by indicating a range (the lower value is from the physical trade model and the higher value from the MRIO).

The physical trade analysis relies on production data for 130 crop commodities, 7 primary livestock products and industrial roundwood, as well as bilateral trade data of ~400 primary and processed agricultural and forestry products obtained from the FAO's statistical database FAOSTAT (FAO, 2017). The calculations aim to track the products along supply chains, including re-exports and basic processing, up to the point where they are physically consumed, either as food, as is the case for ~90% of the included agricultural products, or in industrial processes. The use of crop products as livestock feed is an exception, here indirect trade via feed crops embodied in traded animal products is considered (Kastner et al., 2014a). The level of processing covered in the database excludes highly processed products; for instance, trade in macaroni is included, trade in frozen pizzas is not. The included processed products are translated into primary commodity equivalents based on their carbon content. The primary equivalent data are then arranged into a matrix where each cell corresponds to a trade flow from country A to country B. Along with information on country-level production of primary items, these data are used to create production-consumption links between countries. For methodological details and mathematical formalization we refer to the original publications (Kastner et al., 2014a, Kastner et al., 2011b).

MRIOs are an increasingly popular tool for consumption-based accounting (Wiedmann and Barrett, 2013, Kitzes, 2013), and in this work, we use the EXIOBASE 3 dataset (Stadler et al., 2018, Wood et al., 2015). For tracing deforestation-related emissions through trade in agricultural commodities, EXIOBASE has an advantage compared to other MRIO databases (Tukker et al., 2013) in that it has, (a) a consistent detailed representation of the agricultural and food manufacturing sector, (b) country detail for the most important countries (Brazil, Indonesia), and, (c) annual estimates for the time period 2010–2014. Other MRIO databases such as Eora have more individual countries represented, but lack the agricultural sector resolution, whilst GTAP is only available for a few years (Tukker and Dietzenbacher, 2013).

EXIOBASE is based upon national level supply and use tables for individual EU countries and 15 other major economies. Full global coverage is achieved with estimates for 5 other rest of world regions (Stadler et al., 2014). Individual country tables are disaggregated into 200 products based upon detailed agricultural, energy and trade statistics (Wood et al., 2014) and then trade-linked using data reconciliation methods applied to bilateral trade data (Gaulier and Zignago, 2010). EXIOBASE provides a harmonized time series of MRIO tables from 1995 to 2015; here we use the data for 2010–2014. Agricultural production is broken down into 15 product groups, further resolved downstream into 12 manufacturing product groups related to food. Here we attribute deforestation to production for 10 of these product groups (cattle meat, forestry products and eight crop groups including plant-based fibres); for consumption we consider all product groups (not limited to agricultural production). Information on product resolution is provided in Table A.1.

3. Results

For the period 2010–2014, we estimate net emissions of 2.6 gigatonnes of carbon dioxide ($GtCO_2$) yr^{-1} due to deforestation associated to the expansion of croplands, pastures and forestry plantations in the tropics (Appendix B, temporal trends shown in Fig. A.2). The main commodity groups associated with these emissions were cattle meat (0.9 $GtCO_2$ yr^{-1}) and oilseed products (including both palm oil and soybeans; 0.6 $GtCO_2$ yr^{-1}) (Fig. 1). There are large geographic variations in what commodities are associated with deforestation-related emissions (Fig. 1; Fig. A.3). In Latin America, cattle meat is the dominant contributor (0.8 $GtCO_2$ yr^{-1}), mainly attributed to Brazilian production. In Indonesia almost half of the emissions (0.3 $GtCO_2$ yr^{-1}) come from oilseeds (mainly oil palm). In the rest of Asia-Pacific and Africa, a more diverse mix of commodities drives emissions from deforestation. A fifth to a quarter of the total embodied emissions (0.5–0.7 $GtCO_2$ yr^{-1}) related to deforestation are due to peatland drainage, most of which occurs in Indonesia (0.3–0.4 $GtCO_2$ yr^{-1}) (Fig. A.4).

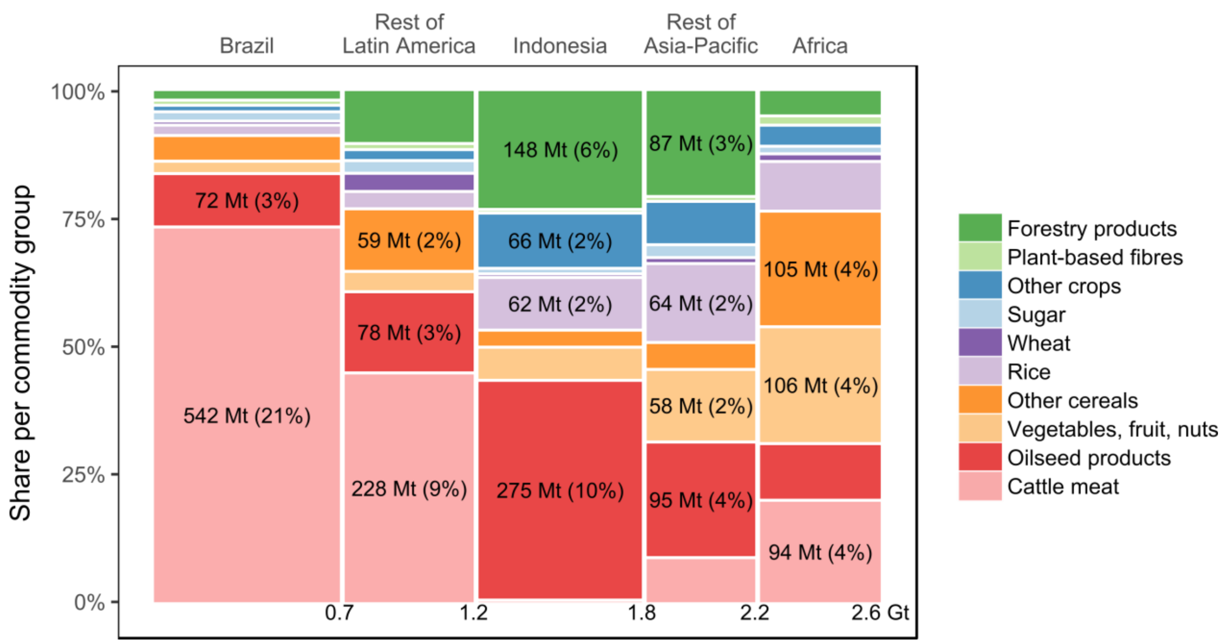

Fig. 1. Emissions sources for deforestation-related carbon dioxide emissions are diverse and vary by region. Emissions embodied in production are quantified for each commodity group within each country (here summarised by region). A region's width on the x-axis corresponds to the embodied emissions produced in that region, while the y-axis shows the share of emission attributed to each commodity group within each region, implying that the rectangles within the plot are scaled according to the emissions embodied in each region-commodity combination. The percentages within the rectangles indicate the share of the total (2.6 $GtCO_2$ yr^{-1}) embodied emissions. For forestry products, the results show emissions associated with tree-plantation expansion, but not emissions due to clearing purely for timber without subsequent land-use expansion.

3.1. International trade

A significant part of the embodied emissions is attributed to commodities consumed internationally (Figs. 2b, 3, Figs. A.5, A.6, Appendix C, D). Looking at physical trade flows in the PT model, 29%

(0.8 $GtCO_2$ yr^{-1}) of emissions embodied in production were attributed to exports. In the MRIO model, this share increased to 39% (1.0 $GtCO_2$ yr^{-1}), as indirect links between economic sectors (where the commodities serve as inputs) are considered. This is a substantially larger share than those found by MRIO studies looking at embodied land footprint (24%, Weinzettel et al. (2013) with high country resolution; 15-20%, with EXIOBASE country resolution (Wood et al., 2018)), and harvested area (20%, MacDonald et al. (2015)), as well as the share of fossil fuel emissions embodied in traded goods (23–26%, Peters et al. (2011), Davis and Caldeira (2010); 20-24%, with EXIOBASE country resolution (Wood et al., 2018)). The share found with the PT model is also somewhat larger than that found for cropland area (21%) with a physical trade approach (Kastner et al., 2014a). The importance of trade is further pronounced if one excludes cattle meat, which is primarily consumed domestically (the export share averaging 10–22%), with the export share rising to 38–48% (from the PT and MRIO model, respectively).

The exported share of embodied emissions varies considerably by commodity and country (Fig. 2). Latin America exports 23–34% of its emissions, though the difference between the two main drivers, cattle meat (11–21%) and oilseeds (71–89%), is large. The Asia-Pacific region exports a higher share (44–49%), and Africa a lower share (9–32%). Oilseeds are produced primarily for export, with 62–76% of embodied emissions exported, mostly from Asia-Pacific and Latin America to Europe, China and the Middle East (Fig. 3, Fig. A.6). The same holds for the “other crops” commodity group, which includes high-value crops such as cocoa, coffee, tea, and spices, with an export share of 68–75%.

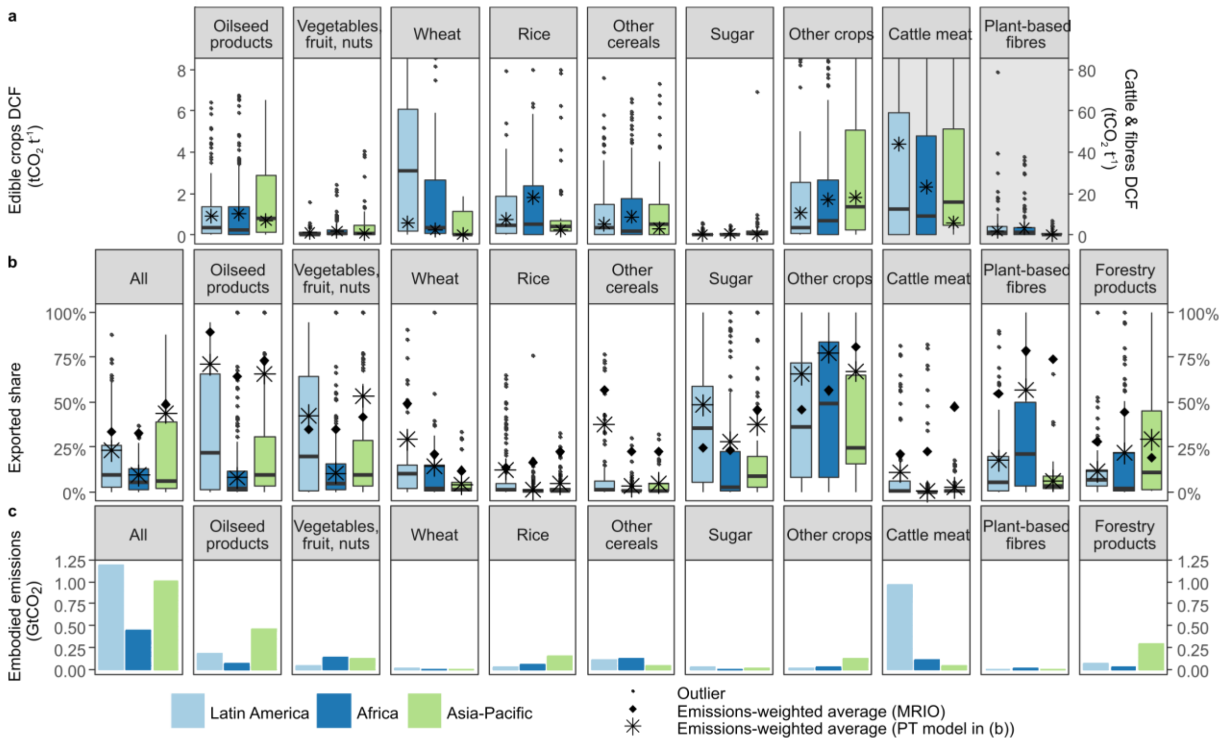

Fig. 2. Country level distribution, by producer region and commodity group, of (2a) deforestation carbon footprints (DCF), expressed in tonnes of carbon dioxide per tonne of product, and (2b) share of carbon emissions embodied in production that is exported, as well as (2c) total absolute amount of carbon emissions from deforestation embodied in production (i.e., both for domestic and export demand), expressed in gigatonnes of carbon dioxide attributed to the production each year. The boxplots (a,b; based on country-year values within each region) represent the median, first and third quartiles, the whiskers show the maximum and minimum values (though extend no further than 1.5 times the interquartile range), and points indicate outliers. Note the different axis scales in (a): carbon footprints for edible crops are shown using the left axis, whereas cattle meat and plant-based fibres (indicated by grey shading) are shown using the right axis. In (a), the y-axis has been truncated to enable presentation, thus excluding several outliers and part of the whiskers. There are large variations between countries and commodity groups in terms of deforestation related carbon footprints, exported shares and embedded emissions. For example, some crops are primarily for export (such as oilseed products and other crops), while others (such as cattle meat) are primarily for domestic consumption.

The largest individual country-to-country physical trade flows make up a disproportionately large part of the embodied emissions (Fig. 3c). The top three alone – all involving exports of oilseeds to India and China – together amount for one eighth of traded emissions (and 3–5% of the total emissions attributed to the production of agricultural and forest plantation products).

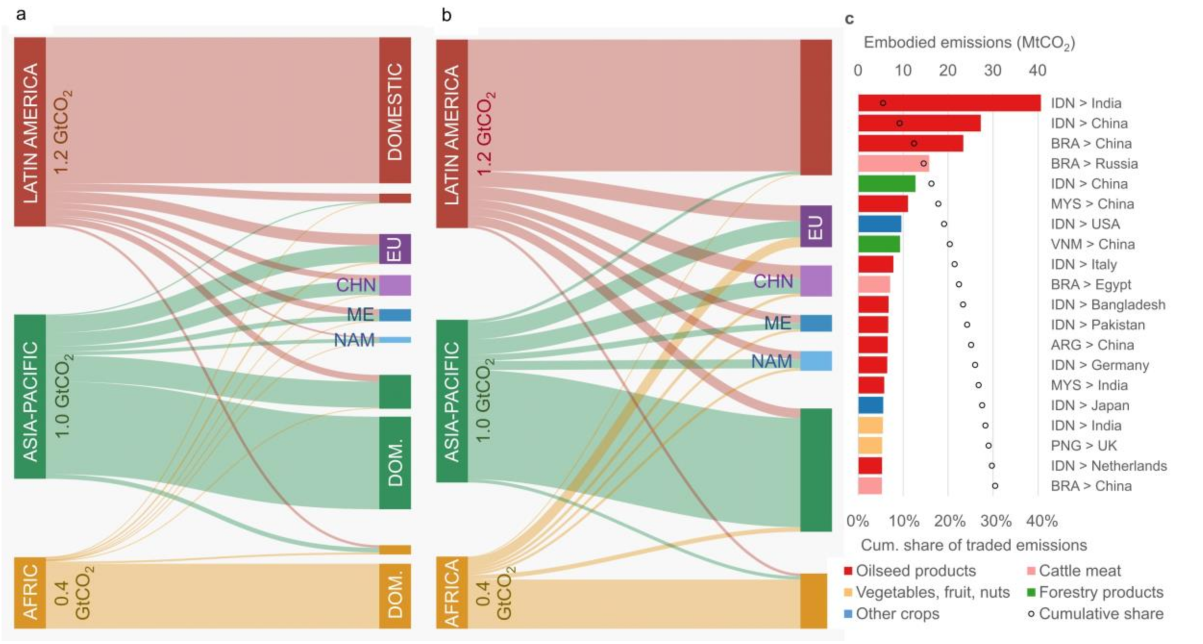

Fig. 3. Trade flows of embodied emissions from deforestation. (a, b) Trade flows of embodied carbon emissions from region of production to region of consumption (left to right), for the (a) physical trade (PT) model and (b) multi-regional input output (MRIO) model. Region abbreviations: EU – Europe, CHN – China, ME – Middle East, NAM – North America. In (a), DOMESTIC (or DOM.) indicates embodied emissions consumed domestically (in the same country as they are produced). In (b), domestic flows are not distinguished due to the regional aggregation, therefore flows from e.g., Asia-Pacific to Asia-Pacific represents both domestic consumption and trade between countries in the region. (c) The 20 largest individual country-to-country physical trade flows of the PT model (bars) together account for 30% of emissions embodied in international trade (dots show the cumulative share of traded emissions; source country codes: IDN – Indonesia, BRA – Brazil, MYS – Malaysia, VNM – Vietnam, ARG – Argentina, PNG – Papua New Guinea).

3.2. Consumption emissions and carbon footprints - comparisons

In relation to consumption-based accounting, we compared Annex-I countries' imports of embodied emissions from deforestation to national agricultural emissions (United Nations Framework Convention on Climate Change (UNFCCC), 2014), including all anthropogenic emissions from agricultural sources within the national territory, such as enteric fermentation, manure, and synthetic fertilizers, but excluding land-use change emissions and fuel combustion (IPCC, 2006). On average, we find that deforestation emissions embodied in imports amount to 17–31% of national agricultural emissions (0.25–0.42 $GtCO_2$ yr^{-1} imported, compared to 1.45 $GtCO_2e$ yr^{-1} national emissions for year 2012) (Fig. 4). For just over one third of the Annex-I countries, imported emissions due to deforestation (as estimated by the MRIO) amount to more than half of the national agricultural emissions and for some (Malta, Japan, Luxemburg, and Belgium) imported emissions exceed national agriculture emissions. This indicates that transfers of deforestation-related emissions through international trade are not negligible, and should be considered by countries in addition to emissions within their national territory.

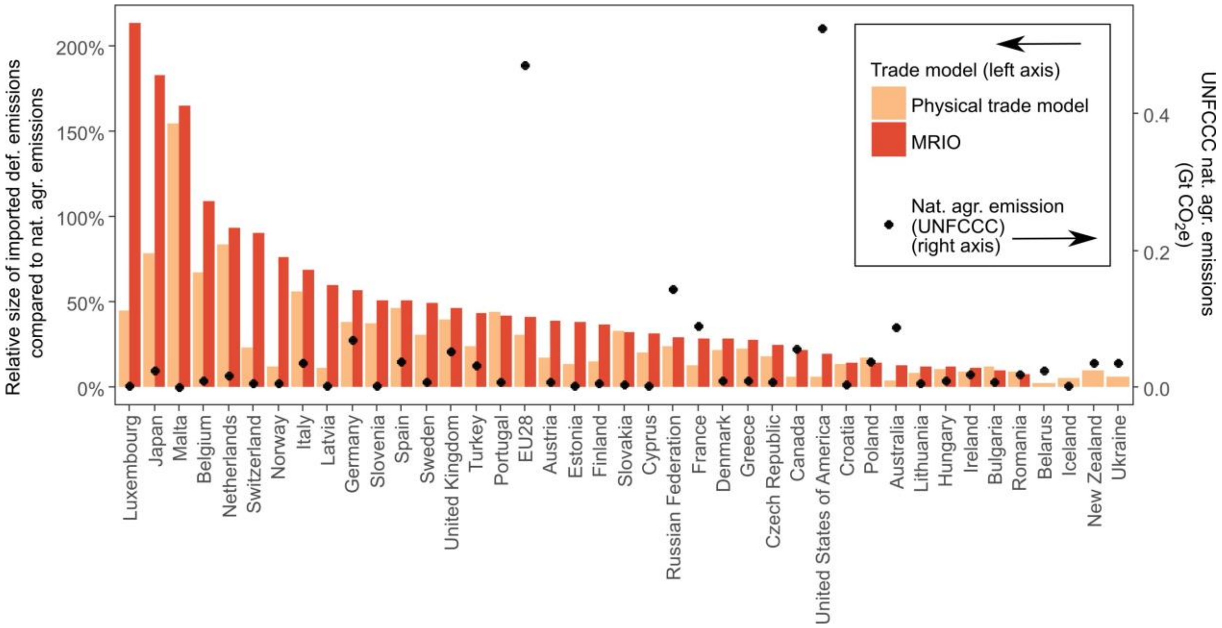

Fig. 4. Imports of embodied deforestation-related carbon emissions are comparable to country-reported national agricultural emissions for many Annex-I countries. The bars (left axis) show the relative magnitude of Annex-I countries' imports of embodied emissions from deforestation compared to agricultural emissions within the country's national territory (i.e., imported embodied emissions divided by territorial emissions). The data on national (territorial) emissions from agriculture are those reported by Annex-I countries to the UNFCCC (United Nations Framework Convention on Climate Change (UNFCCC), 2014) (for 2012), and include most anthropogenic emissions from agriculture. The absolute size of the national emissions from agriculture are indicated with points (right axis). See Fig. A.7 for a comparison of the absolute, rather than relative, emission sizes (per capita).

We also calculated per capita footprints of deforestation emissions for food consumption[1] for the individual countries in the MRIO (Fig. 5). Unsurprisingly, the Brazilian footprint is the highest, given the large share of Brazilian beef being consumed domestically. The average EU footprint is estimated at 0.3 tCO_2/cap/yr for both trade models, implying that deforestation accounts for roughly a sixth of the total carbon footprint of average EU diets (the footprint excluding deforestation emissions estimated to be about 1.5 tCO2/cap/yr; Notarnicola et al., 2017). However, as seen in Fig. 5, there is large variation across import countries, with some EU countries (e.g., Belgium and the Netherlands) having as high a footprint as Indonesia (as estimated by the MRIO). Footprints for most other developed import countries are similar to the EU average, except the US—which is somewhat lower,

[1] In the MRIO this includes the consumption of all primary and processed food commodities, plus service sectors, such as hotels, restaurants, health and education; in the physical trade model this includes all apparent consumption. Further differences between the trade model results are discussed in A2.5.

at 0.2 tCO_2/cap/yr—and Norway—which is somewhat higher, at 0.5 tCO_2/cap/yr—while the footprints of emerging economics (China, India, South Africa) are much lower (<0.1 tCO_2/cap/yr).

Additionally, we find that for many agricultural commodities, the carbon footprint from deforestation and peatland drainage (Fig. 2a) is in the same order of magnitude as non-land use change (non-LUC) emission footprint. For instance, the average deforestation footprint for Latin American beef estimated here, 43 $tCO_2\ t^{-1}$ carcass weight, is almost as high as the estimated non-LUC footprint (Opio et al., 2013). The average deforestation footprints for Latin American and Asia-Pacific oilseeds, 0.9 and 0.7 $tCO_2\ t^{-1}$ oilseeds respectively, are almost twice the non-LUC footprints of Brazilian soybean and Indonesian palm oil, respectively (Persson et al., 2014a). This highlights the need to account for deforestation when assessing the carbon footprint of agricultural commodities from the tropics.

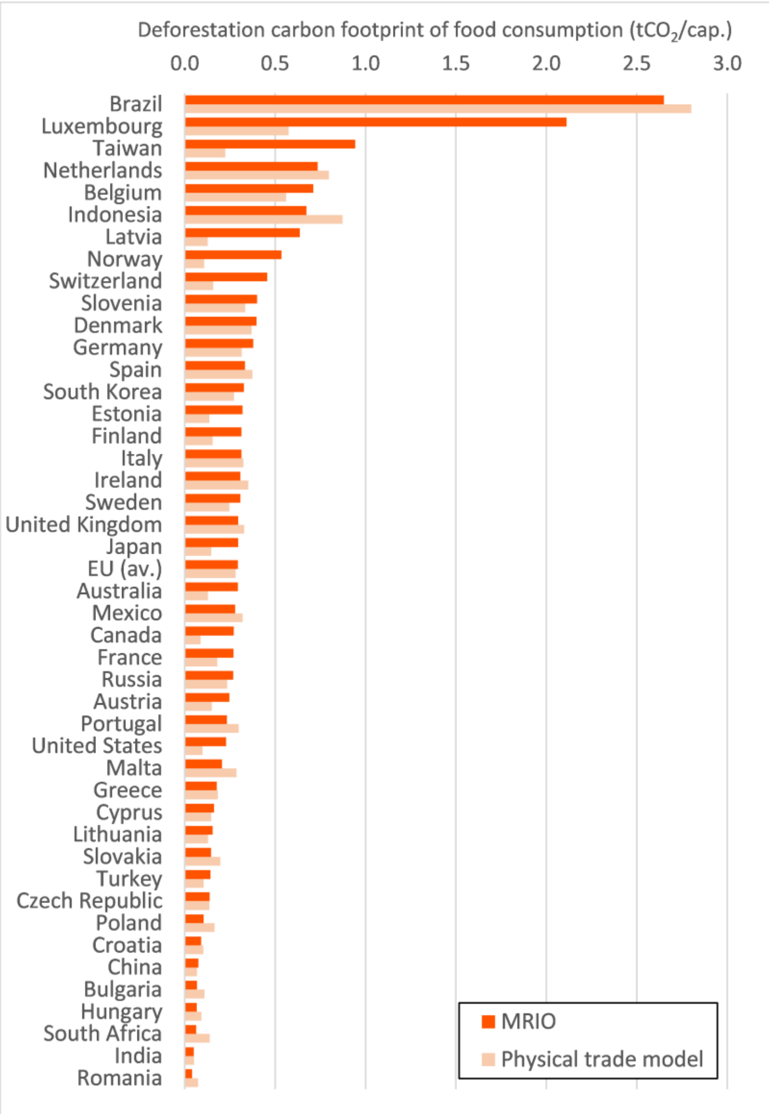

Fig. 5. The average (2010–2014) deforestation carbon footprint for food consumption across countries.

3.3. Sensitivity analyses

We performed sensitivity analyses to test the impact of the assumptions made in attributing deforestation-related emissions to the production and consumption of different commodities (see Appendix A, section A2.3, for a detailed discussion). The total attribution of deforestation-related emissions was stable to variations in assumptions, with some exceptions: as expected, if the canopy cover threshold used to define forest areas prior to forest loss is raised (from 25% to 75%) or if the land-balance model is based on net (rather than gross) expansion of cropland and pasture, the attributed amount is lowered, by 14% and 6%, respectively (see Table A.3). Adopting a more strict forest definition resulted in particularly large differences for Africa and Latin America, mainly affecting the area attributed to cropland (Fig. A.9). Under all alternative model assumptions (i.e., regarding amortization time, canopy cover threshold, and net vs. gross expansion), the share of emissions embodied in international trade was stable at 28%–30% for the PT model, and 39%–40% for the MRIO (Table A.4).

The results were also influenced by the degree of spatial aggregation at which the land-balance model was run for Brazil and Indonesia, especially in terms of the emissions attributed to certain commodity groups (and thus also influencing the share of emissions attributed to international trade) (Appendix A2.3). This is in line with the reasoning behind using sub-national data for these countries: applying the land-balance model for smaller areas better represents the land uses expanding in the areas where deforestation occurred. A less anticipated result was that the choice of dataset (FAOSTAT compared to more detailed agricultural statistics aggregated to national level) for Brazil and Indonesia also had quite a large impact on the result, both in terms of total attribution and on the share of this attributed to international trade especially (Fig. A.9, A1. Methods). This underscores that there are uncertainties in the underlying data, and that the effort to use more detailed data for the countries with large amounts of deforestation is motivated.

4. Discussion & conclusions

The quantification of deforestation-related emissions embodied in production, export and consumption presented here improves on previous estimates (Henders et al., 2015, Karstensen et al., 2013, Saikku et al., 2012) by covering all agricultural commodities in all tropical countries, as well as by using subnational resolution for the two countries with largest deforestation rates, Brazil and Indonesia. While the land-balance model that allows us to assess drivers of deforestation across the tropics depends on some simplifying assumptions, the model overall gives reasonable results, in particular for Brazil and Indonesia, where the model is implemented at sub-national scale. Differences to earlier results, i.e., in Henders et al. (2015), are larger for some Latin American countries, though here the deforestation driver assessment of Henders et al. (2015) (as well as other remote sensing based assessments) also less robust (for a detailed discussion on model validation, see A2.1 Comparisons to earlier (case) studies, as well as Pendrill et al. (2019)). Still, there are a couple of important caveats (see also A2.2 and Tables A.2–A.5 for additional sensitivity analyses).

First, while expanding cropland, pastures and plantations are the main deforestation drivers (Geist and Lambin, 2002, Hosonuma et al., 2012), our approach excludes other deforestation drivers. As a result, a large share (~40%) of tropical deforestation remains unattributed in our approach; this deforestation is likely due to a mix of drivers, such as logging, shifting cultivation not captured by national agricultural statistics, expansion of other land uses (e.g., urbanization and mining), and natural forest fires, in line with the findings of Curtis et al. (2018).

Second, the spatial aggregation of the analysis (i.e., primarily country-level) implies that that we cannot distinguish between commodities directly expanding on recently deforested land, and those pushing other land uses into forests (e.g., soy expansion on pasture land pushing cattle ranchers into forests in Latin America). Disentangling direct and indirect drivers requires improved spatially explicit land-use data, particularly on the extent of crops, pastures and forest plantations. This could also help better distinguish large-scale, commercial clearings from shifting cultivation. Our sub-national analysis of the two main deforestation countries, Brazil and Indonesia, was done as a partial remedy for the lack of spatial data, and the results for deforestation attributed to pasture and oilseeds are in line with studies primarily based on spatially explicit, remote-sensing data (Table A.6, Fig. A.8). Sub-national analyses for additional countries would likely also increase the extent to which the results represent the direct drivers, especially where patterns of land-use change differ between different parts of the county, but determining exactly how this would impact the results would require better knowledge and/or data on the spatial variations of land-use change dynamics within them (Appendix A2.3).

Third, while the results differ between the two trade models, they provide complementary information, as they differ in aim, system boundaries and trade-relationship metric. Thus, model choice has a significant impact on the estimations of embedded carbon emissions and their allocation to commodities and countries, but depends on the research questions or policy aims (Bruckner et al., 2015, MacDonald et al., 2015, Hubacek and Feng, 2016). Understanding country-to-country trade flows as depicted by the physical trade model is more relevant for upstream actors such as trading companies and investors, governments and other actors seeking to reduce deforestation through direct supply chain interventions, such as commodity moratoria, zero-deforestation commitments, and other demand-side measures. The MRIO analysis is more relevant for downstream actors, helping to understand better the underlying distant drivers of deforestation-related emissions, and is more suitable for consumption-based accounting, as it follows the emissions further through the supply chain to the point of final demand (Wiedmann and Barrett, 2013). As expected, while overall trade links are similar between the models, the MRIO import and export flows are generally larger (Figs. 2, 3, Fig. A.5, and A2.5 Supplementary discussion). Future quantifications would also benefit from improved data quality in production and trade data, where large uncertainties remain.

Despite these uncertainties, our results clearly indicate that international trade is a key driver of carbon emissions from tropical deforestation, even more so than for fossil CO_2 emissions. Policies aimed at reducing carbon emissions from deforestation should therefore consider not only territorial emissions in isolation, but also telecouplings through international supply chains (Peters et al., 2011, Davis and Caldeira, 2010). The fact that emissions from consumption of commodities linked to tropical deforestation are high compared to both territorial agricultural emissions and non-land use change carbon footprints for food consumption in importing countries, highlights the need to complement territorial emission accounts with consumption based accounts that include emissions from deforestation to gain a fuller picture. Similarly, our results highlight the need to account for deforestation when assessing the carbon footprint of agricultural commodities from the tropics.

Efforts primarily targeting international consumers and supply chains might benefit from focusing on those commodities which have both large embodied emissions and are largely exported, such as oilseeds. Our results further show that emissions are concentrated in comparatively few trade flows, suggesting that effective efforts to reduce deforestation in supply chains should target specific trade relationships and commodities (as intended by Brazil's Soy Moratorium and zero-deforestation commitments targeting palm oil, beef and high-value crops). Furthermore, the large deforestation carbon footprints of some agricultural and forest products could also be addressed through carbon taxes on food products in export markets (Wirsenius et al., 2011, Edjabou and Smed, 2013).

However, the importance of international trade in driving tropical deforestation does not take away from the need to also tackle domestic demand if deforestation is to be reduced; after all, more than half of deforestation emissions attributed to agricultural and forestry production here were destined for domestic consumption, even when using the MRIO to consider both direct and indirect trade dependencies. This indicates that there is a limit to what can be accomplished by demand-side measures targeting international supply chains, and that these need to be complemented by national-level efforts (which can target both the supply and demand side) if carbon emissions from deforestation are to be effectively reduced (Lambin et al., 2018).

Reducing emissions from deforestation often involves complex trade-offs, for example between preserving ecological and cultural values of forests on the one hand, and meeting increasing global needs for food, fuel, and fibre resulting from increasing populations and affluence, driving life-style changes, on the other. Although more detailed assessments are certainly needed, the data presented here provide information on which agricultural and forest commodities are contributing to large carbon emissions from deforestation and peat drainage, thereby helping to illuminate some of these trade-offs.

In summary, here we have sought to address the need to better understand the increasing role of international demand in driving tropical deforestation, by providing a pan-tropical quantification of carbon emissions from deforestation associated with the expansion of agriculture and tree plantations, and subsequently tracing these embodied emissions through global supply chains to consumers. In total, net emissions of 2.6 $GtCO_2$ per year were attributed to loss of forests due to expansion of agriculture and tree plantations in the period 2010–2014. More than half of these emissions were associated with cattle and oilseed products alone. Further, using trade models to follow the source of the demand for the implicated commodities, we find that a large share of the deforestation-related carbon emissions – 29–39% – was embodied in international trade, especially to Europe and China. Notably, in many developed countries, deforestation carbon emissions embodied in consumption rival or exceed emissions from domestic agriculture, and deforestation emissions constitute a sixth of the carbon footprint of the average EU diet. Put together, these results highlight that consumption-based accounting should include emissions from deforestation to gain a more complete picture, and that—if emissions from deforestation are to be effectively reduced—domestic policy measures can benefit from being complemented by efforts targeting actors in international supply-chains.

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Appendices

Appendix A.

Figs. A.1–A.10, Tables A.1–A.8, Supplementary Methods, Supplementary Discussion (including sensitivity analyses), and Supplementary References.

Appendix B. Supplementary Data 1

Attribution of deforestation emissions.

Appendix C. Supplementary Data 2

Full physical trade flow data of embodied deforestation emissions (average 2010–2014).

Appendix D. Supplementary Data 3

Full multi-regional input output (MRIO) trade flow data of embodied deforestation emissions (average 2010–2014).