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A novel maximum entropy approach to hybrid monetary-physical supply-chain modelling and its application to biodiversity impacts of palm oil embodied in consumption

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Abstract

The environmental and social consequences of clearing tropical forests for palm oil and soybean monoculture have been analyzed in a number of studies and are widely recognized. Some initiatives and studies have examined portions of the supply chain from the perspective of individual companies and stages in the supply chain. We complement this work by providing a consistent, detailed, global trade-linked analysis of the four major vegetable oils, connecting land use for production and its biodiversity impact, through global supply chains, to final consumers. To this end, we develop a global model by fully integrating FAO's physical supply-utilization accounts into the environmentally extended multiregional input–output model EXIOBASE. Global supply chains are linked with the life-cycle impact assessment model LC-Impact to assess biodiversity impact of land use via global maps of oil crop cultivation. For the period 2000–2010, we find significant substitution of domestically produced oils with relatively low biodiversity impacts with Indonesian palm oil and Brazilian soybean oil for the major consuming countries, China, Europe and the US. Whereas soybean oil remains the vegetable oil with the largest impact on biodiversity at a global scale, biodiversity footprints of palm oil have grown substantially larger in the period 2000–2010, driven by demand from Europe and China. Our results suggest that demand-side policies focused on specific oils, such as palm oil, might lead to switching oils and unintended shifts of environmental impacts.

1. Introduction

Numerous studies have shown that land use and land use changes driven by human demand for biomass are the single most important driver for the loss of terrestrial biodiversity (Bateman *et al* 2015, Chaplin-Kramer *et al* 2015). Although the second half of the last century has seen tremendous increases in land productivity due to technological progress, this efficiency gain has been strongly offset by population growth and increasingly meat-intensive diets (Kastner *et al* 2012, Weinzettel *et al* 2013). Apart from deforestation for pasture land, clearing for oil crops cultivation, especially of soybeans in Brazil and oil palms in Indonesia and Malaysia, has been the most aggressive driver of global biodiversity loss (Morton *et al* 2006, Nepstad *et al* 2006, Carlson *et al* 2012).

In the past decades global oil crop production grew more than twice as fast as all other agriculture (Alexandratos and Bruinsma 2012). Besides being a significant input in more affluent diets (Kastner *et al* 2012) the non-food industrial and energy use are the main driving forces of that rapid expansion (Valin *et al* 2015). Whilst biofuels and biomaterials accounted for only 4% of harvested biomass in 2008 (Carus and Dammer 2013), about 12% global oil crop production was required for biodiesel alone (OECD/FAO 2011). In some major economies like Brazil, the EU, or Argentina, between 30%–65% of vegetable oil is used for biodiesel. More recent figures suggest that in 2014 almost half of the EU's palm oil imports were used for biodiesel (Transport and Environment 2016). The increasing demand for bio-based oil for non-food uses is expected to continue as governments and

international organizations have set up strategies for fostering the growth of the bio-economy. These strategies aim at lowering dependency on non-renewable resources, mitigating climate change, and fostering job growth especially in rural areas (OECD 2010, European Commission 2012, Bell *et al* 2017).

Since the pioneering paper of Lenzen *et al* (2012), several studies have shown that large parts of local biodiversity threats are coupled with remote consumer demand, emphasizing the need to complement conservation policies with consumer-focused policies. However, the main consuming countries of embodied biodiversity, as well as the most relevant supply-chains and trade relationships, vary across different studies. Apart from the metrics used for measuring biodiversity impacts (as discussed in Verones *et al* 2017, Wiedmann and Lenzen 2018), the type of accounting framework used to attribute these impacts to final consumers is critically important and can severely limit the explanatory power of footprint analysis (Kastner *et al* 2014, Bruckner *et al* 2015, Hubacek and Feng 2016).

Global multi-regional input–output (MRIO) models provide a comprehensive mapping of the global supply chain network in monetary units and show how consumer demand in one country is linked to biodiversity loss in another (Lenzen *et al* 2012, Kitzes *et al* 2017, Moran and Kanemoto 2017, Verones *et al* 2017, Wilting *et al* 2017). However, the commodity details of MRIOs are too low to allow studying footprints of specific products such as different oil crops and vegetable oils (Wiedmann *et al* 2011). Furthermore, allocating pressures based on monetary values can be problematic in cases when prices of products vary significantly across uses (Weisz and Duchin 2006, Liang and Zhang 2013).

In contrast, biophysical accounting methods (Chaudhary and Kastner 2016, Chaudhary *et al* 2017, Nishijima *et al* 2016, Sandström *et al* 2017), which are based on FAO's physical supply-utilization accounts and bilateral trade data, offer much greater detail in terms of products and countries. This allows for consistent linking between production quantities and environmental stressors, as in Chaudhary and Kastner (2016), where such a model is linked with countryside species-area relationship metrics estimated via high-resolution crop maps. However, due to truncation, biophysical accounting models are unable to trace non-food use of biomass to final consumers, constituting a severe drawback in assessing footprints of crops that are primarily for industrial and energy purposes such as vegetable oil. In order to exploit the advantages of both frameworks some authors link biophysical flows into non-food industries with a monetary EEMRIO (Weinzettel *et al* 2013, Bruckner *et al* 2018). However, highly processed food which embodies a large share of global vegetable oil production still cannot be traced sufficiently, as FAO supply-utilization accounts do not account for trade of oils embodied in these foods (FAO Statistics Division 1972).

In this paper, we develop a novel maximum entropy approach to integrate data from FAO's supply-utilization accounts and high-resolution bilateral trade data into the MRIO model EXIOBASE (Stadler *et al* 2018). As suggested by Bruckner *et al* (2015), our hybrid physical-monetary model provides a 'best of both worlds' approach. We apply the model to a case study of the biodiversity footprints of the major vegetable oils (palm, soybean, rapeseed, and sunflower) as well as their global development between 2000–2010.

2. Methodology

In this section, we describe the three main building blocks of our research. Section 2.1 describes the maximum entropy model that we used to construct the hybrid MRIO (HMRIO). We then explain how the HMRIO is used to estimate land use footprints in section 2.2, and then link with characterization factors describing the biodiversity loss per occupied hectare in section 2.3.

2.1. Mixed unit global MRIO model

The mixed unit HMRIO is constructed using EXIOBASE as a backbone, which maps production, trade and intermediate- and final consumption of 200 products and 49 regions (44 countries and 5 RoW regions) (Wood *et al* 2014, Stadler *et al* 2018). EXIOBASE is particularly useful for this application, as it already includes oil crops and vegetable oils as aggregate sectors. The task here is then to (1) disaggregate the oil crops and vegetable oil in monetary units into the four oil crops and vegetable oils each and (2) transform them into physical units.

This is done using a version of the entropy model developed in Többen (2017), which allows for the simultaneous estimation of monetary and physical commodity flows by incorporating the value-to-weight relationships (i.e. the prices per ton). The main idea of this approach is to treat commodity flows recorded in EXIOBASE and in the supply-utilization accounts, such as intermediate consumption of manufacturing sectors (EXIOBASE) and non-food use (FAO), as constraints both defining the same flow.

We first construct an initial estimate of the physical crop and oil flows between a sector i in region r and a sector j in country s in two steps. In step 1, we use price allocation (Bruckner *et al* 2015) to distribute the physical quantities reported by FAO for domestic consumption in five utilization categories (food, feed, processing (oil production), seed and industrial uses) across the corresponding EXIOBASE sectors. Then, in step 2, we use import shares from the physical layer of the BACI bilateral trade database to breakdown the intermediate and final consumption of oils and crops in each country into the countries of origin.

Afterwards, similarly to the typical approach of constructing EEMRIOs (Golan and Vogel 2000, Robinson *et al* 2001, Lenzen *et al* 2009, Wood *et al* 2014), we reconcile this initial estimate (or prior) with all available data by minimizing the distance between the prior and the final HMRIO, subject to the constraints that the latter be consistent with all available data. The most commonly used distance measure in such applications is cross-entropy, also known as Kullback–Leibler divergence (Kullback and Leibler 1951).

For notational convenience, we summarize the commodity flows between a sector i in region r and a sector j in country s by the compound index k, the data points, γ_l, from FAO and BACI measured in physical quantities by index l and the data points, γ_m, from EXIOBASE and BACI measured in monetary values by index m.

Considering that prices per ton of a type of crop or oil can differ significantly depending on the consuming sector, we further break down the priors and target values into three categories $n = \{1, 2, 3\}$ accounting for commodity flows at minimal, mean, and maximal prices. Hence, the prior and the target values are denoted by q_{kn} and p_{kn} respectively, and π_{kn} denotes the respective price per ton. Note, entropy models require that q_{kn} and p_{kn} are expressed as fractions of the total global amount of crops and oils consumed such that both add up to one.

Since many data points, especially between the different datasets, are mutually inconsistent (Lenzen *et al* 2009, Wood 2011), we split each data constraint into a signal and a noise (error) component, and incorporate cross-entropy measures of the error into the model. The errors of each constraint are expressed as a linear combination of $o = \{1, 2, 3\}$ support points σ_{lo} and σ_{mo} for each data points (defining lower and upper bounds and expected values of errors) and weights, w_{lo} and w_{mo}, that add up to one (Robinson *et al* 2001). Through priors for the constraint weights, v_{lo} and v_{mo}, we can assign subjective judgements of uncertainty to each data point, whereby an even distribution (i.e. $v_{l1} = v_{l2} = v_{l3} = 1/3$) expresses high uncertainty.

The entropy model for the construction of the HMRIO can then be stated as minimizing the change in the target values of the variables (p_{kn}) from the prior (q_{kn}), and the change in the constraint weights (to handle violation) for physical data (w_{lo} from v_{lo}) and monetary data (w_{mo} from v_{mo}):

$$\min obj = \sum_{kn} p_{kn} \ln \frac{p_{kn}}{q_{kn}} + \sum_{lo} w_{lo} \ln \frac{w_{lo}}{v_{lo}} + \sum_{mo} w_{mo} \ln \frac{w_{mo}}{v_{mo}}$$

s.t.

$$\gamma_l = \sum_k g_{kl} \sum_n p_{kn} \sum_o w_{lo}\ \sigma_{lo},\ \forall l$$

(FAO and BACI physical data)

$$\gamma_m = \sum_k g_{km} \sum_n \pi_{kn} p_{kn}\ + \sum_o w_{mo}\ \sigma_{mo},\ \forall m$$

(EXIOBASE and BACI monetary data)

$$\sum_{kn} p_{kn} = 1 \quad \text{(fraction of global amounts)}$$

$$\sum_o w_{lo} = 1,\ \forall l$$

(entropy weights for physical data)

$$\sum_o w_{mo} = 1,\ \forall m,$$

(entropy weights for monetary data),

where g_{kl} and g_{km} are elements of concordance matrices that take the value of one if a commodity flow k corresponds to the data points l and m, respectively, and are zero otherwise. As monetary constraints from EXIOBASE we use total intermediate and final consumption oil crops and vegetable oil of each sector j and households, respectively, in each country s. The model is implemented in GAMS and solved using the non-linear programming solver CONOPT4.

2.2. Land use footprints

Overall, our approach is based on the same methodology that is generally used for the calculation of emission or other environmental footprints (Wiebe *et al* 2012, Tukker *et al* 2016). We use a standard Leontief demand-pull model with the mixed unit HMRIO to calculate the total land use requirement, per crop, by consumers in each country for 2000 and 2010. This trade model follows all trade and transformation steps to reattribute production in s to consumption in r via last supplying country t.

The main assumption of the Leontief demand-pull model is that, in the short run, intermediate inputs from production sector i in producer country r required by sector j in country s per unit of output, $a_{ij}^{rs} \in \mathbf{A}$, are constant. The production level of sector i in country r, $x_i^r \in \mathbf{x}$, that are directly and indirectly required to satisfy final demand for product j produced in country s and consumed in country t, $y_j^{st} \in \mathbf{Y}$, can then be computed by

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} = \mathbf{L}\mathbf{y},$$

where $\mathbf{L}$ denotes the Leontief inverse.

The land use footprint of country s, $F_j^{(c)s}$ is the total land area used by each production sector i in each producer country r to supply final consumption-inclusive of all the intermediate trade and processing steps between original production and final consumption-in country s of the good or service j. It can be written as

$$F_j^{(c)s} = \sum_{i,r} q_i^r \sum_t L_{ij}^{rt} y_j^{ts},$$

where q is the land area required to grow one ton of crop per unit output, i.e. physical tonnes for the oil crops (Kanemoto *et al* 2012). In a mixed-unit MRIO mode, the Leontief inverse consists of four blocks. These show the total requirements of (1) tons of the

four oil crops required to produce one ton of respective the crops (i.e. seed) and oils (i.e. processing), (2) the monetary value of other inputs required to produce one ton of crops and oil (e.g. fertilizers, labour etc), (3) of tons of the four oil crops and oils of other sectors to produce one EUR of output and (4) the monetary value of other inputs of these sectors. Similarly, final demand for oil crops and oils is expressed in tons, while demand for other products is expressed in EUR. Note that the harvested area of each crop in each country, as well as the produced and consumed quantities of each crop and oil, are based on FAO data. Thus, our approach also accounts for changes in the yields per hectare between 2000–2010.

2.3. Estimating biodiversity impacts

The LC-Impact impact assessment method (Verones *et al* 2016) offers a spatially-differentiated approach for assessing environmental impacts on biodiversity and human health. Regarding impacts on biodiversity (species-richness is used as a proxy), different impact categories, such as land use, water consumption, and eutrophication are covered. Only land use is relevant for this work. The model is based on Chaudhary *et al* (2015), modelling the potential damage due to land occupation and transformation. The approach is spatially-explicit for all 804 terrestrial ecoregions (Olson *et al* 2001) and six land use types (annual crops, permanent crops, urban areas, pasture, intensive and extensive forestry). The model provides characterization factors that quantify the biodiversity impact in terms of 'potentially disappeared fraction of species' (PDF) per hectare of land use. A novel concept in LC-Impact and Chaudhary *et al* (2015) is the inclusion of a vulnerability term in the characterization model. This term recognizes that some species and ecosystems may be more susceptible and more vulnerable to anthropogenic changes than others. Thus, we can account not only for spatial differences in the underlying abiotic environmental conditions, but also in the vulnerability of species to pressure. This vulnerability approach is based on geographical distribution and the threat level of species. A description of the approach is included in Chaudhary *et al* (2015).

We multiply the crop maps (You *et al* 2014) (in units of hectares of physical land used per grid cell) with a map of the characterization factors for the occupation of permanent crops for oil palm and of annual crops for the other three oil seeds. Thereafter we compute average PDFs per hectare of harvested area for each EXIOBASE country based on area-averaged weighting. Since the crop maps deliver information on both the physical and the harvested area, multiple harvests within a year are taken into account. This converts the global land use footprints for a given consumer country from hectares to units of PDF, showing the biodiversity impact of consumption. The approach is analogous to (Verones *et al* 2017) and a mathematical exposition of the method can be found there.

3. Results

Globally, the largest impact on biodiversity amongst the 4 oil crops is from soybean cultivation (59%), which also occupies the largest area among the four crops (50%). Oil palms, in contrast, occupy only 10% of the total oil crop land area but are responsible for 37% of the total biodiversity impact. The average biodiversity loss per hectare used for cultivating palm oil is thus more than four times larger than that of soybean. Oil palm are exclusively cultivated in tropical and biodiversity-rich areas, while a large portion of global soybean cultivation (with the exception of in Brazil) takes place in much less vulnerable ecoregions especially in the US. Rapeseeds and sunflowers occupy 19% and 13% of global cropland devoted to oil seed production, but only cause 9% and 4% of the biodiversity loss, respectively. Since 2000, the share of palm oil in the global biodiversity loss due to vegetable oils has strongly increased by 6.3 percentage points (pp) at the expense of sunflower (−2.4 pp) and especially rapeseed oil (−4.2 pp).

3.1. Per capita biodiversity footprints in 2010

Figure 1 shows the per capita biodiversity footprints of countries and world regions in 2010 related to the cultivation of oil palm (a), rapeseed (b), soybeans (c), and sunflowers (d). The per capita footprints are normalized taking the global biodiversity footprint per capita of palm oil as a reference.

Results show that the two major hotspots of biodiversity loss due to oil palm cultivation in South East Asia and soybean cultivation in Latin America are ultimately driven by very different consumption patterns. The biodiversity loss related to oil palm cultivation is mainly driven by consumers from Western Europe and Australia, whose per capita biodiversity footprints are between 3.5 and up to 13 (Luxemburg) times larger than the global average. In other high-income countries, such as USA, Canada and Japan, biodiversity footprints of palm oil are well above the global average with 50%–80%, but significantly lower compared to Western Europe and Australia. In contrast, in the emerging economies of China and India, who are among the major consumers of biodiversity embodied in palm oil in total, per capita footprints are 30% and 60% lower than the global average, respectively.

In comparison, the biodiversity losses related to soybean cultivation, especially in Brazil, are strongly driven by consumers from the same country, who have per capita footprints that are more than 10 times larger than the reference. Interestingly, the USA, who are the world's largest producers of soybeans, also drive significant biodiversity losses in Brazil with per capita footprints that are three times larger than the

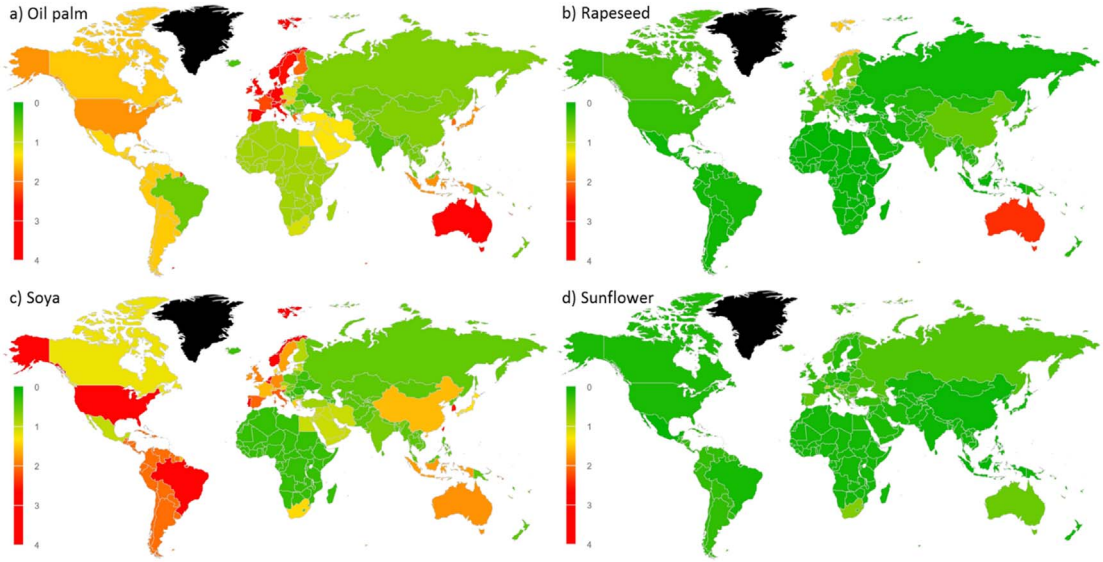

Figure 1. Biodiversity footprints per capita in 2010 of oil seeds and vegetable oils from (a) oil palms, (b) rapeseed, (c) soybean and (d) sunflower. Biodiversity footprints are normalized by global per capita footprint of palm oil. Color scale from −1 (=−100%) to 4 (=400%).

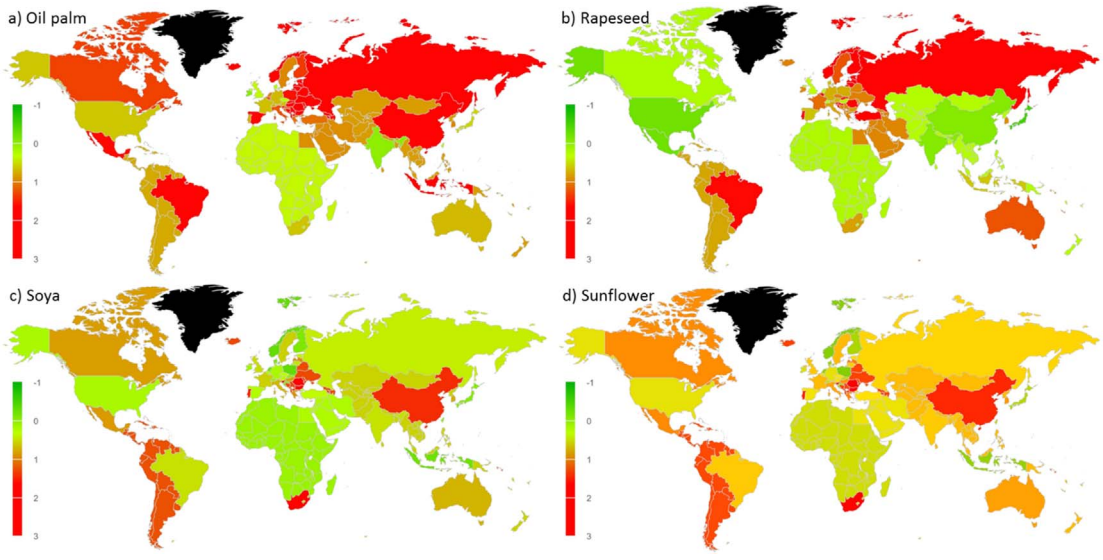

Figure 2. Relative change of biodiversity footprints per capita between 2000–2010 of oil seeds and vegetable oils from (a) oil palm, (b) rapeseed, (c) soybean and (d) sunflower. Color scale from −1 (=−100%) to 3 (=300%).

reference. In contrast to palm oil, where European countries generally showed the largest per capita footprints, high per capita biodiversity footprints related to soybean cultivation can only be observed for few countries, such as Norway, the Netherlands, Spain, and Italy.

Generally, compared to the biodiversity loss due to oil palm and soybean cultivation, the other two major oil crops, rapeseed and sunflowers, play only a very minor role. The only notable exception is the biodiversity loss related to rapeseed cultivation in Australia, by Australian consumption.

3.2. Temporal changes in per capita footprints

In terms of the percentage changes in per capita biodiversity footprints related to palm oil between 2000–2010 as shown in figure 2, the largest increases can be observed for Russia and the eastern European countries of Romania, Bulgaria, and Slovakia, where footprints increased by more than 300%. Apart from increases due to processed food consumption and industrial use, substitution of locally-produced sunflower oil with palm oil can be observed for some countries and products. In Russia, for example, fish is one product with the largest biodiversity footprint

related to vegetable oils. Here, the biodiversity footprint related to sunflower oil decreased by 23% and 40% respectively, while the footprint related to palm oil increased by more than 300%. Among the major consumers of biodiversity embodied in palm oil, China (215%) and Indonesia (180%) show the largest increases in per capita footprints. In comparison, the increases in per capita footprints of Germany, France (both about 70%), the USA (64%), and especially the UK (36%) were much more moderate. The per capita footprint of India remained basically unchanged.

Regarding the percentage changes of per capita footprints between 2010–2000, outcomes for soybean are remarkably different compared to palm oil. Among the major consumers, only China shows an increase of comparable magnitude as increases of footprints observed for palm oil with about 150%. In Brazil and the USA, by contrast, the per capita footprints increased far less starkly, about 50% and 20%, respectively. In Europe, the most populous countries show increases in per capita footprints of similar magnitudes, ranging from 20% in Germany to about 50% in the UK and France. A further difference in per capita footprint changes related to palm oil is that several countries show a significant decrease in the soybean-related footprints, from about −5% in Japan to up to −30% in Norway and Poland.

3.3. Embodied biodiversity in trade

Figure 3 shows the land use (top panel, ha) and biodiversity (bottom panel, 'potentially disappeared fraction of species' pdf) footprints of countries and world regions in 2010 (background bars) and 2000 (foreground bars) related to the cultivation of oil palm, rapeseed, soybean and sunflower. Intra country use (solid), imports (shaded) and exports (hatched) are further distinguished. Countries are rank ordered according to the magnitude of their footprints. The EU countries, Switzerland and Norway are summarized as EU (west) and EU (east), as their respective per capita consumptions differ significantly (see figure 1). Land occupation often serves as a proxy for pressure on ecosystems due to agricultural production, while the biodiversity footprints show the actual consequences of the pressure from land use in biodiversity taking the vulnerability of ecosystems into account.

In absolute terms, by far the largest land use and biodiversity footprints in 2010 are observed for China. Its biodiversity footprint has grown by almost 100% over a decade. While China already was the country with the largest biodiversity footprint in 2000, it has also surpassed the US between 2000–2010 as the largest consumer of cropland used for oil crops. The land use footprint of the USA is twice as large as that of Brazil, however, the actual impact on ecosystems of that land use is substantially lower than that of Brazil as the biodiversity impact of US farming is substantially lower than that of Brazilian farming. In both measures, India is ranked third. Other remarkable cases of countries that show substantially different land use in comparison to biodiversity impacts are Russia and Indonesia.

The growth of biodiversity footprints is to a large extent due to outsourcing of environmental pressure to abroad. Whilst China's consumption of domestic biodiversity related to soybean and sunflowers decreased by 20% and 32%, respectively, imports of biodiversity embodied in palm oil and soybean have increased by 200% and 280% respectively. Our results show similar outcomes for other major consumers of biodiversity. In western and eastern Europe (which taken together are the second largest consumers of cropland and biodiversity) the consumption of domestic biodiversity reduced by 24% and 45% respectively. This reduction in impact is primarily due to cropland used for the cultivation of sunflowers decreasing by 37% and 64%, respectively. At the same time, the EU's imported biodiversity increased by 62%. The main drivers of the increase of EU's biodiversity footprint is the tremendous growth of palm oil imports from Indonesia, soybean oil from Latin American countries other than Brazil (which remained constant), as well as of rapeseed from Australia and Southeast Asia. The biodiversity consumption through soybean from Brazil, by contrast, remained constant and the increase in EU's consumption of biodiversity loss embodied in soybean of 33% is due to a shift to imports from other Latin–American countries.

As for Europe and China, the USA also outsourced substantial environmental impacts between 2000–2010 by reducing the consumption based impacts on domestic biodiversity (−17%) but increasing the consumption based impacts on imported biodiversity loss (64%). Here, especially the sales of soybean to domestic markets reduced, whereas the US exports to China almost tripled. At the same time, the demand of the US was increasingly satisfied by soybean imports from Brazil, which did triple during that period. Overall, the US is the second largest net exporter (after Latin–America) of cropland used for the cultivation of oil crops and the third largest net-importer of biodiversity impacts (after EU and China). Besides the increase in biodiversity imports from Brazil, substantial increases of biodiversity embodied in palm oil consumption can be observed, although it plays a far smaller role compared to Europe and China.

All of the four main exporting countries and regions of biodiversity: RoW Asia (primarily due to palm oil from Malaysia), RoW America, Brazil and Indonesia; have further increased their exports between 2000 and 2010. This is especially true for Indonesia, which almost surpassed Brazil in exported biodiversity loss in 2010 after seeing a growth rate of almost 180% over the decade. In addition to exported biodiversity impacts, all of the four countries and regions also show substantial increases in domestic consumption of biodiversity, whereby in RoW Asia and RoW America consumption within the regions

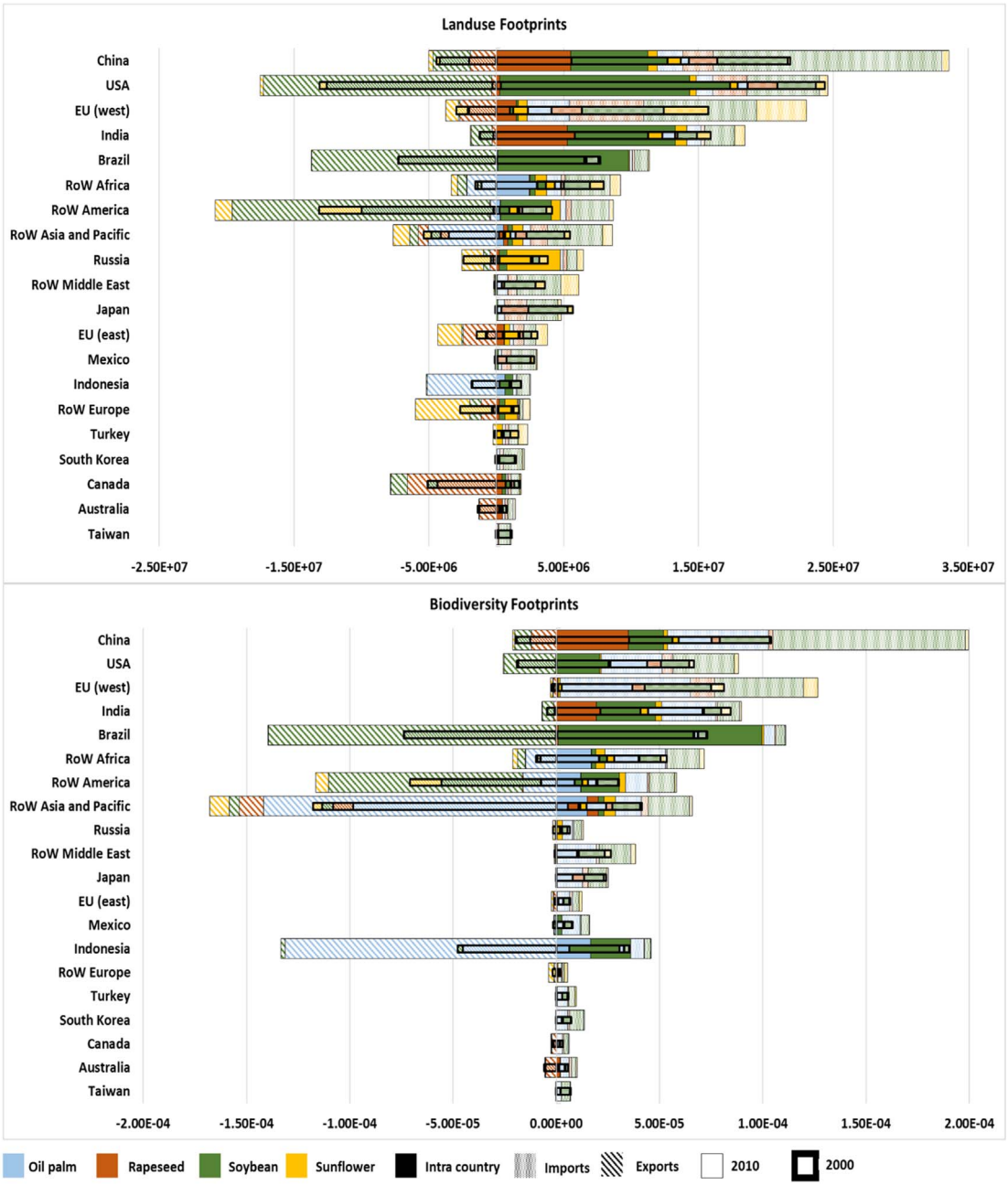

Figure 3. Land use (top panel, ha) and biodiversity (bottom panel, pdf) footprints in 2010 (background bars) and 2000 (foreground bars) related to the cultivation of oil palm, rapeseed, soybean and sunflower. Intra country use (solid), imports (shaded) and exports (hatched) are further distinguished. Countries are rank ordered according to the magnitude of their footprints.

have grown almost twice as fast as exports. However, it should be noted that especially in RoW Asia a large share of this apparently domestic consumption is due to the aggregation of countries. Nonetheless it shows that nearby markets have become more important.

4. Discussion

4.1. Comparison with other studies

Previous work on the biodiversity impacts of international trade dynamics are either purely based on monetary MRIO models (Lenzen *et al* 2012, Kitzes *et al* 2017, Moran and Kanemoto 2017, Verones *et al* 2017, Wilting *et al* 2017) or on biophysical accounting methods (Chaudhary and Kastner 2016, Nishijima *et al* 2016, Chaudhary *et al* 2017, Sandström *et al* 2017). The differences between the results delivered by the two approaches can be attributed to their specific assumptions and limitations. A number of papers have investigated the differences and advantages and disadvantages of monetary versus physical accounts for biophysical accounting; in particular see (Kastner *et al* 2014, Weinzettel *et al* 2014, Bruckner *et al* 2015, Hubacek and Feng 2016, Weinzettel and Wood 2018). Bruckner *et al* (2015) concluded in their review that hybrid monetary/physical models are the

best way forward. That conclusions was part of the motivation for this work.

In this paper, we develop a fully integrated HMRIO model that overcomes the specific limitations of both approaches.

With currently available monetary MRIO models studying embodied environmental impacts related to very specific products such as the different vegetable oil as in our analysis would not be possible, due to insufficient level of product detail. For example, even in the most detailed MRIO databases in terms of agricultural products (i.e. EXIOBASE and GTAP), oil seeds are lumped together into one product category. As a consequence, previous MRIO studies only aim at providing a comprehensive global picture of how consumer demand in one country is linked to biodiversity loss in another, rather than identifying biodiversity losses along the supply chains of specific biomass-based products.

Furthermore, our hybrid monetary-physical approach allows for a much more natural link between production levels, land requirements and resulting biodiversity losses. For example, in monetary MRIO models land requirements are expressed in (ha/$), which can lead to erroneous allocation of land use and biodiversity loss in cases where prices differ for products from the same category, e.g. due to quality differences while we use ha/yield.

Finally, compared to pure biophysical accounting methods, our approach avoids truncation errors, which especially occur for highly processed non-food products. In Chaudhary and Kastner (2016), for example, it was found that the large biodiversity footprints of US consumers in Indonesia are predominantly related to rubber, coffee and cacao, but not to palm oil, which is rather driven by Chinese, Indian and European consumers. In this paper, by contrast, we found that biodiversity footprint related to oil palm cultivation of the USA is actually larger than that of India. The reason for this difference is that purely biophysical accounting systems cannot take highly complex non-food supply chains into account. In fact, the vast majority of the US' biodiversity impacts are embodied in chemical products, machinery and equipment imported from Europe and China.

4.2. Limitations

The HMRIO approach used in this paper constitutes a potentially useful alternative to EEMRIOs and biophysical accounting especially for estimating land use and biodiversity footprints. The advantages of a HMRIO model over its competitors come especially into play in this application, where we compare footprints of a very specific product, i.e. different kinds of vegetable oil, which are substantially used for producing highly processed food products, biofuels and non-food manufactured products. However, while the estimation of biodiversity impacts is done in a spatially explicit manner, a main shortcoming remains with the country resolution of EXIOBASE used as backbone, which prevents a detailed analysis biodiversity embodied in commodity flows within the RoW regions.

Additionally, while the method developed here significantly improves the resolution of products, the well-known problems due to product aggregation may still have an effect on the results. To give a hypothetical example of this, consider a country which grows and exports two types of coffee: monocropped coffee and shade-grown coffee. Say the shade-grown coffee industry has a smaller negative effect on biodiversity. If the trade data for the country only report its exports of coffee in total, but the country exports exclusively shade-grown coffee to one set of trade partners, and exclusively monocropped coffee to another set of destinations, the model will not be able to distinguish these two different products and will treat the two export flows of coffee as identical, even though the two different products have different quality and biodiversity impacts. This is one example of how differences in product quality, and product-level detail can affect model results. Furthermore, MRIO models, like the one used here, currently do not trace flows at the subnational level, that is, if a particular subnational region has export patterns different than the national average. Hence, the model assumes exports are sourced homogenously within a country, but analogously to the previous example, export goods may be sourced from a different region, with a different biodiversity profile, than production as a whole; this could lead to biases in the result footprint calculations. These errors from aggregation and spatial misallocation have been discussed in the literature (Steen-Olsen *et al* 2014, Moran and Kanemoto 2017). Multi-scale MRIOs would help in this regard, and efforts have been initiated (Bachmann *et al* 2015, Godar *et al* 2015, Többen and Kronenberg 2015, Wenz *et al* 2015).

Here we have included the impacts of land occupation from oil crop production globally. Other impacts categories may influence the biodiversity footprints as well, for example water consumption and fertilizer and pesticide application. However, land occupation is generally recognized to be the dominant driver for the loss of (terrestrial) biodiversity (Verones *et al* 2017).

LC-Impact provides characterization factors for 804 terrestrial ecoregions, which were combined with maps showing production, harvested area and physical area of each type of oil crop at 10 km $\times$ 10 km resolution for 2005, in order to compute average characterization factors per hectare by oil crop and country. While changes in yields per hectare over time are taken into account at country level, the use of average characterization factors from 2005 for previous or later years implicitly assumes that expansions of cropland have taken place at locations with the same average vulnerability. This may lead to an over-or underestimation of footprints. In addition, we do not

know the exact configuration of the land used in the characterization models, meaning that we do not account for the impacts of fragmentation. Rather, the model assumes that all natural habitat or human-modified land is available as large chunk of continuous land.

Finally, LC-Impact uses mammals, birds, reptiles, amphibians and plants as proxies for assessing the impacts on biodiversity (species richness). We assume that this selection of taxonomic groups represent different niches of the ecosystem and are therefore suited for acting as proxies for the entire ecosystems and species richness. Information for other taxonomic groups was too scarce to be implemented in a consistent way into the characterization model.

5. Conclusion

Using a HMRIO, we estimate and compare the biodiversity footprints related to the four major vegetable oils. Compared to more traditional accounting methods such as pure monetary EEMRIO or purely biophysical models, our approach is particularly advantageous when analyzing very specific commodities instead of broad commodity groups. The HMRIO was constructed with an entropy model that allows for simultaneously reconciling partial and possibly conflicting information measured in physical and monetary units provided by the MRIO, FAO's supply-utilization accounts and bilateral trade data. By doing this, we are able to add high-resolution data to show the differences in impacts of the four oil crops, which are usually treated as one commodity in the purely monetary model.

The results show that soybeans from Brazil embodied in final products is still responsible for the largest biodiversity losses in 2010. Compared to 2000, biodiversity loss associated with the cultivation of oil palm in Indonesia and Malaysia has increased significantly and was mainly driven by the consumption of highly processed food in China and Europe.

Especially in Europe, the demand for chemical and other manufactured products and biofuels are additional drivers. Recent figures (Transport and Environment 2016) suggest that in particular biofuel production has become the most important use category in Europe, with an increase of from 8% in 2010 to 45% in 2014 of total vegetable oil use in Europe. In the light of the EU's bioeconomy strategy (European Commission 2012) it can be expected that non-food uses further drive cropland expansions in some of the world's most vulnerable ecosystems in the future. To further investigate this, our approach here, could be combined with a forward-looking MRIO analysis (Wiebe *et al* 2018).

First steps to address this issue with demand side oriented policies have been taken by the European Parliament's environment committee by voting for a ban of all vegetable oil from biofuels by 2030 and of palm oil by 2021 (Biofuels International 2018). While this is a promising first step for fostering conservation of rainforest especially in Southeast Asia, it must be taken care that different years of the ban between palm oil and soybean oil from does not lead to unintended shifts from one oil seed to another. Replacing the palm oil currently used for biodiesel with soybean oil from tropical areas potentially leads to more pressure on rainforest due to the much lower yield per hectare.

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