Global Environmental Change 62 (2020) 102067

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

Spatially-explicit footprints of agricultural commodities: Mapping carbon emissions embodied in Brazil's soy exports

Neus Escobar[a,b,*], E. Jorge Tizado[c], Erasmus K.H.J. zu Ermgassen[d,e], Pernilla Löfgren[f], Jan Börner[a,b], Javier Godar[f]

[a] Institute for Food and Resource Economics (ILR), University of Bonn, Bonn, Germany
[b] Center for Development Research (ZEF), University of Bonn, Bonn, Germany
[c] Department of Biodiversity and Environmental Management, Universidad de León, León, Spain
[d] Earth and Life Institute, UCLouvain, Louvain-la-Neuve, Belgium
[e] Fonds de la Recherche Scientifique F. R. S.-FNRS, Brussels, Belgium
[f] Stockholm Environment Institute, Stockholm, Sweden

ARTICLE INFO

Keywords:
Carbon footprint
Deforestation
Greenhouse gas
International trade
Life cycle assessment
Supply chain

ABSTRACT

Reliable estimates of carbon and other environmental footprints of agricultural commodities require capturing a large diversity of conditions along global supply chains. Life Cycle Assessment (LCA) faces limitations when it comes to addressing spatial and temporal variability in production, transportation and manufacturing systems. We present a bottom-up approach for quantifying the greenhouse gas (GHG) emissions embedded in the production and trade of agricultural products with a high spatial resolution, by means of the integration of LCA principles with enhanced physical trade flow analysis. Our approach estimates the carbon footprint (as tonnes of carbon dioxide equivalents per tonne of product) of Brazilian soy exports over the period 2010–2015 based on ~90,000 individual traded flows of beans, oil and protein cake identified from the municipality of origin through international markets. Soy is the most traded agricultural commodity in the world and the main agricultural export crop in Brazil, where it is associated with significant environmental impacts. We detect an extremely large spatial variability in carbon emissions across sourcing areas, countries of import, and sub-stages throughout the supply chain. The largest carbon footprints are associated with municipalities across the MATOPIBA states and Pará, where soy is directly linked to natural vegetation loss. Importing soy from the aforementioned states entailed up to six times greater emissions per unit of product than the Brazilian average (0.69 $t\ t^{-1}$). The European Union (EU) had the largest carbon footprint (0.77 $t\ t^{-1}$) due to a larger share of emissions from embodied deforestation than for instance in China (0.67 $t\ t^{-1}$), the largest soy importer. Total GHG emissions from Brazilian soy exports in 2010–2015 are estimated at 223.46 Mt, of which more than half were imported by China although the EU imported greater emissions from deforestation in absolute terms. Our approach contributes data for enhanced environmental stewardship across supply chains at the local, regional, national and international scales, while informing the debate on global responsibility for the impacts of agricultural production and trade.

1. Introduction

Increasingly globalized supply chains for food, feed, fuel, and fibres are associated with both positive and negative impacts on human wellbeing and the environment (Kastner et al., 2012; Liu et al., 2013; Brown et al., 2014). The global trade in agricultural food products more than doubled between 2000 and 2015, from US$ 600 billion to over US $ 1,300 billion and it is forecasted to grow further (FAO 2015; OECD/FAO 2018). Globalized trade has led to the displacement of resource-intensive activities –and associated impacts– from industrialized to developing countries (Bruckner et al., 2012; Kanemoto et al., 2014; Chaudhary and Kastner 2016; Pendrill et al., 2019a). The result is a growing spatial disconnect between consumption and the impacts of production, which translates into complex environmental and social footprints (Steen-Olsen et al., 2012; Wiedmann and Lenzen 2018; Wood et al., 2018). Several approaches have been developed to quantify these impacts and assess the roles of supply chain actors in driving them.

* Corresponding author: Institute for Food and Resource Economics (ILR), University of Bonn, Nussalle 19, 53115 Bonn, Germany
E-mail address: neus.escobar@ilr.uni-bonn.de (N. Escobar).

https://doi.org/10.1016/j.gloenvcha.2020.102067
Received 19 July 2019; Received in revised form 28 February 2020; Accepted 10 March 2020

Resource and emission footprints can be estimated at the sectoral or national level by using Environmentally-Extended Multi-Regional Input-Output (EE-MRIO) models, at different levels of product detail (Wiedmann et al., 2015; Lutter et al., 2016; Lenzen et al., 2018). Although these commonly rely on economy-wide monetary flows, mass balance of physical flows is also increasingly applied in EE-MRIO analysis (Bruckner et al., 2015; Croft et al., 2018; Bruckner et al., 2019). Alternatively, Life Cycle Assessment (LCA) is a suitable methodology to quantify environmental impacts of products or processes from ‘cradle to grave’. The level of detail in the underlying resource and emission inventories however restricts the scope of application to a limited number of scenarios, which represent steady-state “average” conditions (Udo de Haes et al., 2004). This is why LCA results are usually context-dependent and have a low spatial and temporal resolution (Reap et al., 2008). Emerging LCA approaches, such as the one we present here, try to capture both heterogeneity in supply chains and variability in environmentally-relevant flows and associated negative effects, subject to data collection and impact characterization challenges (Smith et al., 2017; Pelton 2018; Poore and Nemecek 2018; Lee et al., 2020).

Physical trade accounting constitutes another method for estimating impacts embodied in international trade based on commodity-specific data on production, imports, exports and domestic use (Kastner et al., 2011; Kastner et al., 2014; Henders et al., 2015). As with EE-MRIO analysis, physical trade accounting traditionally employs national-level data, which masks heterogeneity in the characteristics of production as well as of domestic and international transport (Pendrill et al., 2019b). Hybrid middle-ground approaches combine production and trade statistics at the national level with regionalized impact characterization methods in LCA for a more comprehensive assessment of both sector- and country-based environmental footprints (Chaudhary and Kastner 2016; Sandström et al., 2018; Cabernard et al., 2019; Corrado et al., 2019). The ‘Spatially-Explicit Information on Production to Consumption Systems’ (SEI-PCS) model developed by the Trase platform[1] constitutes a special case of physical trade accounting model that allows for global supply chains to be tracked at sub-national scales (Godar et al., 2015; 2016). As such, it can be used to quantify production- and consumption-based environmental footprints, e.g. water scarcity footprint, of agricultural products with a high spatial resolution (Flach et al., 2016). Building on Trase's detailed supply chain mapping, we develop a bottom-up LCA framework to quantify carbon emissions embodied in globally traded agricultural commodities in a spatially-explicit manner, shown here for soy exports from Brazilian municipalities. This avoids the need for basing analyses on single values for ‘representative’ production and export pathways, as is the case for conventional LCA studies and databases.

To showcase this new approach, we select soy as the most internationally traded agricultural commodity, which is mainly used worldwide for animal feed (COMTRADE 2018). Brazil is the world's leading soy producer and exporter, together with the United States (OECD/FAO 2017; Cattelan and Dall'Agnol 2018). The expansion of soy in Brazil is directly and indirectly associated with the loss of forests and other natural vegetation (Gibbs et al., 2010; Zalles et al., 2019). This has progressively raised concerns among consumers, leading traders and governments to take measures to prevent deforestation (Arima et al., 2014; Nepstad et al., 2014). The conservation policy mix implemented in the 2000s, including government command-and-control regulations and the multi-stakeholder Soy Moratorium of 2006, helped reduce soy-associated deforestation in the Amazon (Macedo et al., 2012; Nepstad et al., 2014; Gibbs et al., 2015). However, soy has continued to replace native vegetation in the neighbouring Cerrado biome (Morton et al., 2006; Rausch et al., 2019; Zalles et al., 2019). At present, deforestation related to soy production is concentrated in the Cerrado's so-called MATOPIBA region (consisting of the states of Maranhão, Tocantins, Piauí, and Bahia) (Spera et al., 2016; Soterroni et al., 2019). Deforestation hence remains a major contributor to the greenhouse gas (GHG) emissions from Brazil's soy production (Lathuillière et al., 2014; Maciel et al., 2016). While the aforementioned research mostly focuses on land cover change in the Amazon biome and the state of Mato Grosso in particular, there are few studies of the environmental implications of soy expansion in MATOPIBA (Zalles et al., 2019). Most notably, Noojipady et al. (2017) used satellite remote sensing data to estimate that MATOPIBA accounted for 45% of the total CO_2 emissions from overall cropland expansion in the Cerrado between 2010 and 2013.

Besides the location and time in which soy farming takes place, the carbon footprint (CF) of Brazilian soy in the countries of import depends on other factors, such as the CO_2 intensity of freight transport. GHG emissions from both ground and maritime shipping are also highly variable, depending on the distance to be covered and the means of transport involved in export routes (Silva et al., 2010; Schim Loeff et al. 2018). While some LCAs address uncertainty in soy production and associated Land Use Change (LUC) by considering a predefined set of scenarios (Castanheira and Freire 2013; Raucci et al., 2015; Maciel et al., 2016), only a small number of studies tackle other sources of uncertainty, e.g. in domestic and international transport (Silva et al., 2010; Castanheira et al., 2015; Cerri et al., 2017). None of these however provides a consistent estimate of the emissions across the entire sector – a key gap that we address in this study. Based on the integration of traditional LCA into enhanced physical flow accounting, we present a hybrid approach that aims at balancing resolution and scope for the quantification of carbon emissions of globally traded agricultural commodities along their supply chain. Our approach is equivalent to applying an LCA to each of the unique supply chain configurations embedded in agricultural commodity trade, hence capturing heterogeneity in production, transportation and processing systems. The ultimate goal of this study is to contribute data for more coordinated environmental stewardship along supply chains, while assisting the implementation of cost-effective climate mitigation strategies and informing the ongoing debate on global responsibility for the impacts of agricultural production and trade.

2. Methods

We develop a hybrid approach for quantifying the GHG emissions embedded in the production and trade of agricultural products, based on the integration of LCA principles with the SEI-PCS for spatially-explicit physical trade flow analysis (Trase, 2018a). The latter encompasses detailed per shipment customs declarations with taxation, logistic, production and sanitary inspection records, to build an enhanced physical trade flow analysis of the supply chain, tracing commodity trade flows from municipalities of production to the countries of import (Godar et al., 2016). With our bottom-up LCA method, we assess the CF of Brazilian soy for export with a high spatial resolution by capturing the nationwide variation in LUC and crop management practices, domestic transport logistics, industrial processing (into soy's co-products, namely soybean cake and oil), and international shipping across the entire export volume per year. Altogether, we quantify the emissions of roughly 90,000 separate supply chain configurations or individual ‘life cycles’ identified across the period 2010–2015. These are defined as the accumulated volumes of soybeans, cake or oil that are obtained through the same export pathway across the period of study, i.e. from the producing municipality, to the logistic hub where soy is stored or crushed, and then to the port of export from which soy is shipped to the importing country, where beans can additionally be crushed. With Trase's dataset, we are able to map 85.5% of the overall export volume of Brazilian soy back to the specific producing municipalities, with the remaining 14.5% tracked back to the state of origin. The mathematical formulation of the spatially-explicit LCA is included in the Appendix, in line with the methodological steps in the

[1] More information at Trase's website: https://trase.earth/.

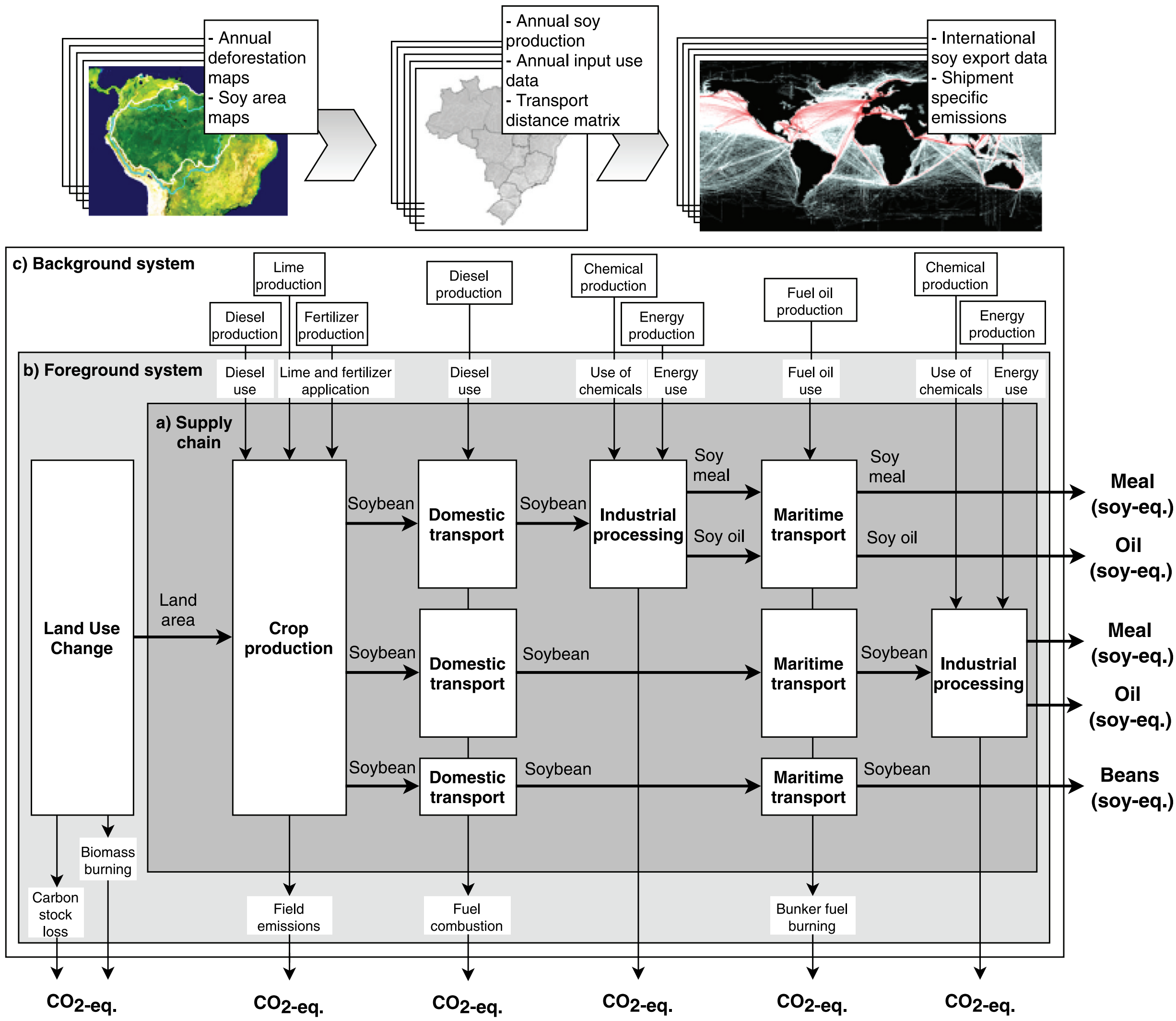

Fig. 1. System boundaries and levels of Life Cycle Inventory data collection across the different life cycles of Brazilian soy for export identified in the period 2010-2015. Source: own elaboration based on images with 'no copyright reserved' (CC0 license).

corresponding ISO standards (14040:2006; 14044:2006), as described below.

2.1. Goal and scope

The CF is here defined as the GHG emissions –as CO_2-eq.– generated from 'cradle to factory gate'; i.e. from agricultural production and export up to the stage in which soybeans and derived products (hereinafter referred to as *soy*) enter the corresponding industry as intermediate inputs in the countries of import. Hence, the system boundaries include the sub-stages shown in Fig. 1; namely *LUC, crop production, domestic transport,* international *maritime transport*, and *industrial processing*, i.e. crushing into oil and cake. The latter can take place either in the country of import or in Brazil prior to export. Although countries of import are not necessarily the countries where soy is finally used as an input to other industries, our approach does not yet account for soy re-exports to a third country (Trase, 2018a). As for the system boundaries, this means that GHG emissions associated with those re-exports, i.e. from additional transport and potential crushing of imported beans, are excluded from this analysis. Given the multi-functional nature of the systems under consideration, the allocation of impacts from upstream soybean production between oil and cake life cycles is based on the relative mass of each co-product after crushing (FAO, 2019). The reference flow or Functional Unit (FU) is one tonne of soybean equivalent (soy-eq.) embodied in soy exports from Brazil across the period 2010–2015. This period allows us to exploit the availability of several key supporting datasets (see below) and captures the aftermath of the Soy Moratorium, which entered into force in 2008. One soy-eq. is defined as the amount of raw soybeans embedded in the flows of oil, cake and beans that are ultimately generated at the end of each supply chain (Godar et al., 2015). In this way, the input-based FU allows the different life cycles to be compared, irrespective of the type of product to be delivered at the industry gate. The CF is thus quantified as CO_2-eq. per soy-eq. as a measure of the carbon intensity of each export pathway.

We use Trase's annual data on export quantities of soybean and derivatives from Brazilian municipalities to the corresponding countries of import in a given year in the period 2010–2015. This allows us to quantify CFs for the soy exporting (importing) territorial units at different scales, based on their relative export (import) quantities across years and the carbon intensity of the underlying supply chains. From the supply side, CFs are firstly estimated at the municipality, state, biome and country levels (Section 3.1). These arise from all the life cycles that have their origin in the soy exporting municipalities identified within a specific territorial unit; and hence include downstream emissions that occur both within and beyond its borders. CFs are secondly estimated, from the demand side, for each of the soy importing countries and world regions, when considering the GHG emission intensity of those import flows that could be tracked to the municipality of origin in Brazil (Section 3.2). In this way, outcomes provide an indicator of the country's global responsibility for upstream impacts of soy production and trade. Finally, we combine relative emission intensities with overall traded volumes to calculate the total CO_2-eq. emissions embodied in Brazil's soy exports in 2010–2015 (Section 3.3). From a *producer perspective*, total GHG emissions are quantified for 2,162 municipalities that exported soy over the period of analysis, covering 85.5% of the overall export volume. From an *importer perspective*, GHG emissions are estimated for each of the soy importing countries, by assuming average state-level CFs for those life cycles for which only the state of origin was known. As a result, total GHG emission estimates cover 99.9% of the overall export volume, which can be understood as the CF of the overall Brazilian exports of soy in the period 2010–2015, in million tonnes of CO_2-eq.

2.2. Life Cycle Inventory

The Life Cycle Inventory (LCI) specifically departs from the Trase's SEI-PCS version 2.3 of Brazilian soy export mapping (Trase, 2019) to subsequently collect spatially-explicit data at three different levels (Fig. 1), namely:

i) Supply chain level, which refers to the quantities of oil, cake and beans (in physical units) that flow along each supply chain to deliver one unit of output –as soy-eq.–, requiring inputs from the foreground and background systems.
ii) Foreground system, covering physical flows of inputs (resources) required for the production and transport of soy at the supply chain level, and outputs (emissions) arising from input use.
iii) Background system, covering the physical flows of resources and emissions arising from the production of inputs employed in the foreground system.

2.2.1. Supply chain level

The LCI integrates Trase's sub-national data on production and trade to map the entire supply of Brazilian soy for export in the period of analysis (Trase, 2018a). To quantify specific export flows, the SEI-PCS version 2.3 relies on public data on National Registry of Legal Entities numbers (*Cadastro Nacional da Pessoa Jurídica* in Portuguese, or CNPJ) (Ministério da Economia, 2018); as combined with custom declarations and bills of lading provided by vendors of trade intelligence data. These datasets are compared with official sources to check for consistency, namely COMEX STAT (2020), COMTRADE (2020), etc. The overall quantities of each product (beans, oil and cake) that are ultimately delivered at the end of the life cycle in the corresponding countries of import are calculated from country-specific crushing ratios (FAOstat, 2018) (see Appendix). This allowed us to identify trade flows of soy derivatives from Brazilian municipalities to the countries of imports at the supply chain level. In this case, 'trade flows' refer to exports of oil and cake previously crushed in Brazil as well as beans to be crushed in the respective countries or remain as such. The spatially-explicit LCI is then complemented with sub-national data on farming systems and export logistics across life cycles at the foreground and background levels, as detailed below. The latter refers to e.g. annual soy-associated deforestation in each municipality, annual yields and agricultural input consumption at the municipal level, amount of soy that is transported through specific means of transport to a given port of export, etc. Data from the 'SEI-PCS Brazil soy 2.3′ (Trase, 2019) is openly accessible via http://www.trase.earth. Additional data sources for the LCI are either openly accessible, accessible upon request or provided in commercial databases, as indicated in the Supplementary Information (see Table S1).

2.2.2. Foreground and background systems

Main assumptions and data sources needed to compile the LCI at the required level of spatial resolution across sub-stages are summarized in Tables S1 and S2 and described below.

- *Land Use Change*: Soy-induced land clearing was firstly identified at the polygon-level by intersecting maps of planted soy areas in the Amazon and Cerrado biomes (Agrosátelite, 2018) with deforestation maps (INPE, 2018a, 2018b). These two biomes cover the largest soy production areas in Brazil and most of the recent natural vegetation loss, with only 1% of the overall cropland expansion in the period 2000–2014 occurring outside the Amazon and Cerrado (Zalles et al., 2019). Deforestation attributed to soy expansion in a given year was retrospectively quantified by considering a 3-year time window, since cleared areas are often sown with pasture or an intermediate crop before soy plantations are established (Osorio, 2018). For example, deforestation attributed to soy exports in 2010 must have occurred between 2008 and 2010 on land planted with soy in 2010. The total land area cleared was subsequently annualized by the number of years in which soy was detected on that land during the 3-year period.

  Emissions from LUC were subsequently quantified by following the IPCC Tier 2 approach (IPCC, 2006), which relies on country- or region-specific estimates of carbon stock changes before and after land conversion. We only considered carbon losses from natural vegetation clearance (i.e. woody biomass), assuming that other land transitions (e.g. from pasture to soy) cause much smaller carbon stock changes (Castanheira and Freire, 2013). This is why we refer to LUC as 'deforestation', though natural vegetation in the Cerrado includes a mosaic of land use types, including forest, shrub, and savannah. High-resolution (ca. $30m^2$) deforestation polygons were intersected with raster data of carbon pools in litter, below- and above-ground biomass (Baccini et al., 2012); assuming that carbon stocks after the conversion are zero. Soil carbon losses were estimated based on reference soils in Brazil and specific land use and management factors for soybean farming (EMBRAPA, 2015; Esteves et al., 2016). Emissions from incomplete combustion of above-ground biomass and litter were included by considering that 20% of the area is burnt in the conversion (Numata et al., 2011). Overall carbon stock losses were ultimately expressed as CO_2-eq. and aggregated to the municipal scale for integration with Trase's supply chain data. Double-cropped soybean areas were derived from municipal production statistics (IBGE, 2018) (Fig. S1) and used to subtract emissions associated with the second crop, assuming that this is responsible for half of the emissions per unit of area (see Eq. (7) in the Annex).

- *Crop production*: emissions from direct field application of lime and fertilizers were estimated based on the IPCC Tier 1 approach (IPCC, 2006). Fertilizer application doses per tonne of soy at the municipal level were derived from the total amount of fertilizers applied annually per crop at the state level (ANDA, 2017); as combined with relative soy production areas with respect to other crops in each municipality and associated yields (IBGE, 2018) (Fig. S2). Relative doses of N, P and K in soy production were estimated by assuming an average ratio of $0\% - 20\% - 20\%$, respectively, based on the most common formulations (Ceccon et al., 2013; Lathuillière et al., 2014) (Fig. S3). The same procedure was followed for the calculation of lime application doses per tonne of soy based on state-level consumption statistics (ABRACAL, 2016) (Fig. S4). It was assumed that all lime is diverted to soy production in those municipalities where soy is single-cropped, while half is allocated to soy in municipalities where soy is produced in rotation with another crop. Fuel consumption in agricultural operations was determined by segmented linear regression based on average consumption values (litres per ha) in Goiás, Mato Grosso, Rio Grande do Sul and Santa Catarina (Castanheira et al., 2015) (Fig. S5). The independent variable was the average size of soybean farms (ha) per state

(IBGE, 2017), by using 50 ha and 500 ha as breakpoints. Double-cropping was also considered (see Eq. (11)), in order to exclude fertilizer requirements for the production of the second crop. This implies one fertilizer application per year also for double-cropped land, assuming that the second crop is maize, which does not require additional fertilization (Raucci et al., 2015; Cattelan and Dall'Agnol, 2018). Emissions from NPK production in the background system were calculated based on the associated energy requirements (Nielsen et al., 2003); as combined with emissions embodied in each of the energy sources required according to Ecoinvent v3 (Wernet et al., 2016). Average emissions for lime production at the global level were also obtained from Ecoinvent v3. Emissions from the production of pesticides were not included, given the diversity of compounds applied and the small contribution that these make to the overall CF of soy (Raucci et al., 2015). Electricity consumption for post-harvest soybean drying was taken from Silva et al. (2010), while associated emissions were estimated from the GHG intensity of electricity production with the average electricity mix in Brazil (Wernet et al., 2016).

- *Domestic transport*: emissions from soy transport inside the country were calculated based on a matrix of transport distances between Brazilian municipalities (Ministério da Infraestrutura, 2015); as combined with spatially-explicit information on the quantities of soy and derivatives transported annually, i.e. from production and processing hubs to ports of export (Trase, 2019). Port-specific transport mixes for the ten most important ports in Brazil in 2015 were then used to calculate distances covered by major means of transport and the associated CO_2-eq. emissions per tkm. Specifically, transport mixes represent the relative shares of road, railway and waterway transport involved in soy (and maize) exports from each port (by weight), which were assumed constant across the period of analysis (EMBRAPA, 2018). The average transport mix for Brazil as a whole was applied to the missing ports, which handled less than 0.3% of soy and maize shipped annually. Transport emissions are thus specific for each life cycle depending on the distance between the municipality of origin and the port, and the port's transport mix. Subsequent CO_2-eq. emissions were estimated based on the global average CO_2-eq. intensity of major means of transport as included in Ecoinvent v3 (Wernet et al., 2016), namely: ‘EURO4 lorry, 16-32 metric tons of freight’ for road transport, ‘diesel freight train’ for rail transport, and ‘barge for inland waterways’ for waterway transport. These means of transport were considered to be representative for Brazil, in the absence of country-specific emission intensity data.
- *International maritime transport*: bunker fuel emissions are based on the work of Schim Loeff et al. (2018), which made use of the Automatic Identification System (AIS). AIS data report semi-continuously the specific position, draft, speed and other operational variables of each vessel. We filtered those vessels that transported soy by using per vessel cargo shipping manifests for the year 2014. When combined with vessel specifications and associated fuel consumption parameters, this allowed us to quantify CO_2-eq. emissions for the specific amounts of soy transported from each port of export to the port of destination in the importing countries in 2014. Average values per export route (as the combination port of export-country of import) and per type of cargo (i.e. beans, cake, oil) were then extrapolated to all the export routes identified by Trase (2019) for the rest of the period 2010–2015.
- *Industrial processing*: emissions from crushing were obtained from reference processes in Ecoinvent v3 (Wernet et al., 2016) for soybean cake and oil production in Brazil and the rest of the world, respectively; by applying mass allocation instead of default allocation based on economic value. This provides a CO_2-eq. emission factor for crushing beans into cake and oil in Brazil and abroad, which already includes average emissions due to the production and transport of chemical and energy inputs. Note that the reference process in Ecoinvent v3 for soy cake and oil production in Brazil employs the country's electricity mix, whereas for the rest of the world it considers the average electricity mix on a global scale.

2.3. Life Cycle Impact Assessment

In the Life Cycle Impact Assessment (LCIA) phase, we quantified climate change potential over a 100-year time horizon at the midpoint level (in CO_2-eq.). Characterization factors from ReCiPe 1.08 (Huijbregts et al., 2017) were applied at the background level of the LCI. Furthermore, the Tier 2 method (IPCC, 2006) was followed to calculate both CO_2 and non-CO_2 emissions, i.e. CH_4 and N_2O, from LUC and crop production at the foreground level; as indicated above.

3. Results

3.1. Carbon footprint at sub-national scales

CFs were firstly quantified for each of the 89,876 individual life cycles identified in Brazilian soy exports in 2010–2015, from the municipality of origin up to the country of import (see Table S3). In this section, we quantify the CF of the soy exporting territorial units from a producer perspective, at different geographical scales (see Eq. (24) in the Appendix). The number of specific municipalities that exported soy during the period 2010–2015 increased steadily from 1,460 in 2010 to 1,939 in 2015. Municipal CFs –as CO_2-eq. per soy-eq.– range from 0.13 to 29.47 t t^{-1} (0.64 ± 1.40) (Fig. 2), highlighting the spatial variability in emission intensities across Brazil. CFs between the 10th and 90th percentiles range from 0.28 to 0.75 t t^{-1}, showing also a very large variability since the upper value limit is more than 2.5 higher than the lower one. The largest CFs are associated with municipalities in the agricultural frontier in the Cerrado and Amazon biomes, namely in the MATOPIBA states and Pará. CFs above the 90th percentile are found for municipalities across the MATOPIBA states in 60% of the cases, mainly in Maranhão and Tocantins; with more than 96% of them being associated with the Cerrado biome. On the other hand, CFs below the 10th percentile are found in the states of Paraná, Santa Catarina, São Paulo and Rio Grande do Sul in 92% of the cases; where municipalities are relatively close to the ports of export and large-scale deforestation occurred several decades ago.

The largest CFs are consistently located across the MATOPIBA region over the years of analysis (see Fig. S6). Relatively large CFs can also be found in states such as Minas Gerais, Goiás or Pará, especially in 2010–2012. The highest variability is observed for the year 2011, when CFs above the 90th percentile (>0.74 t t^{-1}) are more than 3.2 larger than those below the 10th percentile. The largest CF for that year is found for a municipality in Maranhão where soy was produced at the expense of forest cover loss in the Amazon. The year 2012 delivers the highest values for Brazil as a whole (0.81 t t^{-1}), due to large areas of natural cover loss in the period 2010–2012 as combined with relatively smaller export quantities in the year of study. The lowest values for the country-level CF are obtained in 2014 (0.62 t t^{-1}) and 2015 (0.63 t t^{-1}), while the average CF of Brazil across the whole period is 0.69 t t^{-1}.

When considering larger geographical scales, Piauí shows the largest CF among all the states (4.08 t t^{-1}) (Fig. 3a), which is about 6 times larger than the CF of Brazil as a whole (Fig. 3b). The rest of the states in MATOPIBA together with Pará represent the next four largest CFs, ranging from 1.48 to 1.95 t t^{-1}. One of the largest producing states, Mato Grosso shows a CF that is close to the national average (0.69 t t^{-1}). While LUC contributes most to the CF of the MATOPIBA states (72% − 87%), it accounts for only 18% of the emissions associated with Mato Grosso (Fig. 3a) where sizeable deforestation had occurred in the early 2000s. Domestic transport is the sub-stage that makes the second greatest contribution –after LUC– to the country-wide CF, accounting for almost a quarter of emissions (Fig. 3b). This sub-stage plays a particularly important role in landlocked Central-Western states such as Mato Grosso (43%), Goiás (37%) and Mato Grosso do Sul

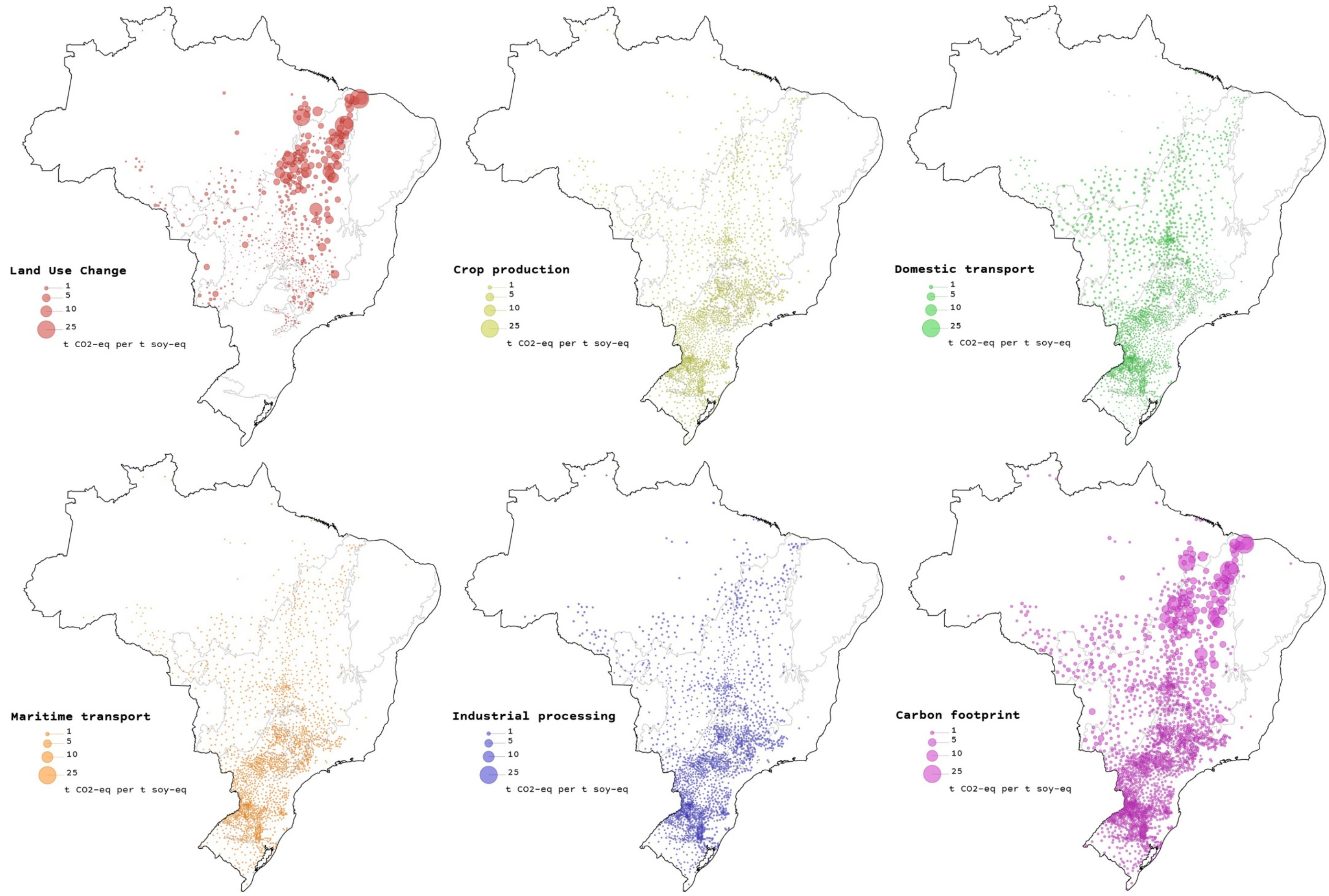

Fig. 2. Carbon footprint of the soy exporting municipalities in the period 2010–2015, as CO_2-eq. per soy-eq. (t t^{-1}).

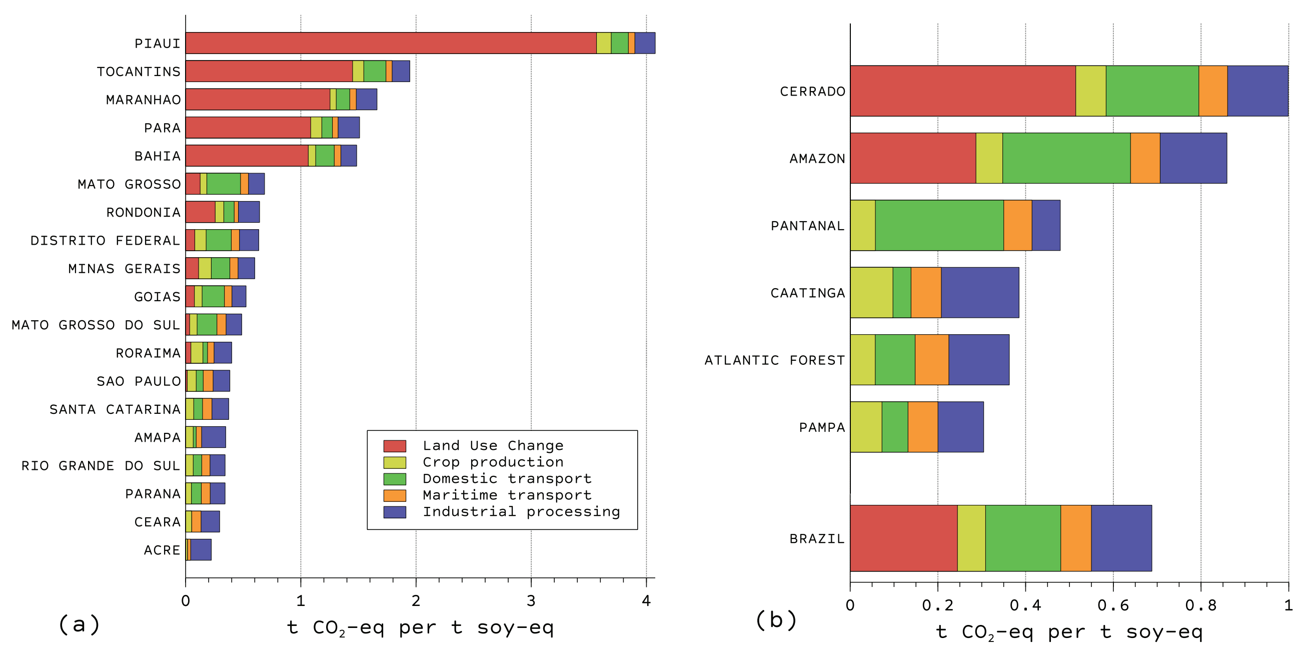

Fig. 3. Carbon footprint of the soy exporting states (a); biomes and the whole country (b) in the period 2010–2015, as CO_2-eq. per soy-eq. (t t^{-1}).

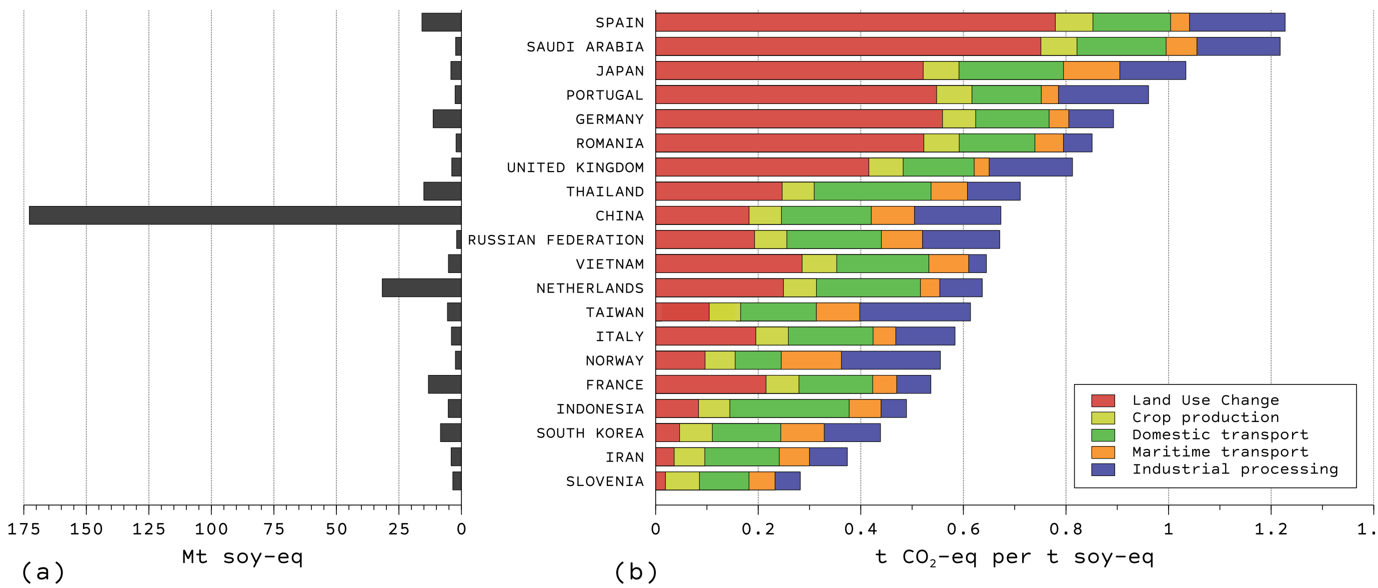

Fig. 4. Carbon footprint of major soy importing countries, as CO_2-eq. per soy-eq. (t t^{-1}) (b), and the total import quantities of soybean and derivatives (oil and cake), as soy-eq., in the period 2010–2015 (Mt) (a).

(35%), where most of the municipalities rely on road transport to export soy to international markets via ports in the Southeast region and increasingly from the North-Northeast. Crop production makes a relatively substantial contribution to the CF across the MATOPIBA states where heavy doses of lime are applied to correct soil pH, as well as in the Southern states, where more intensive farming takes place. In these states, LUC and domestic transport are of small importance as compared to other sub-stages, since deforestation occurred before the time window considered and most of the soy producing municipalities are located in the vicinity of major ports. At the biome-level, the largest CF is quantified for the Cerrado biome (1.00 t t^{-1}), followed closely by the Amazon (0.86 t t^{-1}), with LUC and domestic transport accounting for the largest shares (Fig. 3b). This implies that sourcing soy from the Cerrado entails between 2.7 and 3.3 times more CO_2-eq. emissions –on average- than from the Atlantic forest or Pampa biomes, two leading producers of soy that are particularly linked to Chinese demand (Trase 2018b).

3.2. Carbon footprint of soy importing countries

From an importer perspective (see Eq. (26) in the Appendix), the five largest CFs among the twenty largest soy importers in 2010–2015 are estimated for Spain (1.23 t t^{-1}), Saudi Arabia (1.22 t t^{-1}), Japan (1.03 t t^{-1}), Portugal (0.96 t t^{-1}) and Germany (0.89 t t^{-1}) (Fig. 4b); while the largest CF among all countries is found for Finland (1.64 t t^{-1}). The latter is about 15 times larger than the smallest CF –for Bolivia– and about 2.5 times larger than that of China, the largest importer in terms of quantities (Fig. 4a). In the five largest CFs in Fig. 4b, LUC accounts for more than 60% of the emissions, indicating that soy was sourced from municipalities where soy expansion occurred largely at the cost of natural vegetation losses. Indeed, about 90% of the total LUC emissions embodied in Spanish imports originated from MATOPIBA, while 92% of them are directly linked to land clearing in the Cerrado biome. China, the single largest importer of Brazilian soy, ranks 9th in terms of CO_2-eq. per tonne of soy-eq., since most of its imports came from Mato Grosso, Paraná and Rio Grande do Sul. Among these states, only imports from Mato Grosso are associated with substantial LUC, i.e. 22% of the total LUC emissions embodied in Chinese imports take place in this state. Relatively large contributions of domestic transport are detected in countries that imported soy through more GHG intense routes in Brazil, due to a combination of long export distances with large shares of road transport, such as Thailand or Indonesia (Fig. 4b). As expected, the largest share of maritime transport is found in the CF of countries in East and Southeast Asia, which are the farthest from Brazil.

At the supra-national level, the European Union (EU) shows the largest CF per unit of imported soy-eq. (0.77 t t^{-1}), while China (together with Hong Kong and Taiwan) has a footprint of 0.67 t t^{-1} (Fig. S7). The EU however imported around half of the overall quantity of soy imported by China, Hong Kong and Taiwan in 2010–2015, which translates into fewer GHG emissions in absolute terms, as discussed in Section 3.3. The second largest CF (per tonne of imported soy-eq.) is found for North America (0.74 t t^{-1}), though it imported soy in relatively small quantities as compared to both the EU and China. LUC makes up more than 50% of the EU's CF (per tonne of imported soy-eq.), while it accounts for 34% and 27% of the North American and Chinese CFs, respectively. This is because soy imports into the EU mostly originate from Northern Brazil, due to its geographical proximity to EU ports, as Trase data reflects (Godar et al., 2015; Schim Loeff et al., 2018). The Northern Cerrado biome is the hotspot for soy-related deforestation, generating substantial LUC emissions relative to soy exports from Southern Brazil, where deforestation occurred long time ago. Maritime transport accounts for a relatively small share of total GHG emissions generated by the EU (5%) as compared with, for instance, the Rest of Europe (17%), Eastern Asia (15%), and China (13%) (Fig. S7). Industrial processing makes a significant contribution to the CF of all regions, especially in North America (31%), rest of Europe (29%) and China (25%); while the share of crop production is between 9% and 16% across world regions.

3.3. Total GHG emissions from global trade in Brazilian soy

Total CO_2-eq. embodied in soy exports from Brazil are calculated on a municipal scale based on the respective export volumes in 2010–2015 (Fig. 5), hence identifying those municipalities that are associated with the greatest emissions in absolute terms (Mt). The highest values are observed in the MATOPIBA region, which has a high carbon intensity per tonne of exported product (see Figs. 2 and 3) and in Mato Grosso, which has a relatively smaller CF but exports soy in large quantities, as a very export-oriented state. As a result, 55% of the municipalities with total emissions above the 90th percentile are located in one of the aforementioned states. Looking at biomes, the Cerrado is the source of

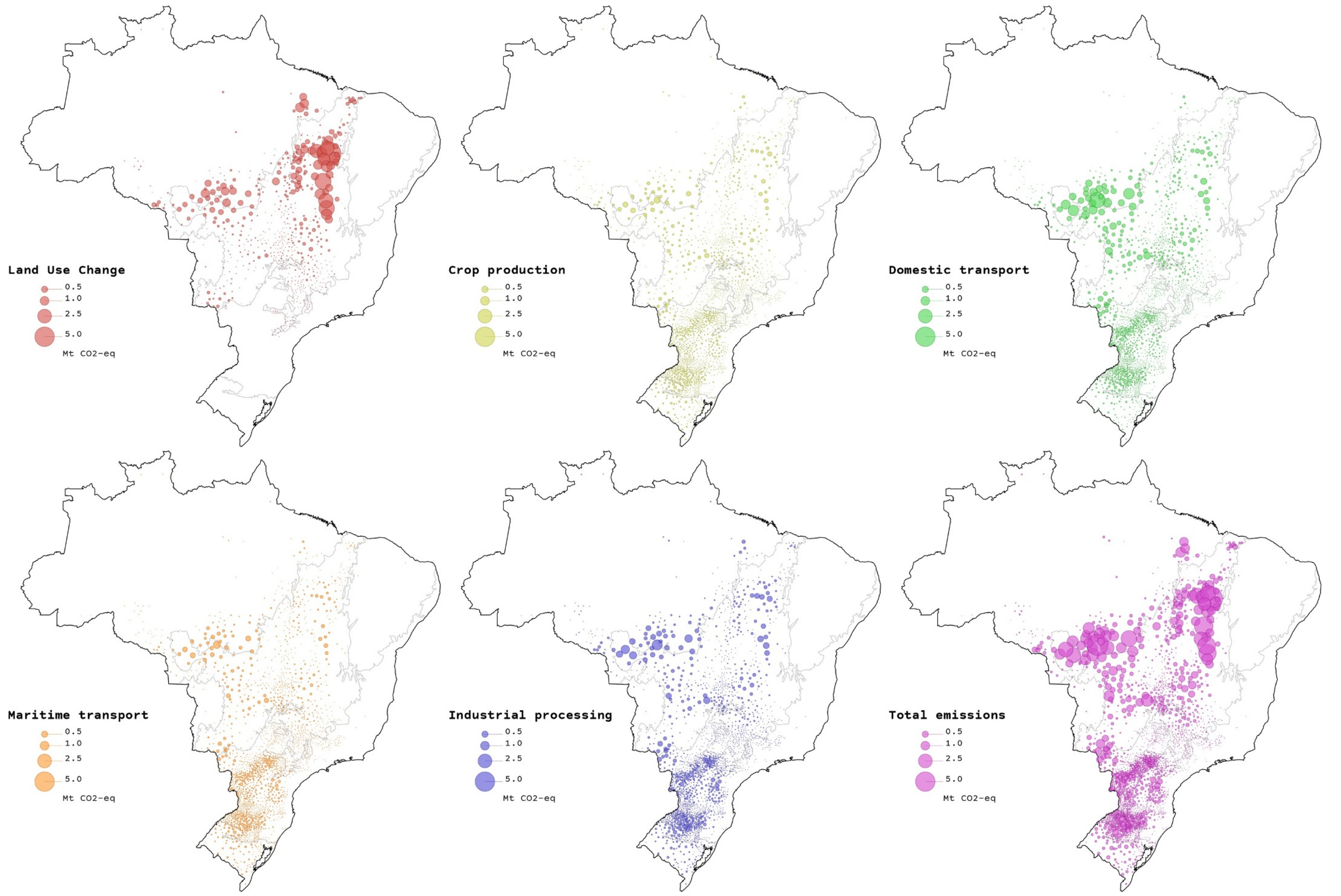

Fig. 5. Total CO_2-eq. embodied in soy exports in the period 2010–2015 at the municipal level (Mt).

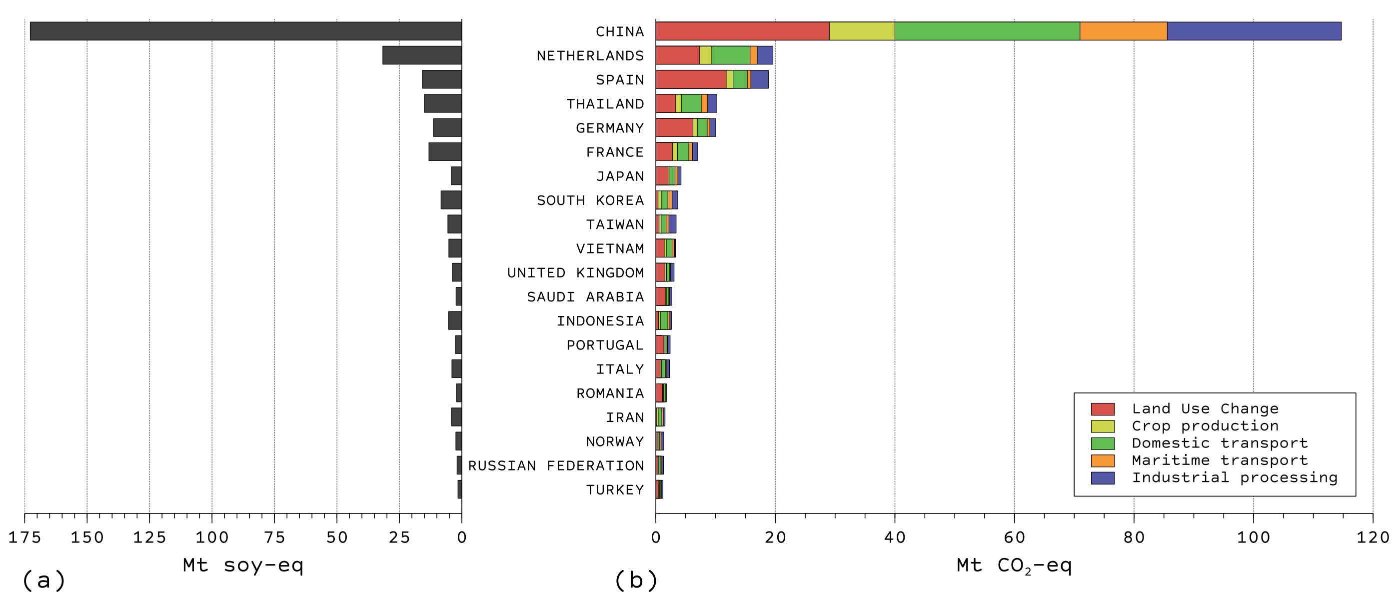

Fig. 6. Total CO_2-eq. embodied in soy imports in major soy importing countries in the period 2010–2015 (Mt).

the greatest emissions in absolute terms (126.60 Mt), followed by the Atlantic forest (35.55 Mt) and the Amazon (34.73 Mt). This highlights the effects of the weaker conservation regulations in the Cerrado, relative to the Amazon.

When we include additional supply chains for which only the state of origin is known (see Section 2.1), total CO_2-eq. emissions from Brazilian soy exports are quantified at 223.46 Mt. These arise from approximately 332.21 Mt of soy-eq., which cover almost the entire export volume in the period 2010–2015. On a global scale, LUC accounts for around a third of the overall CO_2-eq. emissions (74.81 Mt), followed by domestic transport (57.89 Mt) and industrial processing (46.03 Mt). These sub-stages of the supply chain offer the greatest

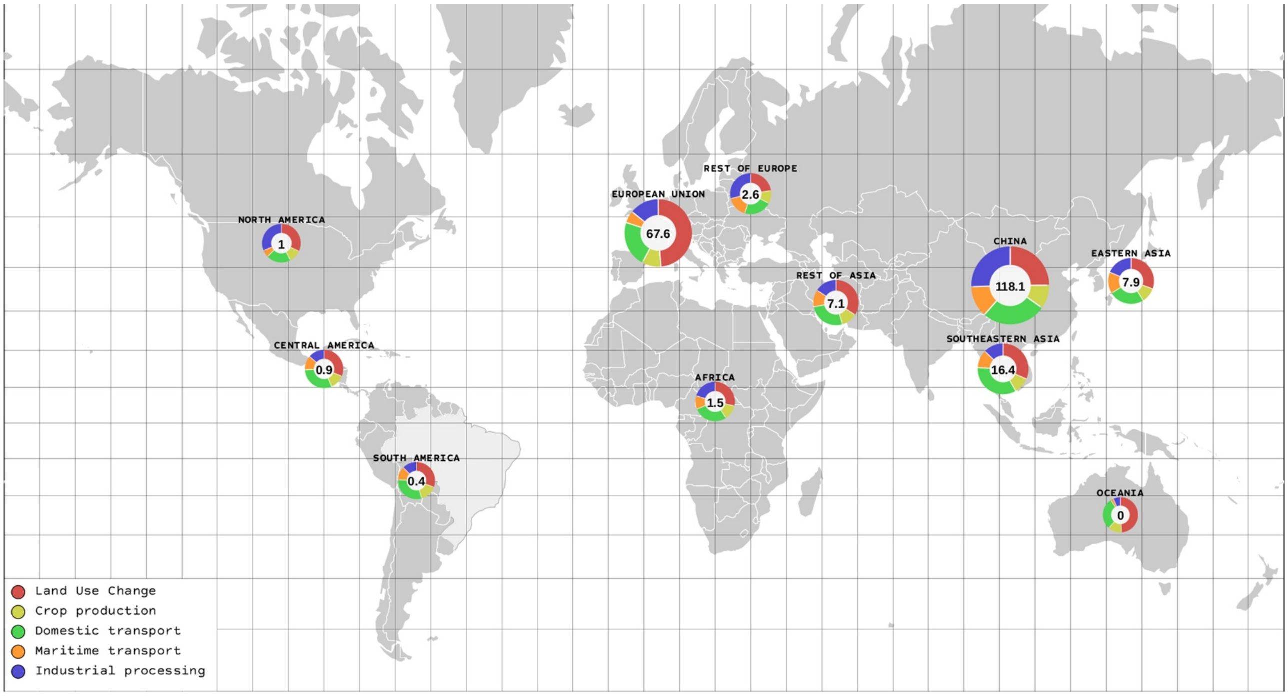

Fig. 7. Total CO_2-eq. embodied in soy imports in the period 2010–2015 at the supra-national level (Mt), based on the classification of the United Nations (1999) but keeping China (plus Hong Kong and Taiwan) and the European Union (EU28) as separate regions.

potential for total GHG emission reductions. Crop production and international maritime transport account for around 10% of the overall emissions, respectively. However, substantial differences can be observed across importing countries and regions (Figs. 6 and 7).[2] China is the single largest importer of CO_2-eq. (114.70 Mt), being associated with 6 times greater emissions than the second largest CO_2-eq. importer, the Netherlands (19.60 Mt), which is a major re-exporter of soybean and derivatives across the world (Kastner et al., 2011). At the supra-national level, China (plus Hong Kong and Taiwan) and the EU import by far the greatest amount of CO_2-eq. emissions (Fig. 7). Due to the larger share of LUC in the CF of the EU, overall LUC emissions embodied in EU's soy imports are greater, in absolute terms, than those in Chinese imports, i.e. 33.42 Mt vs. 29.03 Mt of CO_2-eq. Total GHG results highlight the role of industrial processing as a major contributor to the life cycle CO_2-eq. emissions of soy in regions such as China or the rest of Europe. In these regions, most soy is crushed domestically, processes which are more CO_2-eq. intensive than in Brazil.

4. Discussion

4.1. Methodological discussion

Our bottom-up LCA approach reveals an extremely large spatial variability in CO_2-eq. emissions among the different sourcing areas (municipalities, states, biomes), countries of import, and sub-stages throughout the supply chain. This responds to the level of detail in the underlying LCI, which captures the diversity of land use dynamics, farming conditions, sourcing patterns, and transport modes with sub-national resolution. In this way, our approach overcomes many of the limitations of conventional LCA and traditional physical trade accounting (see Section 1), unveiling a large variability in the CF of Brazil's soy exports per unit of soy-eq. The variability detected is much higher than that in the LCA literature, which provides at best with a range of values at the state level for pre-selected and well-known producing regions (Fig. 8a). Castanheira and Freire (2013) are the only ones assessing variability in LUC emissions across Brazil, based on assumptions on crop management practices and biome-specific carbon stocks in the South and Centre-West regions, by following the IPCC Tier 1 approach (IPCC, 2006). However, none of the selected studies explicitly addresses the situation of the MATOPIBA states, while many of them even exclude LUC emissions from the LCA. Our results illustrate how extreme values across the multiple sub-stages (and especially LUC) can only be captured with a high level of spatial resolution (Fig. 8b).

Even if based on exhaustive scenario analyses, conventional LCA outcomes often consist of point estimates, which can lead to the over- or underestimation of impacts of a given product, depending on the geographical and temporal scope of the study. For instance, the average value for LUC emissions in Mato Grosso (Castanheira et al., 2015) is higher than 98% of the values calculated at municipal scales in Section 3.1. While the latter arise from spatially-explicit data on soy expansion and associated deforestation from 2008 onwards, Castanheira et al. (2015) consider predominantly converted land uses in the period 1985–2006, at the state level. Similarly, Castanheira and Freire (2013) estimate LUC emissions from soy production based on soy area expansion in Brazil in the period 1991-2011 and find a higher CO_2-eq. intensity, e.g. between 3.5 and 7.0 t t^{-1}in Cerrado, whereas it is 0.51 t t^{-1}in our study. Our distribution of soybean farming emissions in Mato Grosso (Fig. 8b) also falls below values in the literature. Likewise, all values estimated for municipal emissions from domestic transport in Mato Grosso are lower than the average value from Castanheira and Freire (2013), who assumed average transport distances between the main ports and the main soybean producing locations in Brazil. On the contrary, our framework generates greater emissions from domestic transport in most Central-Western municipalities than for instance those estimated by Silva et al. (2010) with a lower level of spatial detail. Authors conclude that domestic transport represents up to 19% of the CF of soy in the Centre-West region, but we find that this sub-stage accounts for more than 60% of GHG emissions in many municipalities

[2] United Nations (1999) Standard country or area codes for statistical use. Available at https://unstats.un.org/unsd/methodology/m49/

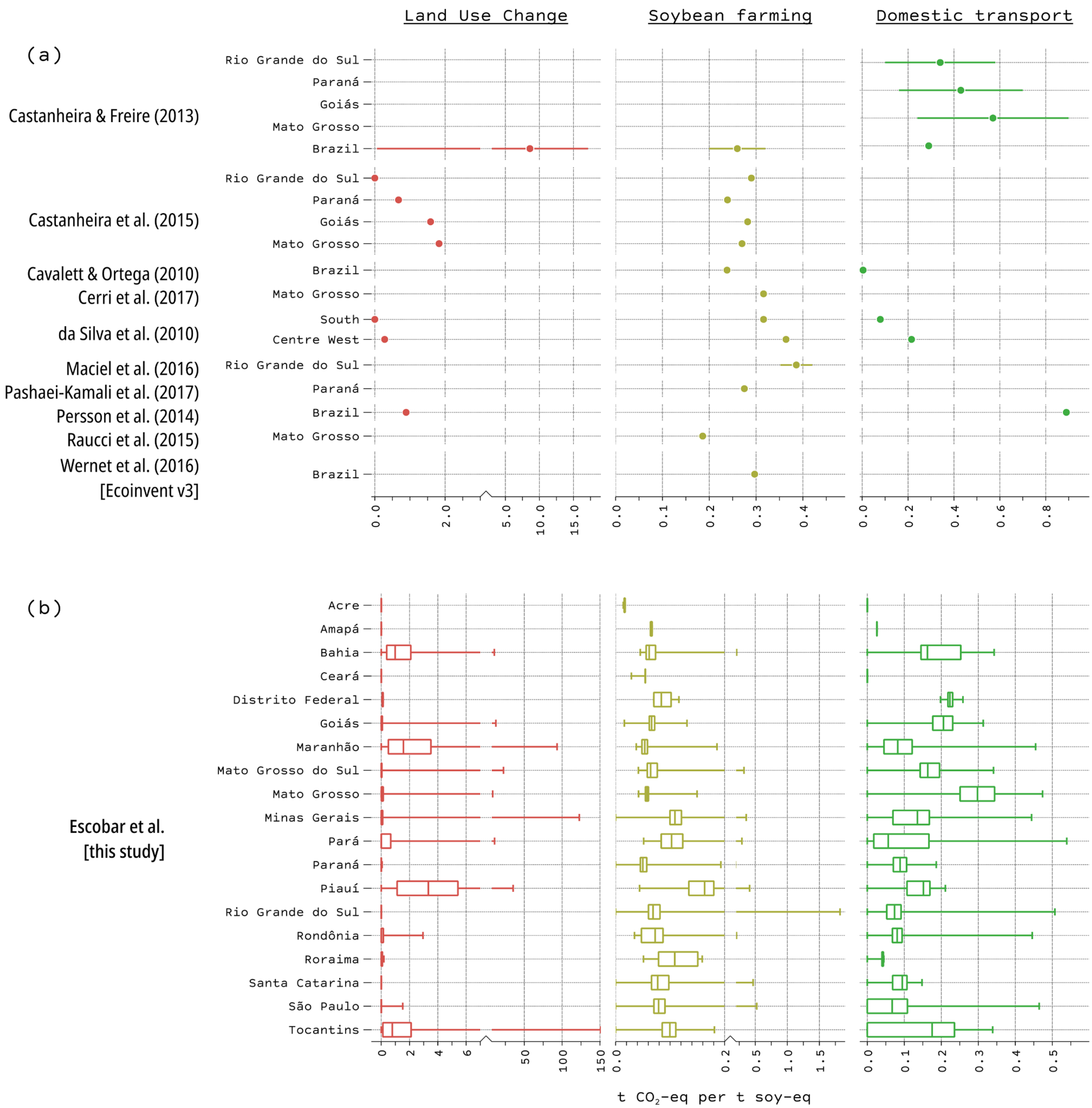

Fig. 8. Carbon footprint of Brazilian soy along different sub-stages at the state or country level in related Life Cycle Assessment studies (a), as compared with the results from this study based on the distribution of municipal carbon footprints per state (b).

in Goiás and Mato Grosso, from which soy is exported through distant ports. None of the studies took into account the fact that lorries often run empty after delivery of the load, which could further increase the CF if such emissions were included.

Our results, though more detailed than previous analyses, are conservative in estimating GHG emissions from soy-induced LUC because we included only carbon stock losses from the conversion of woody vegetation into cropland. Nevertheless, soy has also expanded at the expense of natural grasslands as well as cattle pasture in both the Cerrado and Amazon biomes (Arvor et al., 2013; Carvalho and Mustin, 2017). Although these uses can make up a large share (ca. 80%) of overall cropland area expansion in Brazil (Zalles et al., 2019), they are associated with smaller carbon stocks than forest, shrub, and savannah land areas (Castanheira and Freire, 2013; Esteves et al., 2016). Furthermore, we consider only CO_2 emissions from natural vegetation loss in the Cerrado and Amazon, which however account for the largest share of GHG from land clearing in Brazil in the last decades (Baccini et al., 2012; Galford et al., 2011; Noojipady et al., 2017). It must be noted that by applying the 3-year approach to account for total natural cover loss between clearance and the planting of soy, we also capture deforestation initially associated with intermediate uses such as pasture, which ultimately became soy. Hence, we cover a larger share of potential emissions from carbon stock losses than only those arising from direct land conversion to grow soy. The longer the period the more land use transitions to be indirectly covered in this way. Additional information would be needed to better allocate natural vegetation loss among all agricultural land uses subsequently detected in cleared land and provide more accurate estimates of CO_2 emissions from overall land use transitions. Ideally, this should also take into account carbon fluxes from forest degradation and regeneration dynamics (Morton et al., 2011).

Beyond variability in land carbon stock data, the CF of Brazilian soy exports is highly sensitive to the choice and the length of the period over which natural cover loss and subsequent CO_2 emissions are associated with soy expansion. As a sensitivity analysis, we calculated CFs considering a 10-year window for the retrospective allocation of LUC emissions, i.e. with deforestation maps from 2001 onwards (see Figure S8). Results show additional and sometimes larger CFs across the MATOPIBA region, as well as increased CFs in Mato Grosso and Pará. This translates into a threefold increase in the CF of these two states relative to the values in Fig. 3, i.e. with deforestation maps from 2008 onwards, due to sizeable deforestation observed before the Soy Moratorium entered into force (Gibbs et al., 2015). The time-lag between land clearing and production on cleared land determines how responsive footprint estimates are to changes in deforestation rates. A shorter period implies that these changes affect LUC and associated CO_2 emissions more immediately (Henders et al., 2015). We chose a 3-year period based on land conversion dynamics in the context of Brazil (Gollnow and Lakes, 2014), although the choice of this amortization period is often arbitrary and further harmonization is desirable to make results comparable (Persson et al., 2014).

The additive nature of LCA allows calculating total aggregate environmental burdens from multiple product life cycles within the same system boundaries (Tillman, 2000; Brander et al., 2019). The greatest advantages of our approach, relative to conventional LCAs, are (a) the comprehensiveness of our dataset, covering almost the entire export volume of Brazilian soy in a given period; and (b) the spatial-explicitness of the carbon footprint results, capturing the diversity of life cycles of soy for export in terms of production and transportation systems. As a result, life cycle CO_2-eq. emissions can be consistently aggregated from the supply side at the municipal, state, biome and country levels, to provide an indication of the carbon intensity of larger soy producing geographical units. This also constitutes an advantage over both EE-MRIO and physical trade accounting analyses, which do not usually provide sub-national detail in environmental footprints (Pendrill et al., 2019b; Taherzadeh and Caro, 2019). From the demand side, environmental pressures are in our framework allocated to the country of import, which is not necessarily where final demand occurs (Croft et al., 2018; Cabernard et al., 2019). This constitutes a limitation for estimating consumption-based footprints of soybean and derived products, as compared with EE-MRIO models with the required level of sectoral disaggregation (Bruckner et al., 2019). Including re-exports from soy importing countries to third countries would deliver the carbon footprints of the countries where soy is finally processed and consumed (Kastner et al., 2011; Flach et al., 2016). This could yield different CF results for some specific cases such as the Netherlands, which is a major re-exporter of soy (Croft et al., 2018); while including further GHG emissions from maritime transport and industrial processing could also alter CFs estimated from a producer perspective.

We intend our framework to be applied to other commodities and geographical contexts, though there are also challenges in applying this approach more broadly, notably in data demands in the foreground and background systems as well as at the supply chain level. As a resource- and data-intensive initiative, Trase provides complete export data for a limited but growing number of countries and products. The case of Brazil is however paradigmatic, since the methodology underlying supply chain mapping is standardized and data sources are reliable, hence providing results with high accuracy levels and spatial resolution. Calculating the CF of commodities that undergo further processing, such as beef, would entail case-specific assumptions to allocate CO_2-eq. emissions among multiple co-products, similar to those applied in the example of soy (Henriksson et al., 2012; Vries et al., 2015). Our framework could also be developed further to quantify other environmental footprints arising from life cycle resource consumption and emissions, by including impact categories such as acidification, eutrophication, water scarcity, biodiversity loss, etc. This could certainly contribute to a better understanding of land use mediated impacts and trade-offs linked to agricultural production and trade, although advancements in both regionalized life cycle inventories and impact characterization methods are still needed (Hellweg and Zah 2016; Green et al., 2019; Mutel et al., 2019).

4.2. Relevance and applications

Product-based LCAs are typically employed to inform supply chain actors' decisions (Browne et al., 2005; Čuček et al., 2012). Although LCA is carried out *ex-post*, outcomes give an indication on how production systems will behave in the future, hence being used *ex-ante* as a tool to support decision-making (Yang et al., 2017; Brander et al., 2019). Same as conventional LCA, the proposed framework could be applied prospectively to quantify GHG emission savings brought about by alternative supply chain configurations relative to the carbon intensity of the reference system. As an example, if the EU had met its import demand in 2010–2015 with soy from Paraná and Rio Grande do Sul in the same amounts (see Fig. 3), its CF could have been reduced by more than 60% relative to the value in Fig. S7. Our framework does not however account for further knock-on changes in other actors' sourcing, which could translate into increased or decreased GHG emissions on a global scale, in addition to other market-mediated effects. From a producer perspective, the spatially-explicit CF results specifically show the most carbon intensive areas and sub-stages where additional efforts should be put to effectively reduce CO_2-eq. emissions at the municipal, state, biome, and country levels. CFs at all geographical scales indicate that preventing LUC is crucial to reduce carbon emissions from global trade in Brazilian soy, which implies controlling deforestation in the agricultural frontier. Biome-wide conservation mechanisms could be effective in transitioning towards low-carbon soy supply chains (Garrett et al., 2019; Soterroni et al., 2019), given the role of the Cerrado biome as a major source of LUC emissions, i.e. representing around 60% of the total GHG emissions embodied in Brazil's soy exports. Moreover, total emission estimates help identifying those areas and sub-stages that generate the greatest CO_2-eq. emissions in absolute terms, e.g. LUC in MATOPIBA and Mato Grosso; domestic transport in the Centre-West region; maritime emissions in those countries that are far away from Brazil and rely on relatively inefficient fleets; industrial processing in those countries that crush most of their soybeans domestically with less efficient technologies, etc. Hence, our framework could be further used to assess the cost-effectiveness of specific policies or supply chain adaptations in reducing GHG emissions from both producer and importer perspectives, e.g. conservation mechanisms, investments in rail freight infrastructure, improvements in shipping fleets, etc. In this way, the hybrid approach presented provides transparent data to inform environmental interventions at the local, regional, national, and international scales; while enabling coordinated action for more effective governance towards global climate change mitigation.

Spatially-explicit results from our framework have great potential to be used in LCA case studies and databases, contributing accessible information for regionalized and more accurate environmental footprinting (Hellweg and Milà i Canals, 2014; Godar et al., 2016). Outcomes from the soy example could particularly be used in LCAs of meat products, which constitute the main application of soy as a feedstock in the feed industry (Brack et al., 2016). Finally, our approach can also be used to quantify CFs of intermediate sectors and actors in the middle of the supply chain, based on the information contained in Trase. More specifically, GHG emissions could be aggregated per sub-stage to estimate *sectoral footprints*; or agent-specific *organizational footprints* (e.g. per trader), which are especially hard to trace for commodity crops (Poore and Nemecek, 2018). Such indicators could better support stakeholder groups' decisions for reducing impacts from a supply chain perspective (Schmidt, 2009); while providing critical information for multi-actor supply chain governance initiatives, such as commodity roundtables (Brander et al., 2019; Gardner et al., 2019). Although the CF is an entry point for increasing consumer awareness, it is not sufficient as a sustainability indicator for product labeling and certification, since it overlooks potential trade-offs, such as among other environmental or social impacts.

5. Conclusions

The potential negative impacts of globally traded agricultural commodities and the underlying complex supply chain dynamics pose significant challenges for climate change mitigation and environmental governance. We present a hybrid approach for the quantification of carbon emissions embodied in agricultural exports, based on the integration of bottom-up LCA with enhanced physical trade accounting. Taking soy as an example, we provide the first estimate of the distribution of CFs for Brazilian exports of beans, oil and cake between 2010 and 2015 at sub-national levels, by using high-resolution data on supply chain mapping from the Trase platform. Results show a large variability in the carbon intensity of Brazilian soy (as CO_2-eq. per soy-eq.) due to differences in land use dynamics, farming conditions, and supply chain configurations up to the stage in which soybean and derivatives are delivered in the respective countries of import. Specifically, we find that the largest CFs have their origin in the MATOPIBA states and Pará, where soy is directly linked to natural vegetation loss. Importing soy from municipalities in the MATOPIBA region implies up to 6 times greater emissions per unit of product than the Brazilian average (0.69 $t\ t^{-1}$). LUC is the main contributor to the CF of Brazil as a whole, accounting for 36% of its overall emissions in 2010–2015. From the demand side, CFs of the soy importing countries range from 0.11 to 1.64 $t\ t^{-1}$, depending on the sourcing municipalities. For instance, European countries tend to import soy from Northern Brazil, which makes the EU the region with the largest CF (0.77 $t\ t^{-1}$) in the world, e.g. 13.8% larger than that of China, the largest soy importer.

A key innovation of our approach is that it captures the whole distribution of CFs in agricultural commodity exports at unique levels of temporal and spatial disaggregation to date. As such, it bears potential to enhance supply chain governance at multiple levels to minimize trade-offs among economic and environmental dimensions of sustainability while informing the debate on global responsibility for the impacts of agricultural production and trade. This approach can also contribute to the development of regionalized LCIs for more accurate product analyses by means of conventional LCA methodologies. New challenges arise from the application of the data-intensive analysis presented to the increasingly complex supply chains and value-webs in the global bioeconomy (El-Chichakli et al., 2016). Moreover, extensions to cover more stages along global supply chains, such as re-exports, final consumption, and waste treatment, are required for mapping carbon emissions from 'cradle to grave'.

Author statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in this journal.

Declaration of Competing Interest

The authors confirm that funding for this research has been adequately acknowledged. There are no potential conflicts of interest in submitting and publishing this research paper.

Acknowledgements

NE and JB acknowledge the financial support from the German Federal Ministry of Education and Research (BMBF) as part of the project 'Sustainable Trade and Innovation Transfer in the Bioeconomy' (STRIVE) (project number 031B0019). PL and JG acknowledge the support from the Gordon and Betty Moore Foundation for the Trase project (www.trase.earth) and from the Swedish Research Council 'Formas' as part of the project LEAKAGE (grant number 2016-00351). All authors give thanks to Prof. Neus Sanjuán from the Polytechnic University of Valencia (UPV) for her help with data collection.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.gloenvcha.2020.102067.

Appendix

List of sets, parameters and variables

• Sets	
c	Greenhouse gases
i	Soy producing municipality
j	Importing country of soybean and derivatives, excluding Brazil
k	Port of export of soybean and derivatives in Brazil
p	Type of product, i.e. beans, oil, cake
y	Year of study
• Parameters	
ch_c	Characterization factor of greenhouse gases for climate change at the midpoint level, as CO_2-eq. per unit of gas, i.e. CO_2, CH_4, N_2O ($t\ t^{-1}$)
EF^{bg}	Emission factor for inland waterway transport, as CO_2-eq. per unit of cargo ($t\ tkm^{-1}$)
EF_p^{BR}	Emission factor for the extraction of soybean derivatives in Brazil, as CO_2-eq. per unit of product output ($t\ t^{-1}$)
EF^D	Emission factor for soybean drying, as CO_2-eq. per unit of beans ($t\ t^{-1}$)
EF^F	Emission factor for the production of diesel fuel, as CO_2-eq. per unit of product ($t\ t^{-1}$)
EF^K	Emission factor for the production of average K-fertilizer, as CO_2-eq. per unit of K ($t\ t^{-1}$)
EF^L	Emission factor for the production of limestone, as CO_2-eq. per unit of product ($t\ t^{-1}$)
EF^N	Emission factor for the production of average N-fertilizer, as CO_2-eq. per unit of N ($t\ t^{-1}$)
EF^P	Emission factor for the production of average P-fertilizer, as CO_2-eq. per unit of P ($t\ t^{-1}$)
EF^{rd}	Emission factor for road transport, as CO_2-eq. per unit of cargo ($t\ tkm^{-1}$)
EF_p^{ROW}	Emission factor for the extraction of soybean derivatives in the rest of the world, as CO_2-eq. per unit of product output ($t{\cdot}t^{-1}$)

EF^{tr}	Emission factor for rail freight transport, as CO_2-eq. per unit of cargo (t tkm^{-1})
$Fu_{i,y}$	Average diesel fuel consumption for agricultural machinery operations (t ha^{-1})
$K_{i,y}$	Application dose of potassium for soybean production per municipality, as K (t ha^{-1})
$L_{i,y}$	Application dose of limestone for soybean production per municipality (t ha^{-1})
$N_{i,y}$	Application dose of nitrogen for soybean production per municipality, as N (t ha^{-1})
$p^{dc}_{i,y}$	Share of double-cropped soybean area in each municipality per year (%)
$P_{i,y}$	Application dose of phosphorus for soybean production per municipality, as P (t ha^{-1})
R_j	Share of soybeans that are crushed in the importing countries (%)
$S_{i,y}$	Total soybean produced annually by a given municipality (t)
s^{bg}_k	Share of transport distance to port of export covered by inland barge (%)
s^{rd}_k	Share of transport distance to port of export covered by lorry (%)
s^{tr}_k	Share of transport distance to port of export covered by freight train (%)
t	Amortization period for Land Use Change (years)
W_p	Average conversion ratio of beans into soybean derivatives (dimensionless)
$X_{i,k}$	Domestic transport distance matrix between municipalities (km)
$Y_{i,y}$	Annual soybean yields per municipality (t ha^{-1})
• Variables	
$\Delta C_{i,y}$	Total losses in the carbon pools considered, due to Land Use Change (t ha^{-1})
$\Delta C^{agb}_{i,y}$	Carbon losses in above-ground biomass due to annual soybean expansion in a municipality (t)
$\Delta C^{bgb}_{i,y}$	Carbon losses in below-ground biomass due to annual soybean expansion in a municipality (t)
$\Delta C^{lit}_{i,y}$	Carbon losses in litter due to annual soybean expansion in a municipality (t)
$\Delta C^{soil}_{i,y}$	Soil organic carbon loss due to annual soybean expansion in a municipality (t)
$A_{p,i,j,k,y}$	Area of deforestation embodied in annual flows of soybean and derivatives (ha)
$A^{am}_{i,y}$	Total deforested land that is retrospectively associated with the production of soybean in a given municipality in the year of analysis (ha)
$A^{def}_{i,y}$	Deforestation due to soybean expansion in a municipality per year of the amortization period (ha)
$CF_{p,i,j,k,y}$	Carbon footprint of a product life cycle, as CO_2-eq. per soy-eq. (t t^{-1})
$CF_{p,i,j,k}$	Carbon footprint of a product life cycle throughout a period of analysis, as CO_2-eq. per soy-eq. (t t^{-1})
$CF_{i,y}$	Annual carbon footprint of a producing municipality, as CO_2-eq. per soy-eq. (t t^{-1})
CF_i	Carbon footprint of a producing municipality throughout a period of analysis, as CO_2-eq. per soy-eq. (t t^{-1})
$CF_{j,y}$	Annual carbon footprint of a country of import, as CO_2-eq. per soy-eq. (t t^{-1})
CF_j	Carbon footprint of a country of import throughout a period of analysis, as CO_2-eq. per soy-eq. (t t^{-1})
$EDT_{p,i,j,k,y}$	Total CO_2-eq. emissions from domestic transport of each life cycle (t)
$EIP_{p,i,j,k,y}$	Total CO_2-eq. emissions from industrial processing of each life cycle (t)
$EIT_{p,i,j,k,y}$	Total CO_2-eq. emissions from international transport of each life cycle (t)
$ELUC_{p,i,j,k,y}$	Total CO_2-eq. emissions from Land Use Change of each life cycle (t)
$ESF_{p,i,j,k,y}$	Total CO_2-eq. emissions from soybean farming of each life cycle (t)
$ETOT_{p,i,j,k,y}$	Total CO_2-eq. emissions across the full life cycle (t)
$GHG^{fire}_{i,y}$	CO_2-eq. emissions form combustion of above-ground biomass and litter (t)
$M_{p,i,j,k,y}$	Imports of soybean derivatives into each country of import from a given municipality (t)
$P_{p,i,j,k,y}$	Final quantity of soybean derivatives delivered in each country of import (t)
$Q_{p,i,j,k,y}$	Mass flow of beans entering life cycle delivering soybean derivatives (t)
$Z_{k,j,c}$	Matrix of greenhouse gas emissions from international transport of soybean and derivatives (t)

Mathematical formulation

Trase provides annual data on imports of oil, cake and beans –as three separate products– into countries across the globe, i.e. $M_{p,i,j,k,y}$. Each trade flow is characterized by the specific municipality from which it is originated in Brazil and the corresponding port from which it is shipped. Most of the imported beans are also crushed into oil and cake in the respective countries of import, hence translating into three additional life cycles from the same import flow. The overall quantity of each product delivered in the country of import at the end of the life cycle is calculated according to Eqs. (1)–(3):

$$P_{oil,i,j,k,y} = M_{beans,i,j,k,y} \times R_j \times W_{oil} + M_{oil,i,j,k,y} \tag{1}$$

$$P_{cake,i,j,k,y} = M_{beans,i,j,k,y} \times R_j \times W_{cake} + M_{cake,i,j,k,y} \tag{2}$$

$$P_{beans,i,j,k,y} = M_{beans,i,j,k,y} \times (1 - R_j) \tag{3}$$

The quantity of soy beans that each municipality ultimately diverts to each life cycle, i.e. $Q_{p,i,j,k,y}$, is calculated according to Eqs. (4)–(6):

$$Q_{oil,i,j,k,y} = \left(\frac{M_{oil,i,j,k,y}}{W_{oil}} + M_{beans,i,j,k,y} \times R_j\right) \times W_{oil} = P_{oil,i,j,k,y} \tag{4}$$

$$Q_{cake,i,j,k,y} = \left(\frac{M_{cake,i,j,k,y}}{W_{cake}} + M_{beans,i,j,k,y} \times R_j\right) \times W_{cake} = P_{cake,i,j,k,y} \tag{5}$$

$$Q_{beans,i,j,k,y} = M_{beans,i,j,k,y} \times (1 - R_j) = P_{beans,i,j,k,y} \tag{6}$$

Mass allocation is applied in Eqs. (4),(5) to avoid double counting of the beans that are required for the joint production of oil and cake in crushing operations, with the subsequent emissions.

The area of land converted ($A_{p,i,j,k,y}$), i.e. deforested, which is embodied in the annual flows of soybean and derivatives ($Q_{p,i,j,k,y}$) is calculated by following Eq. (7):

$$A_{p,i,j,k,y} = Q_{p,i,j,k,y} \times \frac{A^{am}_{i,y}}{S_{i,y}} \times \left(1 - \frac{p^{dc}_{i,y}}{2}\right) \tag{7}$$

The total land converted at the municipal level ($A^{am}_{i,y}$) is reduced by half in those areas where soybean is produced in rotation with other crop, based on the annual share of double-cropped area ($p^{dc}_{i,y}$), relative to total agricultural land area available on a municipal scale. $A^{am}_{i,y}$ is, in turn, calculated by annualizing the accumulated deforestation that is geographically linked to soybean expansion in a given municipality ($A^{def}_{i,y}$) during the amortization period considered (t) as shown in Eq. (8):

$$A^{am}_{i,y} = \frac{\sum_{y}^{y-2} A^{def}_{i,y}}{t} \tag{8}$$

Where t is number of years in which soy was detected on that land in the period from y-2 to y, being y the year of analysis.

$ELUC_{p,i,j,y}$ are estimated according to Eq. (9)–(10), by considering carbon losses in above- and below-ground biomass, litter and soil; and including emissions from incomplete combustion of above-ground biomass and litter, as follows:

$$\Delta C_{i,y} = \Delta C^{agb}_{i,y} + \Delta C^{bgb}_{i,y} + \Delta C^{lit}_{i,y} + \Delta C^{soil}_{i,y} \tag{9}$$

$$ELUC_{p,i,j,k,y} = \left(\Delta C_{i,y} \times \frac{44}{12} + GHG_{i,y}^{fire}\right) \times A_{p,i,j,k,y} \tag{10}$$

While $\Delta C^{agb}_{i,y}$, $\Delta C^{bgb}_{i,y}$ and $\Delta C^{lit}_{i,y}$ are given by Trase; $\Delta C^{soil}_{i,y}$ and $GHG^{fire}_{i,y}$ are estimated following the Tier 1 procedure of the IPCC (2006) (see Section 2.2.2).

$ESF_{p,i,j,k,y}$ are calculated according to Eq. (11), based on the available data; also adjusted by considering double-cropping (see Section 2.2.2):

$$\begin{aligned} ESF_{p,i,j,k,y} &= Q_{p,i,j,k,y} \times \left((\alpha + \beta + \delta + \varepsilon) \times \frac{\left(1 - \frac{p^{dc}_{i,y}}{2}\right)}{Y_{i,y}} + EF^{D} \right) \\ \alpha &= Fu_{i,y} \times EF^{F} \\ \beta &= N_{i,y} \times \left(EF^{N} + 0.1 \times 0.01 \times \frac{44}{28} \times 298\right) \\ \delta &= P_{i,y} \times EF^{P} + K_{i,y} \times EF^{K} \\ \varepsilon &= L_{i,y} \times \left(EF^{L} + 0.12 \times \frac{44}{12}\right) \end{aligned} \tag{11}$$

$EDT_{p,i,j,k,y}$ are calculated for each type of product exported as such from Brazil, based on the average CO_2-eq. emission intensity of soy transport between municipalities in Brazil, according to Eqs. (12)–(14):

$$EDT_{\mathrm{oil},i,j,k,y} = X_{i,k} \times (s^{rd}_{k} \times EF^{rd} + s^{tr}_{k} \times EF^{tr} + s^{bg}_{k} \times EF^{bg}) \times M_{\mathrm{oil},i,j,k,y} \tag{12}$$

$$EDT_{\mathrm{cake},i,j,k,y} = X_{i,k} \times (s^{rd}_{k} \times EF^{rd} + s^{tr}_{k} \times EF^{tr} + s^{bg}_{k} \times EF^{bg}) \times M_{\mathrm{cake},i,j,k,y} \tag{13}$$

$$EDT_{\mathrm{beans},i,j,k,y} = X_{i,k} \times (s^{rd}_{k} \times EF^{rd} + s^{tr}_{k} \times EF^{tr} + s^{bg}_{k} \times EF^{bg}) \times M_{\mathrm{beans},i,j,k,y} \tag{14}$$

$EIT_{p,i,j,k,y}$ arise from a three-dimensional matrix containing data on greenhouse gas emissions associated with export routes between Brazil and the corresponding countries ($Z_{k,j,c}$), which depend on the ports and vessels involved. Emissions are ultimately expressed as CO_2-eq. by considering characterization factors for climate change at midpoint level (ch_c) from IPCC (2006), based on Eqs. (15)–(17):

$$EIT_{\mathrm{oil},i,j,k,y} = \sum_{c} (Z_{k,j,c} \times ch_{c}) \times M_{\mathrm{oil},i,j,k,y} \tag{15}$$

$$EIT_{\mathrm{cake},i,j,k,y} = \sum_{c} (Z_{k,j,c} \times cf_{c}) \times M_{\mathrm{cake},i,j,k,y} \tag{16}$$

$$EIT_{\mathrm{beans},i,j,k,y} = \sum_{c} (Z_{k,j,c} \times cf_{c}) \times M_{\mathrm{beans},i,j,k,y} \tag{17}$$

Finally, $EIP_{p,i,j,k,y}$ are calculated by applying product- and region- specific emission factors for the extraction of oil and cake to the corresponding quantities that are processed in Brazil (BR) or in the rest of the world (ROW), according to Eqs. (18),(19):

$$EIP_{\mathrm{oil},i,j,k,y} = M_{\mathrm{beans},i,j,k,y} \times R_{j} \times W_{\mathrm{oil}} \times EF^{ROW}_{\mathrm{oil}} + M_{\mathrm{oil},i,j,k,y} \times EF^{BR}_{\mathrm{oil}} \tag{18}$$

$$EIP_{\mathrm{cake},i,j,k,y} = M_{\mathrm{beans},i,j,k,y} \times R_{j} \times W_{\mathrm{cake}} \times EF^{ROW}_{\mathrm{cake}} + M_{\mathrm{cake},i,j,k,y} \times EF^{BR}_{\mathrm{cake}} \tag{19}$$

Total life cycle emissions ($ETOT_{p,i,j,k,y}$) are calculated in Eq. (20), while the carbon footprint of each life cycle ($CF_{p,i,j,k,y}$) is finally quantified in Eq. (21):

$$ETOT_{p,i,j,k,y} = ELUC_{p,i,j,k,y} + ESF_{p,i,j,k,y} + EDT_{p,i,j,k,y} + EIT_{p,i,j,k,y} + EIP_{p,i,j,k,y} \tag{20}$$

$$CF_{p,i,j,k,y} = ETOT_{p,i,j,k,y} / Q_{p,i,j,k,y} \tag{21}$$

Carbon footprints can be subsequently quantified for the different product life cycles detected throughout a period of analysis ($CF_{p,i,j,k}$); according to Eq. (22):

$$CF_{p,i,j,k} = \frac{\sum_{y} ETOT_{p,i,j,k,y}}{\sum_{y} Q_{p,i,j,k,y}} \tag{22}$$

Carbon footprints are calculated annually for the producing territorial units at larger geographical scales ($CF_{i,y}$); and further accumulated over a period of analysis (CF_i), according to Eqs. (23),(24):

$$CF_{i,y} = \frac{\sum_k \sum_j \sum_p ETOT_{p,i,j,k,y}}{\sum_k \sum_j \sum_p Q_{p,i,j,k,y}} \tag{23}$$

$$CF_{i} = \frac{\sum_y \sum_k \sum_j \sum_p ETOT_{p,i,j,k,y}}{\sum_y \sum_k \sum_j \sum_p Q_{p,i,j,k,y}} \tag{24}$$

Carbon footprints for the countries of import are calculated annually ($CF_{j,y}$) or throughout a period of analysis (CF_j), following Eqs. (25),(26):

$$CF_{j,y} = \frac{\sum_k \sum_i \sum_p ETOT_{p,i,j,k,y}}{\sum_k \sum_i \sum_p Q_{p,i,j,k,y}} \tag{25}$$

$$CF_{j} = \frac{\sum_y \sum_k \sum_i \sum_p ETOT_{p,i,j,k,y}}{\sum_y \sum_k \sum_i \sum_p Q_{p,i,j,k,y}} \tag{26}$$

References

ABRACAL, 2016. Associação Brasileira dos Produtores de Calcáreo Agrícola. Estatísticas Available at. http://www.abracal.com.br/estatisticas (09.12.2019).

Agrosátelite, 2018. Agricultural Expansion in the Cerrado and Amazon MapS. Agrosatélite Geotecnologia Aplicada Ltda. Available at. https://agrosatelite.com.br/en/cases/#expansao-agricola (20.12.2019).

ANDA (2017) Fertilizantes. associação nacional para difusão de adubos. Available athttp://www.anda.org.br(09.12.2019).

Arima, E.Y., Barreto, P., Araújo, E., Soares-Filho, B., 2014. Public policies can reduce tropical deforestation: lessons and challenges from Brazil. Land Use Policy 41, 465–473. https://doi.org/10.1016/j.landusepol.2014.06.026.

Arvor, D., Dubreuil, V., Simões, M., Bégué, A., 2013. Mapping and spatial analysis of the soybean agricultural frontier in Mato Grosso, Brazil, using remote sensing data. Geo J. 78 (5), 833–850. https://doi.org/10.1007/s10708-012-9469-3.

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A., et al., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nat. Clim. Chang. 2, 182–185. http://dx.doi.org/10.1038/NCLIMATE1354.

Brack, D., Glover, A., Wellesley, L., 2016. Agricultural Commodity Supply Chains Trade, Consumption and Deforestation. Chatham House. London, United Kingdom Edited by.

Brander, M., Burritt, R.L., Christ, K.L., 2019. Coupling attributional and consequential life cycle assessment. A matter of social responsibility. J. Clean. Prod. 215, 514–521. https://doi.org/10.1016/j.jclepro.2019.01.066.

Brown, C., Murray-Rust, D., van Vliet, J., Alam, S.J., Verburg, P.H., Rounsevell, M.D., 2014. Experiments in globalisation, food security and land use decision making. PLoS One 9 (12), e114213. https://doi.org/10.1371/journal.pone.0114213.

Browne, M., Rizet, C., Anderson, S., Allen, J., Keïta, B., 2005. Life cycle assessment in the supply chain. A review and case study. Transport Rev. 25 (6), 761–782. https://doi.org/10.1080/01441640500360993.

Bruckner, M., Fischer, G., Tramberend, S., Giljum, S., 2015. Measuring telecouplings in the global land system. A review and comparative evaluation of land footprint accounting methods. Ecol. Econ. 114, 11–21. https://doi.org/10.1016/j.ecolecon.2015.03.008.

Bruckner, M., Giljum, S., Lutz, C., Wiebe, K.S., 2012. Materials embodied in international trade – Global material extraction and consumption between 1995 and 2005. Global Environ. Change 22 (3), 568–576. https://doi.org/10.1016/j.gloenvcha.2012.03.011.

Bruckner, M., Wood, R., Moran, D., Kuschnig, N., Wieland, H., Maus, V., Börner, J., 2019. FABIO-The construction of the food and agriculture biomass input-output model. Environ. Sci. Technol. 53 (19), 11302–11312. https://doi.org/10.1021/acs.est.9b03554.

Cabernard, L., Pfister, S., Hellweg, S., 2019. A new method for analyzing sustainability performance of global supply chains and its application to material resources. Sci. Total Environ. 684, 164–177. https://doi.org/10.1016/j.scitotenv.2019.04.434.

Carvalho, W.D.de, Mustin, K., 2017. The highly threatened and little known Amazonian savannahs. Nat. Ecol. Evol. 1 (4), 0100. https://doi.org/10.1038/s41559-017-0100.

Castanheira, E.G., Freire, F., 2013. Greenhouse gas assessment of soybean production. Implications of land use change and different cultivation systems. J. Clean. Prod. 54, 49–60. https://doi.org/10.1016/j.jclepro.2013.05.026.

Castanheira, E.G., Grisoli, R., Coelho, S., Anderi da Silva, G., Freire, F., 2015. Life-cycle assessment of soybean-based biodiesel in Europe. comparing grain, oil and biodiesel import from Brazil. J. Clean. Prod. 102, 188–201. https://doi.org/10.1016/j.jclepro.2015.04.036.

Cattelan, A.J., Dall'Agnol, A., 2018. The rapid soybean growth in Brazil. Oilseeds Fats Crops Lipids (OCL) 25 (1), D102. https://doi.org/10.1051/ocl/2017058.

Ceccon, G., Staut, L.A., Sagrilo, E., Machado, L.A.Z., Nunes, D.P., Alves, V.B., 2013. Legumes and forage species sole or intercropped with corn in soybean-corn succession in Midwestern Brazil. Rev. Bras. Ciênc. Solo 37 (1), 204–212. http://dx.doi.org/10.1590/S0100-06832013000100021.

Cerri, C.E.P., You, X., Cherubin, M.R., Moreira, C.S., Raucci, G.S., Castigioni, B.A., Alves, P.A., Cerri, D.G.P., Mello, F.F.C., Cerri, C.C., 2017. Assessing the greenhouse gas emissions of Brazilian soybean biodiesel production. PLoS ONE 12 (5), e0176948. https://doi.org/10.1371/journal.pone.0176948.

Chaudhary, A., Kastner, T., 2016. Land use biodiversity impacts embodied in international food trade. Global Environ. Change 38, 195–204. https://doi.org/10.1016/j.gloenvcha.2016.03.013.

COMEX STAT, 2020. Exports and Imports of cities. Ministério da Indústria. Comércio Exterior e Serviços Available at. http://comexstat.mdic.gov.br/en/municipio (27.02.2020).

COMTRADE, 2018. Resource Trade.Earth. Chatham House Edited byAvailable at. https://resourcetrade.earth (25.10.2018).

COMTRADE, 2020. World, Region and Country Profile. United Nations Database Available at. https://comtrade.un.org/pb/ (27.02.2020).

Corrado, S., Rydberg, T., Oliveira, F., Cerutti, A., Sala, S., 2019. Out of sight out of mind? A life cycle-based environmental assessment of goods traded by the European Union. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.118954. (in press).

Croft, S.A., West, C.D., Green, J.M.H., 2018. Capturing the heterogeneity of sub-national production in global trade flows. J. Clean. Prod. 203, 1106–1118. https://doi.org/10.1016/j.jclepro.2018.08.267.

Čuček, L., Klemeš, J.J., Kravanja, Z., 2012. A review of footprint analysis tools for monitoring impacts on sustainability. J. Clean. Prod. 34, 9–20. https://doi.org/10.1016/j.jclepro.2012.02.036.

El-Chichakli, B., von Braun, J., Lang, C., Barben, D., Philp, J., 2016. Five cornerstones of a global bioeconomy. Nature 535 (7611), 221–223.

EMBRAPA, 2015. Mapa De Estoque De Carbono Orgânico Do Solo (COS) a 0-30Cm Do Brasil. Empresa Brasileira de Pesquisa Agropecuária Available at. http://geoinfo.cnps.embrapa.br/documents/1115 (09.12.2019).

EMBRAPA, 2018. Macrologística Da Agropecuária Brasileira. Empresa Brasileira de Pesquisa Agropecuária Available at. https://www.embrapa.br/macrologistica/caminhos-da-safra (02.12.2019).

Esteves, V.P.P., Esteves, E.M.M., Bungenstab, D.J., Loebmann, D.G.S.W., Castro Victoria, D., Vicente, L.E., Fernandes Araújo, O.Q., Vaz Morgado, C.R., 2016. Land use change (LUC) analysis and life cycle assessment (LCA) of brazilian soybean biodiesel. Clean Technol. Environ. Policy 18 (6), 1655–1673. https://doi.org/10.1007/s10098-016-1161-8.

FAO, 2015. The state of agricultural commodity markets 2015–2016. Trade and Food security: Achieving a Better Balance Between National Priorities and the Collective Good. Food and Agriculture Organization, RomeItaly.

FAO (2019) Technical conversion factors for agricultural commodities. Available athttp://www.fao.org/economic/the-statistics-division-ess/methodology/methodology-systems/technical-conversion-factors-for-agricultural-commodities/en/(03.05.2019).

FAOstat (2018) Production data. Crops processed. Available athttp://www.fao.org/(17.08.2018).

Flach, R., Ran, Y., Godar, J., Karlberg, L., Suavet, C., 2016. Towards more spatially explicit assessments of virtual water flows: linking local water use and scarcity to global demand of Brazilian farming commodities. Environ. Res. Lett. 11 (7), 75003. https://doi.org/10.1088/1748-9326/11/7/075003.

Galford, G.L., Melillo, J.M., Kicklighter, D.W., Mustard, J.F., Cronin, T.W., Cerri, C.E.P., Cerri, C.C., 2011. Historical carbon emissions and uptake from the agricultural frontier of the Brazilian Amazon. Ecol. Appl. 21 (3), 750–763. https://doi.org/10.1890/09-1957.1.

Gardner, T.A., Benzie, M., Börner, J., Dawkins, E., Fick, S., Garrett, R., Godar, J., Grimard, A., Lake, S., Larsen, R.K., et al., 2019. Transparency and sustainability in global commodity supply chains. World Dev. 121, 163–177. https://doi.org/10.1016/j.worlddev.2018.05.025.

Garrett, R.D., Levy, S., Carlson, K.M., Gardner, T.A., Godar, J., Clapp, J., Dauvergne, P., Heilmayr, R., le Polain de Waroux, Y., Ayre, B., et al., 2019. Criteria for effective zero-deforestation commitments. Global Environ. Change 54, 135–147. https://doi.org/10.1016/j.gloenvcha.2018.11.003.

Gibbs, H.K., Rausch, L., Munger, J., Schelly, I., Morton, D.C., Noojipady, P., Soares-Filho, B., Barreto, P., Micol, L., Walker, N.F., 2015. Brazil's soy moratorium. Science 347 (6220), 377–378. https://doi.org/10.1126/science.aaa0181.

Gibbs, H.K., Ruesch, A.S., Achard, F., Clayton, M.K., Holmgren, P., Ramankutty, N., Foley, J.A., 2010. Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. Proc. Natl. Acad. Sci. U.S.A. 107 (38), 16732–16737. https://doi.org/10.1073/pnas.0910275107.

Godar, J., Persson, U.M., Tizado, E.J., Meyfroidt, P., 2015. Towards more accurate and policy relevant footprint analyses. Tracing fine-scale socio-environmental impacts of production to consumption. Ecol. Econ. 112, 25–35. https://doi.org/10.1016/j.ecolecon.2015.02.003.

Godar, J., Suavet, C., Gardner, T.A., Dawkins, E., Meyfroidt, P., 2016. Balancing detail and scale in assessing transparency to improve the governance of agricultural commodity supply chains. Environ. Res. Lett. 11 (3), 35015. https://doi.org/10.1088/1748-9326/11/3/035015.

Gollnow, F., Lakes, T., 2014. Policy change, land use, and agriculture: the case of soy production and cattle ranching in Brazil, 2001–2012. Appl. Geogr. 55, 203–211. https://doi.org/10.1016/j.apgeog.2014.09.003.

Green, J.M.H., Croft, S.A., Durán, A.P., Balmford, A.P., Burgess, N.D., Fick, S., Gardner, T.A., Godar, J., Suavet, C., Virah-Sawmy, M., et al., 2019. Linking global drivers of agricultural trade to on-the-ground impacts on biodiversity. Proc. Natl. Acad. Sci. U.S.A. 116 (46), 23202–23208. https://doi.org/10.1073/pnas.1905618116.

Hellweg, S., Milà i Canals, L., 2014. Emerging approaches, challenges and opportunities in life cycle assessment. Science 344 (6188), 1109–1113. https://doi.org/10.1126/science.1248361.

Hellweg, St., Zah, R., 2016. What is new at the data front? Int. J. Life Cycle Assess. 21 (9), 1215–1217. https://doi.org/10.1007/s11367-016-1126-5.

Henders, S., Persson, U.M., Kastner, T., 2015. Trading forests. Land-use change and carbon emissions embodied in production and exports of forest-risk commodities. Environ. Res. Lett. 10 (12), 125012. https://doi.org/10.1088/1748-9326/10/12/125012.

Henriksson, P.J.G., Guinée, J.B., Kleijn, R., Snoo, G.R.de, 2012. Life cycle assessment of aquaculture systems—a review of methodologies. Int. J. Life Cycle Assess. 17 (3), 304–313. https://doi.org/10.1007/s11367-011-0369-4.

Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., van Zelm, R., 2017. ReCiPe2016. A harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assess. 22 (2), 138–147. https://doi.org/10.1007/s11367-016-1246-y.

IBGE, 2017. Censo Agropecuário 2017 - Resultados Definitivos. Instituto Brasileiro de Geografia e Estatística Available at. https://sidra.ibge.gov.br/pesquisa/censo-agropecuario/censo-agropecuario-2017#caracteristicas-estabelecimentos (12.12.2019).

IBGE, 2018. Produção Agrícola Municipal. Instituto Brasileiro de Geografia e Estatística Available at. https://sidra.ibge.gov.br/tabela/839 (10.12.2019).

INPE, 2018. PRODES – Desmatamento nos Municípios. Instituto Nacional de Pesquisas Espaciais Available at. http://www.dpi.inpe.br/prodesdigital/prodesmunicipal.php (09.12.2019).

INPE, 2018. Monitoramento Do Desmatamento No Cerrado Brasileiro Por Satélite. Instituto Nacional de Pesquisas Espaciais Available at. http://cerrado.obt.inpe.br/ (09.12.2019).

IPCC, 2006. IPCC Guidelines for National Greenhouse Gas Inventories. Edited by Intergovernmental Panel on Climate Change Available at. https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html (02.07.2019).

Kanemoto, K., Moran, D., Lenzen, M., Geschke, A., 2014. International trade undermines national emission reduction targets. New evidence from air pollution. Global Environ. Change 24, 52–59. https://doi.org/10.1016/j.gloenvcha.2013.09.008.

Kastner, T., Kastner, M., Nonhebel, S., 2011. Tracing distant environmental impacts of agricultural products from a consumer perspective. Ecol. Econ. 70 (6), 1032–1040. https://doi.org/10.1016/j.ecolecon.2011.01.012.

Kastner, T., Ibarrola-Rivas, M.J., Koch, W., Nonhebel, S., 2012. Global changes in diets and the consequences for land requirements for food. Proc. Natl. Acad. Sci. U.S.A. 109 (18), 6868–6872. https://doi.org/10.1073/pnas.1117054109.

Kastner, T., Schaffartzik, A., Eisenmenger, N., Erb, K.H., Haberl, H., Krausmann, F., 2014. Cropland area embodied in international trade. Contradictory results from different approaches. Ecol. Econ. 104, 140–144. https://doi.org/10.1016/j.ecolecon.2013.12.003.

Lathuillière, M.J., Johnson, M.S., Galford, G.L., Couto, E.G., 2014. Environmental footprints show China and Europe's evolving resource appropriation for soybean production in Mato Grosso, Brazil. Environ. Res. Lett. 9 (7), 74001. https://doi.org/10.1088/1748-9326/9/7/074001.

Lee, E.K., Zhang, X., Adler, P.R., Kleppel, G.S., Romeiko, X.X., 2020. Spatially and temporally explicit life cycle global warming, eutrophication, and acidification impacts from corn production in the U.S. Midwest. J. Clean. Prod. 242https://doi.org/10.1016/j.jclepro.2019.118465. in press.

Lenzen, M., Sun, Y.Y., Faturay, F., Ting, Y.P., Geschke, A., Malik, A., 2018. The carbon footprint of global tourism. Nat. Clim. Chang. 8 (6), 522–528. https://doi.org/10.1038/s41558-018-0141-x.

Liu, J., Hull, V., Batistella, M., DeFries, R., Dietz, T., Fu, F., Hertel, T.W., Izaurralde, R.C., Lambin, E.F., Li, S., et al., 2013. Framing sustainability in a telecoupled world. E&S 18 (2). https://doi.org/10.5751/ES-05873-180226.

Lutter, S., Pfister, S., Giljum, S., Wieland, H., Mutel, C., 2016. Spatially explicit assessment of water embodied in European trade: a product-level multi-regional input-output analysis. Global Environ. Change 38, 171–182. https://doi.org/10.1016/j.gloenvcha.2016.03.001.

Macedo, M.N., DeFries, R.S., Morton, D.C., Stickler, C.M., Galford, G.L., Shimabukuro, Y.E., 2012. Decoupling of deforestation and soy production in the southern Amazon during the late 2000s. Proc. Natl. Acad. Sci. U.S.A. 109 (4), 1341–1346. https://doi.org/10.1073/pnas.1111374109.

Maciel, V.G., Zortea, R.B., Grillo, I.B., Lie-Ugaya, C.M., Einloft, S., Seferin, M., 2016. Greenhouse gases assessment of soybean cultivation steps in southern Brazil. J. Clean. Prod. 131, 747–753. https://doi.org/10.1016/j.jclepro.2016.04.100.

Ministério da Economia, 2018. Receita Federal. Dados públicos CNPJ. Available online at. http://receita.economia.gov.br/orientacao/tributaria/cadastros/cadastro-nacional-de-pessoas-juridicas-cnpj/dados-publicos-cnpj (27.02.2020).

Ministério da Infraestrutura, 2015. Mapas e Bases dos Modos de Transportes. Brasília DF (Brazil) Available online at. http://www.infraestrutura.gov.br/ (09.12.2019).

Morton, D.C., DeFries, R.S., Shimabukuro, Y.E., Anderson, L.O., Arai, E., del Bon Espirito-Santo, F., Freitas, R., Morisette, J., 2006. Cropland expansion changes deforestation dynamics in the southern Brazilian Amazon. Proc. Natl. Acad. Sci. U.S.A. 103 (39), 14637–14641. https://doi.org/10.1073/pnas.0606377103.

Morton, D.C., Sales, M.H., Souza, C.M., Griscom, B. (2011) Historic emissions from deforestation and forest degradation in Mato Grosso, Brazil. 1) source data uncertainties. Carbon Balance and Management 6, 18. DOI: 10.1186/1750-0680-6-18.

Mutel, C., Liao, X., Patouillard, L., Bare, J., Fantke, P., Frischknecht, R., Hauschild, M., Jolliet, O., de Souza, D.M., Laurent, A., et al., 2019. Overview and recommendations for regionalized life cycle impact assessment. Int. J. Life Cycle Assess. 24 (5), 856–865. https://doi.org/10.1007/s11367-018-1539-4.

Nepstad, D., McGrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., DiGiano, M., Shimada, J., da Motta, R.S., et al., 2014. Slowing Amazon deforestation through public policy and interventions in beef and soy supply chains. Science 344 (6188), 1118–1123. https://doi.org/10.1126/science.1248525.

Nielsen, P.H., Nielsen, A.M., Weidema, B.P., Dalgaard, R., Halberg, N., 2003. LCA Food database. Faculty of Agricultural Science. Aarhus University, Denmark 2.-0 LCA Consultants. Available at. http://www.lcafood.dk/ (07.02.2018).

Noojipady, P., Morton, C.D., Macedo, N.M., Victoria, C.D., Huang, C., Gibbs, K.H., Bolfe, L.E., 2017. Forest carbon emissions from cropland expansion in the Brazilian Cerrado biome. Environ. Res. Lett. 12 (2), 25004. https://doi.org/10.1088/1748-9326/aa5986.

Numata, I., Cochrane, M.A., Souza, C.M., Sales, M.H., 2011. Carbon emissions from deforestation and forest fragmentation in the Brazilian Amazon. Environ. Res. Lett. 6 (4), 44003. https://doi.org/10.1088/1748-9326/6/4/044003.

OECD/FAO, 2017. Agricultural Outlook 2017–2026. Special Focus: Southeast Asia. OECD Publishing, Paris (France)/Rome (Italy).

OECD/FAO, 2018. Agricultural Outlook 2018–2027. Special Focus: Middle East and North Africa. OECD Publishing, Paris (France)/Rome (Italy).

Osorio, R.M.L., 2018. A Produção De Soja No Oeste Do Pará : a tomada De Decisão Do Produtor Rural e As Características Da Atividade Produtiva Em Meio à Floresta Amazônica. Universidade de Brasília, Brasília DF (Brazil) Available at. http://repositorio.unb.br/handle/10482/33908 (09.07.2019).

Pelton, R., 2018. Spatial greenhouse gas emissions from US county corn production. Int. J. Life Cycle Assess. 46 (9), 9155. https://doi.org/10.1007/s11367-018-1506-0.

Pendrill, F., Persson, U.M., Godar, J., Kastner, T., 2019a. Deforestation displaced: trade in forest-risk commodities and the prospects for a global forest transition. Environ. Res. Lett. 14 (5), 55003. https://doi.org/10.1088/1748-9326/ab0d41.

Pendrill, F., Persson, U.M., Godar, J., Kastner, T., Moran, D., Schmidt, S., Wood, R., 2019b. Agricultural and forestry trade drives large share of tropical deforestation emissions. Global Environ. Change 56, 1–10. https://doi.org/10.1016/j.gloenvcha.2019.03.002.

Persson, U.M., Henders, S., Cederberg, C., 2014. A method for calculating a land-use change carbon footprint (LUC-CFP) for agricultural commodities - applications to Brazilian beef and soy, Indonesian palm oil. Global Change Biol. 20 (11), 3482–3491. https://doi.org/10.1111/gcb.12635.

Poore, J., Nemecek, T., 2018. Reducing food's environmental impacts through producers and consumers. Science 360 (6392), 987–992. https://doi.org/10.1126/science.aaq0216.

Raucci, G.S., Moreira, C.S., Alves, P.A., Mello, F.F.C., Frazão, L.A., Cerri, C.E.P., Cerri, C.C., 2015. Greenhouse gas assessment of Brazilian soybean production. A case study of Mato Grosso state. J. Clean. Prod. 96, 418–425. https://doi.org/10.1016/j.jclepro.2014.02.064.

Rausch, L.L., Gibbs, H.K., Schelly, I., Brandão, A., Morton, D.C., Carneiro Filho, A., Strassburg, B., Walker, N., Noojipady, P., Barreto, P., et al., 2019. Soy expansion in Brazil's Cerrado. Conserv. Lett. 12 (6). https://doi.org/10.1111/conl.12671.

Reap, J., Roman, F., Duncan, S., Bras, B., 2008. A survey of unresolved problems in life cycle assessment. Int. J. Life Cycle Assess. 13 (5), 374–388. https://doi.org/10.1007/s11367-008-0009-9.

Sandström, V., Valin, H., Krisztin, T., Havlík, P., Herrero, M., Kastner, T., 2018. The role of trade in the greenhouse gas footprints of EU diets. Glob. Food Sec. 19, 48–55. https://doi.org/10.1016/j.gfs.2018.08.007.

Schim Loeff, W.van der, Godar, J., Prakash, V., 2018. A spatially explicit data-driven approach to calculating commodity-specific shipping emissions per vessel. J. Clean. Prod. 205, 895–908. https://doi.org/10.1016/j.jclepro.2018.09.053.

Schmidt, H.J., 2009. Carbon footprinting, labelling and life cycle assessment. Int. J. Life Cycle Assess. 14 (1), 6–9. https://doi.org/10.1007/s11367-009-0071-y.

Silva, V.P., da, van der Werf, H.M.G., Spies, A., Soares, S.R., 2010. Variability in environmental impacts of Brazilian soybean according to crop production and transport scenarios. J. Environ. Manage. 91 (9), 1831–1839. https://doi.org/10.1016/j.jenvman.2010.04.001.

Smith, T.M., Goodkind, A.L., Kim, T., Pelton, R.E.O., Suh, K., Schmitt, J., 2017. Subnational mobility and consumption-based environmental accounting of US corn in animal protein and ethanol supply chains. Proc. Natl. Acad. Sci. U.S.A. 114 (38), E7891–E7899. https://doi.org/10.1073/pnas.1703793114.

Soterroni, A.C., Ramos, F.M., Mosnier, A., Fargione, J., Andrade, P.R., Baumgarten, L., Pirker, J., Obersteiner, M., Kraxner, F., Câmara, G., et al., 2019. Expanding the soy

moratorium to Brazil's Cerrado. Sci. Adv. 5 (7). https://doi.org/10.1126/sciadv.aav7336. eaav7336.
Spera, S.A., Galford, G.L., Coe, M.T., Macedo, M.N., Mustard, J.F., 2016. Land-use change affects water recycling in Brazil's last agricultural frontier. Glob. Chang. Biol. 22 (10), 3405–3413. https://doi.org/10.1111/gcb.13298.
Steen-Olsen, K., Weinzettel, J., Cranston, G., Ercin, A.E., Hertwich, E.G., 2012. Carbon, land, and water footprint accounts for the European Union: consumption, production, and displacements through international trade. Environ. Sci. Technol. 46 (20), 10883–10891. https://doi.org/10.1021/es301949t.
Taherzadeh, O., Caro, D., 2019. Drivers of water and land use embodied in international soybean trade. Journal of Cleaner Production 223, 83–93. https://doi.org/10.1016/j.jclepro.2019.03.068.
Tillman, A.M., 2000. Significance of decision-making for LCA methodology. Environ. Impact Assess. Rev. 20 (1), 113–123. https://doi.org/10.1016/S0195-9255(99)00035-9.
Trase, 2018. Supply Chain Mapping in Trase. Summary of Data and methods. Stockholm Environment Institute, StockholmSweden.
Trase, 2018. Sustainability in forest-risk sustainability in forest-risk supply chains: spotlight on Brazilian soy. Trase Yearbook 2018. Stockholm Environment Institute/Global Canopy, Stockholm (Sweden).
Trase, 2019. Trase Data sources. SEI-PCS Brazil soy (v.2.3); SEI-PCS Paraguay soy (v.1.1) and Paraguay Beef (v.1.0). Stockholm Environment Institute, Stockholm (Sweden).
Udo de Haes, H.A., Heijungs, R., Suh, S., Huppes, G., 2004. Three strategies to overcome the limitations of life-cycle assessment. J. Ind. Ecol. 8 (3), 19–32. https://doi.org/10.1162/1088198042442351.
Vries, M., de, van Middelaar, C.E., Boer de, I.J.M., 2015. Comparing environmental impacts of beef production systems: a review of life cycle assessments. Livest. Sci. 178, 279–288. https://doi.org/10.1016/j.livsci.2015.06.020.
Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B.P., 2016. The ecoinvent database version 3 (part I): overview and methodology. Int. J. Life Cycle Assess. 21 (9), 1218–1230. https://doi.org/10.1007/s11367-016-1087-8.
Wiedmann, T., Lenzen, M., 2018. Environmental and social footprints of international trade. Nature 11 (5), 314–321. https://doi.org/10.1038/s41561-018-0113-9.
Wiedmann, T., Schandl, H., Lenzen, M., Moran, D., Suh, S., West, J., Kanemoto, K., 2015. The material footprint of nations. Proc. Natl. Acad. Sci. U.S.A. 112 (20), 6271–6276. https://doi.org/10.1073/pnas.1220362110.
Wood, R., Stadler, K., Simas, M., Bulavskaya, T., Giljum, S., Lutter, S., Tukker, A., 2018. Growth in environmental footprints and environmental impacts embodied in trade. resource efficiency indicators from EXIOBASE3. J. Ind. Ecol. 22 (3), 553–564. https://doi.org/10.1111/jiec.12735.
Yang, Y., Heijungs, R., Brandão, M., 2017. Hybrid life cycle assessment (LCA) does not necessarily yield more accurate results than process-based LCA. J. Clean. Prod. 150, 237–242. https://doi.org/10.1016/j.jclepro.2017.03.006.
Zalles, V., Hansen, M.C., Potapov, P.V., Stehman, S.V., Tyukavina, A., Pickens, A., Song, X.P., Adusei, B., Okpa, C., Aguilar, R., et al., 2019. Near doubling of brazil's intensive row crop area since 2000. Proc. Natl. Acad. Sci. U.S.A. 116 (2), 428–435. https://doi.org/10.1073/pnas.1810301115.