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ANALYSIS

Trends in national biodiversity footprints of land use

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ABSTRACT

Rising incomes (and associated expenditures) have been shown to be a major driver of environmental problems. Lately, several studies have pointed to a break between the income driver and biodiversity loss on a per-capita level. The increase in land-use efficiency is pointed to as a key factor in this decoupling. However, a lot of the previous work on biodiversity footprints has been cross-sectional and there is limited analysis with a temporal perspective. In this work, we couple a database that links land use to potential biodiversity impacts for ecoregions, with a multiregional environmentally-extended input-output database available in a time series, with high regional detail. We perform a panel regression analysis for three regional quantile groups and six consumption categories that links trends in affluence to trends in biodiversity loss. The findings suggest that high-income regions from 2005 to 2015 have an income elasticity of biodiversity footprint higher than one, while the production-based accounts show that high-income countries have a declining impact on biodiversity in the time period, suggesting a strong outsourcing of biodiversity loss to low-income countries. In the early 2000s a peak in biodiversity footprint for the high-income region is not explained by increasing income, but rather consumption of traded goods associated with land use in countries in South East Asia prone to biodiversity loss. On a product level we find that although food consumption is causing the largest share of biodiversity footprints in all regional groups, manufacturing products, shelter, and clothing and footwear have the strongest income elasticity of footprint in high-income countries, suggesting that these are consumption areas to focus on as affluence grows, particularly in developing regions.

1. Introduction

Biodiversity loss is a major concern for the welfare of our ecosystems. Extinction rates are currently about 1000 times higher than the background rates (Pimm et al., 2014). Vertebrate species populations have declined overall by 60% since 1970 (WWF, 2018) and approximately 25% of the species (in the well-studied taxonomic groups) are currently threatened with extinction according to the International Union for Conservation of Nature's (IUCN) Red List criteria (IUCN, 2019). Land use, resulting in habitat loss and degradation, is the pressure with the largest relative impact on ecosystems (Millennium Ecosystem Assessment, 2005; IPBES, 2019; WWF, 2018). Seventy-seven percent of the ice-free landcover has been affected directly by humans (Watson et al., 2018; Allan et al., 2017), mostly due to agricultural activity (Ellis and Ramankutty, 2008), and reduction in the current global forest cover, which is estimated to be only 62% of the area it covered prior to humans (Steffen et al., 2015).

Although land use negatively affects ecosystems globally, the effect of this land use on ecosystems, as well as the ecosystem responses (and hence biodiversity impacts) are not uniform across the globe (WWF, 2018). While local studies of biodiversity loss and extinctions can resort to individual field studies, this is not possible on a global scale. In the global Life cycle assessment (LCA) models, species richness is therefore used to indicate the potential for species extinctions. The resulting biodiversity impacts are measured as “potentially disappeared fraction of species” (PDF) (Verones et al., 2017a). Species-area relationships are commonly used to estimate the effects of land use on species richness (e.g., Chaudhary and Brooks (2018)). Chaudhary et al. (2015) developed land use impact factors estimating the PDF (bird, mammal, amphibian, reptile, and plant) per area occupied by specific land use types. These species thus act as a proxy for the entire “biodiversity”. This is a simplification, of course, as is the assumption that species are equally distributed throughout a terrestrial ecoregion. However, the advantage of the approach is that it provides a comparable model across the world

Abbreviations: CB, Consumption-based; LCA, Life Cycle Assessment; LPI, Living Planet Index; PB, Production-based; PDF, Potentially disappeared fraction of species; RoW, Rest-of-the-world.

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that is easy to communicate to stakeholders and is based on relatively easily available data. The method of Chaudhary et al. (2015) is incorporated in the standardized life cycle impact assessment (LCIA) method LC-IMPACT) and includes regionalization at a rather fine level, i.e. it contains information about potential biodiversity impacts for every ecoregion. Moreover, it takes the vulnerability of species into account in that it tries to consider the fact that some species might be widespread, while others are endemic and at higher risk of being pushed to extinction (Verones et al., 2020).

Studies on biodiversity trends indicate that biodiversity continues to deteriorate, although at a decreasing rate (Butchart et al., 2010; WWF, 2018). In the literature, the temporal effects have often been analyzed through the perspective of the link between affluence and biodiversity loss. However, key policy documents on biodiversity conservation often have ambiguous views on the relationship between biodiversity loss and economic growth, or neglect the link altogether (Otero et al., 2020).

An example of an indicator that has linked the state of biodiversity to levels of affluence in a temporal dimension is the living planet index (LPI) (McLellan et al., 2014). The LPI is an indicator for the global state of biodiversity measuring average change in vertebrate population sizes ($n = 16,704$ representing 4005 species) relative to 1970 (WWF and ZSL, 2018). In the 2014 Living Planet Index, McLellan et al. (2014) used three country income groups, finding that low-income countries display sharper declines than middle-income countries, while high-income countries even had a slightly increasing index compared to the 1970 baseline. We should, however, be aware that high-income countries have caused a substantial part of their biodiversity impacts pre-1970, thus the increasing trendline only shows a relative change. However, it may also reflect the ability of the high-income countries to pay for species conservation, or due to their production-based (PB) approach, it might reflect that high income countries have had a less harmful domestic biodiversity impact development from 1970 to 2011 compared to low- and middle-income countries. PB accounts neglect the biodiversity impacts embodied in trade, which can comprise a significant proportion of the total biodiversity impact (Lenzen et al., 2012; Moran et al., 2016; Marques et al., 2019). As such, the drivers of land use and subsequent biodiversity loss are nowadays often remote, “tele-coupled” by global value chains, and can be traced to consumption, often in Western countries, far from the actual impact on biodiversity.

In order to provide consumption-based (CB) assessments that solve the issues of the PB approach, a range of analyses on the impact that trade has on biodiversity has been attempted, some through detailed investigation of production areas and traded goods (Chaudhary and Kastner, 2016; TRASE, 2020), and some through multi-regional input-output (MRIO) analysis (Lenzen et al., 2012; Marques et al., 2019). MRIO tables describe the production of goods and services in different regions of the world and have trade-linked tables showing the import of products as both intermediate and final goods. MRIO analysis compared to physical trade approaches has the advantage of modelling multiple supply-chain steps but has the disadvantage of often lower sectoral and regional detail. Due to the possibility to use MRIO tables to model increasingly complex supply chains linked to consumer demands, it has been suggested as an appropriate tool to calculate biodiversity footprints (i.e., biodiversity loss induced by consumption) (WWF, 2018; Moran et al., 2016; Marques et al., 2017).

MRIO databases such as EXIOBASE (Wood et al., 2015), Eora (Lenzen et al., 2013), and GTAP (Aguiar et al., 2016) have been already connected to measures of biodiversity loss in order to give insight into these trade (Lenzen et al., 2012) and consumption effects (Marques et al., 2019; Marquardt et al., 2019). In the first work on biodiversity modelling, Lenzen et al. (2012) connected the IUCN red list of endangered species to Eora, which was further refined through a spatialized model in Moran et al. (2016). Other attempts have used a pressure-impact relationship by characterizing the effect land use has on biodiversity through either PDF (Kosłowski et al., 2020; Verones et al., 2017b), bird species lost (as an indicator of overall biodiversity loss)

(Marques et al., 2019), or mean species abundance (Wilting et al., 2017; Kosłowski et al., 2020).

MRIO analysis has further been used to study biodiversity footprints in order to understand the link to affluence and associated consumption, by time series work (Marques et al., 2019), by use of cross-sectional consumer expenditure survey data (Kosłowski et al., 2020), and by specific analysis on the effects of consumption (Marquardt et al. (2019). Although Kosłowski et al. (2020) found there was a correlation between affluence and biodiversity loss based on cross-sectional data, they observed a decline of 10% in the European per capita footprint between the two years included in their study (2005 and 2010). Hence, whilst they indicate a decoupling of biodiversity loss from affluence, their approach is limited by the years covered in the study.

In their study with global coverage in the time period 2000–2011, Marques et al. (2019) found that increasing population and economic growth resulted in increasing impacts on bird diversity, but that the impact per unit of GDP decreased between 2000 and 2011. This trend was found for all world regions in the study. Further, they found for high-income regions such as Western Europe and North America a decrease in both PB and CB biodiversity- and ecosystem services impacts per unit of GDP, attributing this to one or both of reduced consumption within the regions and/or increased efficiency in the origin-regions of their imported goods. A decrease in per capita CB biodiversity impacts was attributed to decrease in impacts from food consumption in hotels and restaurants, and clothing, as well as reduced activity in the construction sector, all resulting from the financial crisis.

Marquardt et al. (2019) compared four types of biodiversity footprint indicators using the GTAP database. Three of these were alpha diversity indicators which measure local diversity within a site, while the last was a gamma diversity indicator which measures global biodiversity. They found that household expenditure was positively related to the three alpha indicators, while the link to the gamma indicator was weakly positive and highly uncertain. In addition, using the gamma indicator, they found that human consumption patterns particularly threaten tropical biodiversity.

The existing literature using MRIO to study biodiversity loss have largely been descriptive, such as studying the state of biodiversity loss for one specific year (Lenzen et al., 2012; Kosłowski et al., 2020; Wilting et al., 2017; Moran et al., 2016). Some studies break down biodiversity impacts into consumption categories, but do not investigate the temporal trends in biodiversity loss for different regions (Wilting et al., 2017; Moran et al., 2016; Marquardt et al., 2019). Marques et al. (2019) investigate the temporal changes in biodiversity loss broken down into consumption categories for different world regions. In many ways our study seeks to verify the findings of Marques et al. (2019) who found strong evidence of decoupling, as well as that of McLellan et al. (2014)’s production-based approach. In addition, we seek to further Marquardt et al. (2019)’s findings which revealed ambiguous results for the gamma (global) biodiversity indicator’s correlation with expenditure. We expand on Marquardt et al. (2019)’s work by exploring the temporal trends in biodiversity loss on an even more detailed regional level. We are able to go to a much higher regional detail than Marques et al. (2019) and Marquardt et al. (2019) by using EXIOBASE 3rx, a newly developed extension of the MRIO database EXIOBASE, where the countries previously part of rest-of-the-world (RoW) regions are explicitly covered, with a total of 214 regions. It was created based on the wish to explicitly cover the extent and diversity of land use for countries within the RoW regions, thus the database is tailored for an analysis linking biodiversity impacts to land use directly.

Building on this previous research, we seek to answer the question of whether there is a strong link between affluence and biodiversity loss from a consumption-based perspective. We aim to capture differences in development status of countries and to specifically provide insights into product level drivers. With globally applicable methods and metrics to quantify biodiversity loss being called for (Chaudhary and Kastner, 2016), we approach this by linking EXIOBASE 3rx to a database of

characterization factors (LC-IMPACT) with a similar regional coverage as EXIOBASE 3rx. Unlike the LPI, our analysis is on an extinction level (i.e., potential species loss), not a population level (i.e., abundance of individuals). Supply-chain impacts are identified in the input-output calculations to investigate the difference between CB and PB impacts for each region. To investigate the extent of a decoupling between affluence and biodiversity impacts, we first examine the trend in biodiversity impacts from both a PB and CB perspective in the years covered in EXIOBASE 3rx (1995–2015) and then run panel regressions with country-fixed effects for six groups of consumption categories (plus total consumption) and regions split into three income quantiles. The following results are then compared with similar literature findings, along with a discussion of limitations and uncertainties. Finally, we discuss how these results can be used to mitigate future biodiversity loss.

2. Methods

The two data sources used for biodiversity impact calculations are the MRIO EXIOBASE 3rx which provide the economic and land use data, and the life cycle impact method LC-IMPACT providing characterization factors of biodiversity impacts from land use. In the following section we explain how the two data sources are combined and how the PB and CB biodiversity impacts are calculated. Next, we explain the approach taken for measuring decoupling, and finally the approach for the panel regression analysis. In this analysis yield is an independent variable, which is acquired from the crops data from FAOSTAT (2020).

Here we take a MRIO approach, using the regionally extended version of EXIOBASE 3 (Stadler et al., 2018) called EXIOBASE 3rx (Bjelle et al., 2020). The database contains data on 200 sectors and 214 countries describing production requirements and demand. Whilst official input-output tables are not available for many of these countries, in EXIOBASE 3rx proxy estimates were made based on technology data, estimated outputs and trade data. The database contains extensions for six land use types (available as 40 detailed land use types upon reasonable request) and is available online at DOI: <https://doi.org/10.5281/zenodo.2654460>.

In previous work (Bjelle et al., 2020), a bilaterally trade-linked approach was used to link domestic input-output tables (as per emissions embodied in bilateral trade approaches described in Peters et al. (2012)). In this paper, we extend that work by using a MRIO approach, but through a network-based procedure rather than with fully populated tables (Rodrigues et al., 2016). The MRIO and network approaches give exactly the same result, but the network approach is computationally much less demanding. Full details are in Rodrigues et al. (2016) and not repeated here. The advantage of the MRIO approach compared to a bilateral trade approach is that full global supply-chains (covering processing in multiple countries) are covered in assigning biodiversity impacts to final consumers.

Letting matrices be identified by bold-upper case letters, vectors by bold lower-case letters, and scalars by normal lower-case letters, the standard environmental CB impact calculations for a specific year using EXIOBASE 3rx are given by:

$$\mathbf{E} = \mathbf{S}\mathbf{L}\mathbf{Y} \quad (1)$$

Letting r , q and g represent the number of regions, sectors, and environmental impact categories (e.g. types of land use) respectively, the variables are:

E: Total impacts (e.g. land use or biodiversity footprint) with dimensions g by r

S: The impact multipliers per monetary unit (e.g. km²/million Euro for land use) with dimensions g by $(r * q)$

L: The Leontief inverse matrix describing the production requirements per unit of final demand with dimensions $(r * q)$ by $(r * q)$

Y: Final demand given in million euros (current year pricing) with dimensions $(r * q)$ by r

In the multiregional input-output system the diagonal blocks of the

S, **L** and **Y** matrices represent the domestic systems, while the off-diagonal blocks represent the traded parts of the systems (the off-diagonal parts of the **S** matrix are zero as there are no traded impact multipliers of production). To distinguish between impacts associated with specific sectors of consumption or domestic vs. traded consumption, the **Y** matrix can be aggregated, split or diagonalized according to the specific impact in question.

As the inverse of such a large matrix is computationally demanding, we use the Taylor series expansion instead:

$$\mathbf{E} = \mathbf{S}(\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \mathbf{A}^4 + \dots)\mathbf{Y} \quad (2)$$

A: The coefficient matrix with dimensions $(r * q)$ by $(r * q)$ showing domestic and import input-output tables, trade-linked by bilateral trade flows as described in Rodrigues et al. (2016).

Taylor series expansion should theoretically be infinite but converges quickly (all elements of **A** are less than 1), and the calculation was cut off at 20 orders here. The PB impacts are similarly calculated as:

$$\mathbf{E} = \mathbf{S}\hat{\mathbf{x}} \quad (3)$$

$\hat{\mathbf{x}}$: The diagonalized vector of total output from EXIOBASE 3rx in million Euros (current year pricing) with dimensions $(r * q)$ by $(r * q)$

EXIOBASE 3rx includes land use directly caused by households. These land uses have varying intensity, but are mainly the subsistence use of forest land with very low intensity (see the supporting information of Bjelle et al. (2020)). Including them in the analysis will likely lead to an overestimation of biodiversity impacts since the characterization factors do not adjust for these low land use intensities. In addition, direct household use is not linked to expenditure on goods and services, which complicates the analysis of the link between affluence and impact. For these two reasons, we exclude these land uses from the analysis.

The sections above explain the framework for calculating CB and PB land use footprints, but the link to biodiversity impacts is still missing. This link and the needed modifications to the framework is explained in the following paragraphs.

Natural systems respond to human pressures in various ways, making it difficult to quantify and compare impacts on ecosystems. Biodiversity indicators, reflecting biodiversity aspects in simple metrics, can be helpful tools to measure changes in natural systems resulting from human pressures (WWF, 2018). The use of standardized indicators eases the interpretation of nature's responses to human activity, allows to track changes over time, and facilitates consistent comparisons.

LC-IMPACT is a life cycle impact assessment method combining impacts for human health, ecosystem quality and resources. It is freely available on www.LC-IMPACT.eu and described in Verones et al. (2020).

Impacts from land use are modelled in LC-IMPACT for land occupation (use) and land transformation, but only land use was applied in this work. The model is based on the countryside species-area relationship (SAR), taking into account that species may be able to survive in the absence of natural habitat, i.e. live in human-modified land only (Verones et al., 2019; Chaudhary et al., 2015). Land use impacts are modelled for mammals, birds, amphibians, reptiles and plants individually for local losses and then adapted with a "vulnerability score" to transform local losses to global species extinction (for more detailed information see Verones et al. (2019) and Chaudhary et al. (2015)):

The countryside SAR predicts how many species are lost ($P_{lost, u, j}$) of taxonomic group u in ecoregion j if the area available changes (from B_{org} to B_{new}). It takes the habitat affinity $h_{u, i, j}$ (where land use types are represented by i) of species in different habitats into account (based on local characterization factors. See De Baan et al. (2013) for more details).

$$P_{lost, u, j} = P_{org, u, j} \cdot \left(1 - \frac{B_{new, j} + \sum_i h_{u, i, j} \cdot B_{ij}}{B_{org, j}} \right) \quad (4)$$

The average characterization factor per ecoregion and taxon is then calculated as:

$$CF_{u,j} = \frac{P_{lost,u,j} \cdot b_{i,j} \cdot VS_{u,j}}{N \cdot P_{u,world} \cdot VS_{u,world}} \quad (5)$$

b is the allocation factor for each land use type i in each ecoregion j and VS the vulnerability score for each taxon. N is the number of taxa and P and $VS_{u,world}$ are the number of species in taxon u globally and the global vulnerability, respectively. Details about the vulnerability score are presented in Verones et al. (2019). The CF for animal taxa and for plants is the aggregated with a weight of 50% each. Aggregation to countries is made based on area-weighted averages over land use type.

The characterization factors indicate the per unit of area potentially disappeared fraction of species (PDF/m²) due to current land use (B_{new}) relative to the natural state (B_{org} ; i.e., the unimpacted state prior to human influence). Biodiversity impacts are calculated by multiplying the characterization factors (PDF/m²) with land use data (m²/year) and indicate the biodiversity impacts at a certain point in time (PDF/year) relative to a hypothetical natural state without any human land use. This means that the biodiversity indicator used here represents a snapshot of the biodiversity footprint of global land use in a certain year relative to the natural state, rather than accounting for the cumulative biodiversity impacts of land use over several years. The exposure duration is usually included in the characterization factors, reflecting the fact that land occupation will most likely not lead to immediate species loss, but a potential species extinction over time. As pointed out in Verones et al. (2020), these indicators are rather reflecting an increase in the risk of extinction rather than an instantaneous loss.

The regional coverage of global characterization factors of biodiversity loss in LC-IMPACT makes it a suitable match for EXIOBASE 3rx. Most of the regions covered in EXIOBASE 3rx overlap with the LC-IMPACT regions. Where the EXIOBASE 3rx country is not covered in LC-IMPACT, we use LC-IMPACT values from similar countries to approximate the missing country's characterization factor (e.g. Tanzania as a proxy for Zanzibar and China for Taiwan) See SI1 for a full overview of the regional bridging. Some countries in LC-IMPACT have values equal to zero for certain land use types. This is either due to no area being registered for that land use type or missing taxonomic coverage. To ensure consistency with EXIOBASE 3rx in that all land use is associated with biodiversity loss values, we replace zero-values with the smallest recorded value for that specific land use type across all regions in LC-IMPACT. As can be seen in SI2 these are mostly tropical island states (and Greenland), regions which typically do not contain the types of land for which there are zero-values in LC-IMPACT.

The land use intensities (S_1) for EXIOBASE 3rx are given in km²/Million Euro, while the LC-IMPACT global biodiversity loss characterization factors (CF) are in PDF/m². To arrive at biodiversity loss intensities (S_b), the total land use associated with production in each sector and country of EXIOBASE 3rx (F_b) must first be aggregated to the six land use types in LC-IMPACT (See SI1 for aggregation), which are annual crops, permanent crops, intensive and extensive forestry, urban area, and pasture. These land use types can exist side-by-side and do not overlap. Characterization factors per taxa are different for the land use types in each country due to the different area shares present, but more importantly also due to the species and habitat affinity of species living in these areas.

Next, we replace the land use intensities associated with production in each region in EXIOBASE 3rx with biodiversity loss intensities:

$$S_b = \frac{10^6 \cdot (F_1 \cdot CF)}{x} \quad (6)$$

F_1 : Total land use from EXIOBASE 3rx aggregated to the six LC-IMPACT land use categories

x : Total output from EXIOBASE 3rx in Million Euros.

In the last step, we calculate the biodiversity footprints using Eq. (2),

replacing S with S_b . The biodiversity footprint results for the 200 sectors in EXIOBASE 3rx are aggregated to six categories of consumption according to the aggregation key found in SI1. We use biodiversity footprints as term for the consumption-based (CB) impacts and refer to the production-based (PB) impact as the PB results.

Some countries are merged or split (e.g. Netherlands Antilles and Serbia) throughout the time series of EXIOBASE 3rx. This causes issues for time series analysis on individual countries, but not on aggregated regions as we use in this work. However, a total of 16 countries have unbalanced supply-and use tables for some years (see overview in SI3) due to poor raw data availability, or inconsistencies in raw data causing the procedure that balances supply-use tables to not find an optimal solution. In addition, the macroeconomic data for Sudan and South Sudan is inconsistent across the time period. To keep the time series figures consistent (to avoid sudden jumps or drops in the figures), we exclude these countries from the analysis. For the regression analysis, only the specific years with inconsistent data are excluded (reported in SI3).

We measure decoupling (OECD, 2002) of biodiversity impacts as:

$$D = \frac{bf_t/bf_{1995}}{GDP_t/GDP_{1995}} \quad (7)$$

D : Decoupling ratio

bf : Biodiversity footprint or PB impacts

GDP : The GDP of the region in constant 2005 Euro

t : year

Absolute decoupling occurs when the biodiversity impact reduces in absolute terms, irrespective of change in GDP, and relative decoupling occurs when the biodiversity impact increases, but at a slower rate than GDP.

We follow a similar approach to earlier papers in estimating income elasticities of footprint (a modification of income elasticities of demand, but the dependent variable being the footprint of a consumption category rather than the actual consumption), see e.g. Hamilton et al. (2018). Instead of arriving at global income elasticities of footprint, we build on the findings in McLellan et al. (2014) and group the countries in EXIOBASE 3rx into three income quantiles based on their average GDP/cap measured in constant 2005 Euro calculated for EXIOBASE 3 (Stadler et al., 2018). Thus, we arrive on region group-specific income elasticities of biodiversity footprint. If this elasticity is larger than 1 the interpretation is that a 1% increase in GDP/cap leads to a larger than 1% increase in biodiversity footprint. The possible mechanisms behind this value are explained in the discussion section.

For testing the robustness of our model, and due to the potential explanatory effect of changes in land use efficiency as identified by Marques et al. (2019), we include country-specific crop yields as an independent variable. This data was gathered from FAOSTAT's crop data that covers the physical production and area harvested for 173 products for all years of our analysis (1995–2015) (FAOSTAT, 2020). The yield was calculated by aggregating over all products to arrive at a measure of production (in tons) per area harvested (in hectares). The regression function is thus given by:

$$\ln(bf_{ct}) = \alpha_c + \beta_0 + \beta_1(\ln GDPpc_{ct}) + \beta_2(\ln yield_{ct}) + \epsilon_{ct} \quad (8)$$

α : Time-invariant unobserved heterogeneity (country-fixed effects)

$\beta_0, \beta_1, \beta_2$: Regression coefficients

bf : Biodiversity footprint per capita (in PDF)

c : Region

t : Year

$GDPpc$: GDP per capita in constant 2005 Euro

$yield$: Crop yields

ϵ : Error term

We perform the Hausman's test (Hausman, 1978) to choose between a random- or fixed-effects regression model. We check the resulting test statistic against the critical value in the chi-squared distribution with

two degrees of freedom: $\chi^2_{0.95}(2)$. If the test statistic is larger than this critical value, we conclude that only the fixed effects estimation is consistent, otherwise both the random effects and fixed effects are consistent, but random effects is more efficient.

We perform tests of model fit to support our choice of random vs. fixed effects. These tests are the log-likelihood ratio, Akaike information criterion (AIC), Bayesian information criterion (BIC), and root mean squared errors. We also perform the Durbin-Watson test to detect autocorrelation at lag 1 in the residuals. All model statistics, model fits, and country-fixed effects (and their significance) can be found in SI9–12. SI9 shows that 77% of the country-fixed effects are significant at level 0.10. The low R^2 -values observed for the model with country-fixed effects (SI10) versus the high R^2 -values for the model with dummy variables explicit for the countries (equivalent to the country-fixed effects model) (SI12) indicate that most of the variance is explained by the country-fixed effects, rather than the other variables in Eq. (8).

3. Results

The global biodiversity footprint has increased by 5–6% from 1995 to 2015 (Fig. 1 - black dotted line in first column).¹ The increase in impact is largest in low-income countries (PB account), with a 14% increase over the time period, compared to a 3% increase for middle income and a 4% decrease for high income. High-income countries have in other words managed to achieve absolute decoupling from a PB perspective over the last 20 years. In the CB results (second row of Fig. 1), biodiversity impacts embodied in imports are accounted for, and thus show highly differing trends compared to the PB results. Whilst from beginning to the end of the period, we see similar results to the PB accounts, there are large intermediary changes. Low-income countries have increased footprints by roughly 20% over the period, while the middle- and high-income regions have seen a 2% increase – i.e. the absolute decoupling does not occur for high income countries in the CB account. However, the results are affected by a large spike in the CB account for high-income countries around year 2000. This is coupled with a reduction in the CB account in low- and middle-income countries in similar years, before the trends invert around 2005.

From a per-capita perspective, the footprint has decreased by 16% globally (Fig. 1 - black dotted line in the middle column). The low-income region has the largest decrease (18%) which illustrates that population growth drives the increased biodiversity impacts in this region. The per capita footprint in the high-income region has decreased by 11%. However, up until 2005, the footprint is increasing. To understand what is causing the discrepancy between the PB and CB results, impacts need to be examined at a product level (which we return to in Fig. 2) and the country-level origin and destination results (see SI4). It appears that there was a large increase in trade of wood-based materials from biodiversity hotspots such as Indonesia, Malaysia, and Papua New Guinea to high-income countries such as the United States and Japan. This trade subsequently declined in the mid-2000s. It is clear that the CB footprint in the high-income region is heavily affected by impacts embodied in trade with the low-income region from 1995 to 2005 (comparing the PB results to the simultaneous increase in absolute CB footprint for the high-income region and decrease in CB footprint for the low-income region).

Given the much larger relative increase globally in GDP per capita than biodiversity footprint per capita from 1995 to 2015, the decoupling index in Eq. (7) is expected to decrease over time. However, the trends highly differ for the three region groups. Looking at the decoupling figures (right column of Fig. 1), there is a strong relative decoupling

globally between impact and GDP throughout the time period ($D = 0.6$). Again, the exception is the high-income region from 1995 to 2005, where the decoupling is close to unity for the CB-decoupling metric. This trend is caused by the sharp relative increase in the CB biodiversity footprint per capita in the same period, which increases similarly to the GDP per capita in relative terms in this region. The same is not found for the PB decoupling as the PB per capita impact stays relatively unchanged in the same period. This suggests increased consumption in the high-income region of goods that are produced in biodiversity hotspots. Decoupling in the low- and middle-income regions ($D = 0.4$) is much stronger than in the high-income region ($D = 0.7$) when considering the full time period (1995–2015). The decoupling seems to be flattening out in all regions for both PB impacts and biodiversity footprints around 2010 after a rapid decline from 2003 to 2008. After 2010, the decreasing trend resumes.

Whilst the low- and middle-income groups have shown a consistently declining trend in the per capita footprint in the time period (Fig. 1 (middle column) and Fig. 2), total per capita consumption has increased (Fig. 2). Increase in consumption largely is due to increases in “Mobility” and “Manufactured products”, which are associated with low footprint intensities. Consumption of product groups with high footprint intensities such as “Food”, and partly “Shelter”, remain relatively unchanged in 2015 compared to 1995. Food consumption makes up the largest component (40–61%) of per capita footprints in all regions. “Services”, which makes up the main component of consumption in the high-income region, has a low footprint intensity, resulting in a relatively lower share of the total footprint. From 2004 to 2015, decreasing footprint intensities for “Shelter” and “Food” is largely causing the downward trend in the per capita footprint. The footprint intensities are declining for most consumption categories in all three regions, but particularly so for “Food” that is by far the most footprint-intensive product group.

To better understand the relationship between biodiversity footprint and affluence, we perform a panel regression analysis where the average consumer in each country is represented by a data point over the time period (1995–2015). Based on Hausman’s test showing that only the fixed effects estimation is consistent in 11 out of 18 cases (see SI11) and the focus on temporal changes in footprint in our analysis we chose a model with fixed effects. Data points on average consumers are observed for the biodiversity footprint and GDP per capita. In addition, we include the crop produced per land area for each country. In Fig. 3 these metrics are shown as natural logarithms split into the three regions (represented by different colors) with linear regression model fits for each year and region group (off-diagonal) along with kernel density estimation plots on the diagonals.

The peak of the kernel density estimation plot of the biodiversity footprint per capita (first row, first column plot) for the high-income region (black graphs) indicates that generally the footprints per capita are found at a value somewhat higher than those for the low-income group (red graphs), the middle-income group, however, has two distinct peaks, one of which are to the right of the high-income group, indicating that these observation have a higher biodiversity footprints per capita than the distinct peak of the high-income group.

The scatter plots reveal that apart from a few outliers that indicate that the highest footprints are found in the high-income group, while the lowest footprints are found in the low- and middle-income groups, there is no clear positive correlation between per capita GDP and per capita biodiversity footprint. The per capita footprint seems to be decreasing in the low-income group with increasing affluence and time (third row, first column plot), indicated by increasing color saturation towards the top-left corner of the graph. The same is not evident for the two other income regions. The efficiency metric (yield) shows a clear trend of increase with rising affluence in all income groups (third row, second column plot).

The income elasticities of biodiversity footprint derived from the country-fixed panel regressions reveal highly differing trends between

¹ There is a slight difference between the PB- and CB graphs caused by small mismatches between production and land-use values in 1995 (the base year for this figure) due to imbalances in the data but is within the expected error range (about 1%).



Fig. 1. Footprints development, total (left) and per capita (middle), as well as decoupling of biodiversity impacts from GDP (right) for PB (top row) and CB (bottom row) accounts. Values are relative to 1995. The colors represent the regions grouped by income quantile. CB: Consumption-based, PB: production-based. Global values in black dotted line.

the regions (Table 1).

Table 1 is based on results for 2005–2015 to get the most recent trends in the income elasticities of footprint (see SI5 for equivalent results for 1995–2004 and 1995–2015). The time period covered in Table 1 includes the financial crisis and therefore is particularly interesting for studying the response of environmental footprints to changes in affluence. For the high-income group, all elasticities are higher than one (see explanation on meaning in methods and discussion). As such, for the average consumer in high-income countries, there is a distinct positive relationship between affluence and biodiversity footprint per capita that is not captured for the overall regional average consumer (Figs. 1 and 2). For the low- and middle-income groups, most values are non-significant, except for “Manufactured products” in both groups, “Shelter” in the middle-income group and the negative elasticity for “Food” in the low-income group. “Manufactured products” makes up a relatively small, but increasing share of the total footprint (Fig. 2), but the high- and significant income elasticities of footprint indicate that as affluence grows in the future, this consumption category is a concern for biodiversity loss. The yield (Eq. (8)) was found to be significant at level 0.05 for four of the product groups in the middle income region, and not significant otherwise (see SI10).

4. Discussion

Assuming that the metric in LC-impact, which measures probability

of extinction is comparable to the metric in the 2014 Living Planet Index (McLellan et al., 2014) that estimates the state of global biodiversity, we can compare the trends in the two metrics broken down into three regional groups from 1995 and onwards. There are at least three distinct similarities in trends of our PB results (Fig. 1) and the 2014 LPI. Firstly, the high-income group’s total impact is quite stable, with even a bettering state for biodiversity from the early 2000s and onwards. Secondly, in both the middle-income and low-income groups the biodiversity has declined, and thirdly, the largest decline is found in the low-income group. Although our results do not capture the slight increase in biodiversity in the 2014 LPI observed in the period in the mid-2000s for the low- and middle-income regions, the similarity in the general trend in both sets of results serve as a first robustness check for the results at the level of detail presented in our work. The difference between PB impacts and CB footprints in Fig. 1 shows the importance of both assessing where the biodiversity impact is taking place, and who is responsible for the biodiversity impact. Our results show that the increasing biodiversity footprints in the period 1995–2005 is fully caused by the high-income consumers, while the two other income groups largely cause the increasing impacts after 2006. A comparison between CB and PB impacts for the LPI could be a valuable future improvement for further robustness checks.

We show the country-specific biodiversity footprints per capita for 2015 in SI13. These results largely coincide with findings in the literature. Marquardt et al. (2019) identified Caribbean states, Madagascar

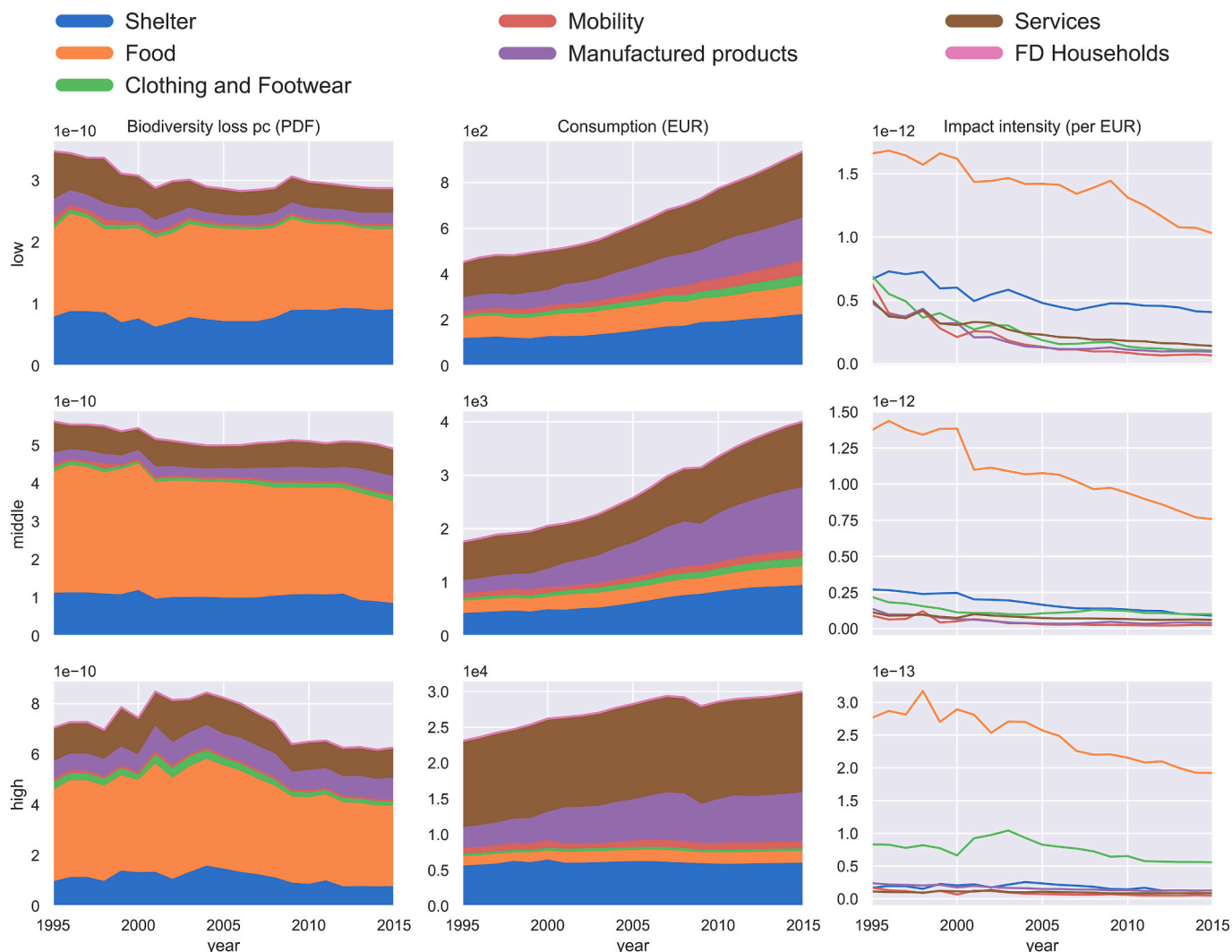


Fig. 2. Biodiversity footprint, consumption, and footprint intensities (PDF/EUR) for six consumption groups and the three income groups.

and Brazil as countries with high per capita footprints and Pakistan, Mongolia and Bangladesh as countries with low per capita footprints. Our results confirm these trends. Koslowski et al. (2020) found a strong relationship between affluence and biodiversity footprints in European countries and identified Luxembourg as the country with the highest per capita footprint. Of the countries covered explicitly in their study, Luxembourg is also the country with the highest per capita footprint in our results, although it ranks as low as 44 in our list of all countries. Compared to these studies, our results show the significance of performing the analysis on a finer regional detail. The top countries ranked by biodiversity footprint per capita in our results are small island states such as New Caledonia, Seychelles and Dominica that are not explicit in Marquardt et al. (2019), but rather aggregated to larger regions. A second consequence of finer regional detail is that the relationship between affluence and per capita footprint is more ambiguous in our results compared to Koslowski et al. (2020)'s European results. The top-ranking countries in our results are mostly less affluent than European countries. Although, we can confirm the trend in European per capita footprints with rich countries such as Monaco ranking first, Luxembourg second and Liechtenstein third of all European countries (Monaco and Liechtenstein are not covered explicitly in their study).

Our results show on an aggregate regional level a relative decoupling of biodiversity loss from affluence (Fig. 1) for all regions (except for the high-income from 1995 to 2005). On a global level (S17), our findings share high similarities with Marques et al. (2019). The regression results

however (Table 1) indicate no sign of decoupling in the high-income region. A likely explanation for this is that the high-income region is composed of several countries with small populations and high levels of affluence. Population differences are not accounted for in the regression analysis, meaning e.g. that an average consumer in the US is weighted equally to an average consumer in Norway. Thus our regression results confirm the trend found by Koslowski et al. (2020) suggesting a high correlation between per capita biodiversity footprint and affluence for high-income regions. We find a much stronger decoupling for developing regions that typically have seen a great development in land use efficiency in the time period covered in our analysis, while the richest countries already reached high land use-efficiency pre-1995.

Food consumption is the main component of the biodiversity footprint (Fig. 2). The "Food" share makes up half of the footprint globally (S14), compared to 40% found by Wilting et al. (2017). However, "Food" has the lowest income elasticity of footprint of all consumption categories in all regions (Table 1). Consumption on "Shelter" is responsible for the second highest global share of total biodiversity footprint (20.3%) and has an income elasticity of footprint above one for the high-income group, but below one for the two other groups. "Services" rank third (16.0%) and the income elasticities of footprint is in the middle range of all consumption categories in all regions. The two highest income elasticities of footprint in the high-income group are for "Clothing and footwear" (1.37) and "Manufactured products" (1.94). The share of total footprint is increasing for "Manufactured products" for the high-

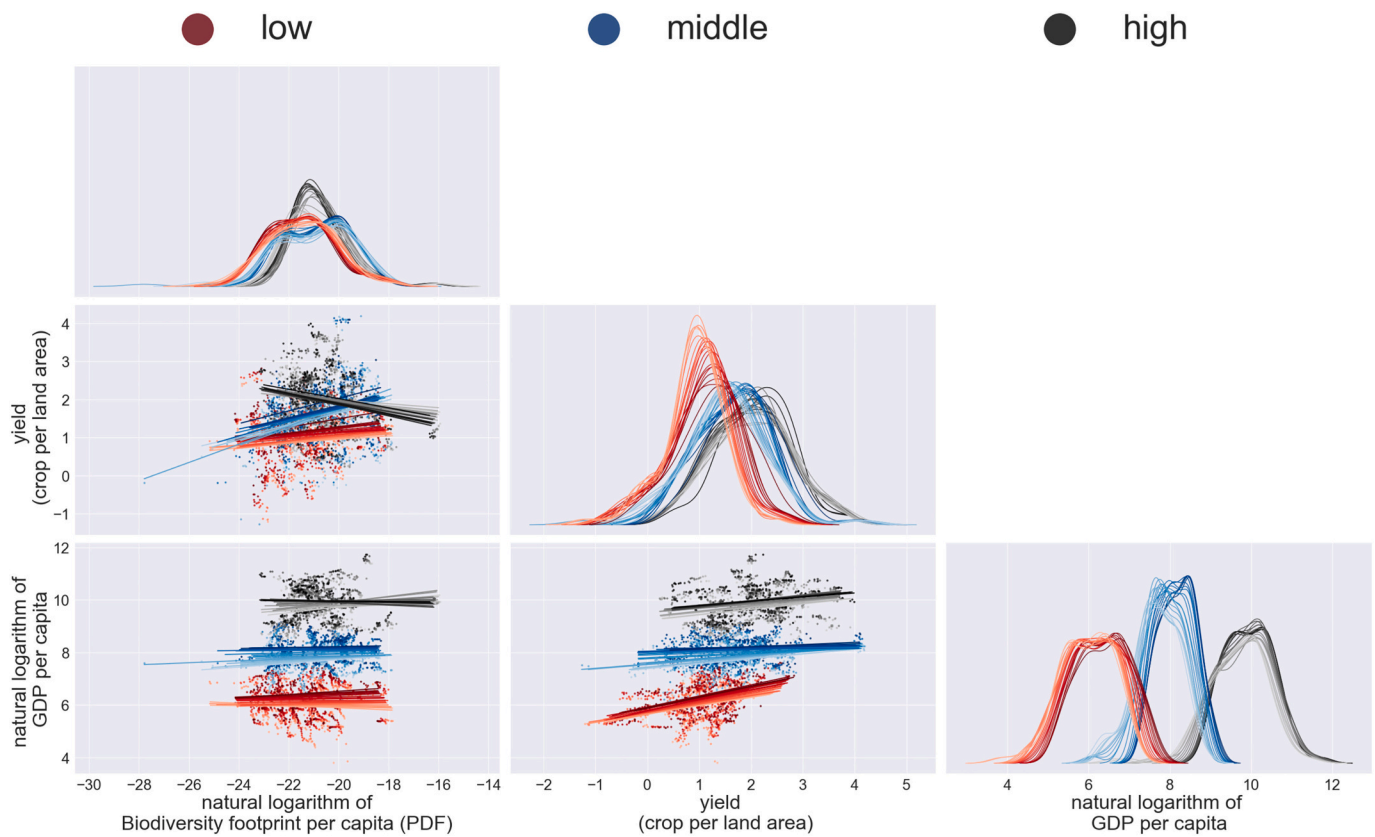


Fig. 3. Scatter plots of individual countries with linear regression model fits (off-diagonal) and kernel density estimation (diagonal): Natural logarithms of GDP per capita (in 2005 constant Euros), biodiversity footprint per capita (in PDFs), and efficiency (crop per land area). Years are represented with increasing color saturation approaching 2015.

Table 1
Income elasticities of biodiversity footprint by consumption categories (2005–2015).

	Shelter	Food	Clothing and Footwear	Mobility	Manufactured products	Services	Total
high	1.18 (***) (0.48 1.88)	1.02 (**) (0.16 1.87)	1.37 (**) (0.05 2.69)	1.25 (**) (0.16 2.35)	1.94 (***) (1.2 2.69)	1.34 (***) (0.62 2.07)	1.3 (***) (0.63 1.97)
middle	0.92 (*) (-0.13 1.96)	0.3 () (-0.53 1.13)	0.56 () (-0.54 1.66)	0.46 () (-0.55 1.48)	0.98 (**) (0.12 1.85)	0.77 () (-0.78 2.33)	0.62 () (-0.37 1.6)
low	0.14 () (-0.1 0.38)	-0.31 (**) (-0.56 -0.05)	0.19 () (-0.13 0.5)	0.14 () (-0.3 0.59)	0.38 (**) (0.05 0.7)	-0.05 () (-0.34 0.24)	-0.0 () (-0.22 0.21)

Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. 95% confidence intervals in parenthesis.

and middle-income regions and make up 14.0% and 9.4% of the total footprint in the two regions respectively.

Wilting et al. (2017)'s cross-sectional analysis on the relationship between the per capita biodiversity footprint and affluence is comparable with our results for the high-income group as they use the MRIO database WIOD, which has mostly high-income countries explicit (along with five RoW regions). Our results correspond well with their findings for "Food", "Manufactured products" (their category is called "Goods") and "Shelter" ("Housing" in their work). The findings differ for "Services", where they find a strong positive relationship between affluence and biodiversity footprint. Differences in findings can be due to differences in data (they use cross-sectional data), regional aggregation, differences in biodiversity footprint metric, and the use of RoW regions.

Income elasticities of biodiversity footprint as we report here, has to our knowledge not been investigated in the MRIO literature. A similar metric was reported by Clausen and York (2008), who used cross-sectional data for 140 countries on the number of threatened marine- and freshwater fish species. Their "income elasticity of biodiversity footprint" was in the range of 0.06–0.12, which is at the lower end

compared to our results, except for the low-income region.

The significance for several of the income elasticities of footprint are low (Table 1), so they should be interpreted with caution. We find particularly low elasticities for "Food", while elasticities for "Shelter", "Services", and "Manufactured products" are high. "Clothing and Footwear" has a high elasticity in the high-income region and low elasticities in the two other regions. The relationship between income elasticities of demand and income elasticities of biodiversity footprint is not necessarily straightforward (We report the income elasticity of demand for 2005–2015 in SI6). Three points below illustrate the connection between income elasticities of demand and income elasticities of biodiversity footprint and how to interpret the income elasticities of biodiversity footprint. Firstly, income elasticities of demand are expected to be close to one since total demand and income have a close to one-to-one relationship. This is not the case for the biodiversity footprint, where global total biodiversity loss has increased by 6.9% from 1995 to 2015 whilst GDP has increased by about 80% (in constant prices). The income elasticity of biodiversity footprint is in addition to being influenced by preferences (also captured in the income elasticity

of demand), heavily influenced by the footprint intensity (PDF/EUR), which again is dependent on the origin of the biodiversity impact since characterization factors greatly vary between regions. Secondly, the small changes in per capita biodiversity footprint for the low- and middle-income countries in the time period covered are causing several of the income elasticities of biodiversity footprint to become non-significant. Thirdly, the differences in impact intensities (as discussed above) are highlighting some of the focal areas for biodiversity loss mitigation through the income elasticities of biodiversity footprint. Examples include “Manufactured products” and “Clothing and footwear” for the high-income region.

The distributional effects of increased land use efficiency on biodiversity footprint also depends on the impacts embodied in trade. We find that the traded part of the biodiversity footprint globally has risen from 19% in 1995 to 33% in 2015 (SI4), which is in line with other findings (Marques et al., 2019; Wilting et al., 2017; Wood et al., 2018), but does not correspond with Verones et al. (2017b)’s findings, particularly for high-income countries. In 2012 we find the traded share of the footprint of the high-income region to be 68%, compared to 6% in Verones et al. (2017b). This can in part be explained by their split into four income regions, but most likely the difference is caused by their inclusion of the biodiversity impact of GHG emissions and water consumption in addition to land use.

Our results show that the imported share of the footprint is rapidly increasing in the low-income (374% increase) and middle-income (327% increase) groups, while the increase in the high-income group is modest (26% increase). However, the regions differ significantly in the imported share of total footprint, with 17%, 24% and 72% for the low-, middle-, and high-income groups respectively in 2015. Other studies (Marques et al., 2019; Wilting et al., 2017) have focused on the high import share of total footprint, but the temporal development in our results, showing such a rapid development for the populous developing regions, highlights the importance of also addressing strategies for consumption to mitigate biodiversity loss in the future.

The amount of land use and the geographical location of the land used are the dominant drivers for the biodiversity footprint. The differentiated response to land use is reflected by distinct species vulnerabilities to land use types and the importance of some regions for global biodiversity (Chaudhary et al., 2015). For this reason, the biodiversity footprint in Russia (0.5% of global total) is substantially smaller than that of Madagascar (5.9% of global total), even though the amount of land use is higher in Russia (4.9% of global total vs 0.7% for Madagascar) (SI13). Generally, biodiversity impacts per area land use are highest in tropical regions and especially in islands due to higher species richness and numbers of endemic species, and highlights the importance of where imported products are sourced (Chaudhary and Kastner, 2016; Chaudhary and Brooks, 2017). The origin country of the biodiversity footprint (see SI4) reveals some interesting trends. For example, the growth in footprint for the high-income region observed in Fig. 1 can largely be traced back to an increase in footprints sourced from low-income countries. Looking at the trends for the high-income region’s footprint originating in Indonesia, Malaysia, Philippines, and Papua New Guinea we see that in 2005, 17.5% of the high-region’s biodiversity footprint can be traced back to these four countries. The equivalent share was 14.6% in 1995, and 10.2% in 2013. In addition to being highly relevant for outsourcing of biodiversity footprint, it is a highly plausible explanation for the differing income elasticities of biodiversity footprint observed for the high-income region using 2005–2015 data (Table 1) compared to using 1995–2004 data (SI5). For 1995–2004 the origins of the imports are causing the increase in biodiversity footprint in the high-income group (Fig. 1). We see a distinct break in trends in the high-income group where the location of imported land is driving biodiversity loss up until 2005, while income is the main driver after 2005.

In SI4 we trace the footprint sourced from the four countries (Indonesia, Malaysia, Philippines, and Papua New Guinea) to the high-

income region (sheet name: *driversFootprint*) to the underlying bilateral trade data (sheet name: *driversTrade*), on a detailed sectoral level (the 200 EXIOBASE sectors). This exercise is a test of validity of our results. Trends in footprints should follow the trends in trade for products that use resources (in our case land area) in the source country and end up as final consumption in the destination country. This is not necessarily the case for goods and services that require land use in the source country, that is then exported to an intermediate country, goes through processing, and end up as a final good ultimately consumed in the destination country. Particularly “Products of forestry, logging and related services (02)” and “Construction work (45)” show trends of increasing share of the high-income region’s total footprint originating in these four countries. While similar trends are clearly found in the bilateral trade data for the four countries for “Products of forestry, logging and related services (02)”, the trend is less distinct for “Construction work (45)” in the bilateral trade data, but this would largely be due to “Construction work (45)” being a (non-traded) item of final consumption that has significant trade of forestry products in its supply-chain. For other products, the footprint data show such trends for only certain of the four countries. For example, “Oil seeds” originating in Malaysia clearly show a peak in 2005 for both bilateral trade and footprints. The same is true for “Food products nec” from the Philippines in 2001. On the other hand, some of the services, such as “Health and social work services (85)” that show a peak in footprints from all four countries in 2002, do not show the same trends in the bilateral trade data. These examples show that for products that have a short supply chain from use of land to consumption, trends in the bilateral trade data and footprint data correlate well, while for goods with a longer supply chain, the input-output approach is needed to capture the indirect effects of traded goods.

In SI13 we show the effect of using biodiversity footprint as a metric compared to land use when applying a MRIO with high regional detail, such as EXIOBASE 3rx. The discussion on pressure footprint (e.g. land use) vs. impact footprint (e.g. biodiversity loss) is well covered by Verones et al. (2017b) who use Eora coupled with LC-IMPACT to calculate biodiversity footprints. For country-specific results, they find that Brazil has a relatively higher impact footprint compared to pressure footprint, while the opposite is true for countries such as China and Russia. Comparing the land use share and the biodiversity footprint share out of the global total, we find similar trends for these countries, although less distinct for Brazil, and more distinct for Russia. There are several differences in approaches between our work and the work of Verones et al. (2017b). Although Eora and EXIOBASE 3rx are similar in terms of a detailed regional coverage which make them suitable for analyses where spatial detail is important, such as for biodiversity, the difference in approaches highlight the difference between the databases and show how they suit different purposes. Firstly, Eora includes other pressures, such as GHG emissions and water that are currently not available for EXIOBASE 3rx. Secondly, because of a consistent sectoral classification in EXIOBASE 3rx across countries (compared to a variable sector classification for Eora), EXIOBASE 3rx is better suited for analyses on consumption categories, such as studying the per capita biodiversity footprint drivers.

In terms of policy implications of our results, there are many aspects that could, and should, be taken up in policy design. Firstly, at the highest level, we show a strong relationship between affluence and biodiversity impact for high-income countries. Thus, policy design must effectively engage with this driver. Either we need a systematic shift of our view on affluence and its link to consumption (Wiedmann et al., 2020), or there needs to be significant efforts to offset the effect. As most biodiversity loss occurs in low to middle income countries, there are obvious implications for consideration of aid directed at biodiversity preservation, as well as the instigation of trade-related measures to protect or value the biodiversity. In some ways, none of these insights are new, although our results do highlight the importance that trade can have, especially in driving the spike in the biodiversity footprint of high-

income countries during the trade expansion of the 1990's and early 2000's. Considering the increase in deforestation in places like Brazil linked to the import of soy and beef cattle products into high income countries (Pendrill et al., 2019), there is clearly a stronger need for addressing these trade flows and "hidden impacts". Lessons from international efforts on climate change mitigation may be relevant here, including the imposition of border tax adjustments, more recently proposed to be in relation to mitigation efforts, membership of "climate clubs", and imposition of effective costing of the externality of climate impacts. For biodiversity, similar efforts could be done to offset the price signal of importing cheap goods from regions that do not adequately price in ecosystem protection. The product group results in our analysis reaffirm the importance of the focus on food and forestry products – areas where price signals are likely to have significant impacts in the global trade market. Alternative options may consider focusing on information to drive changes in consumer choices. Labelling systems here have perhaps had mixed levels of success. Certification schemes are now common, and ideally would consider the full life-cycle impacts of products being labelled, whilst quantitative measures geared towards influencing consumer choice through things like biodiversity (or carbon) footprint indicators on products has arguably had less success. One would hope that without blaming consumers, the availability of this type of information will better enable consumers in high income countries to consider the totality and connection of their choices to global environmental issues.

4.1. Limitations

Due to low data availability, particularly for developing countries and small economies, the supply- and use-tables in EXIOBASE 3rx for several of these countries have been estimated using generic coefficients (originally from the RoW regions the country belongs to in EXIOBASE 3, see Bjelle et al. (2020) and Stadler et al. (2018) for details on compilation of the databases). The economic structures of these countries are then updated with available raw data on product output (mainly agricultural and energy production) and trade, and then re-balanced based on country-specific macroeconomic data. This approach is common in the MRIO field, as representing the countries is important to ensure supply chains are not cut off (Stadler et al., 2014). Representing countries individually is particularly important for biodiversity loss analyses because of the high share of global land embodied in the RoW regions (Stadler et al., 2014).

However, there is a high variance in the per capita footprints for several of the top-ranking countries. In SI8 the biodiversity footprints per capita for all countries and years are shown as boxplots. Unsurprisingly, island states (particularly in the middle- and low-income groups) such as New Caledonia, Vanuatu, Samoa, Dominica, Solomon Islands, Sao Tome and Principe, and Madagascar are showing large variations in per capita footprint. Tropical island states are expected to have a larger spread in per capita footprint because of high characterization factor values in LC-IMPACT but are in addition among the countries with poor raw data availability in EXIOBASE 3rx. Generally, the uncertainty in MRIO studies becomes higher as the scope becomes more narrow (Moran et al., 2016), which applies to both the sectoral, and regional level in our analysis.

The LC-IMPACT characterization factors are designed to reflect impacts of marginal changes in land use and are not balanced at the global scale. Hence, when used in combination with global land use data, the sum of the country footprints may be higher than expected (see SI4). The results represent relative differences between countries and over time, but the sum of the country-based impacts does not add up to the actual number of global species extinctions. However, this is an issue of scaling due to much larger land use area included in EXIOBASE 3rx than in LC-IMPACT. Our values are in the same order of magnitude as Marquardt et al. (2019) who used a similar approach.

On the other hand, intensification levels of land use are likely to be a

source of uncertainty in our results (Marques et al., 2019; Marques et al., 2017). The land area in EXIOBASE 3rx includes area that is used less intensively and should possibly be assigned a lower PDF value than what we apply (see the supporting information of Bjelle et al. (2020) for an overview of land use types in EXIOBASE 3rx). In this case, the PDF values applied will vary based on intensification level of land use, which will have distributional impacts that we do not account for. Ensuring matching of land use area and intensification level of land use in MRIOs, such as EXIOBASE 3rx, and biodiversity loss databases, such as LC-IMPACT, is a future improvement that is critical for sound analyses using MRIOs for studying biodiversity impacts of consumption. Furthermore, the characterization factors do not comprehensively differentiate between land use intensities, potentially missing increased impacts due to increasing land use efficiencies (and related intensities). In addition, there are factors that we do not include that are likely to influence biodiversity footprint results, such as the introduction of invasive species (Otero et al., 2020) and overexploitation (Marques et al., 2017). Although land use is the most important stressor for biodiversity, other stressors we do not include, such as GHG emissions, can constitute a significant portion of the biodiversity footprint (Wilting et al., 2017). Considering multiple stresses together (Oliver and Morcroft, 2014; Haberl et al., 2009) is vital since species extinctions are rarely (though occasionally) caused by a single stressor (Verones et al., 2017b).

Based on the discussion above we suggest three future improvements to increase robustness of biodiversity impact analyses using MRIO. First, a high regional detail in MRIOs to account for highly differing characterization factors in different ecoregions. Second, to account for all stressors including land use, GHG emissions, and water use. Third, to align the land use data used in MRIOs to equivalent data in biodiversity impact databases such as LC-IMPACT. This includes accounting for different land use intensities and to ensure that total land areas match.

5. Conclusion

In this work we investigate the changes in drivers of biodiversity loss by coupling biodiversity loss characterization factors of land use from LC-IMPACT with consumption data from the multiregional input-output database EXIOBASE 3rx. We assess the country total biodiversity footprint, the per capita biodiversity footprint, and the average consumer's footprint over the time period 1995–2015, using a measure of the potentially disappeared fractions of species (PDF). Overall, there is a 6–7% increase in global biodiversity footprint measured in PDF over the time period, which gives a relatively strong decoupling of biodiversity footprint from growth in affluence. Grouping countries into three quantiles according to average income per capita, we find the decoupling is strongest in the low-income group and weaker in the high-income group for biodiversity footprints. The per capita footprints per consumption category show overall decreased trends due to decreasing footprint intensity per monetary unit, while food consumption is the largest component of the footprint as a result of a high footprint intensity per monetary unit. The footprint share caused by consumption of manufactured products is increasing rapidly in wealthier countries. The panel regression analysis shows that the average consumers in the richest countries have an income elasticity of biodiversity footprint above unity. High elasticities particularly for manufactured products, clothing and footwear, and shelter in the high-income region give indications about areas of focus for mitigation strategies targeted at consumers in high-income countries. A peak in the high-income group's biodiversity footprint in the early 2000s was caused by land embodied in imports rather than increasing income, showing the importance of addressing trade in policy design.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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