

A global life-cycle inventory database of deforestation area and emissions for agricultural products

U. Martin Persson^{1*}, Chandrakant Singh¹, Thomas Kastner², Michael J. Lathuillière³, Carina Mueller³, Chris West⁴

¹ *Physical Resource Theory, Dept. of Environmental & Energy Sciences, Chalmers University of Technology, 412 96 Göteborg, Sweden*

² *Senckenberg Society for Nature Research, Senckenberganlage 25, 60325 Frankfurt, Germany*

³ *Stockholm Environment Institute, 120 30 Stockholm, Sweden*

⁴ *Stockholm Environment Institute York, University of York, York, YO10 5NG, UK*

* Corresponding author: martin.persson@chalmers.se

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ABSTRACT: Food-system actors are increasingly required to quantify and report the greenhouse gas emissions from agriculture-driven deforestation in their supply chains, yet comprehensive, up-to-date and openly accessible data to support such Scope 3 reporting remain scarce. Here we present a harmonized life-cycle inventory (LCI) database of deforestation area and carbon footprints covering 183 agricultural commodities across 179 countries for 2005–2024, conforming to the newly adopted GHG Protocol Land Sector and Removals Standard (LSRS). Combining spatially explicit deforestation and carbon-emission estimates from the Deforestation Driver and Carbon Emissions (DeDuCE) model with agricultural production and bilateral trade data, we calculate footprints under three emission-allocation methods and complement them with supply-mix-weighted footprints for consuming countries. Footprints vary by orders of magnitude across commodities and countries, driven primarily by the share of production on recently deforested land and, secondarily, by forest carbon stocks and crop yields. We further show that the combination of a long (20 year) amortization period and allocating emissions over time—as the LSRS mandates—implies that changes in footprints track changes in production, rather than deforestation, undermining the value of footprints calculated this for decision support. Allocating emissions equally over production avoids this problem, even for long amortization periods. We also find that global average emission factors misrepresent country-level consumption by two to three orders of magnitude. We argue that production-based allocation should be permitted alongside the mandated metric, and that readily computed supply-mix footprints should replace global averages—providing more accurate and decision-relevant support for efforts to reduce deforestation.

KEYWORDS: deforestation; land-use change; carbon emissions; greenhouse gas reporting, life-cycle inventory; Scope 3 emissions.

INTRODUCTION

The global food system is a key driver of climate change and unless greenhouse gas (GHG) emissions from agricultural production, processing and trade are reduced, we will not be able to meet the climate targets agreed upon in the Paris Agreement [1]. A key component of agricultural GHG mitigation is halting the extensive conversion of natural ecosystems to cropland and pastures. Agricultural expansion is estimated to have led to the global loss of around 5 and 10 million hectares (Mha) of forest [2] and other natural lands [3], respectively, each year in the first two decades of the 21st Century. Agriculture-driven deforestation alone resulted in emissions of ~2 billion tonnes of carbon dioxide (GtCO₂) annually, constituting almost 20% of total food system GHG emissions. [2, 4]

Increasingly, food system actors are called upon to monitor and report on deforestation and GHG emissions in their supply chains—typically referred to as *Scope 3* emissions—both through voluntary and regulatory measures [5]. Organizations and initiatives like the Accountability Framework initiative (AFi), the Science Based Target initiative (SBTi), and Greenhouse Gas Protocol (GHG Protocol) have developed guidance and standards for companies to adopt towards identifying, quantifying and setting targets for mitigating land-use change GHG emissions in their operations and supply-chains [6, 7]. This ongoing standardization of GHG accounting and reporting has been key in engaging the industry and ensuring that data is comparable across studies and companies.

To support these initiatives there is an urgent need for accurate, up-to-date, comprehensive and consistent, and openly accessible data on the deforestation carbon footprint of agricultural commodities. Recent years have seen major advances in spatial, remote sensing-based data pertaining to forest loss [8], its drivers [9], associated carbon losses [10], as well as agricultural land-use [e.g., 11, 12]. While significant gaps still remain, these data allow for a much more detailed

quantification and understanding of agricultural commodity-driven deforestation across space and time [13], and increasingly this data is being used to estimate more accurate commodity deforestation footprints (e.g., [14-19]). However, these studies remain limited in their geographical and commodity-specific coverage. Because of this, actors reporting Scope 3 deforestation emissions need to rely on life cycle inventory (LCI) databases with more comprehensive geographical and commodity extent, but which are typically based on crude (national-scale) statistics of varying quality and simplistic models to estimate land-use change (or ‘land transformation’ [20]) for agricultural products (see, e.g., [21]).

To fill this data gap, here we present an up-to-date, harmonized LCI database of deforestation carbon footprints for all countries and crops in the FAO database [22], conforming to the GHG Protocol Land Sector and Removals standard (LSRS) [7]. Our footprint data are based on the Deforestation Driver and Carbon Emissions (DeDuCE) model [2], which estimates deforestation driven by agricultural expansion and associated carbon emissions in the 2001-2024 period by combining remote sensing data on forest loss, crop and land-use extent, and forest carbon stocks with agricultural statistics, in a procedure that prioritizes data with higher spatio-temporal resolution and accuracy, to identify deforestation and attribute it to the commodities produced on cleared forest land. Where commodity-specific spatial data exist, we calculate so-called *jurisdictional direct land-use change* (jdLUC) footprints, which provide information of about the total amount of land-use change (here limited to deforestation) emissions per ton of a commodity from a specific area (here, country); where the DeDuCE model relies on broader land-use data and/or agricultural statistics for deforestation attribution, we provide estimates *statistical land-use change* (sLUC) [23], in order to achieve comprehensive commodity and country coverage.

Moreover, to support Scope 3 emissions reporting where neither the sourcing country, nor previous land-use is known, we provide consumption-weighted average LCIs reflecting the commodity supply mix [24] for each country in the world, based on bilateral trade in agricultural commodities [25]. This is likely to provide more accurate emission estimates than simply adopting globally averaged emission factors, as recommended in the GHG Protocol guidance [23], as commodity sourcing patterns can differ widely between countries.

MATERIALS AND METHODS

Deforestation and carbon emissions data

The DeDuCE model [2] provides annual data on deforestation extent and associated carbon emissions due to the expansion of cropland, pastures and forest plantations into natural forests across 179 countries, in the 2001-2024 time period, and further attributes cropland and pasture-driven deforestation to 183 agricultural commodities. The model does so by spatially overlaying global, annual data on tree cover loss [8] with best-available regional and global datasets on the spatial extent of individual crop commodities (e.g., cocoa [26], oil palm [27], rapeseed [28], rice [29], and soybeans [12]), land uses [11, 30], dominant deforestation drivers [9], state of forests [31, 32], and forest carbon stocks in biomass above ground [10] and below ground [33], as well as soil organic carbon stocks [34].

For each 30-by-30 meter pixel, the model determines whether the tree cover loss represents deforestation—distinguishing permanent conversion of forests from rotational clearing of managed forests and tree plantations, as well as forest fires without subsequent land-use—and attributes identified deforestation to either a specific crop, land-use or broad driver of deforestation. Where a deforestation pixel is not spatially attributed to a specific commodity, the model uses agricultural statistics—at national [22] and sub-national level—to allocate deforestation to expanding land-uses

and crops (in GHG Protocol guidance terms, taking a *product expansion approach* [7]), accounting for key land-use change dynamics such as competition between cropland, pasture, and other land uses, as well as cropland and pasture abandonment.

Carbon emissions are calculated as *committed*—i.e., disregarding temporal carbon loss-dynamics and attributing all emissions to the year of the deforestation event [35]—and account for changes in above- and below-ground biomass, dead wood, litter and soil organic carbon pools. We calculate both gross and net emissions, as the GHG Protocol requires the reporting of the former separately when carbon stocks in the replacing land-use exceed the initial stocks, resulting in net sequestration (something that occurs in the DeDuCE data). The carbon stocks in different agricultural land-uses used to calculate net emissions are detailed in table S1.

Where deforestation, and associated carbon emissions, are attributed directly to commodities (including pasture, for beef production) using spatially explicit data, the estimates represent jdLUC estimates. That is, the data is an estimate of the total annual extent of conversion of forests to the production of a given commodity in a given jurisdiction (for the data presented here, at country-level). Where deforestation is attributed to commodities based on statistical data, it represents sLUC. For sLUC estimates, it is not possible to distinguish between whether a commodity expanding in area is driven deforestation directly or indirectly, by pushing other land-uses into forests.

This hierarchy, where jurisdictional jdLUC is calculated where data is available and sLUC where it is not, follows the LSRS [7]. Note that in the results below, we report jdLUC and sLUC footprints without differentiation, but in the LCI database it is specified for each data point whether it is an estimate of jdLUC, sLUC, or a mix of the two. The latter can happen where spatial data for a given commodity is available only for a certain time-frame, and not the full time-series (2001-2024). The commodities and countries for which DeDuCE data is based on spatially explicit data, and for which

years, are listed in Table S2. As spatial data layers become available for more crops, these will be incorporated into the DeDuCE model, extending the coverage of jdLUC estimates over time. Regardless of whether the estimated footprint is based on jdLUC or sLUC data, it represents a jurisdictional average and is therefore relevant for Scope 3 emissions reporting where actors do not know whether products are sourced from deforested land or not (if actors do have this information, they will likely have farm-specific data on which to base calculations of emissions).

Footprint calculation methods

To convert the estimates of aggregate, jurisdictional levels of deforestation and carbon emissions for each commodity into deforestation area or carbon footprints, it needs to be allocated to production over time following the initial deforestation event (what is typically referred to as *amortization*). The LSRS mandates that emissions are allocated over at least 20 years of production (for perennial crops the rotation period can be used if it exceeds 20 years) and to use a linear discounting factor to allocate more of the emissions to the years directly following the deforestation event (see Fig 1).

Taking this approach, we calculate the deforestation carbon footprint (DF) for a given commodity (c), in a given jurisdiction (j), in any given year (t), by summing up the amount of deforestation emissions over the last T years (the amortization period, with the default value of 20 years) using a linear discount factor (ω_t) for each year t , then dividing by the functional unit (here production, $P_{c,j,t}$):

$$DF_{c,j,t}^{disc} = \frac{\sum_{t-T}^t [\Delta A_{c,j,t} \Delta C_{c,j,t} \omega_t \varphi_{c,j,t}]}{P_{c,j,t}}; \omega_t = [0.0025, 0.0075, \dots, 0.0975] \quad (1)$$

Here $\Delta A_{i,j,t}$ is the amount of deforestation for a given commodity, in a given jurisdiction and year (in hectares), and $\Delta C_{c,j,t}$ is the carbon stock change due to deforestation (gross or net, in tCO₂ per

hectare), and $\varphi_{c,j,t}$ is a product allocation factor, determining how much of the deforestation emissions that should be attributed to product c . The product allocation factor allows for accounting for multiple cropping, producing several products from the same land, crop rotations between years, or land dynamics such as transitions from forests to pasture and then soybean production. However, a limitation with the DeDuCE data is that it currently allocates deforestation and associated emissions to a single commodity, based on the land-use identified in the three years following a pixel being identified as deforested. Here, it will therefore be assumed that $\varphi_{c,j,t} = 1$.

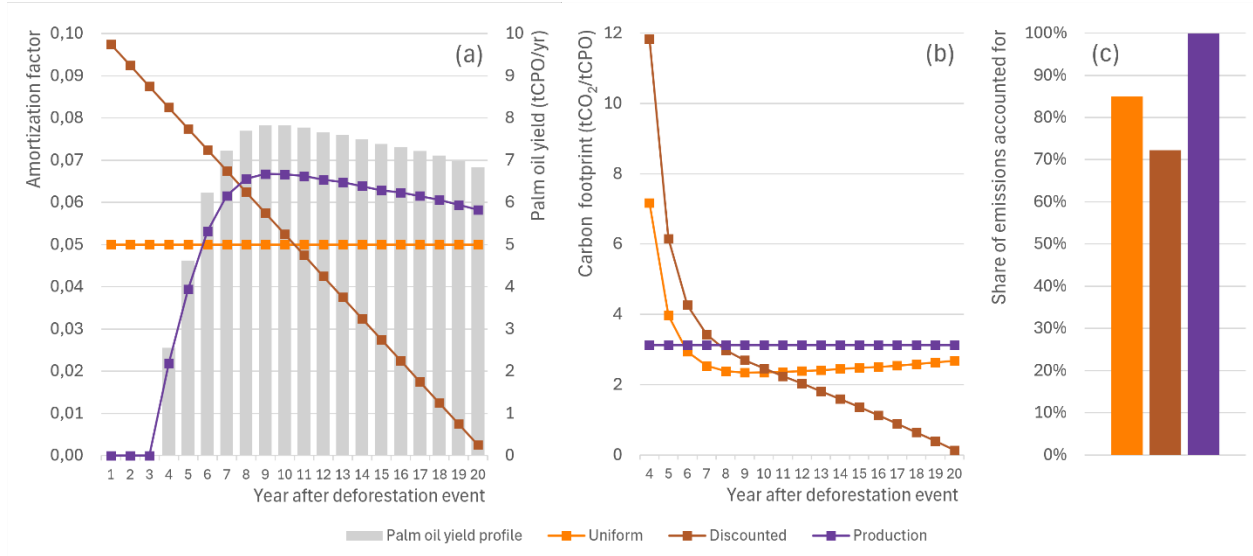


Figure 1. Differences between three alternatives for allocating deforestation emissions to production over time, based on an illustrative example of production of crude palm oil (CPO) from one hectare of forest land converted to oil palm in year 0. Panel (a) shows the three emissions allocation methods: uniform and linearly discounted distribution over 20 years (amortization time), respectively, and equal distribution to each ton of production over 20 years. Panel (b) shows the resulting carbon footprints (here assuming a carbon loss of 100 tC/ha). Because the uniform and discounted allocation approaches allocate some emissions to the first three years, when the immature oil palm plantation does not produce any CPO, these emissions are left unaccounted for (panel c).

The draft LSRS guidelines [36] offered two alternatives to using linear discounting when amortizing deforestation emissions. The first is simply to allocate emissions uniformly over time (Fig 1), in which case the deforestation carbon footprint is calculated as:

$$DF_{c,j,t}^{unif} = \frac{\sum_{t-T}^t [\Delta A_{c,j,t} \cdot \Delta C_{c,j,t} \cdot \frac{1}{T} \varphi_{c,j,t}]}{P_{c,j,t}} \quad (2)$$

The second option was to apportion deforestation emissions not over years, but over actual production, resulting in a carbon footprint that is equal for each ton of product produced on the cleared land (Fig 1). This amortization option was suggested as the recommended approach when annual (plot or land management unit) yield data was available [36, p. 43]. However, the approach of apportioning deforestation emissions equally over production can also be applied at larger, jurisdictional levels [37]. To do so, one first calculates an annual deforestation footprint (AF):

$$AF_{c,j,t} = \frac{\Delta A_{c,j,t} \cdot \Delta C_{c,j,t} \cdot \varphi_{c,j,t}}{\sum_t^{t+T} P_{c,j,t}} \quad (3)$$

In contrast to Eqs. 1-2 above, which attribute deforestation emissions to production over time using fixed factors (uniform or discounted), the AF calculation attributes deforestation by production which may vary over time. For more recent years (or long enough amortization periods) it therefore requires assumptions to be made about future production. Below we simply assume constant production over time, based on average production levels in the last three years for which we have data (akin to simply allocating deforestation equally over time, as in the standard amortization approach).

Eq. 3 apportion deforestation emissions evenly over production in the T years following the deforestation event; to get the full deforestation emissions footprint for jurisdictional production in a given year t , one needs to sum all deforestation emissions the preceding T years attributed to that year's production:

$$DF_{c,j,t}^{prod} = \sum_{t-T}^t AF_{c,j,t} = \sum_{t-T}^t \left[\frac{\Delta A_{c,j,t} \cdot \Delta C_{c,j,t} \cdot \varphi_{c,j,t}}{\sum_{t-T}^{t+T} P_{c,j,t}} \right] \quad (4)$$

Implications of different amortization approaches

As illustrated in Fig. 1, attributing emissions to production by amortizing it over time—either using a discounting factor (Eq. 1) or simply uniformly (Eq. 2)—rather than production (Eqs. 3-4) can be problematic for two reasons, especially if evaluated at high resolution (e.g., plot level). First, some emissions may be allocated to years when there is no production, and hence these emissions will be left unaccounted for. Second, when production changes over time—e.g., due to yield dynamics or weather shocks—changes in carbon footprint over time will reflect these variations in production, rather than variation in deforestation. This means that the changes in the carbon footprint, or comparisons across producer regions or commodities, may not convey meaningful information on trends in, or amounts of, deforestation associated with a given commodity in a given jurisdiction.

Since the ultimate aim of emissions reporting is to provide decision support to actors that want to reduce their (deforestation) carbon emissions, it is interesting to assess the extent to which DFs calculated using the three different allocation methods (Eqs. 1-2, 4) reflect—or track—trends in deforestation. As noted above and illustrated in Fig. 1, we would expect the uniform and discounted allocation methods to be more influenced by variations in production levels, compared to the production allocation method, meaning we would also expect the latter to be more stable over time. Lower temporal variability also means more stable decision support, which is advantageous as

decisions to change sourcing patterns (to reduce land-use change emissions) may entail high transaction costs (cf. [38]) and negatively impact producers in regions being abandoned. On the other hand, as can also be seen in Fig. 1, more stability may come at the price of not reflecting changes in deforestation emission rates; i.e., despite deforestation only occurring in year zero, $DF_{c,j,t}^{prod}$ remains constant over 20 years, whereas $DF_{c,j,t}^{prod}$ and $DF_{c,j,t}^{disc}$ both drop quickly when there is no further deforestation. Below we therefore report estimates of deforestation carbon footprints using all three amortization methods— $DF_{c,j,t}^{disc}$ (Eq. 1), $DF_{c,j,t}^{unif}$ (Eq. 2), and $DF_{c,j,t}^{prod}$ (Eq. 3-4)—at country level. We then assess empirically whether the three allocation methods differ both in terms of temporal stability (or variability) and in their responsiveness to changes in deforestation and production over time (see Supplementary text for details).

Analyzing factors explaining footprint variability

We also analyze the factors that explain differences in $DF_{c,j,t}^{disc}$, across commodities and countries. To facilitate that analysis, consider this simplified expression for $DF_{c,j,t}^{disc}$ (Eq. 1), where we have replaced the time-varying deforestation and carbon stock change variables with their averages over the amortization period ($\overline{\Delta A}_{c,j,t}$ and $\overline{\Delta C}_{c,j,t}$), noting that production can be expressed as a function of the average yield ($y_{c,j,t}$) and harvested area ($H_{c,j,t}$) as $P_{c,j,t} = y_{c,j,t} \cdot H_{c,j,t}$, and that the sum of the linear discount factors (ω_t) equals 1:

$$DF_{c,j,t}^{simp} = \frac{\sum_{t=0}^T [\overline{\Delta A}_{c,j,t} \cdot \overline{\Delta C}_{c,j,t} \cdot \omega_t]}{y_{c,j,t} \cdot H_{c,j,t}} = \overline{\Delta C}_{c,j,t} \cdot \frac{1}{y_{c,j,t}} \cdot \frac{\overline{\Delta A}_{c,j,t}}{H_{c,j,t}} \quad (5)$$

What this simplified expression tells us is that that we should expect deforestation carbon footprints to be higher, *ceteris paribus*, (i) the higher the carbon loss in cleared forests, (ii) the lower the yield of products produced on cleared land, and (iii) the higher the ratio between average deforestation for

the commodity over the amortization period and the total harvested area for the commodity. The latter, if multiplied by the amortization time, represent the share of production occurring on land deforested in the last T years.

Note that Eq. 5 also suggests that the amortization time in itself should not affect the deforestation footprint; i.e., a lower amortization period should not unequivocally raise or lower the estimated footprint. However, changing the time period over which deforestation is assessed may change the footprint estimate, due to temporal dynamics in clearing of forests for the production of a given commodity, resulting average deforestation rates for a given commodity differing between time periods. Below we test this hypothesis, analyzing how the choice of amortization period affects estimated deforestation emission footprints by calculating $DF_{c,j,t}^{disc}$ for amortization periods of 5, 10, 15 years, in addition to the standard 20 years. We do so by assuming the same discount factor (i.e., annual change in the weight factors, ω_t , by 0.05), but adjusting the yearly weights so they always sum to one.

While the GHG Protocol have mandated a minimum amortization period of 20 years, they also motivate the method for linearly discounting deforestation emissions by arguing that it “provides more ‘benefits’ [for reporting companies] if actions (e.g., sourcing decisions) are taken in more recent years” [36, p. 39]. It is therefore interesting to test what the “effective amortization period” for the discounted footprint is and we do so by comparing the correlation between $DF_{c,j,t}^{disc}$ for a standard 20 year amortization period with that of $DF_{c,j,t}^{unif}$ for an amortization period of 5, 10, 15, and 20 years (as well as with the production allocation footprint, $DF_{c,j,t}^{prod}$).

Calculating consumption-weighted footprints

Finally, the GHG Protocol recommends that if the origin of a commodity is unknown, companies should use a global average sLUC factor. However, given that we have information of bilateral trade in agricultural commodities, we can calculate more accurate deforestation emission footprints by accounting for the supply mix [24] of the country where the commodity is consumed. This will provide better support for actors' sourcing decision, as a company located in a country sourcing mainly from producer countries with high deforestation risk has a stronger incentive to improve traceability and look over sourcing, than one located in a country sourcing solely from low-risk countries. To provide this information, here we calculate a consumption-weighted deforestation emission footprint for consumer countries:

$$DF_{c,i,t}^{cons} = \frac{\sum_j [DF_{c,j,t}^{prod} \cdot C_{c,i,j,t}]}{C_{c,i,t}}, \quad (6)$$

where $C_{c,i,j,t}$ is the (apparent) consumption (in tons) in consumer country i of commodity c , produced in country j . Data on apparent consumption is taken from a global model based on bilateral trade data for primary and low-level processed agricultural products, thus accounting for processing and re-exports up to a point where commodities are either used as intermediary inputs in production (e.g., as livestock feed or in processed foods) or directly consumed [39].

LCI inventory data produced and presented

We calculate deforestation carbon footprints using annual data on deforestation and (gross and net) carbon stock changes from DeDuCE [2] and production of primary crop and livestock products from FAOSTAT [22]. For cattle meat, total production is calculated as the sum of 'Meat of cattle with the bone, fresh or chilled', 'Edible offal of cattle, fresh, chilled or frozen', and 'Cattle fat, unrendered'. For the main results presented below we use estimates for $DF_{c,j,t}^{disc}$ calculated using

gross emissions data, but the accompanying LCI database also includes emission footprints calculated using net carbon stock changes and deforestation area footprints (in [ha/t], calculated by simply dropping $\Delta C_{c,j,t}$ in Eqs. 1-2, 4) for all amortization methods and periods assessed. Results below are presented for the year 2023, as the last year in the data (2024) relies on data extrapolations which substantially reduces the quality of the estimates [2], but the LCI database includes time-series for all years for which footprints can be calculated (the extent of which depends on the amortization period).

RESULTS

The distribution of estimated deforestation carbon footprints, across world regions and major agricultural commodity groups—for year 2023, using a 20-year linearly discounted amortization approach, as mandated by the LSRS—are shown in Fig. 2. As can be seen, there are huge variations, both within and between commodities and regions, with even mean carbon footprints per region spanning a range from close to zero to over 30 tCO₂/t product (for Latin American cattle meat), with outliers well beyond that (though most of these are for commodities with very low production volumes and based on poor quality, non-spatial data). There are some obvious patterns in this variability, though: In terms of commodities, cattle meat—which by far accounts for the largest amount of deforestation over the 20-year amortization period (2004-2023)—also displays the highest carbon footprints, in particular for Latin America. The group of stimulants, spices, and aromatic crops is also among those with the highest carbon footprints, particularly in Latin America (cocoa and coffee) and Southeast Asia (cocoa and spices). It is also clearly visible in Fig. 2 that carbon footprints tend to be higher in tropical regions (Latin America, Africa, and Southeast Asia and Oceania) than in the non-tropics.

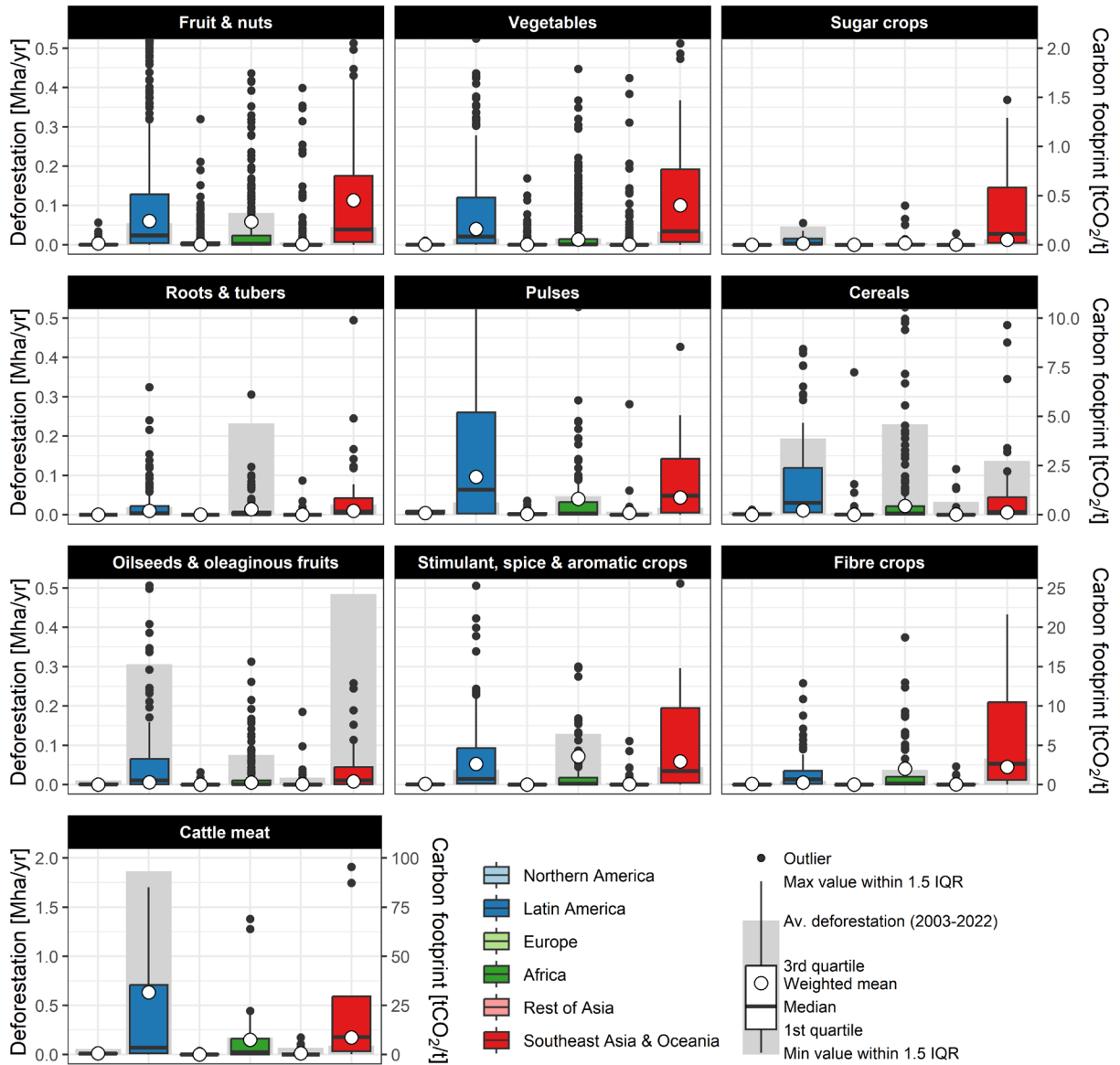


Figure 2. Distribution of average annual deforestation (left axes) in the 2004-2023 period and carbon footprint estimates calculated using a 20-year, linearly discounted amortization period (right axes) for 2023, by commodity group and regions. Note that the carbon footprint scales differ across rows, with commodity groups ordered by increasing numbers, that the deforestation area scale is higher for cattle meat than for other commodity groups, and that the vertical axis is clipped (implying not all outliers are displayed for some commodities and regions).

These results are in line with the intuition suggested above, that we should expect carbon footprints to be higher where carbon stock losses are larger (tropics), product yields are lower (cattle meat and stimulants, spices, and aromatic crops), and where a larger share of production occurs on recently deforested land (tropical countries, which constitute the ongoing agricultural-forest frontiers, compared to the Global North where the clearing of forests for agricultural land happened centuries ago). This is also confirmed by Fig. 3, which shows the relationship between the estimated carbon footprints and these explanatory factors. Below we examine each of their contribution to deforestation footprint variability in turn.

Factors explaining footprint variability

As can be seen in Fig. 3a, higher carbon losses per hectare of cleared land (averaged over the amortization period, and net of carbon sequestered in replacing land-use) tend to imply higher deforestation carbon footprints, with carbon stocks being a relatively strong predictor of footprint values (Pearson's $r = 0.25$). Carbon losses are generally larger in tropical regions with higher forest biomass stocks—in particularly Southeast Asia, Oceania and Rest of Asia where it exceeds 130 tC/ha—and lower in Europe (73 tC/ha) and Northern America (60 tC/ha), but variations within regions are also very large (see Fig. S1). There are also very large variations in the carbon losses per hectare for individual commodities-country footprints, with very high losses for certain commodities, particularly fruits, nuts, vegetables, roots and tubers in Southeast Asia and Oceania (see Fig. S2).

Yields are also found to be a major explanatory factor for variances in our estimated deforestation carbon footprints across commodities and regions, with the correlation coefficient for the inverse yield (which should be expected to have a linear relationship to footprints according to Eq. 5) being

the same as that for carbon stock losses (Pearson's $r = 0.28$; see Fig 3b). As expected, yields are higher precisely for those commodities that show overall lower carbon footprints—sugar crops, vegetables, fruits and nuts (top row in Fig. 1)—and lower for commodity groups which have higher carbon footprints—primarily cattle meat (bottom row in Fig. 2) (see Fig. S3 for distribution of yields across regions and commodities).

While carbon stocks on cleared land and average yields are both strong predictors of estimated deforestation carbon footprints, the most important determinant is the share of production on land deforested within the amortization period (Pearson's $r = 0.47$; see Fig. 3c). This is also reflected in the fact that the two regions with the highest overall deforestation carbon footprints—Latin America and Southeast Asia and Oceania—also have the largest share of production on deforested land, an order of magnitude higher than the in old agricultural frontiers in Northern America, Europe and Rest of Asia (even if well over 90% of production in these regions is on land not deforested in the last 20 years for most commodities and in most countries; see Fig. S4).

Interestingly, however, the commodity with the highest average footprint—cattle meat—exhibit among the lowest shares of production on recently cleared forest land across regions. This illustrates how the jurisdictional footprints are jointly determined by carbon stocks in cleared land, yields, and share of production in the jurisdiction on land cleared during the amortization period (with low yields driving the high footprint of cattle meat). The temporally averaged values for these three factors together account for 96% of the variability in carbon footprints across commodities and countries (Fig. 3d), with temporal dynamics in these factors explaining the rest. This does not mean that temporal dynamics are unimportant—notably, the simple footprint estimates deviate by more than $\pm 50\%$ from that calculated using the full expression for 15% of the sample—only that it

explains less of the variability in estimated deforestation footprints than that of average carbon losses, yields and share of production on cleared land.

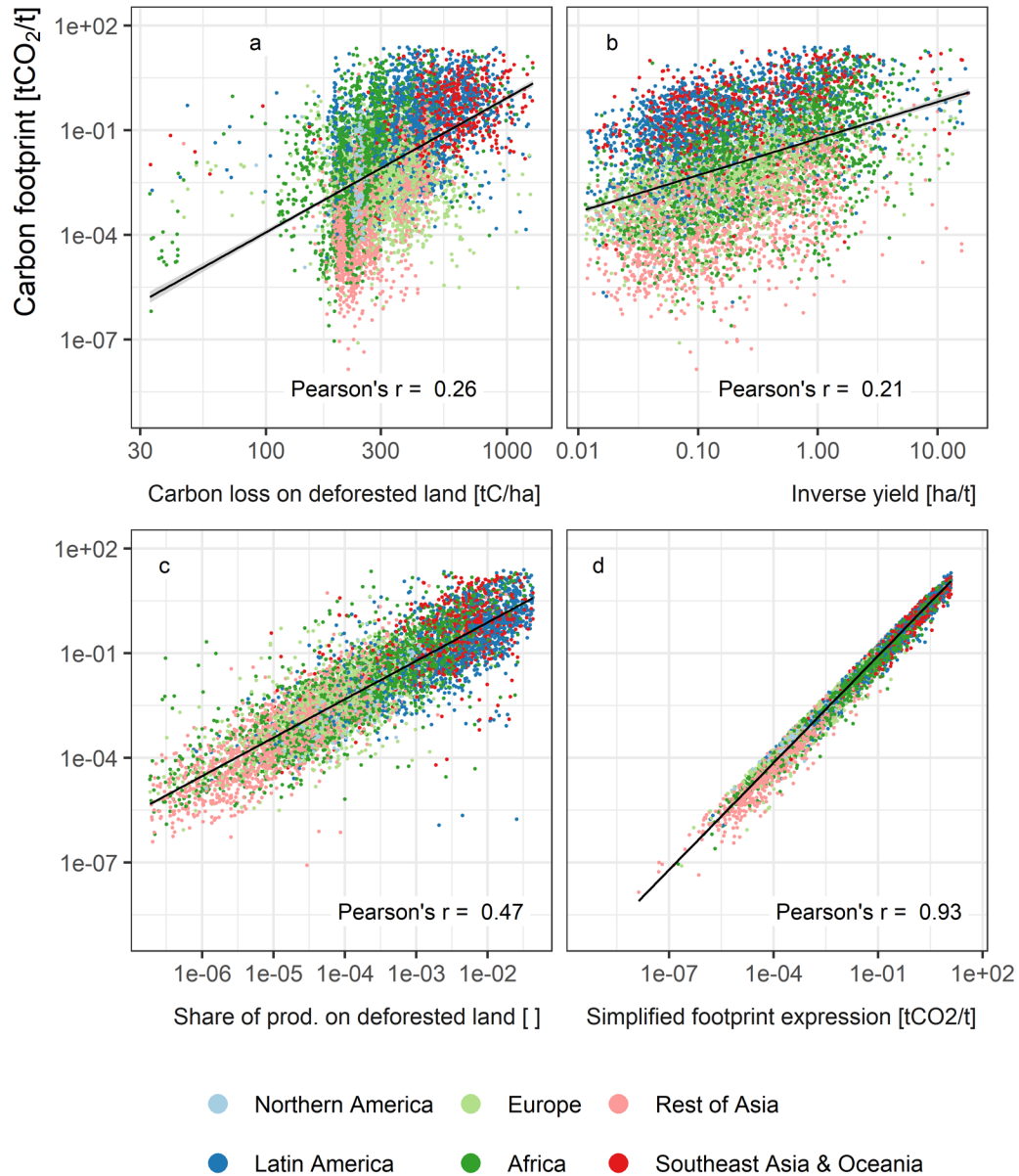


Figure 3. Estimated deforestation carbon footprints in 2023, calculated using a 20-year, linearly discounted amortization period (vertical axes), plotted against (a) the carbon loss on cleared land, (b) the inverse yield for each commodity (i.e., amount of hectares required to produce one ton), and (c) the share of production in 2023 coming from land cleared within the 20-year amortization period. Each panel also shows the correlation

between the estimated carbon footprint and each explanatory variable, after having removed outliers (top and bottom percentile for each variable). The relationship between the deforestation carbon footprint and these explanatory variables are as expected, with footprints being higher, the higher the carbon content of cleared forests (e.g., in Southeast Asia and South America), the lower the commodity yield (e.g., Africa, Southeast Asia, and South America), and the higher the share of production on deforested land (again, in Africa, Southeast Asia, and South America), with the latter factor explaining most of the variance in footprints (see also Supplementary Figs S2-4 for variations in carbon stocks, yields, and share of production on cleared land across commodities and regions). Panel (d) shows the correlation between the carbon footprints calculated using the full expression (Eq. 1) and the simplified one (Eq. 5), where the latter utilizes the values for the variables displayed in panels (a-c).

Impacts of changing the amortization period

One way in which the temporal dynamic in deforestation rates for a given commodity affects the estimated footprint is through the choice of amortization period. Figure 4 plots the relationship between carbon footprints calculated over a 5 vs 20-year amortization period (for year 2023) and as can be seen, these are highly correlated (Pearson's $r = 0.68$). Importantly, the graph confirms the notion that where carbon footprints calculated over different amortization periods diverge, this can to a large extent be explained by changes in deforestation rates for the commodity in question. That is, where the average deforestation rate over the last 5 years is lower than that over the last 20 years (decreasing deforestation), the 20-year carbon footprint is higher than that calculated over 5 years; conversely, where deforestation for the commodity in question has increased in the last 5 years, the 5-yr carbon footprint typically exceeds the 20-yr one.

There are still examples where the footprint evaluated over 20 years is higher than for a 5-year amortization despite deforestation having increased over the latter period, or vice versa (see Figure S5; some of these being visible also in Figure 4). However, these are relatively few ($n = 515$, or just

over 6% of the sample) and mostly represent commodities with little deforestation (a few hundred hectares per year or less on average). These cases are primarily due to the interplay between temporal dynamics in deforestation rates and carbon stocks of cleared forests. To take a prominent example (in terms of total deforestation), the deforestation footprint for Brazilian maize is substantially (27%) higher when calculated over a 5-year amortization period, compared to over 20 years, despite the average deforestation rate having dropped slightly in recent years (the 2019-2023 average being 8% lower than the 2004-2023 average). This can be explained by the average (net) carbon losses for expanding maize production in Brazil has increased over time, from 65 tC/ha in the 2004-2023 period, to 70 tC/ha in the 2019-2023 period. Conversely, the footprint for Indonesian cattle meat is lower if evaluated over 5 compared to 20 years, despite recent deforestation rates for pasture being higher than averages over 20 years, because the carbon stock losses are lower for more recent deforestation.

These temporal dynamics are also the reason why the choice of method for allocating deforestation emissions to products over time affects the estimated footprints. Fig. 5 shows the difference between footprints calculated with the three different approaches to allocating emissions to production over time: linearly discounted over 20 years, equally to each ton produced, and equally to each year (for amortization periods ranging from 5-20 years). Starting with the approaches allocating emissions of time, it is interesting to note that linearly discounting emissions over 20 years most closely corresponds to a 15-year uniform allocation (having higher correlation and a lower median difference to the linearly discounted footprint than any of the other amortization period), with a shorter uniform amortization period (5 or 10 years) typically resulting in lower footprints and a longer uniform amortization period (20 years) in higher footprints. Thus, the linearly discounted footprint effectively reflects dynamics over ~15 years, despite the fact that it allocates three-quarters of emission to the first 10 years of production following a deforestation event.

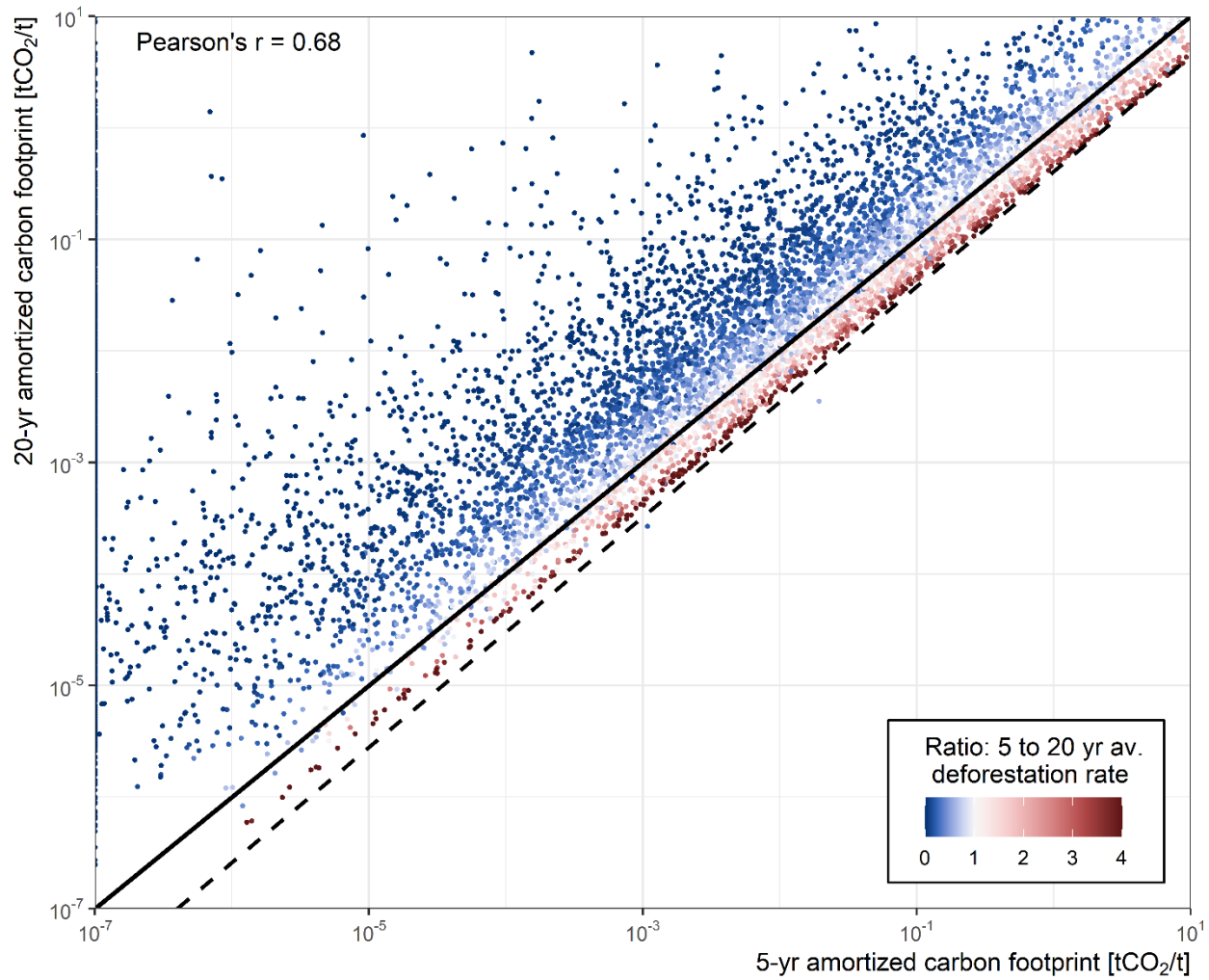


Figure 4. Carbon deforestation footprints calculated using a 5-year (horizontal axis) and 20-year (vertical axis) amortization period in year 2023. The coloring of each footprint data point reflects the ratio between the average deforestation rate for the corresponding commodity and country, calculated over 5 and 20 years prior to year 2023, showing that where deforestation is increasing (red shades) the 5-year footprints typically is higher than the 20-year footprint, and vice versa. The dashed line represents the theoretical upper limit between the 5- to 20-year average deforestation rate, reflecting a situation where there was only non-zero deforestation in the last 5 years prior to 2023.

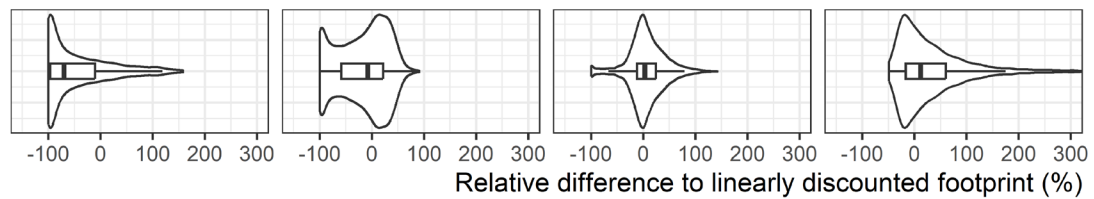
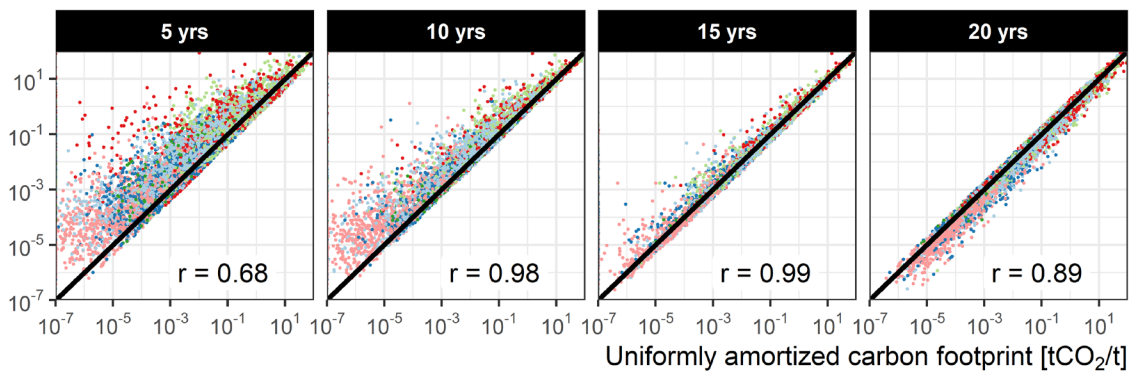
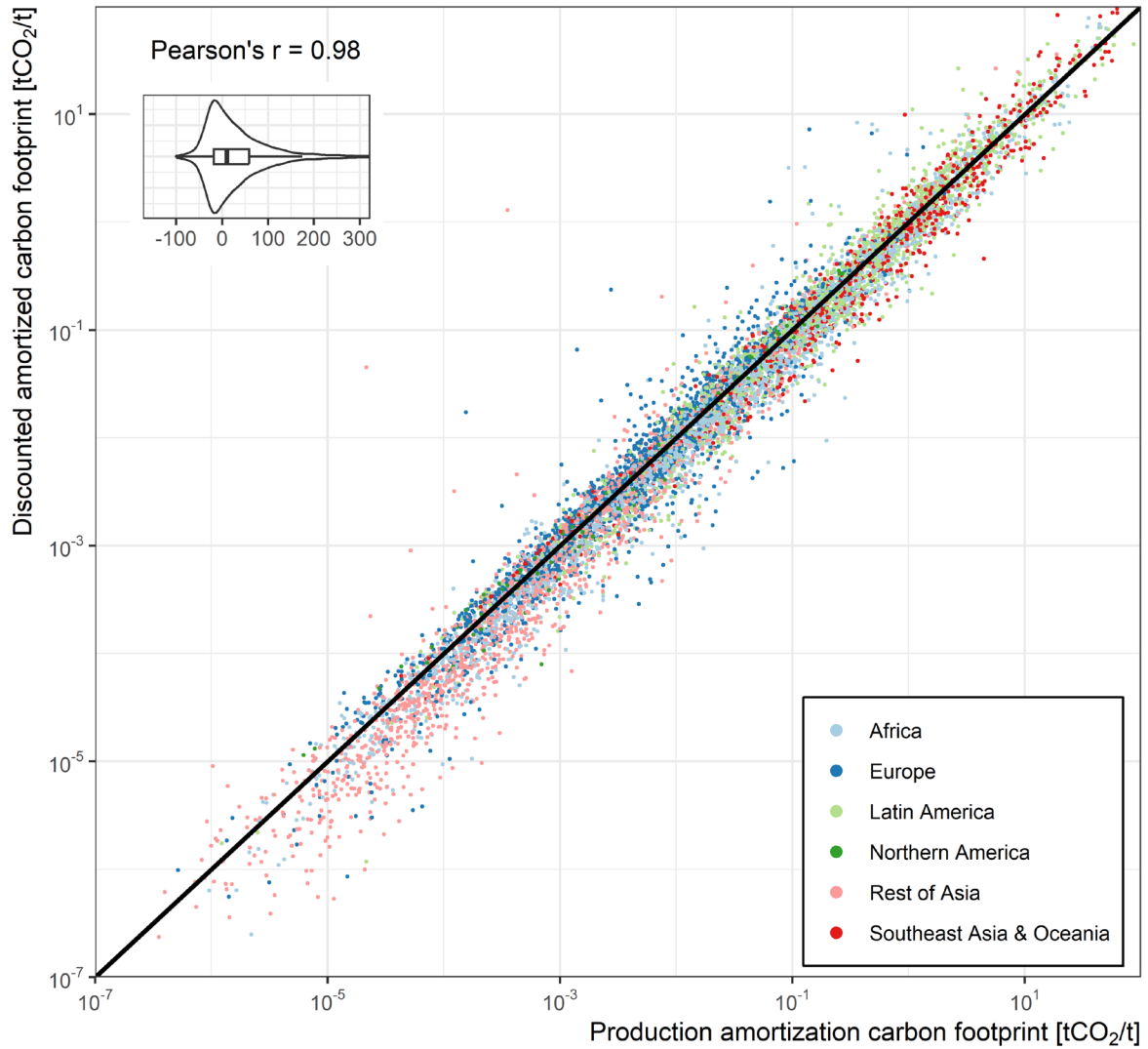


Figure 5. Comparison between deforestation carbon footprints estimated using different methods for allocating emissions to products over time. The upper panel compares allocating emissions over time using a linear discount factor (vertical axis) and over production (horizontal axis), both using a 20 year amortization period; the middle panels compare the linearly discounted allocation over 20-years (vertical axes) to a uniform allocation over 5, 10, 15 and 20 years (horizontal axes); the lower panel (and the inset in the upper panel) shows the distribution of relative differences to the 20-year, linearly discounted allocation footprint (with boxes displaying 25-75% interquartile range, horizontal lines median values, and whiskers the largest value within 1.5 times the interquartile range).

The correspondence between the footprints calculated using the linearly discounted and production allocation methods is also high, with a high correlation and a relatively low median difference (+10%, compared to +3% for the 15-year uniform footprints). A notable, and illustrative, example where the discrepancy between the two methods is substantially higher than the median is estimated footprint for Indonesian palm oil: it is estimated to be 74% higher when using the production allocation method (0.90 tCO₂ per ton fresh fruit bunches), compared to when using the linear discounting allocation method (0.52 tCO₂ per ton fresh fruit bunches), reflecting the fact that oil palm-driven deforestation in Indonesia dropped dramatically between 2016-2021 and has remained at a lower level since.

Differences in footprint stability and responsiveness between allocation methods

This brings us to the question of how the three allocation methods differ in terms of temporal stability and responsiveness to deforestation emission and production trends. Starting with the former, the results confirm the hypothesis that allocating deforestation equally over production, rather than uniformly or discounted over time, results in a more stable deforestation footprint across

a range of different stability metrics (see Fig S6). As expected, a longer amortization period (20 vs 5 years) also produces footprints with lower temporal variability.

As can be seen in Fig. 6, the higher stability of the production allocation method comes partly at the price of lower responsiveness to temporal changes in deforestation emissions, compared to the uniform and discounted time allocation approaches (though differences are relatively minor, especially for shorter amortization periods). However, as hypothesized, the footprints calculated using the latter two methods are also much more responsive to changes in production volumes. This is particularly the case for footprints calculated using longer amortization periods (10 and 20 years), where responsiveness to production trends is more pronounced than that to changes in deforestation emissions. The footprints calculated using the production allocation method, on the other hand, are uncorrelated with production changes across all amortization periods (as expected, since the method allocates emissions equally over production, making it unresponsive to changes in this variable; see Fig. 1).

It can also be noted that the amount of deforestation emissions that remains unaccounted for when amortizing over time (equally or linearly discounted) because it gets allocated to years without production of the commodity in question is, as expected, low, amounting to around one percent of total emissions (the number of footprints with a resulting infinite value—because the denominator in Eqs. 1-2 is zero—is quite small: 613, or just under seven percent of all 2023 commodity-country footprints).

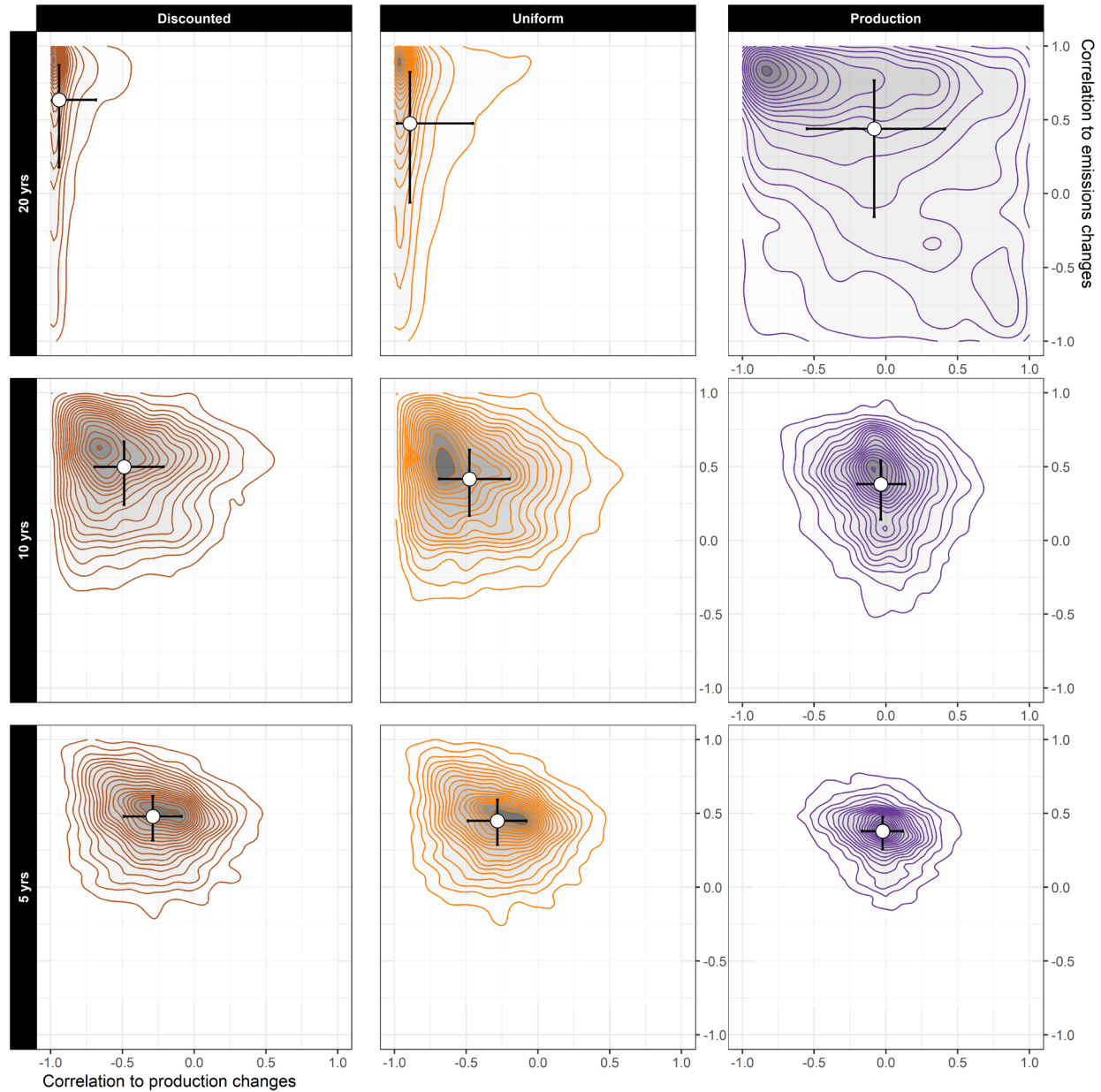


Figure 6. Density plots showing the distribution of responsiveness of estimated deforestation carbon footprints to temporal changes in deforestation emissions (vertical axes) and production volumes (horizontal axes), for across different methods for attributing deforestation to products (Discounted: linearly discounted over 20 years; Uniform: equally to each year; Production: equally to each ton produced) and for a range of amortization periods (5, 10 and 20 years). Responsiveness is calculated as the correlation between annual changes in the footprint value and that of deforestation emissions and production volumes, respectively, over

the available time-series (20, 15 and 5 years, respectively, for the 5, 10 and 20 years amortization periods). Darker grey shades show high density of estimated correlations and the white dot and whiskers shows median values and the 25/75 percentile range, respectively. While footprints calculated using the uniform and discounted allocation methods are slightly more responsive to changes deforestation emissions trends than the production allocation method, they are also substantially more responsive to changes in production volumes, potentially resulting in reductions in deforestation footprints due to increased production being misinterpreted as reflecting lower deforestation emission rates.

Consumption-weighted footprints

Finally, we turn to a comparison of the consumer country footprints, calculated as weighted averages using supply-mix data, to the global (production-weighted) average footprints, displayed in Fig. 7. This clearly shows that the global average footprint can be a very poor estimate of the average footprint of commodities consumed in a given country, with the latter frequently being two to three orders of magnitude smaller or larger than the former. This is particularly the case for countries being both major producers and consumers of key forest risk commodities, such as Bolivia, Brazil and USA for beef, and the Democratic Republic of Congo for staple commodities such as cassava, maize and rice. While differences to the global average typically are smaller for major consumers, even here large discrepancies exists: for instance, the supply-mix average footprint for EU consumption of cocoa is just over half of the global average, while China's supply-mix footprint for bananas is over 16 times the global average.

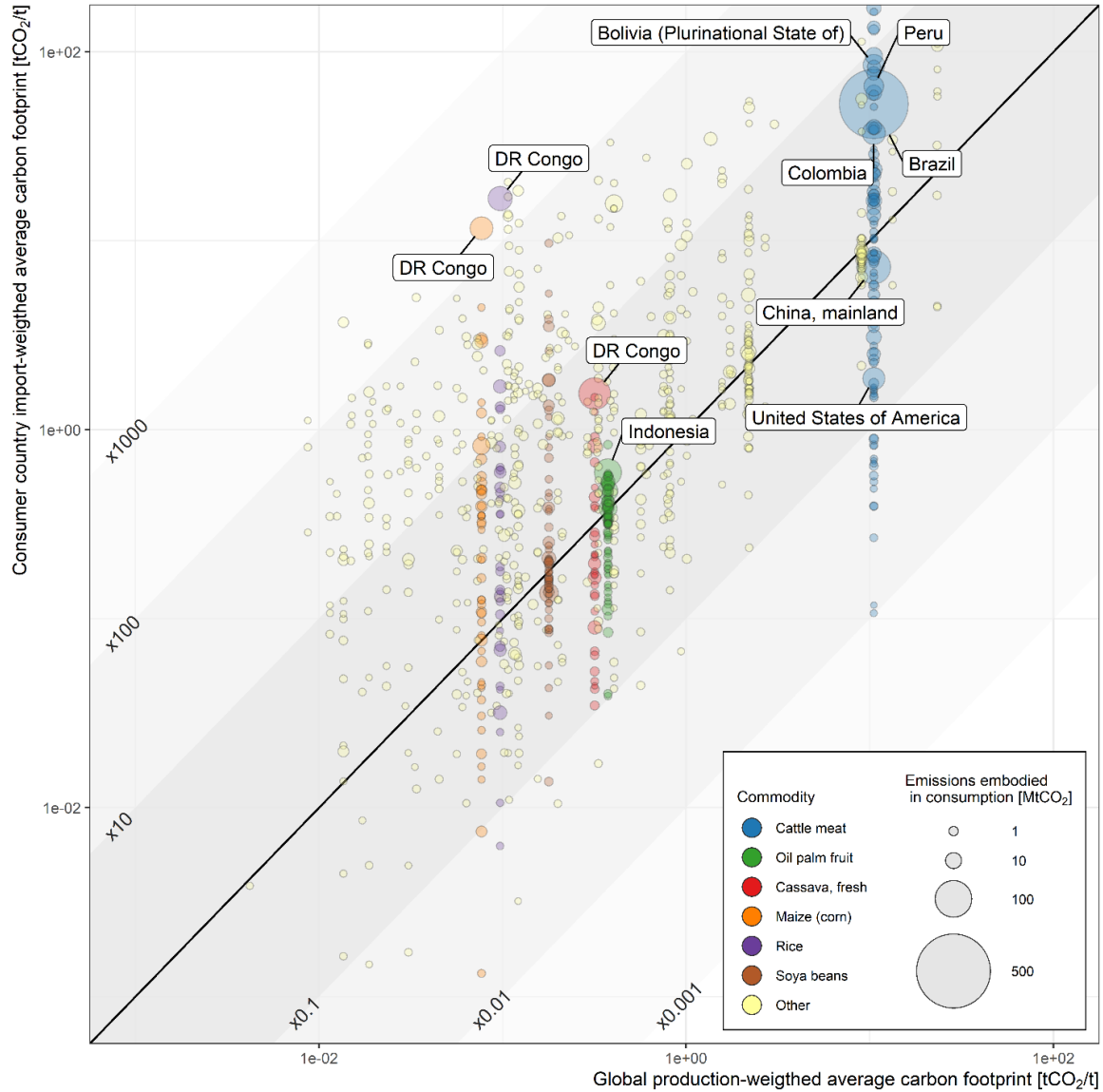


Figure 7. Comparison of global average (production-weighted) deforestation carbon footprints (horizontal axis) and consumer country average footprints weighted by supply-mix (country of origin) (vertical axis). Each bubble represents a specific consumer country and commodity footprint in year 2023, with the bubble size representing the total carbon emissions due consumption (both from domestic production and imports, filtering out total footprints below 0.1 MtCO₂) of that commodity in that country. All country and commodity combinations with emissions exceeding 20 MtCO₂ are labelled and the top six commodities in terms of total emissions shown in separate colors. The shaded bands show where the supply-mix averages differ from the global average by one, two and three orders of magnitude (up or down) respectively.

DISCUSSION & CONCLUSIONS

Carbon footprints are not an end in themselves but provide decision support to actors seeking to reduce emissions, such as those from agriculture-driven deforestation. This is the yardstick against which the methodological choices examined above should be measured: accuracy, comprehensiveness and comparability, stability and responsiveness matter as it helps actors see where their exposure lies and whether changes in actor footprints are due to actions taken or changes in external factors.

Our results show that deforestation carbon footprints vary by orders of magnitude across commodities and producer countries, and that most of this variation is explained by three factors: The share of production on land deforested within the assessment period is by far the strongest predictor, trailed by carbon losses on cleared land and agricultural yields. These are aggregate, empirical regularities across a global sample; however, they reflect the fact that even if moratoria on the conversion of high-carbon forests or extension services and other support that raise yields on land already cleared may help reduce the carbon footprint of agricultural commodities, the only way to eliminate these emissions (and bring footprints to zero) is to stop clearing new land for agriculture.

We also show that the choice of approach for allocating deforestation emissions to production over time involves a trade-off between stability and responsiveness: A less volatile metric provides a more stable basis for long-term decisions on where to invest and with whom to establish business relations, as trade patterns have been found to be “sticky” [38] meaning that changing sourcing carries real transaction costs. But a more stable metric also lags changes in deforestation emissions, weakening the incentive to act and obscuring emerging deforestation frontiers, since it takes time for footprint values to reflect reductions or increases in deforestation.

However, our findings suggest that this trade-off is more or less pronounced depending on how deforestation footprints are calculated: Allocating emissions equally to each ton produced yields a more stable footprint, at the price of only slightly lower responsiveness to changes in deforestation emissions, compared to the discounted time-allocation method mandated by in the LSRS guidelines. The latter is substantially more responsive to changes in production volumes than in deforestation rates, whereas the production-allocation footprint is uncorrelated with production changes (regardless of the amortization period used).

This is an accounting integrity problem, not a statistical curiosity: under the discounted time-allocation method recently mandated by the GHG Protocol, a company can report a declining deforestation footprint driven entirely by rising production in its sourcing jurisdictions, with no reduction, or even an increase, in deforestation (or conversely, a company may see increases in Scope 3 deforestation emissions not due to increased clearing for sourced commodities, but to production reductions, for instance due to weather shocks). This problem with amortizing emissions over time is further compounded by the choice of a standard 20-year amortization period. Our analysis shows that for amortization periods of 10 years or more, deforestation footprint trends are typically as much or more influenced by production dynamics than changes in deforestation emissions (even when discounting deforestation further back in time), resulting in poor information to decision-makers using the metric.

We therefore argue that the decision to mandating 20-year linear amortization in the final LSRS and dropping the option—tabled in the draft guidance [36]—of apportioning emissions over production should be revisited. At minimum, production allocation should be permitted as an alternative metric reported alongside the linearly discounted figure. Importantly, while a uniform standard facilitates comparisons of footprints and performance across actors, companies themselves are of course free

to use a range of different metrics to assess and inform their own risk screening and sourcing decisions. The results here suggest that using complementary deforestation footprints, calculated over different amortization periods (as reported) here, might help companies better understand deforestation dynamics for the regions or upstream suppliers they source from. This mirrors recent calls in literature to monitor and assess the impacts of land-use changes over different spatial and temporal scales (including complementing backward-looking footprints with prospective or forward-looking modeling) [18, 40, 41].

Where sourcing origin is unknown, the LSRS directs companies to use global average emission factors [7]. Our results show that such averages can be very poor representation of what is actually consumed in a given country, differing by two to three orders of magnitude. This is particularly the case for countries that are both major producers and consumers of forest-risk commodities, but differences are substantial also for major importers. Because supply-mix weighting requires only bilateral trade data that already exist [23, 24], and is here calculated for every country and commodity, there is little reason to fall back on the global average. Supply-mix footprints also signal to companies where investment in traceability is likely to pay off.

Jurisdictional averages should nonetheless be used with care. By construction they assign the same footprint to every producer in a jurisdiction, penalizing those that have cleared no forest while rewarding those that have, and they can be lowered simply by exiting a landscape—which shifts, rather than reduces, global land demand [7] and withdraws engagement precisely where leverage is greatest. This is the rationale for the LSRS hierarchy, in which jurisdictional estimates are a fallback in cases of limited traceability, rather than a goal in themselves.

Recent advances in providing sub-national deforestation footprints at scale are promising in this regard: the WRI-Quantis benchmark sLUC factors cover 42 crops for 2020-2024 [19] and

AdAstra's Orbae currently covering 15 commodities globally [17]. However, the comprehensiveness and comparability of the LCI dataset presented here also matters for making good decisions, especially for (large) actors using a wide range of crop commodities sourced from many different regions, since it is what allows them to see what the alternatives are (even if data availability and quality is uneven). And compared with the land-use change data in existing LCI databases, which generally rely on national statistics and simple allocation models, the database presented here is a large leap forward, being open access, spatially derived (hence providing jdLUC estimates where possible) and covering 183 commodities across 179 countries for 2005-2024. Recent implementations of DeDuCE at sub-national level for the Amazon basin [42], as well as increasing availability of sub-national agricultural statistics (e.g., [43]) means that we will soon be able to expand the LCI database presented here also with sub-national (municipal) footprints.

Three further points are worth noting for LCA practitioners and data users: First, we calculate jdLUC footprints where spatial data permit and sLUC footprints where they do not, following the LSRS hierarchy [7], and some commodity-country time series therefore combine both. This is unavoidable, but has consequences, as the LSRS directs companies to use a single calculation approach per product and sourcing jurisdiction, and requires re-baselining whenever they move between sLUC and dLUC approaches [7]. Users of a living database will thus face repeated re-baselining as new crop maps become available and jdLUC coverage expands.

Second, the deforestation area footprints (in hectares per ton) constitute land transformation inventory data [19] (albeit only for forest biomes) and can as such be combined with existing land use characterization factors to assess impacts on biodiversity and ecosystem services [41], extending the database's relevance beyond carbon.

Third, our analysis of difference between amortization methods and periods illustrates the distinction, argued for by Maciel et al. [42], between the period over which land-use change is inventoried and the period over which its emissions are amortized. Eq. 5 shows that footprints are in theory neutral to the latter choice, while our empirical results show that in practice the choice of amortization period affect footprints because deforestation, carbon stocks and yields change over time.

Several limitations should also be borne in mind by those using the data: The database covers the conversion of forests only; conversion of other natural ecosystems—woodlands with a canopy cover lower than 25%, grasslands and wetlands—is not included, although such conversion is of at least comparable magnitude globally [3] and falls within the scope of both the LSRS [7] and FLAG [6]. This reflects a fundamental data limitation: global data on non-forest conversion is at present much more uncertain and does not present time-series long enough to calculate 20-year footprints. Our footprints are therefore a lower bound on land-use change emissions, particularly for livestock products, cereals and oil crops shown to drive extensive conversion of non-forest ecosystems globally [44].

We also do not account for methane or nitrous oxide from clearing fires or subsequent management, though these are typically very small (accounting for 1-2% of LUC emissions [19]). Emissions from the oxidation of drained peat are likewise excluded, being annual rather than committed emissions and hence not amenable to amortization; these are available in the underlying DeDuCE dataset [2] and can be combined with the footprints presented here. Nor do we cover land management emissions and removals. The footprints presented here are thus one component of, and not a substitute for, a complete FLAG inventory.

Because deforestation is allocated to a single commodity (i.e., assuming unit allocation factors in Eq. 1), co-production, crop rotations and multiple cropping are not resolved, and users propagating these farm-gate factors to processed and animal products—including embodied feed, which FLAG now explicitly requires [6]—must apply their own downstream allocation. Finally, we report point estimates, while the accuracy of the underlying deforestation attribution varies considerably across regions and commodities [2].

Land-use change emission factors are becoming compliance-relevant infrastructure: use of the final LSRS is required for SBTi FLAG target setting from 1 January 2027 [6, 7]. Numbers of this consequence should rest on data that are open, documented and ideally peer-reviewed (at minimum available for scientific scrutiny), rather than proprietary. The database presented here is a step in that direction, but realizing its potential depends on continued public investment in monitoring: crop and pasture mapping in data-poor regions and for staple crops, tracking of secondary forest dynamics, and better sub-national production statistics. These are the binding constraints on the accuracy of deforestation footprints, and hence on the quality of the decisions they are meant to support.

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SUPPLEMENTARY MATERIAL

Statistical analyses of differences in footprint volatility and responsiveness to changes in deforestation emissions and production

To assess the temporal volatility the estimated deforestation carbon footprints calculated using different methods for allocating emissions to production over time (equally over production, equally over years, or linearly discounted over years), we computed four different volatility indices for each of the allocation methods:

- (i) Coefficient of Variation (CV), which is the (sample) standard deviation divided by the mean:

$$CV = \sqrt{\frac{1}{n-1} \sum (x_t - \bar{x})^2} / \bar{x}$$

- (ii) Normalized Root Mean Square Error (nRMSE): $nRMSE = \sqrt{\frac{1}{n} \sum (x_t - \bar{x})^2} / \bar{x}$

- (iii) Mean Absolute Percentage Deviation (MAPD): $MAPD = \frac{1}{n} \sum \left| \frac{x_t - \bar{x}}{\bar{x}} \right|$

- (iv) CV of first differences ($\Delta x = x_t - x_{t-1}$): $CV_{FD} = \sqrt{\frac{1}{n-1} \sum (\Delta x_t - \overline{\Delta x})^2} / |\overline{\Delta x}|$

We calculated these volatility indices for each commodity (*i*) and jurisdiction (*j*) combination, for footprints estimated using the three different allocation methods ($DF_{c,j,t}^{prod}$, $DF_{c,j,t}^{unif}$, $DF_{c,j,t}^{disc}$), for both a 20 and 5 year amortization period, and for the shortest common time-series (2020-2023, as year 2020 is the first year that footprints can be calculated if using a 20 year amortization period).

This yielded about 7,300 observations, where it was possible to calculate all volatility estimates for all allocation methods and amortization periods. The distribution of volatility across commodities and jurisdictions for each of the volatility indices and footprint methods are shown in Figure S6. As can be seen, when comparing between the three allocation methods (for a 20 year amortization period), the production allocation approach consistently displays the lowest temporal volatility (more stability), across volatility indices. The temporal volatility of for the production allocation method is 2-5% lower than the uniform allocation method (across volatility indices), and 5-11% lower than the discounted allocation method, and all differences are statistically significant (p-values below 10^{-6} , evaluated with a pairwise Wilcoxon test). However, differences are negligible (though still statistically significant at the 2%-level) when comparing the 5-year amortized production and uniform allocation estimates, though—as can be expected—these footprint time series exhibit much higher volatility than those calculated over a 20-year amortization period.

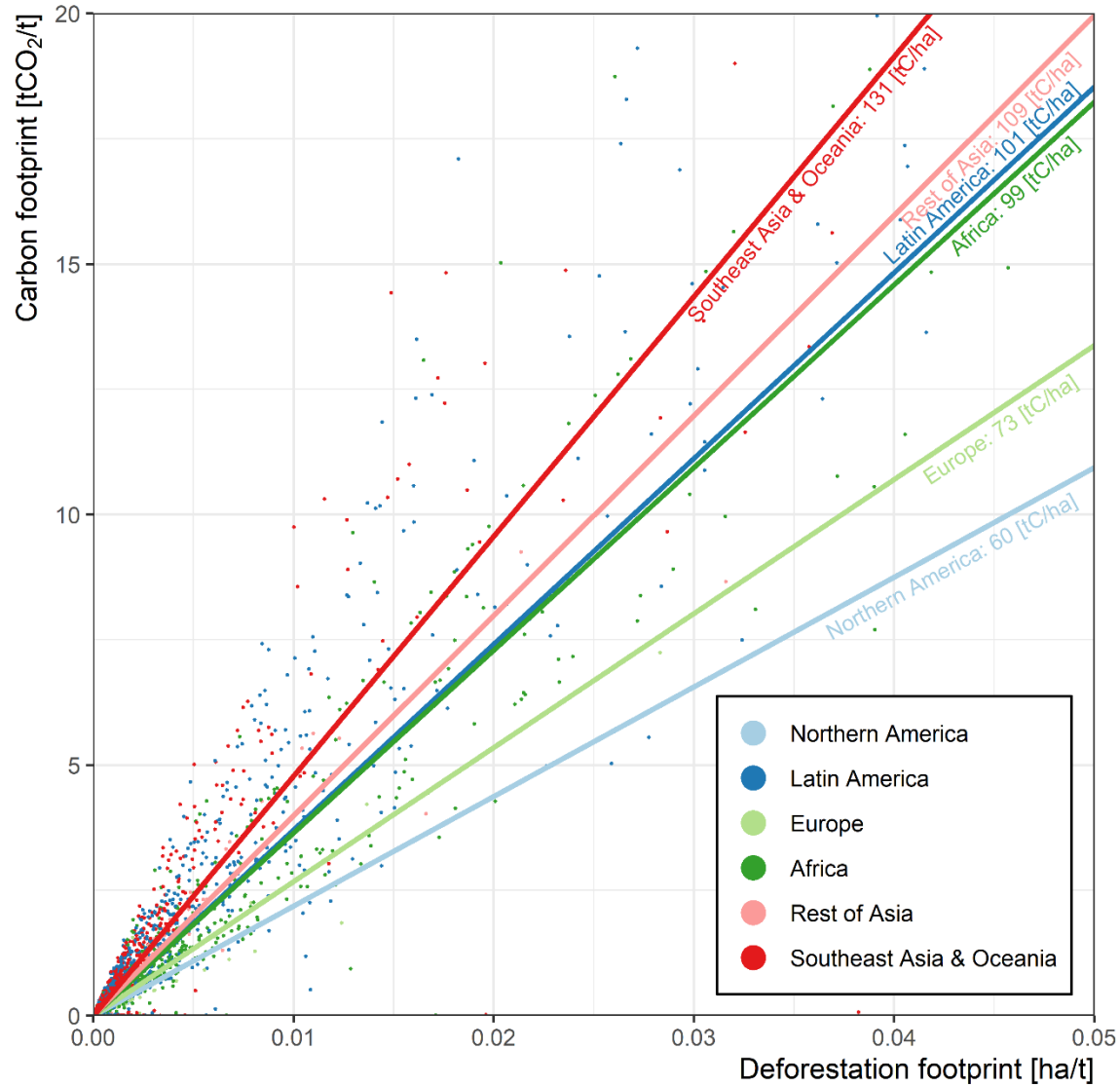


Figure S1. Deforestation carbon footprints (vertical axis) plotted against deforestation area footprints (horizontal axis). Footprints are for year 2023, calculated using a 20-year amortization period. The lines represent the average carbon loss per hectare of forest cleared by region, which are heavily influenced by commodities accounting for a large share of deforestation. This is the reason why many individual data points deviate from the mean lines (see text and Figure S2 for further explanation).

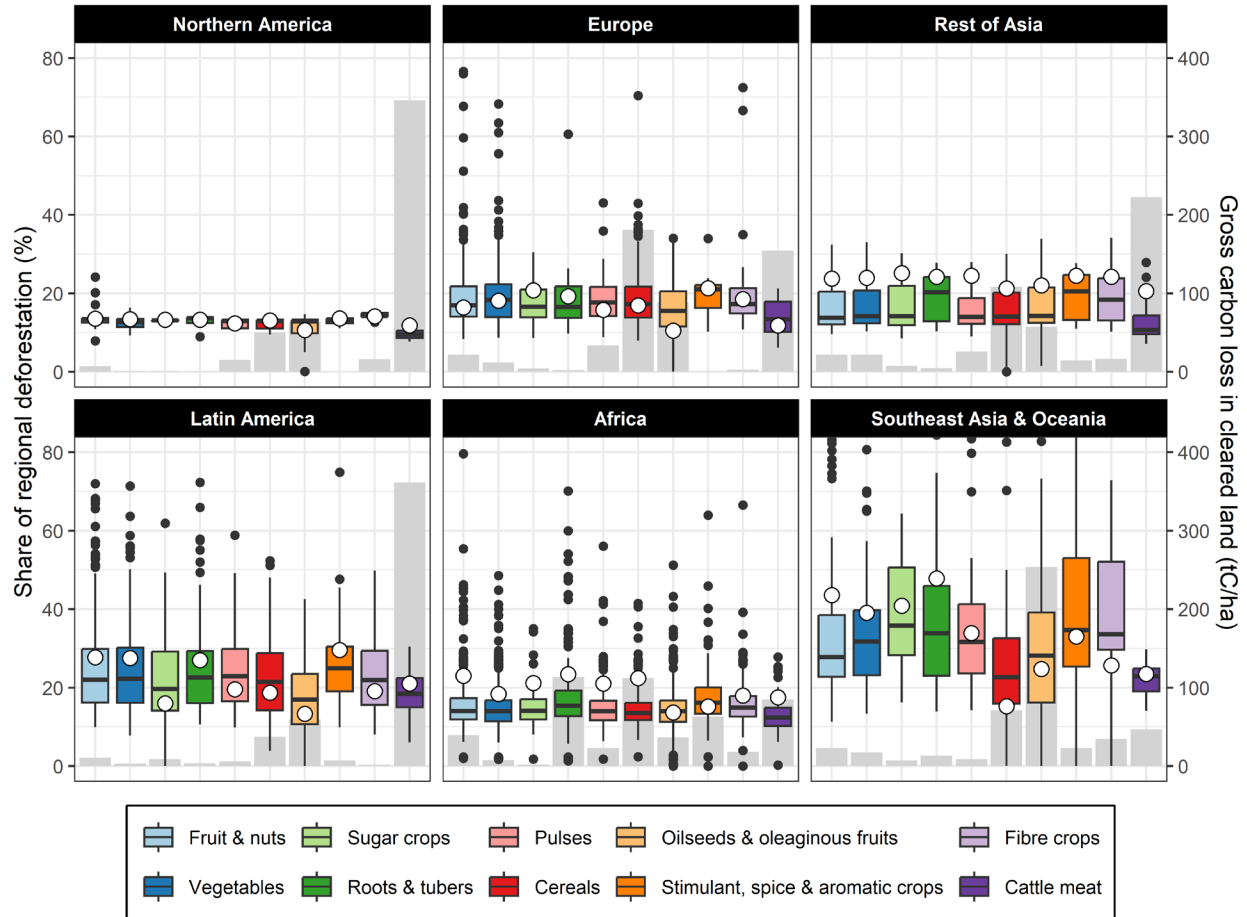


Figure S2. Distribution of average carbon losses per hectare (right axes) for carbon footprint estimates for 2023 calculated using a 20-year amortization period, by region and commodity group. Boxes reflect 25-75% interquartile range (IQR), horizontal lines median values, whiskers the largest value within 1.5 times the IQR, black circles outliers, and white circles area-weighted averages. Grey bars show the share of deforestation for each commodity group, within each region, in the 2004-2023 period. Comparing with the average carbon loss per hectare of cleared land by region (displayed in Fig. S2), it is clear that there are large variations in carbon losses across commodity groups within each region, the average values reflect that of main deforestation drivers (e.g., cattle meat in Northern and Latin America, and Rest of Asia, oilseeds in Southeast Asia).

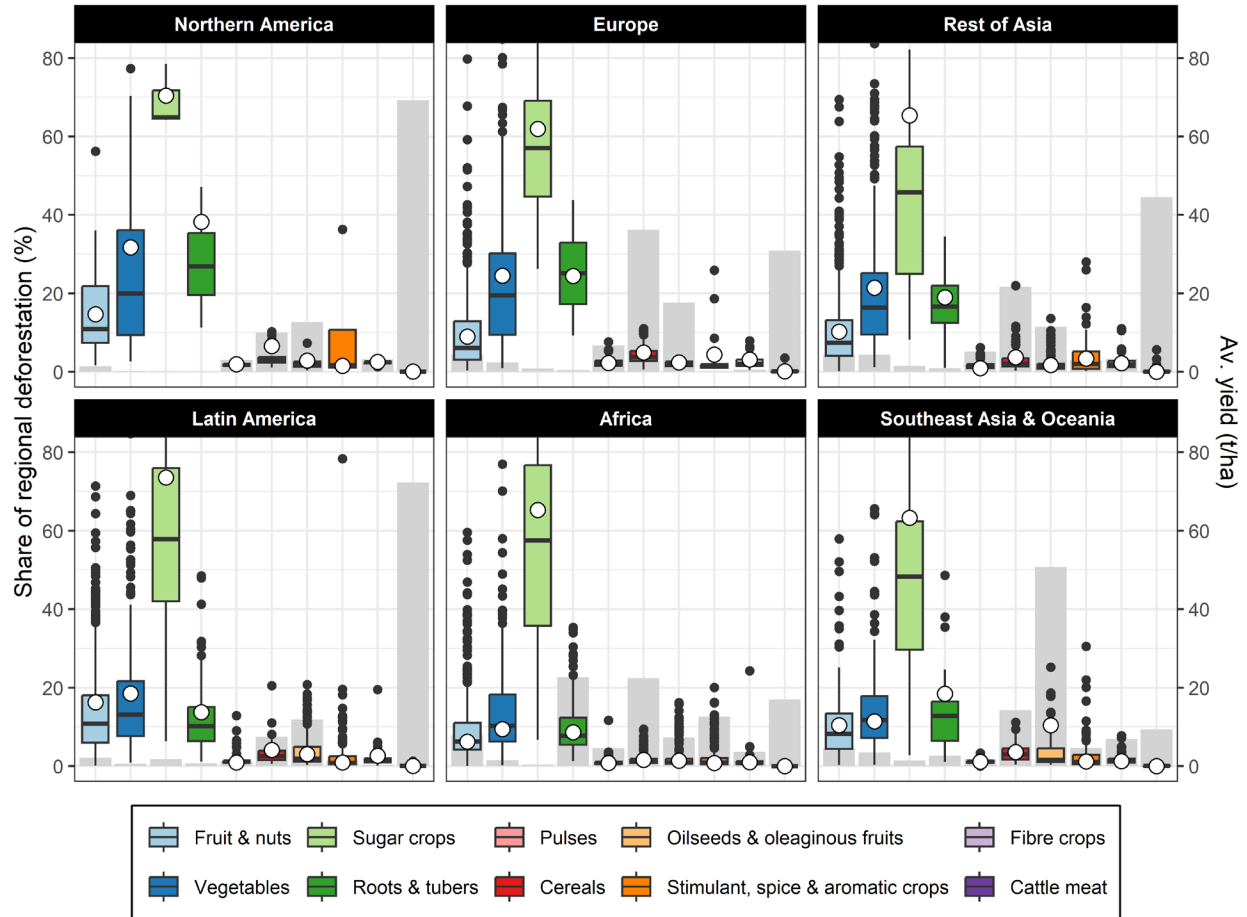


Figure S3. Distribution of yields by region and commodity group (right axes) for carbon footprint estimates for 2023 calculated using a 20-year amortization period, by region and commodity group. Boxes reflect 25-75% interquartile range (IQR), horizontal lines median values, whiskers the largest value within 1.5 times the IQR, black circles outliers, and white circles area-weighted averages. Grey bars show the share of deforestation for each commodity group, within each region, in the 2004-2024 period.

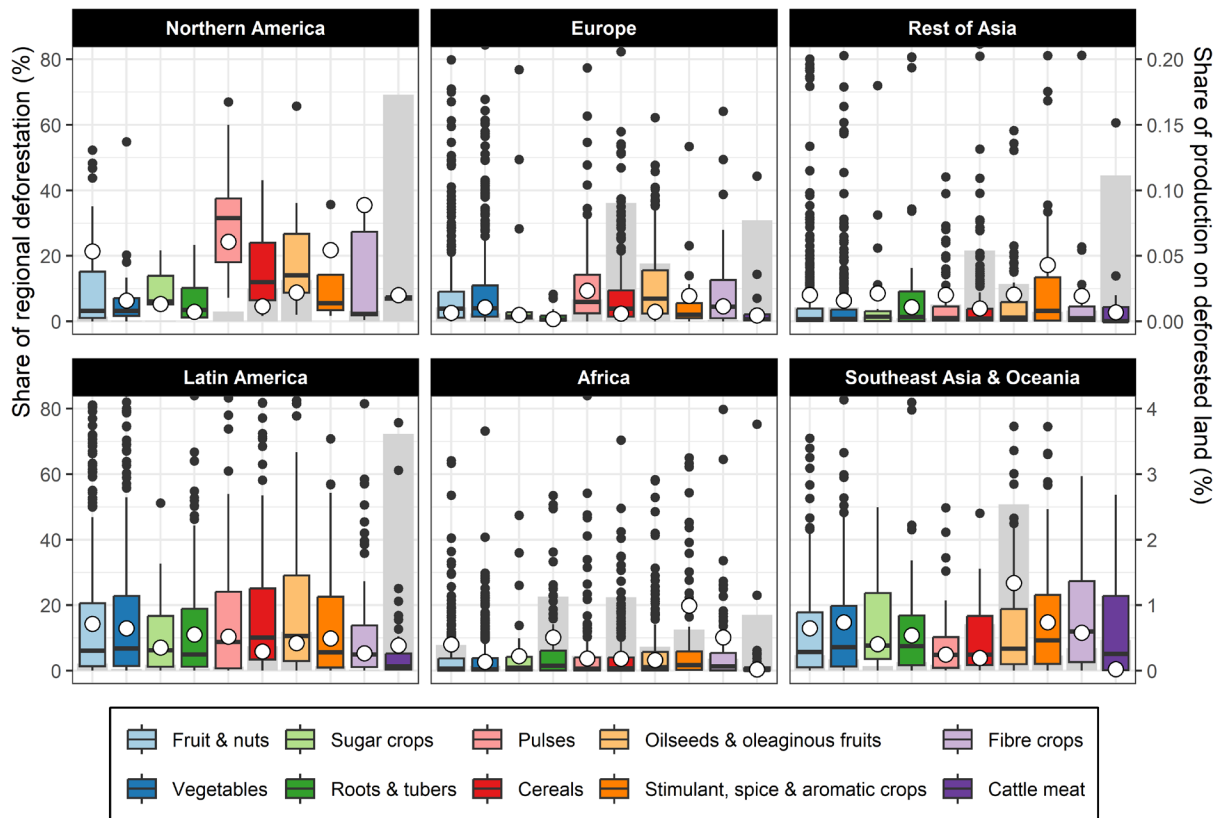


Figure S4. Distribution of the share of production in 2023 that occurs on land deforested within the previous 20 years, by region and commodity group (right axes). Boxes reflect 25-75% interquartile range (IQR), horizontal lines median values, whiskers the largest value within 1.5 times the IQR, black circles outliers, and white circles area-weighted averages. Note the difference in scale between the upper and lower row: in Northern America, Europe and Rest of Asia the share of production on land cleared in the last two decades is typically around a few hundredths of a percentage point (with the exception in pulses, stimulants, and fibre crops in Northern America), while in tropical regions the share is an order of magnitude higher (or more so in Latin America and Southeast Asia and Oceania, where agriculture-driven deforestation have exceeded those in Africa). Grey bars show the share of deforestation for each commodity group, within each region, in the 2004-2023 period.

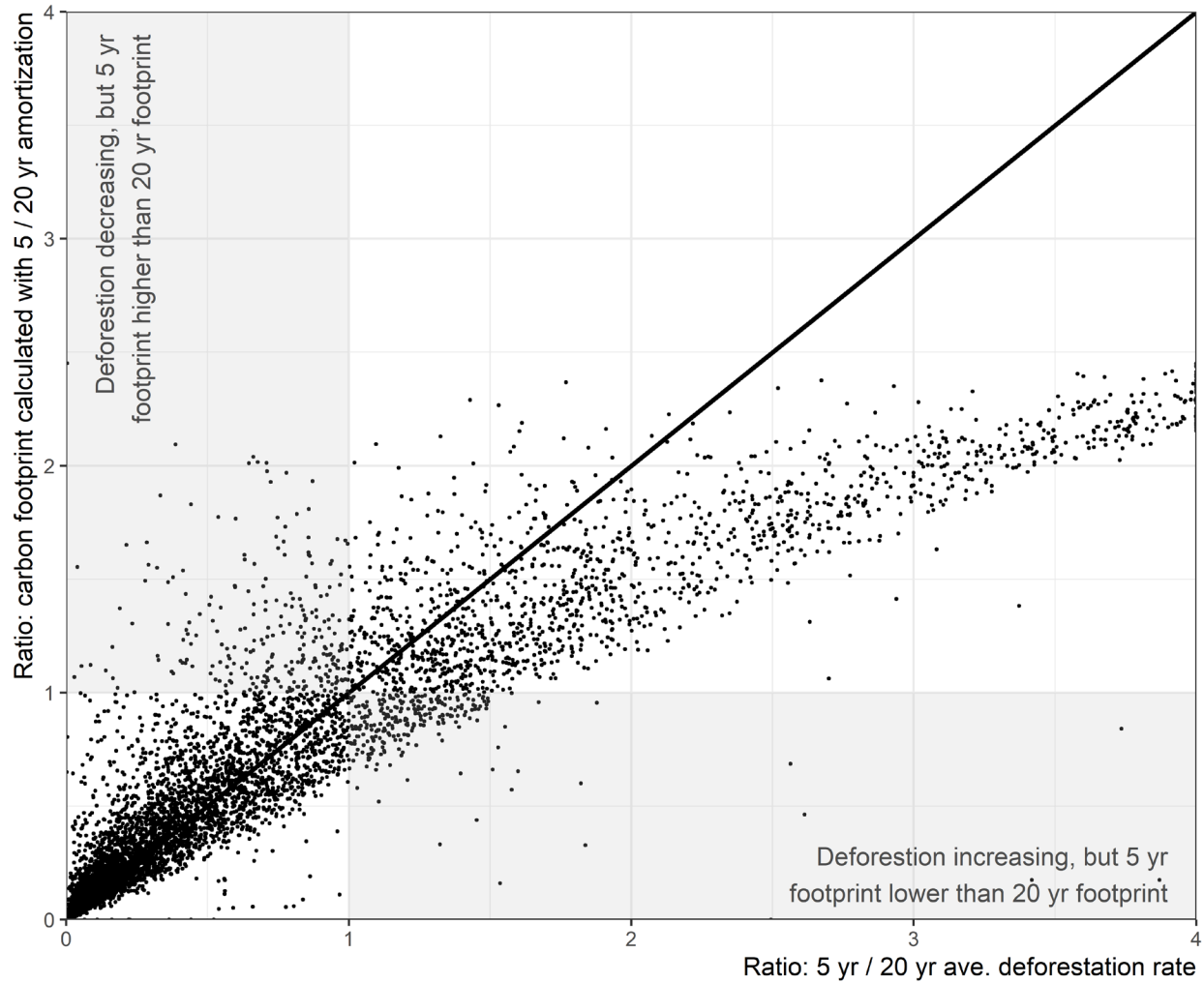


Figure S5. The ratio between deforestation carbon footprints (for year 2023) calculated using a 5- and 20-year amortization period (vertical axis) plotted against the ratio of the average deforestation rates calculated over the same time periods. The grey areas represent combinations where the relationship between trends in deforestation and ratio between deforestation footprints calculated over different periods are not as expected, which is the case for 515 footprints (6% of the full sample) and mostly are commodities with little deforestation (a few hundred hectares per year or less on average).

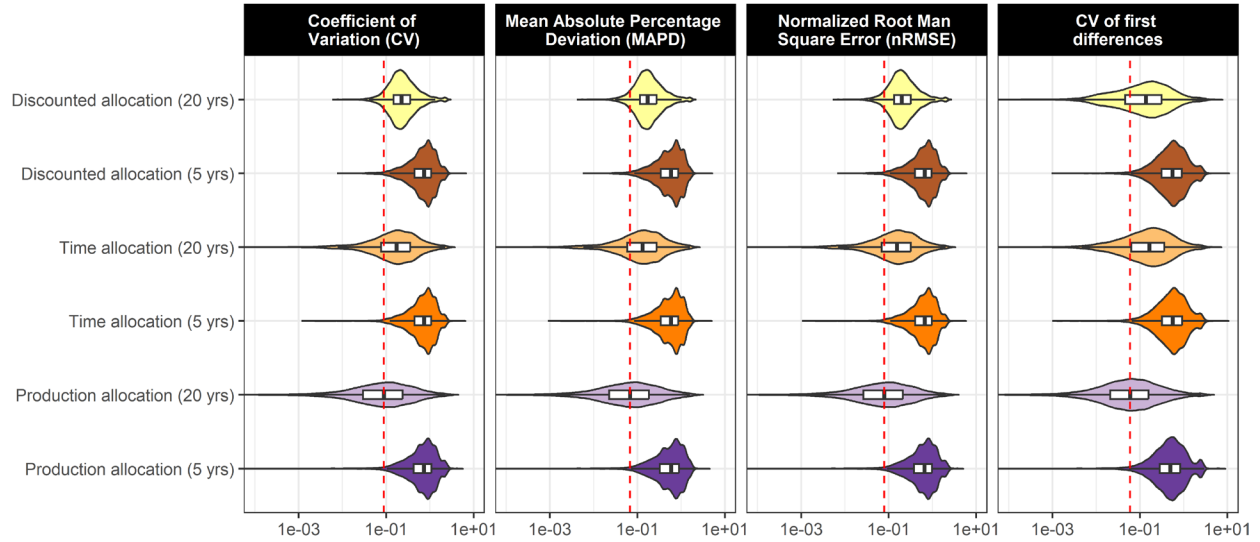


Figure S6. These violin plots show the temporal volatility of deforestation carbon footprints as calculated using different allocation methods— linearly discounted (Discounted allocation), equally to each year (Time allocation), and equally to each ton produced (Production allocation)—and amortization periods—5 vs. 20 years. Temporal volatility (or, inversely, stability) is calculated using four different metrics—the Coefficient of Variation (CV), the Mean Absolute Percentage Deviation (MAPD), the Normalized Root Mean Square Error (nRMSE), and the CV of first differences (for mathematical expressions, see text above)—over the time-series for which there is data for both the 5 and 20 year amortization footprints (2020-2024). The production allocation method exhibits the lowest temporal volatility across metrics, for footprints calculated using both a 5 and a 20-year amortization period, and apart for the 5-year MAPD measures all differences are highly statistically significant (p-value lower than 10^{-7} , tested using a pairwise Wilcoxon test).

Table S1. Carbon stocks of replacing commodities and commodity groups across different biomes. The values below reflect maximum carbon stocks (e.g., at harvest for annuals and at the end of rotational periods for perennials, like oil palms), so in the calculation of net carbon emissions we multiply these values by 0.75 to reflect an average carbon stock over a rotation period. See Supplementary material in Singh & Persson [2] for original references.

(Values in MgC ha ⁻¹)			
Crop or Commodity group	Tropical	Temperate	Boreal
Cereals	4.44	3.15	
Maize (corn)	6.3		
Rice	4.5		
Wheat	2.3		
Barley	5.5		
Sorghum	4.12		
Millet	3.13		
Edible roots and tubers with high starch or inulin content	3		
Cassava	4.5		
Potatoes	0.5		
Fibre crops	3.71		
Natural rubber in primary forms	79.05		
Jute, raw or retted	3.9		
Seed cotton, unginned	4.3		
Forest plantation	120.23	130.99	96.07
Fruit and nuts	31.96	39.53	
Apples	26.48		
Bananas	6.2		
Cashew nuts, in shell	37.6		
Grapes	12.3		
Mangoes	84.75		
Oranges	7.69		
Other citrus fruit, n.e.c.	20.65	23.73	
Plantains and cooking bananas	6.2		
Oilseeds and oleaginous fruits	31.96	39.53	

Oil palm fruit	52.28	
Soya beans	3	
Sunflower seed	1.1	
Groundnuts, excluding shelled	1.1	
Olives	5.3	
Coconuts, in shell	57.38	65.93
Pasture	6.8	
Pulses (dried leguminous vegetables)	1.56	
Beans, dry	2.39	
Chick peas, dry	1.28	
Cow peas, dry	1.82	
Pigeon peas, dry	3	
Lentils, dry	1.25	
Peas, dry	0.9	
Stimulant, spice and aromatic crops	31.96	39.53
Coffee, green	77.12	
Cocoa beans	34.55	
Tea leaves	21.06	
Sugar crops	10.17	
Sugar beet	8.32	
Sugar cane	12.02	
Vegetables	0.43	
Cabbages	1.65	
Lettuce and chicory	1.15	
Tomatoes	3.48	
Cauliflowers and broccoli	4.05	

Table S2. Commodities for which the Deforestation Driver and Carbon Emissions (DeDuCE) model employs spatially explicit data on extant and therefore provide direct land-use change (dLUC) estimates for deforestation area and carbon footprints. See Supplementary material in Singh & Persson [2] for original references.

Crop	Geographical coverage	Spatial resolution	Temporal resolution
Sugarcane	Brazil	30 m	Aggregated temporally using data for year 2016-2019
Soya beans	South America	30 m	2001-2022
Rice	Northeast and Southeast Asia	10 m	Aggregated temporally using the data for year 2017-2019
Rapeseed	Argentina, Europe, United States and Canada	10 m	Aggregated temporally using data for year 2017-2019
Maize (corn)	China	30 m	2001-2020
Cocoa	Côte d'Ivoire and Ghana	10 m	Aggregated temporally using data for year 2018-2021
Coconut	Pan-tropical	20 m	2020
Oil palm fruit	Indonesia	Vector	2000-2019
	Malaysia	100 m	2001-2018
	Pan-tropical	10 m	2019
Cattle meat (pastures); Coffee; Maize (corn)	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, French Guiana, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela, Indonesia	30 m	2001-2022 (for all countries, except Bolivia); 2001-2021 (for Bolivia)