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Norwegian University of Science and Technology

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Preface

This thesis has been submitted to the Faculty of Engineering (IV) at the Norwegian University of Science and Technology (NTNU) as a partial fulfilment of the requirements for the degree of Philosophiae Doctor. The work was carried out at the Industrial Ecology Programme (IndEcol), Department of Energy and Process Engineering (EPT), under the supervision of Professor Richard Wood and co-supervision of Dr. Kirsten S. Wiebe and Dr. Konstantin Stadler.

Eivind Lekve Bjelle

Trondheim, March 2021

Abstract

We increasingly need to rely on demand side changes to complement technological improvements to mitigate environmental impacts such as global warming and loss of biodiversity. To do so we must better understand how different types of consumers vary in their impact on the environment and to understand the role of consumer behavior in impact mitigation.

The drivers-pressures-states-impact-response (DPSIR) framework describes the interactions between the human and natural systems. As the pressures, states, and impacts components of DPSIR are used to inform environmental policy making, it is crucial to both accurately account for, and to understand the linkages between these components and the underlying drivers. This thesis contributes to better understating of drivers (D), pressures (P) and impacts (I). The first contribution is made by estimating how changes in household income affect greenhouse gas emissions across a range of regions (drivers). By linking a demand system to the multiregional input-output model EXIOBASE 3, results show that by 2030 changing consumer preferences triggered by changes in household income lead to a 1% decrease in global warming from greenhouse gas (GHG) emissions globally compared to static consumer preferences. The largest contributors to this relative decrease in emissions are developing regions driven by lower preference of certain emission intensive food products, while the income effect on emissions of developed regions remain relatively unchanged. However, large expected population and affluence increases in developing regions more than cancel out the small negative effect of a modified consumption structure.

Secondly, accuracy of environmental footprint studies is improved by increasing the regional resolution in a multiregional input-output (MRIO) model (pressures). Using a regionally extended version of EXIOBASE with detailed land use extensions, results show that regional aggregation errors are introduced when countries are aggregated to rest-of-the-world regions in the MRIO. Aggregate land use embodied in imports of regions differs by up to 68%, while individual sector-level flows differ by up to 600% when using rest-of-the world regions compared to treating countries explicit.

Finally, by linking biodiversity characterization factors of land use to the new EXIOBASE version, biodiversity footprints for numerous new regions are estimated (impacts). Biodiversity footprints have globally increased by 5-6% between 1995 and 2015. Countries rich in biodiversity, and not necessarily affluence, have the highest footprint per capita.

However, looking at trends over time, a one percent increase in income leads to a more than one percent increase in biodiversity footprint across all consumption categories for the average consumer in the most affluent countries, while this is not found for developing countries.

The subsequent discussion shows that the potential is large for extending on the work in this thesis by further developing the database for understanding how demand-side changes and consumer behavior can contribute to reaching environmental mitigation goals.

Acknowledgements

I would first like to thank my main supervisor Richard Wood for teaching me everything I know about input-output analysis throughout the last six years. Your input in my most desperate times of paper writing, MRIO development and preparing for conference talks has been crucial to finishing the PhD. We have had a good collaboration through all these years, and your calm nature and patient guidance have greatly contributed to this. The complementary expertise of you and my co-supervisors Kirsten S. Wiebe and Konstantin Stadler provided me with the perfect PhD-toolbox. Thank you, Kirsten for guiding me through econometrics and various economic models and for moral and intellectual support at conferences. Thank you, Konstantin for unraveling the maze of balancing input-output tables.

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My family has supported me my entire life. Thank you Sondre, for several years spent together studying in Trondheim and for dragging me along on skiing trips to mountain tops. Thank you, Mari, for always being there and giving advice in challenging times during the PhD. Thanks to my parents for inspiring me to push my academic limits.

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List of publications

Primary publications

I. Bjelle, E. L., Többen, J., Stadler, K., Kastner, T., Theurl, M. C., Erb, K. H., Steen-Olsen K., Wiebe K. S., & Wood, R. (2020). Adding country resolution to EXIOBASE: impacts on land use embodied in trade.
Journal of economic structures, *9*(1), 1-25.
Author contribution: Research design, modeling, data analysis, visualization, and writing.

II. Bjelle, E. L., Wiebe, K. S., Többen, J., Tisserant, A., Ivanova, D., Vita, G., & Wood, R. (2021). Future changes in consumption: The income effect on greenhouse gas emissions.
Energy Economics, 105114.
Author contribution: Research co-design, modeling, data analysis, visualization, and writing.

III. Bjelle, E. L., Kuipers, K., Verones, F., & Wood, R. (2021). Trends in national biodiversity footprints of land use. *Ecological Economics*, *185*, 107059.
Author contribution: Research design, modeling, data analysis, visualization, and writing.

Other Publications

IV. Bjelle, E. L., Steen-Olsen, K., & Wood, R. (2018). Climate change mitigation potential of Norwegian households and the rebound effect. *Journal of Cleaner Production*, *172*, 208-217.
Author contribution: Research design, modeling, data analysis, visualization, and writing.

V. Wiebe, K. S., Bjelle, E. L., Többen, J., & Wood, R. (2018). Implementing exogenous scenarios in a global MRIO model for the estimation of future environmental footprints. *Journal of Economic Structures*, *7*(1), 1-18.
Author contribution: Research co-design, writing.

VI. Osei-Owusu A. K., Thomsen M., Wood R., Bjelle E. L., & Caro D. Understanding the trends in Denmark's global food trade-related greenhouse gas and resource footprint. Accepted at Journal of Cleaner Production (JCLEPRO-D-20-15682).
Author contribution: Research co-design, modeling

VII. Cimpan C., Bjelle E. L., & Hammer-Strømman A. Plastic packaging flows in Europe: A Hybrid Input-Output approach. First round of revision at Journal of Industrial Ecology (20-JIE-6883.R1).
Author contribution: Research co-design, modeling

Contents

Abbreviations

ABM	Agent-based modeling
CB	consumption-based
EEBT	Emissions embodied in bilateral trade
GDP	Gross domestic product
GHG	Greenhouse gas
ICIO	inter-country input-output
IO	Input-output
MRIO	Multiregional input-output database
PB	production-based
RoW	Rest-of-the-world
SAM	Social accounting matrix
SDA	Structural decomposition analysis
SEEA	System of Environmental Economic Accounting
SUT	Supply and use table

1 Introduction

Rising wealth and population growth are causing increasingly more stress on our environment beyond the planetary boundaries (Hoekstra and Wiedmann, 2014) , and our so far limited ability to mitigate these impacts has caused consequences that are likely or most certainly irreversible (IPCC, 2018). At the same time there is reason for optimism as humanity is now in a historically unique position where we have more knowledge than ever before on what needs to be done, how much our actions contribute, and when we need to act. As technology advancements are not progressing rapidly enough to do the work required for us, we need to supplement with demand-side actions to avoid environmental degradation (Alfredsson et al., 2018, Wiedmann et al., 2020, Creutzig et al., 2018).

1.1 Human impact on the environment

In the following sections (chapters 1.1 to 1.4) I introduce frameworks that link human activities to environmental impacts. These are referred to later in the thesis to pinpoint where the different pieces of work fit into the more general frameworks, and how the work contributes to increased understanding of these different components.

The most famous concept developed to explain the human impact on the environment is the IPAT equation (Ehrlich and Holdren, 1971). Here, impact (I) is a function of affluence (A), human population (P), and technology (T). While the technological solutions to mitigating environmental impacts are covered by the T, the key to demand-side solutions are found in the A. The IPAT equation handles the human drivers of environmental impacts, but it does not describe the effects these drivers have on ecosystems and the actions we can take to mitigate our impacts. This full interaction chain between the human and natural systems is given in the DPSIR framework (Figure 1) (Smeets and Weterings, 1999).

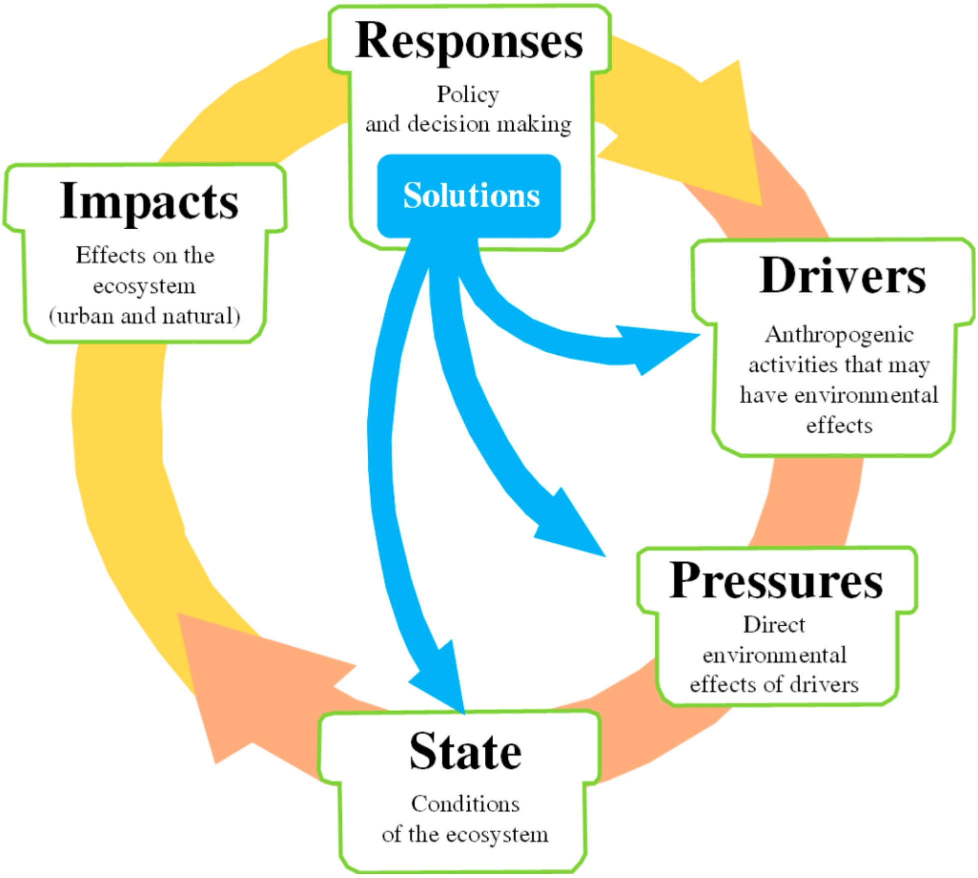

Figure 1: The DPSIR framework (De Gisi et al., 2021)

Drivers (D) such as social and economic developments exert pressures (P) on the environment, which consequently changes the state of the environment (S) such as biodiversity and resource availability. Finally, this leads to Impacts (I) as biodiversity loss or impacts on human health, which again evokes social responses (R) such as taxes or environmental laws.

1.2 Drivers of environmental impacts

Handling the link between drivers and pressures, the environmental Kuznets curve (EKC) theory links affluence to environmental footprints. It can be traced back to the 1950s and Simon Kuznets' work on the relationship between income inequality and economic development (Kuznets, 1955). Later this was adapted to environmental impacts, and here the hypothesis is that environmental pressures per capita increase up to a certain level as income increases, before declining when countries reach later stages of industrialization (Dinda, 2004). Although the story is appealing, such a relationship has rarely been found to exist, except for some local air pollutants (Dinda, 2004) and the theory has been heavily criticized for lack of empirical foundation (Stern, 2004, Dasgupta et al., 2002).

1.2.1 Accounting principles

The idea of the existence of environmental Kuznets curves became even more distant as consumption-based (CB) accounting of environmental impacts came into play (Rothman, 1998, Suri and Chapman, 1998, Peters and Hertwich, 2008a). In the Kyoto protocol from 1997 countries obliged to reduce their GHG emissions. Here the traditional production-based (PB) approach that accounts for impacts occurring within a country's border was applied. However, using this approach countries could achieve their GHG emission reduction targets by moving polluting industries to other countries, a phenomenon known as carbon leakage. This triggered a discussion about how environmental impacts should be accounted for (Babiker, 2005), and the consumption-based (CB) approach was put forward as an alternative (Peters and Hertwich, 2008b). In the CB approach all environmental impacts throughout the supply chain are allocated to the consumer of a good, including those impacts embodied in imports.

1.2.2 Telecoupling and MRIO

Telecoupling describes the environmental and socioeconomic interactions between human and natural systems over distances (Liu et al., 2013). In recent years the spatial disconnect between production and consumption has rapidly increased (Kastner et al., 2014a) and this increase is strongly linked with expansions in global trade (Schaffartzik et al., 2015, Bruckner et al., 2015). A CB accounting framework that can trace goods and services and associated environmental impacts across country borders from the point of resource extraction, through the supply chain, and finally to the consumer has thus become increasingly relevant. This has become possible with the development of several environmentally extended multiregional input-output (MRIO) databases in the last 10-15 years. These MRIOs combine national input-output (IO) tables with bilateral trade data and environmental satellite accounts to describe the flows of goods and services in the economy and their associated environmental impacts. Today, MRIO has become the standard tool for studying the CB environmental impacts of GHG emissions, energy use, water use, land use, material use, and several other pressures (Wiedmann, 2009, Hoekstra, 2010, Tukker et al., 2018, Lenzen et al., 2012a).

1.2.3 Affluence

Despite being the main driver of several environmental impacts (Ivanova et al., 2016, Hertwich and Peters, 2009), households are represented with very little detail in MRIOs. The consumption of households usually is represented by one consumption vector describing the average consumer of a country although recent findings suggest that different types of consumers substantially vary in environmental pressures resulting from their consumption (Moran et al., 2018, Sommer and Kratena, 2017, Steen-Olsen et al., 2016). The top income decile drives 30-45% of GHG emissions (Chancel and Piketty, 2015, Hubacek et al., 2017, Moran et al., 2018), while the richest percent of consumers in the EU are found to have a carbon footprint 22 times beyond the limit for mitigating global warming to 1.5-2°C (Ivanova and Wood, 2020).

Mapping out environmental impacts for different types of consumers as in the above examples is essential for focusing effort on environmental impact mitigation, but further insight can be gained from also studying the underlying mechanisms of consumption (D in DPSIR of Figure 1). In the economics literature on demand systems, changes in consumption patterns are related to changes in income and relative prices. The idea that consumers adjust their preferences for goods with changes in household income can be traced back to Engel (1895) who noticed that the expenditure share on food decreased as income increased in a given population (Chakrabarty and Hildenbrand, 2016). This concept has been transferred to the environmental impacts literature where both within nations (Weber and Matthews, 2008, Jones and Kammen, 2014, Lenzen et al., 2006) and among nations (Hertwich and Peters, 2009) affluence is found to be a strong predictor of carbon footprint and other environmental impacts, but the increase seems to be less than proportional to the increase in income/expenditure (Sommer and Kratena, 2017, Tukker et al., 2010, Lenzen et al., 2006, Weber and Matthews, 2008).

The sensitivity of CB environmental impacts to changes in income has become known as the income or expenditure elasticities of footprint and these describe the links between consumer preferences, income, and environmental impact intensities of goods and services. The concept has been applied to carbon footprint (Steen-Olsen et al., 2016, Hertwich and Peters, 2009), energy use (Oswald et al., 2020) and eutrophication (Hamilton et al., 2018) in the MRIO literature. These elasticities differ from conventional income/expenditure elasticates of demand. For example, comparing services and transport that both typically are luxury goods with an income/expenditure elasticity of demand higher than one, but might have highly differing income/expenditure elasticities of carbon footprint due the a lower GHG emission intensity of services compared to transport (Hertwich and Peters, 2009, Steen-Olsen et al., 2016).

Beyond estimating income/expenditure elasticities of footprint, the role of consumer preferences in mitigating environmental impacts have in MRIO studies received limited attention as studies have generally focused on past events. However, a framework for studying how income changes over time affect environmental impacts is readily available as all the MRIOs with global coverage now cover several years, and new versions are continuously being published with further extensions of the time series (see e.g. Stadler et al., 2020).

1.3 Land use pressures

Moving focus from drivers to pressures in DPSIR (Figure 1), these are in environmentally extended MRIO covered by satellite accounts of environmental pressures per economic sector. The details of these accounts are limited to the sectoral, spatial, and temporal details of the MRIO system. Aggregation of regions, sectors, and environmental satellite accounts is present in all MRIOs for various reasons. The effects of aggregation of regions (Su and Ang, 2010, Andrew et al., 2009, de Koning et al., 2015, Bouwmeester and Oosterhaven, 2013), environmental satellite accounts (Lenzen, 2011, Steen-Olsen et al., 2014), and particularly economic sectors (Piñero et al., 2015, Steen-Olsen et al., 2014, Andrew and Peters, 2013, Wood et al., 2014, Park and Gordon, 2005, de Koning et al., 2015, Su et al., 2010, Miller and Shao, 1990, Bouwmeester and Oosterhaven, 2013) are well covered in the literature. In general findings show that aggregation of satellite accounts to fit a sectoral classification might lead to aggregation of highly heterogeneous environmental multipliers (Steen-Olsen et al., 2014, de Koning et al., 2015) and the preferred approach is disaggregation of economic sectors, even based on few data points (Lenzen, 2011).

Due to lack of data, several regions in MRIOs are typically gathered in rest-of-the-world (RoW) regions to ensure that supply-chains are not cut off. However, as these countries can differ substantially in terms of economic structure and environmental accounts, they matter for environmental analyses. Of environmental satellite accounts, particularly natural land stands out as having a high share located in RoW regions (Stadler et al., 2014).

Natural land is a scarce, limited, and immobile resource, and about 60-85% of forests and 70-90% of other natural ecosystems are today affected by human use in some degree. Its use for anthropogenic purposes in the agriculture, forestry and other land use sectors contributes to 23% of total human-induced GHG emissions (IPCC, 2019). Available land area is further put under pressure by an increasing human population and an increase in calory uptake per capita (IPCC, 2019). At the same time, consumption in developing countries is causing an increasing displacement of land use, and rich countries' food consumption in some cases require an arable land area larger than the total available arable land area of some of these rich country (Lambin and Meyfroidt, 2011). In developed countries with limited land resources such as the Netherlands (Wiedmann, 2009) and Japan (Yu et al., 2013) over 90% of the land use area required for domestic consumption is located outside the country borders.

1.4 Impacts on biodiversity

While land use or GHG emissions are useful for quantifying the environmental pressures of human activity, they do not inform about the consequences for ecosystems. In light of the trend in recent years to have environmental policy making to be based more on consequences (I in DPSIR in Figure 1) instead of pressures (P in DPSIR) (see e.g. Verones et al., 2017) it has become increasingly relevant to link consumption to impacts on biodiversity. Furthermore, the difference in using pressures versus impacts as indicator can be large. In Verones et al. (2017) for example, they found that 11.5% of total land pressure embodied in trade comes from China, while the equivalent value for total biodiversity impact embodied in trade was only 3.7%.

Today, 28% of all species are threatened by extinction (IUCN, 2020) with few indications of the rate of biodiversity loss slowing down despite targets being set to reduce this rate (Butchart et al., 2010). Land use and land use change are the main drivers of biodiversity loss (Souza et al., 2015, Baillie et al., 2004, Verones et al., 2017, Sanderson et al., 2002, Chaudhary et al., 2016) and human use of land has caused an 11-14% decrease in biodiversity (IPCC, 2019).

The link between biodiversity impacts and affluence as a driver was made by McLellan et al. (2014), but using PB accounting. Efforts to analyze this using CB accounting has only in the last 2-3 years been covered in the literature. These findings show that the relatively larger increase in GDP compared to biodiversity impacts leads to a relative decoupling of biodiversity impacts from economic growth (Marques et al., 2019, Koslowski et al., 2020, Wilting et al., 2017). On a per capita level, the link between affluence and biodiversity impacts is less clear. Conclusions from studies on European countries are somewhat deviating (Wilting et al., 2021, Koslowski et al., 2020), while studies on a global level find a positive correlation between GDP per capita and biodiversity footprints overall (Wilting et al., 2017) and that affluence is the largest contributor to increasing biodiversity impacts of the components in the IPAT framework (Marques et al., 2019). However, the studies vary in terms of years, regions, pressures, and sectors covered, in addition to differences in unit of biodiversity impacts, MRIO and biodiversity impact datasets they apply. In addition, recent work has questioned the appropriateness of using RoW regions in MRIOs, finding that biodiversity loss footprint in the EU might be significantly underestimated due to aggregation into RoW regions (Cabernard and Pfister, 2021).

1.5 Research Gap and overall objective

Given the important role of demand-side changes in mitigating environmental impacts there is potential for improved understanding of the role of consumer behavior and demand-side changes in environmental MRIO studies.

While some studies exist on the sensitivity of changes in income on environmental impacts in form of income elasticities of footprints, a framework that also controls for how consumers respond to other factors that might affect consumption decisions, such as price changes, is still lacking for all regions represented in MRIOs.

Given that recent findings suggest that the use of RoW regions in MRIOs can introduce aggregation errors for estimating certain environmental impacts, there is both a need to explicitly cover the countries embodied in RoW regions, and to understand the effects of regional aggregation on a larger number of relevant environmental indicators. RoW regions in MRIOs represent a large share of global natural land area. Still, studies exploring the effects of regional aggregation in MRIOs have focused on other pressures and are yet to investigate the consequences of spatial aggregation on land use footprints.

The literature that links changes in affluence to changes environmental impacts have mainly so far focused on GHG emissions, while the link between affluence and biodiversity impacts have been studied from a PB perspective and more recently from a CB perspective, but globally or for broad world regions covering often only one year. The availability of MRIOs in increasingly longer time series facilitates exploring how impacts develop over time and with changes in affluence. With recent studies suggesting that the spatial resolution in MRIOs can also introduce potential errors in biodiversity footprints, there is room for improvements in both the temporal and spatial dimension of accounting for CB biodiversity impacts.

1.6 Thesis structure

In the remaining sections I provide a more thorough overview of environmental MRIO analysis and how the research gaps fit with the state of the art (chapter 2) before describing the contributions of the thesis and the thesis objectives (chapter 3). The paper summaries are given in chapter 4. Finally, the limitations and potential for further work are discussed in chapter 5. The papers are found in the appendices of the thesis.

2 Background

A crucial step to answer to these research objectives has been to develop a regionally extended version of the MRIO EXIOBASE. This section therefore gives a thorough background consisting of the basic components of environmental IO analysis, an overview of MRIO, MRIO development, and its application to environmental analyses.

2.1 The building components of IO

The core piece of data for IO analysis is the supply-use framework (Figure 2).

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="3">Products</th><th colspan="3">Industries</th><th colspan="3">Final uses</th><th rowspan="2">Total</th></tr>
<tr><th>Agri-cultural products</th><th>Industrial products</th><th>Services</th><th>Agri-culture</th><th>Industry</th><th>Service activities</th><th>Final con-sumption</th><th>Gross capital formation</th><th>Exports</th></tr>
<tr><td rowspan="3">Products</td><td>Agricultural products</td><td colspan="3" rowspan="3"></td><td colspan="3" rowspan="3">Intermediate consumption by product and by industry</td><td colspan="3" rowspan="3">Final uses by product and by category</td><td rowspan="3">Total use by product</td></tr>
<tr><td>Industrial products</td></tr>
<tr><td>Services</td></tr>
<tr><td rowspan="3">Industries</td><td>Agriculture</td><td colspan="3" rowspan="3">Output of industries by product</td><td colspan="3" rowspan="3"></td><td colspan="3" rowspan="3"></td><td rowspan="3">Total output by industry</td></tr>
<tr><td>Industry</td></tr>
<tr><td>Service activities</td></tr>
<tr><td colspan="2">Value added</td><td colspan="3"></td><td colspan="3">Value added by component and by industry</td><td colspan="3"></td><td>Total value added</td></tr>
<tr><td colspan="2">Imports</td><td colspan="3">Total imports by product</td><td colspan="3"></td><td colspan="3"></td><td>Total imports</td></tr>
<tr><td colspan="2">Total</td><td colspan="3">Total supply by product</td><td colspan="3">Total output by industry</td><td colspan="3">Total final uses by category</td><td></td></tr>
</table>

Figure 2: Supply-use framework (Eurostat, 2008)

The supply- and use framework comprises the matrix of industries supplying products (supply table), the matrix of products used by industries (use table), the value added vector/matrix (**V**) by industries containing compensation of employees, taxes etc., the vector of total imports of products, as well as the final demand matrix (**Y**) by final users of products.

To transform supply-use tables to symmetric input-output tables some assumptions must be applied depending on whether the IO tables is to be a product-by-product table or an industry-by-industry table. For a product-by-product symmetric IO table, these assumptions, or constructs, deal with the off-diagonal entries of the supply tables (some industries produce more than one product). Without going too much into detail, the most commonly used (Eurostat, 2008) are the industry-technology and the product technology constructs (see Jansen and Raa (1990) for a more detailed discussion of constructs).

The result is a symmetric IO table (product-by-product)

Table 1: Symmetric IO table, adapted from (Eurostat, 2008)

	Products	Final demand	Total use
Products	**Z**	**Y**	**Total use by products**
Value added	**V**		
Imports	**imports**		
Supply	**Total supply**	**Final use by category**	

A fundamental identity of input-output tables is that total supply by product = total use by product (Eq. 1)

$$\mathbf{Zi}' + \mathbf{Vj} + \mathbf{imports} = \mathbf{Zi} + \mathbf{Yi} \tag{1}$$

Where $\mathbf{Z}$ is the matrix of flows between sectors, $\mathbf{i}$ is a row vector of length equal to the number of products (n), $\mathbf{j}$ is a column vector of length equal to the number value added categories and $'$ denotes the transpose.

The total output $(\mathbf{Zi} + \mathbf{Yi})$ from Eq. 1 is from here on referred to as $\mathbf{x}$.

From these components we can derive the technical coefficient matrix ($\mathbf{A}$) containing the "production recipe" for each product or industry as:

$$\mathbf{A} = \mathbf{Z}\,\hat{\mathbf{x}}^{-1} \tag{2}$$

Where $\hat{\mathbf{x}}$ is the diagonalized version of vector $\mathbf{x}$.

Based on Eq. 1 and Eq.2 we can rewrite this as:

$$\mathbf{x} = \mathbf{Ax} + \mathbf{y} \tag{3}$$

Where $\mathbf{y} = \mathbf{Yi}$.

Which simply states that total output is the sum of intermediate demand and final demand.

The Leontief inverse (**L**) can then be written as:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} = \mathbf{Ly} \tag{4}$$

Where the **L** matrix gives the requirements, both direct and indirect through the value chain, needed to produce one unit of final demand. **I** is an identity matrix of size n.

In the MRIO model, Eq. 3 is expanded with data on multiple countries. Letting c be the number of countries, we can illustrate the MRIO framework as:

$$\begin{bmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^\mathrm{n} \end{bmatrix} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \cdots & \mathbf{A}^{1c} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \cdots & \mathbf{A}^{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{c1} & \mathbf{A}^{c2} & \cdots & \mathbf{A}^{cc} \end{bmatrix} \begin{bmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^\mathrm{n} \end{bmatrix} + \begin{bmatrix} \mathbf{Y}^{11} & \mathbf{Y}^{12} & \cdots & \mathbf{Y}^{1c} \\ \mathbf{Y}^{21} & \mathbf{Y}^{22} & \cdots & \mathbf{Y}^{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{Y}^{c1} & \mathbf{Y}^{c2} & \cdots & \mathbf{y}^{cc} \end{bmatrix} \begin{bmatrix} \mathbf{i} \\ \mathbf{i} \\ \vdots \\ \mathbf{i} \end{bmatrix} \tag{5}$$

For region number 1 in Eq. 5, the output $\mathbf{x}^1$ is now equal to the domestic intermediate demand $\mathbf{A}^{11}\mathbf{x}^1$ plus the intermediate demand from abroad $[\mathbf{A}^{12} \quad \mathbf{A}^{13} \quad \cdots \quad \mathbf{A}^{1c}]\mathbf{x}^1$ plus the final domestic demand $\mathbf{Y}^{11}$ plus the final demand from abroad $[\mathbf{Y}^{12} \quad \mathbf{Y}^{13} \quad \cdots \quad \mathbf{Y}^{1c}]$. The procedure for getting the Leontief inverse (**L**) is the same as described in Eq. 4.

To enable environmental analyses with the MRIO system, environmental extensions or satellite accounts must be added for each of the regions and relevant sectors of the MRIO. Letting **F** represent the total environmental impacts per industry, region, and category of environmental impacts (Stadler et al., 2018), we can then calculate the environmental impact multipliers **S** as:

$$\mathbf{S} = \mathbf{F}\hat{\mathbf{x}}^{-\mathbf{1}} \tag{6}$$

And finally, the consumption-based impacts (**E**) by environmental impact category and final demand category are given by:

$$\mathbf{E} = \mathbf{SLY} \tag{7}$$

In addition to the impacts from industries accounted for in $\mathbf{F}$, impacts directly caused by households, such as GHG emissions from driving or from heating using a fireplace, are accounted for in $\mathbf{F_{hh}}$.

Production-based impacts are then given as $\mathbf{F} + \mathbf{F_{hh}}$ while consumption-based impacts are given as $\mathbf{E} + \mathbf{F_{hh}}$. The difference between them gives the net impacts embodied in trade. The equations presented above compose the framework for all environmental MRIO analysis. Depending on the research question, the impacts can be traced through value chains, decomposed per sector and region, and differences across time can be analyzed if the MRIO exists in a time series.

2.2 Available MRIOs and their uses

Using input-output (IO) for environmental analyses escalated after 1995, whereas the focus on impacts embodied in trade came later and after 2005 (Hoekstra, 2010 as cited in , Tukker and Dietzenbacher, 2013). Since these distinguished developments, MRIOs used for environmental- and socioeconomic analysis have developed rapidly towards greater regional, temporal, and sectoral coverage as well as a richer coverage of satellite accounts.

Available multiregional input-output databases (MRIOs) all vary in level of detail in covered sectors, economic and environmental satellite accounts, years, and regions. Although the development of the individual MRIOs point towards increased level of detail in all these domains, different MRIOs are still applicable for different types of analyses. Eora (Lenzen et al., 2013, Lenzen et al., 2012a) was constructed with the idea of not diverging from the original data (Tarne et al., 2018), and thus has a mixed sector classification IO tables due to different classifications in the national IO tables. It comes in a time series (1990-2015) and has a high regional level of detail with 189 countries represented but linking flows that go across country borders to specific sectors can be challenging unless using the harmonized 26-sector version of the database (Eora26). The OECD inter-country input-output (ICIO) tables (OECD, 2021) comes in a time series from 2005-2015, has 34 sectors, 64 regions, and CO_2 emissions connected to the database where the IEA CO_2 fuel combustion data is largely directly allocated to the industries and regions (Tukker et al., 2020). The Global Trade Analysis Project (GTAP) database (Aguiar et al., 2019) includes in its 10th version 141 regions and 65 sectors for four years (2004, 2007, 2011, and 2014). The agriculture and food sectors are well covered, while other sectors of the economy are quite aggregated (Aguiar et al., 2019, Tarne et al., 2018). It has become the standard underlying database in applied general equilibrium models (Aguiar et al., 2019). The World Input Output Database (Timmer et al., 2015) is more aggregated on both the regional (43) and sectoral (35) level, but has harmonized sectors and also comes in a time series (1995-2011). It is tailored to economic trade analysis rather than environmental analysis like GTAP, EXIOBASE, and Eora (Tarne et al., 2018). EXIOBASE 3 (Stadler et al., 2018) contains 163 industry sectors and 49 regions and comes in a time series (1955-2011). The historically strong focus on European regions (Tukker et al., 2013, Wood et al., 2015) is still evident in the database, where large economies like Saudi Arabia, Thailand, Iran, and Argentina are aggregated to rest-of-the-world (RoW) regions.

2.3 Challenges in MRIO development

MRIO developers face numerous challenges along the way that complicates the development steps outlined above. MRIOs cover the majority of global GDP (Tarne et al., 2018) and should cover the entire global economy in order to ensure that global supply chains are not cut off (Stadler et al., 2014). By disrupting supply chains through ignoring RoW regions, ignoring imports, and using average environmental impacts, research has shown that not including the full global economy can lead to significant errors in environmental results from MRIOs (Andrew et al., 2009, Xu and Dietzenbacher, 2011).

However, supply- and use tables (SUTs) (Figure 2) are only available for selected countries and years. In addition, different countries use different product/industry classifications (see Supporting Information 1 of Stadler et al. (2018) for the data sources of SUTs used to build EXIOBASE 3). Estimating missing country data can be solved by either using proxy countries with thought similar economic structure (approach used in Eora and GTAP) or by compiling countries with poor data in RoW-regions (approach used in WIOD and EXIOBASE) (Stadler et al., 2014).

For the construction of MRIOs in time series, technical coefficients (**A**) for missing years can be estimated using a linear interpolation routine for data missing between years with available data or an extrapolation routine based on average annual change in coefficients for missing start year and end year (see Supporting information 1 of Stadler et al., 2018 for the routine applied for EXIOBASE 3).

For different sector classifications a range of concordance tables converting between classifications can be applied. The different MRIOs have here adopted widely different strategies (Owen, 2015). Eora has non-harmonized sectors kept to the original classifications of the countries to avoid the unwanted error potentially introduced by switching between sector classifications. In WIOD sectors are aggregated to a classification in the country with the lowest sectoral resolution. In GTAP and EXIOBASE harmonization of sectors through disaggregation is applied. Concordance matrices were developed for EXIOBASE to disaggregate the monetary SUTs (see Wood et al., 2014 for a detailed desciption of the routine applied). In GTAP the IO tables of other regions (belonging to the same regional group) are used to disaggregate a country's non-agricultural sectors, while data from the Food and Agriculture Organization of the United Nations (FAOSTAT) is used to disaggregate the agriculture sectors (Owen, 2015).

Each approach has its advantages and disadvantages. Eora's non-harmonized sector classifications stays close to the raw data, which likely reduces uncertainty. Eora also allows for analyses on detailed sectors for the countries with a high sector resolution but is limited and requires more work on the traded components. The OECD-ICIO closely follows the sectoral detail of the CO_2 emissions raw data, but low sectoral detail might introduce larger aggregation errors if the database is extended with other environmental impacts such as land use, material use, and water (Tukker et al., 2020). WIOD stays close to the raw data by avoiding disaggregation, and harmonized sectors allow for analyses of flows across country borders. However, it is limited by the number of sectors, and aggregation of environmental extensions can therefore be a source of uncertainty (Lenzen, 2011). This uncertainty is arguably reduced in EXIOBASE and GTAP given the higher detail of sectors. EXIOBASE was tailored for environmental analyses and to avoid errors introduced by aggregating environmental accounts (Wood et al., 2014) as highlighted by Lenzen (2011). However, disaggregation of sectors can also be a source of uncertainty (Wood et al., 2014).

2.4 Differences between MRIOs

In 2013, which marked the 25th anniversary for the International Input-Output Association, Dietzenbacher et al. (2013) looked into the next 25 years of IO analysis. Here, they foresaw a future where all countries are included separately in a global MRIO to enable analyses on impacts from resources that are extracted at a few locations, such as scarce metals. Since then the development has gone in this direction, facilitated by the simultaneous increase in computational power and better data availability.

Dietzenbacher et al. (2013) further foresaw the establishment of a global statistical office by 2019 that would start the work towards "harmonization of data, classifications, and accounting standards amongst statistical agencies across the world" which by 2023 combines the Systems of National Accounts (SNA) and System of Environmental Economic Accounting (SEEA) guidelines into one framework. With 2019 out of the way and 2023 approaching, we are certainly more than a few steps away from the path to such a development. MRIO developers still do not have access to such a database, and much of the time spent on constructing an MRIO is allocated to processing some form of raw data (or missing raw data) into the final format of the MRIO.

MRIOs increasingly rely on large amounts of data, and the unavailability of data has held back the IO literature (Hoekstra, 2010). MRIO developers have therefore developed sophisticated methods for data extrapolation to deal with low data availability. However, the efforts have been considered worthwhile as particularly for environmental analysis using MRIO, even small amounts of proxy information and additional geographical and sector detail improves the reliability of these analyses (Tukker and Dietzenbacher, 2013, Lenzen, 2011).

Due to differences in raw data applied, classification schemes, and types of analyses for which the database is tailored, there is no standardized approach for data processing and balancing between the MRIOs. Different routines are applied in the choice of supporting data, set-up of the initial estimate, optimization methods, and number of partitioning and optimization steps (Lenzen et al., 2017). In addition, numerous assumptions must be applied in different stages of the MRIO construction. These include, but are not limited to, choosing a representative country for the RoW region, converting to basic prices, disaggregating the trade vectors, and assigning emissions to each sector (Owen and Barrett, 2013).

These differences in approach unfortunately also cause differences in the final environmental results between the MRIOs (Tarne et al., 2018, Moran and Wood, 2014, Wieland et al., 2018, Owen et al., 2016, Arto et al., 2014, Owen et al., 2014), which again harms the policy uptake (Moran and Wood, 2014, Owen et al., 2016, Giljum et al., 2019). Considerable amounts of literature have tried to pinpoint the causes of these MRIO differences.

Some studies try to identify the parts of the MRIO structure causing differences, where often structural decomposition analysis (SDA) or structural path decomposition (Wood and Lenzen, 2009) are applied. These studies identify key countries and sectors for the difference in environmental impacts (Wieland et al., 2018, Owen et al., 2014, Owen et al., 2016, Moran and Wood, 2014, Arto et al., 2014). Most studies point to the emission accounts as the main cause of discrepancies in results between the MRIOs. Authors point to disparity in accounting (Owen et al., 2014, Owen et al., 2016) and deviations from the SEEA principles of emissions accounting (Usubiaga and Acosta-Fernández, 2015) as the causes of differences. Carbon footprint results are for example found to converge after harmonizing emission accounts (Moran and Wood, 2014). Other studies assess whether the traded or domestic blocks of the MRIO system are more important for differences in carbon footprint, but these results point in different directions (Wieland et al., 2018, Moran and Wood, 2014). The fact that developers of different MRIOs prioritize different data in MRIO constructions (trade versus domestic) could also be a cause of discrepancies (Arto et al., 2014).

Another approach to identifying discrepancies is to exchange parts of the construction process and constraints datasets between the MRIO production pipelines to estimate the effect these routines have on the resulting MRIO (Geschke et al., 2014). These results indicate that with a well-constructed initial estimate and set of constraints, balancing routines can be exchanged between EXIOBASE and Eora without large impacts to the original database.

2.5 Level of detail as cause of uncertainty

While increasingly finer splits are viewed as a positive and necessary development for MRIOs, it comes with potential costs of increased uncertainty, and balancing of conflicting information (Andrew and Peters, 2013). Although results indicate that a medium high coverage of sectors (approximately 50) can be enough to avoid large aggregation errors at a national footprint level (Su et al., 2010, de Koning et al., 2015, Bouwmeester and Oosterhaven, 2013), this can highly differ depending on indicator chosen with outlier regions deviating by 30-50% (de Koning et al., 2015, Wood et al., 2014). Yet, due to the potential aggregation of heterogeneous environmental multipliers, disaggregation of sectors is in general recommended over aggregation of satellite accounts (Steen-Olsen et al., 2014, Lenzen, 2011), and particularly when studying results at a detailed sectoral level.

The less studies regional aggregation has previously been understood as having a smaller effect on national footprints than sectoral aggregation (de Koning et al., 2015, Miller and Shao, 1990), and it has been shown that a limited resolution of regions are needed to approximate the carbon footprint embodied in trade of certain countries (Andrew et al., 2009). However, the effects of regional aggregation had not been explored for the full range of environmental indicators until Stadler et al. (2014) pointed to significant sensitivity of choice of proxy information for estimating the RoW for environmental impacts that are associated with specific parts of the economy, such as land use. This is further underpinned by recent findings that show that the use of RoW regions significantly affects national water stress and biodiversity footprints (Cabernard and Pfister, 2021).

2.6 Affluence and footprints

Moving from the level of detail in environmental MRIO analysis, which concerns the accuracy of accounting for pressures in DPSIR (Figure 1), I now turn to the drivers of DPSIR and how these have been covered in environmental MRIO studies.

The terms of the IPAT equation can be related to each of the terms in Eq. (7) as:

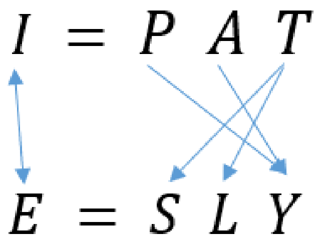

Figure 3: IPAT in MRIO

Total environmental impact (I and E) is a function of population (P), which in MRIOs are embedded in total final demand (Y), affluence (A), which is also part of Y as consumption per capita, and technology (T) composed of the economic multipliers (L) and the environmental impact multipliers per monetary unit (S).

SDA is often used to decompose the changes in a variable over time into the changes in its determinants (Dietzenbacher and Los, 1998) and has been applied to study the drivers of GHG emissions (see e.g. Munksgaard et al., 2000, Roca and Serrano, 2007, Wood, 2009), but has also to material (Wood et al., 2009), water (Zhang et al., 2012), biodiversity (Marques et al., 2019) and energy footprints (Lan et al., 2016). All these studies show that scale increases on the demand side have offset technological improvements.

While the purpose of SDA is to decompose the drivers of environmental impacts, environmental elasticities look at the sensitivity of environmental impacts to changes in consumption. Extensive studies on the sensitivity of environmental impacts to changes in other variables such as income has been covered in the economic literature before the arrival of MRIOs (see e.g. Stern, 2010, Soytas et al., 2007, Hatzigeorgiou et al., 2008). However, the strength of MRIO in accounting for impacts embodied in trade and allocating supply chain impacts to the good or service consumed provides a significant improvement over these previous studies. The underlying data can be temporal or cross-sectional, or a combination of the two. Data can be cross-sectional of different countries (Hertwich, 2011, Hamilton et al., 2018), based on consumer expenditure data (Steen-Olsen et al., 2016) or panel data on average consumers in different countries over time (Hamilton et al., 2018), and sometimes in addition, households are broken down into income quantiles (Sommer and Kratena, 2017).

There are two components affecting the income/expenditure elasticities of footprint. First, the income/expenditure elasticity of demand (although they might not be explicitly estimated), and secondly the environmental impact multiplier. The environmental impact multiplier is affected by technological advancements that typically over time lower the environmental impacts per monetary output produced (**S** in Figure 3), changes in the production recipe (**L** in Figure 3), as well as changes in the import structure (both intermediate and final demand). Thus, a low income/expenditure elasticity of footprint for a specific product can be a result of the good or service being an inferior good (has a low income/expenditure elasticity of demand), a result of changes in the factors affecting the environmental impact multipliers or a combination of the two. In some cases, the two components can pull in opposite direction, resulting in a normal income/expenditure elasticity of footprint.

2.7 Environmental impacts of types of consumers

Given the increasing recognition that consumers play an important role in mitigating environmental impacts (Creutzig et al., 2018, Intergovernmental Panel on Climate Change, 2019) and the fact that consumers differ in their pattern and level of consumption depending on factors such as income level, household size, education level, etc. (Lenzen et al., 2006, Ivanova and Wood, 2020, Steen-Olsen et al., 2016) there is a need to distinguish the environmental impacts of different types of consumers. To address consumer heterogeneity in environmental analyses, MRIO studies disaggregate the household consumption vector by linking to external consumption data, often from consumer expenditure surveys (Steen-Olsen et al., 2016, Mongelli et al., 2010, Koslowski et al., 2020, Kim et al., 2015), requiring assumptions to ensure balancing and harmonization of data (Di Donato et al., 2015, Ivanova and Wood, 2020). Several recent MRIO studies find that different types of consumers within the same country highly differ in their environmental footprints (Moran et al., 2018, Sommer and Kratena, 2017, Steen-Olsen et al., 2016) and particularly so with respect to differences in income (Chancel and Piketty, 2015, Hubacek et al., 2017, Moran et al., 2018, Ivanova and Wood, 2020).

2.8 Demand Systems to model consumer behavior

Income/expenditure elasticities of footprint to link between affluence and environmental impacts do not consider how consumers respond to price changes, while this is accounted for in demand systems. In the 1950s full-fledged demand systems consistent with utility maximization were developed (Stone, 1954) and later in the 1970s, 1980s and 1990s more complex demand systems materialized as computational power increased (see e.g. Deaton and Muellbauer, 1980, Pollak and Wales, 1978, Banks et al., 1997, Almon, 1998).

Integrating a demand system into an MRIO opens possibilities for new types of analyses like studying the effects of a policy measure as a CO_2-tax on production (Mongelli et al., 2010) that changes the relative prices consumers are faced with, and in turn the consumption decision taken by the consumer and the resulting consumption pattern. A second strand of literature linking MRIO and demand systems looks at predicting how environmental impacts develop given exogeneous scenarios of changes in GDP per capita and variables relating to technical changes, such as the International Energy Agency's Energy Technology Perspectives (IEA ETP) scenarios (used in Wiebe et al., 2018) or the shared socioeconomic pathways (O'Neill et al., 2014) (used in Xu et al., 2020, Chen et al., 2019).

When linking the demand system to MRIO data, an important question is what level of sector detail to use. EXIOBASE with its 200 products is too detailed as several of the products are irrelevant to household consumption. In addition, some products might have very low levels of consumption, and changes in consumption through the time series might cause problems (Blundell and Robin, 1999, Bardazzi and Barnabani, 2001) such as large effects in income- and price elasticities. In previous studies using demand systems, a resolution of between 5 and 22 has been used (Sommer and Kratena, 2017, Bardazzi and Barnabani, 2001, Blundell and Robin, 1999, Banks et al., 1997, Almon, 1998, Deaton and Muellbauer, 1980, Golan et al., 2001, Meade et al., 2014, Mongelli et al., 2010) and generally when multiple countries are used in the demand systems a lower product resolution is used. The highest resolution is often in food categories. In this regard EXIOBASE is a good choice with the highest harmonized product resolution of all MRIOs for food products (Tarne et al., 2018). WIOD and the harmonized Eora have sector resolutions that almost match the upper limit of what is used in demand systems, but they lack detail in key household consumption areas such as food and services.

2.9 Land use

Switching from how drivers of environmental impacts in general have been covered in MRIO analysis, I now switch focus to land use as a pressure and its link to biodiversity impacts.

MRIO provides a framework for accounting for the ever-increasing distance between the location of the land used to produce a good and the location of the consumption of this good (Seto et al., 2012), and has in recent years been used to calculate land use footprints of consumption activities (Steen-Olsen et al., 2012, Weinzettel et al., 2013, Weinzettel et al., 2014, Yu et al., 2013, Ivanova et al., 2016).

As much as 70% of land use can be traced to household consumption (Ivanova et al., 2016) and differences in availability of both area and type of land between countries and increases in global trade, cause countries' territorial and consumption-based land use impacts to highly differ (Ivanova et al., 2016, Wiedmann, 2009, Steen-Olsen et al., 2012, Yu et al., 2013). When comparing land use results based on MRIO with other methods, deviations in results led some researchers to question the applicability of MRIO for land use studies (Weinzettel et al., 2014, Bruckner et al., 2015, Kastner et al., 2014b). This has been connected to a low sectoral resolution, particularly for food sectors, as well as the process of attributing land use data to monetary production data (Weinzettel et al., 2014, Bruckner et al., 2015). Even at a quite aggregated level, not split by sector, contradicting results have been found for land embodied in trade when comparing MRIO studies to physical trade accounting studies (Kastner et al., 2014b). These discrepancies in results have later been linked to differences in system boundaries, where MRIO is suggested for looking at total land embodied in trade and drivers of land use, while physical trade accounting is suited for looking at flows of specific primary food products among countries (Hubacek and Feng, 2016).

Nevertheless, MRIO stands out as the method of choice for studying CB land use impacts. There is significant improvement potential in allocating land use to areas where it has the best global benefits. Natural climate solutions such as reforestation and avoided forest conversion could for example contribute to 20-39% of the needed mitigation in global carbon emissions to reach the 2°C target of global warming (Griscom et al., 2017). This requires that consumption in the global North takes into consideration the stress it is causing on natural resources in the global South such as degradation of arable land in Africa (see e.g. the discussion in Yu et al. (2013)). However, studying the drivers of damaging land use requires a regional resolution that is not found in many MRIOs today. The considerable share of global land area existing in RoW regions (Stadler et al., 2014) is a clear limitation. This for example means that land used in Vietnam cannot be distinguished from that used in Thailand, which makes it difficult to tell if consumption of a food product in Europe requires land area on a piece of land in a country that is prone to degradation or not. It can only show that the piece of land used exists somewhere within the RoW region.

2.10 Land use-induced biodiversity loss

Regional resolution in MRIOs has relevance for land-use induced biodiversity loss given the strong link between the human use of land and negative biodiversity impacts (see chapter 1). Efforts on mapping land used for human purposes and its effects on biodiversity have been pursued for a few decades (see e.g. Hannah et al., 1995), but the availability of global maps of land use, human infrastructure, and human population density, as well as development in geographic information systems is what enabled mapping of the human footprint on land area (Sanderson et al., 2002). Today, methods that estimate species loss from different types of land use on a highly detailed (5 min x 5 min grid) level have been developed (Chaudhary et al., 2016). In other words, the S (Status) and I (Impacts) in the DPSIR framework (Figure 1) have been covered thoroughly. However, the link to D (driving forces) is yet to be explained in these models, and such studies have pointed to MRIO as the tool to make this link (Chaudhary et al., 2016, WWF, 2018, Marques et al., 2017, Moran et al., 2016).

The first study to make the link between consumption and biodiversity impacts was Lenzen et al. (2012b) who associated 25 000 threatened species to more than 15 000 goods in 187 countries and found that 30% of species threats are due to international trade. Furthermore, consumption of goods and services in developed countries in several cases was found to cause a biodiversity footprint that was larger abroad than at home. The first work on biodiversity impacts using MRIO directly linked threatened species to economic sectors (Moran and Kanemoto, 2017, Lenzen et al., 2012b), and thus skipping the pressures (e.g. land) in the DPSIR framework (Figure 1). These studies inspired several others to further investigate biodiversity impacts by also including the pressure pathway using MRIO (Wilting et al., 2017, Marquardt et al., 2019, Marques et al., 2019, Koslowski et al., 2020, Verones et al., 2017, Moran and Kanemoto, 2017, Wilting et al., 2021, Kitzes et al., 2017, Cabernard and Pfister, 2021) and combining ecological models with biophysical trade flows (Chaudhary and Kastner, 2016).

Some of these studies use an MRIO with high regional resolution (Lenzen et al., 2012b, Moran et al., 2016, Verones et al., 2017, Wilting et al., 2017, Marques et al., 2019, Kitzes et al., 2017), some break down the footprint into consumption categories (Koslowski et al., 2020, Marques et al., 2019, Wilting et al., 2017), for a specific year (Lenzen et al., 2012b, Koslowski et al., 2020, Wilting et al., 2017, Verones et al., 2017), and sometimes including temporal trends (Marques et al., 2019), but no studies combine all of these aspects.

3 Thesis contribution and objectives

The main work has consisted of building EXIOBASE 3rx based on the production pipeline of EXIOBASE 3. The papers coming out from the work of this PhD represent stages in the development of EXIOBASE 3rx, from analyses using the previous versions of the database (paper II in addition to paper IV-VII), to describing the methods used to develop EXIOBASE 3rx along with improvements compared to the previous database version (paper I), and finally to expanding into new types of analyses enabled by the newly developed database (Paper III). In the second version of EXIOBASE several improvements were made (Wood et al., 2015). The base year was updated to 2007, one RoW region was split into five, and the number of sectors and environmental accounts increased. The main update in EXIOBASE 3 was the time series covering 1995-2011 (Stadler et al., 2018). In EXIOBASE 3rx, all countries which in EXIOBASE 3 were part of rest-of-the-world (RoW) regions are disaggregated and represented as separate regions.

Following this development, the objectives of the work in this thesis are:

O1: To increase coverage of CB accounting in the developing world for environmental analyses

None of the available MRIO databases couple a high level of harmonized sector detail with a detailed country resolution. Developing such an MRIO contributes to increasing the coverage of countries in the developing world for CB environmental impact analyses in addition to decreasing uncertainty for CB environmental impacts in the developed world. The resulting MRIO (EXIOBASE 3rx) is the most detailed published to date and the process of producing this database is described in paper I.

O2: To investigate the effects of regional aggregation for CB land use impact embodied in bilateral trade.

The analysis in paper I continues by estimating the effects of using RoW regions in previous versions of EXIOBASE for land use embodied in trade. Land use extensions are processed for all 214 regions of EXIOBASE 3rx for over 40 land use types. This contributes to improving the accuracy of land use studies using MRIO. Key regions that should be treated explicitly in MRIOs will be identified, but also how aggregation errors are introduced for land embodied in imports, both in terms of regions and sectors.

O3: To study the effects of changes in household income on GHG emissions

Previous MRIO studies looking at income effects on environmental impacts have not adjusted for factors such as price changes. This is studied in Paper II by developing a demand system based on EXIOBASE 3 data. The paper contributes to understanding the effect altered consumer preferences triggered by future changes in income has on GHG emissions. This is done by linking demand system results to exogeneous future scenarios of GDP and population. This is the first study to link a demand system to all regions covered in an MRIO.

O4: To determine if there is a link between affluence and CB land use related biodiversity impacts

Studies linking biodiversity impacts and affluence are limited by lack of regional detail or do not study how impacts change over time from a CB perspective. In Paper III land use data from EXIOBASE 3rx covering 1995-2015 is coupled with characterization factors of biodiversity impacts from land use to study how biodiversity footprints develop over time at different levels of income. This work contributes to mapping biodiversity footprints across sectors and regions at the most detailed level published to date and to understand the role of affluence by developing expenditure elasticities of biodiversity footprint. Hotspots of biodiversity impacts are identified by tracing impacts through supply chains to guide policy making aimed at mitigating biodiversity loss.

4 Summary of papers

4.1 Paper I: Adding country resolution to EXIOBASE: impacts on land use embodied in trade

The goal of this paper was to assess the effects of using RoW regions for land use embodied in trade. AS mentioned in the introduction 40% of global natural land exists in RoW regions of EXIOBASE and there is potential large sensitivity to choice of proxy information used to build the RoW for land use results (Stadler et al., 2014), but the effects of using RoW regions for land use studies are yet to be quantified. Merely a high share of global natural land does not mean that there is a high regional aggregation error. A regional aggregation error only arises if there are large differences between the land use intensity per monetary unit within the RoW region which affects the land use embodied in imports of countries outside the specific RoW region.

This analysis was enabled by developing EXIOBASE 3rx. Although the development of EXIOBASE 3rx follows the production pipeline in EXIOBASE 3 there was a considerable amount of work needed to disaggregate individual countries from RoW regions. We processed raw data individually for each country that previously were part of RoW regions which involved disaggregation, aggregation, and filling gaps were necessary. The supply and use tables of each country and year were balanced individually based on the country-specific raw data and information from the previous RoW regions. Conflicting constraints sometimes caused infeasible solutions in the optimization routine applied and identifying the cause of the issue often meant going back to the raw data to pinpoint inconsistencies.

Using the new database with 214 regions and updated to 2015, we found that cropland footprint per capita was largest in Monaco (24 700 m^2/cap) followed by Luxembourg (19 100 m^2/cap) and the United Arab Emirates (9 100m^2/cap) and lowest in Timor-Leste (257 m^2/cap), Bermuda (336 m^2/cap), and Zanzibar (353 m^2/cap).

Aggregating to RoW regions introduced errors in countries' balance of land embodied in trade up to 6% and up to 68% in total land embodied in imports of countries. By ranking the top land use flows by aggregation error, we found a high concentration around imports to Asian countries originating in RoW Asia and RoW Africa and a handful of sectors with high biomass demand such as forestry and food products. For land use studies using MRIO, the countries embodied in these RoW regions should be included as separate regions in an MRIO. The hotspots for aggregation errors we identified compared with previous findings show that errors differ depending on environmental indicator chosen. Mapping out these hotspots for all environmental impact categories will give important guidelines to future MRIO developers and EXIOBASE 3rx provides the appropriate framework to study this as new environmental and socio-economic extensions in the future are added to the database.

4.2 Paper II: The income effect on greenhouse gas emissions

Here we link a demand system based on consumption and price data for 49 regions in the period 1995-2011 using EXIOBASE 3 to study the future effects of household income changes on carbon footprint. Previous studies have included the income effect on environmental impacts, while we also adjust for changes in consumer preferences triggered by price changes. The demand system is developed for all regions in EXIOBASE 3 and thus contributes with a framework for assessing environmental impacts for each of the 49 regions. We combine the demand system results with exogenous scenarios of GDP and population to project GHG emissions up until 2030 and to study the income effect on GHG emissions for each region, keeping prices, GHG emission intensity, as well as the MRIO structure unchanged.

Compared to a scenario where consumption patterns remain unchanged, there is a global decrease in GHG emissions by 1% when considering how consumer preferences change with income in 2030 compared to 2011. However, regions differ substantially, with the BRICS (Brazil, Russia, India, China, and South-Africa) and RoW regions as main contributors to the global reduction due to a move away from consumption of food products with a high GHG emission intensity towards services with lower GHG emission intensities. For developed regions however, GHG emissions slightly increase compared to the baseline scenario. This is mainly attributed to increased consumption within transport.

This clearly reflects that countries are at different stages of development. While developing regions still have potential for less polluting consumption patterns by moving away from necessities such as food, towards luxuries such as services, this potential has already been tapped in developed regions. As countries develop, it is not the composition of consumption that is causing increases in GHG emissions, but the BRICS and RoW regions are expected to respectively see a 12% and 35% increase in population and 60% and 90% in expenditure levels between 2012 and 2030, causing a substantial total increase in emissions. Considering this, we identify key areas of focus for policy makers, highlighting consumption relating to housing, transport, and some types of food as critical due to a high GHG emission intensity and increasing future demand in RoW and BRICS.

4.3 Paper III: Trends in national biodiversity footprints of land use

In this paper we explore the link between biodiversity impacts and affluence using land use data from EXIOBASE 3rx coupled with characterization factors of biodiversity impacts from land use from LC-impact. Studies are yet to cover how changes in affluence over time affect biodiversity impacts. We assess the CB and PB impacts by grouping regions by their income per capita level. Globally land use-induced biodiversity footprint increased by 5-6% from 1995-2015 while population has increased much more, resulting in a decrease in per capita biodiversity footprint of 16%. From a PB perspective, the high-income group has lowered its total biodiversity footprints by 4-5% in the period. From a CB perspective on the other hand, footprints increased by over 25 % up until 2005 before lowering and stabilizing around 1995 levels in 2015. Footprints per capita decreased in all regions, except for the high-income group from 1995-2005. We find relative decoupling of biodiversity from economic growth in all grouped regions, but strongest in the low- and middle-income groups. Food consumption makes up the largest component (40-61%) of per capita footprints in all regions, while the effect of increased expenditure on services on biodiversity footprint in the low and middle-income groups is small due to decreasing biodiversity footprint intensity.

We estimate the sensitivity of biodiversity impacts to changes in expenditure using the average consumer's biodiversity footprint and expenditure for each country and year as observations in a panel regression. The high-income group has on average the highest per capita footprint and the expenditure elasticity of biodiversity footprint is larger than one for all consumption categories in the high-income group, and lower than one for all consumption categories in the low- and middle-income groups. This shows that in rich countries, increased affluence is associated with a higher per capita biodiversity footprint for the average consumer.

We rank footprints per capita per country and find that the top-ranking countries are not the most affluent, but small biodiverse island states such as New Caledonia, Seychelles, and Dominica indicating that location at biodiversity hotspots is the most important driver for high biodiversity footprint, which highlights the need for using a regionally detailed database for biodiversity footprint studies.

In the discussion we show how biodiversity footprints embodied in trade is increasing, which highlights the importance of using a CB perspective. Further, we trace the increase in CB footprint of the high-income group through the supply chain to imports of forestry products from Indonesia, Malaysia, Philippines, and Papua New Guinea. For policy making, we discuss how the elasticities of footprint and tracing of footprints to the place of impact can inform about where efforts to mitigate biodiversity impacts should be made.

4.4 Paper IV: Climate change mitigation potential of Norwegian households and the rebound effect

In addition to the three main papers above, the thesis includes a supporting paper investigating the potential for carbon footprint reductions triggered by a shift to a green lifestyle for Norwegian households. As the lifestyle shift consisting of 34 behavioral actions comes with a significant cost reduction for the households, rebound effects when the savings are re-spent are of high importance. We find that an initial 58% reduction in carbon footprint of the lifestyle shift is reduced to 24-35% when households re-spend the money. In addition, we show using an optimization routine, that total reductions (including rebound effects) in the order of 35-45% can be achieved by restricting re-spending to specific goods and services associated with low greenhouse gas emissions.

5 Discussion

The contributions of this thesis have been to improve and widen the range of analyses that can be performed within environmental impacts of consumption using MRIO, and to shed light on the advantages of explicitly cover individual countries as separate regions in the MRIO versus aggregating to RoW regions (paper I). To do so involved developing the most detailed MRIO with global coverage published to date (paper I), to integrate a demand system into an MRIO that enabled investigating future income effects on environmental impacts (paper II), and to couple land use data from an MRIO with a database of land use-induced biodiversity loss characterization factors (paper III).

This has contributed to increasing the number of countries that an environmental footprint analysis can be applied to (paper I) and to highlight that the use of RoW regions introduces errors in land use embodied in trade (paper I). Changes in consumption patterns triggered by changing income levels do not significantly affect GHG emissions globally but do so on a regional level (paper II). Decoupling of biodiversity footprint from economic growth is largest for developing regions, while the biodiversity footprint for the average consumer in affluent countries increases more than 1% per percentage increase in expenditure (paper III).

There are limitations of the work pertaining to the development of EXIOBASE 3rx and coupling of EXIOBASE 3rx with other databases and model systems. These are discussed in the following section. Finally, potential for further work to build on the work done in this thesis is discussed in the ending section.

5.1 Limitations

5.1.1 Balancing an MRIO versus staying close to raw data

There are several stages of data uncertainty involved in building an MRIO (Wiedmann, 2009). These range from uncertainties introduced in raw data processing, balancing and aggregation in the regional IO tables used to build the MRIO, to uncertainties introduced when combining the regional IO tables in the construction of the MRIO such as converting to a common sectoral classification, monetary exchange rates, balancing trade data, adding satellite accounts to mention some of the most prominent ones. Even if IO tables had been available for all the regions and years in EXIOBASE 3rx, the MRIO developer is faced with this challenge, unless data had been perfectly balanced and standardized between regions. For the regions in EXIOBASE 3rx that lack national IO tables, the corresponding RoW region's table is used and adjusted according to available raw data as described in paper I and Stadler et al. (2018) to get a first estimate that later goes through a balancing routine. This is a way of imitating the process of compiling regional IO tables by using the raw data available but backed up by the RoW IO tables. The MRIO developer does not have to rely on perfect data availability to build the MRIO, but it can mean that IO tables of countries with limited raw data available are built on few pieces of information. This can again affect e.g. the consistency of a detailed flow such as the environmental footprint of a particular food product if tracked over time. Despite this, I argue that the pros of building the MRIO by far outweighs the cons of data uncertainty based on the potentially large errors introduced by regional aggregation identified in paper I and previous findings suggesting even small amounts of information improves reliability of environmental MRIO results (Tukker and Dietzenbacher, 2013, Lenzen, 2011). In addition, developing an MRIO is an iterative process where priority should be to get the MRIO operational based on the raw data available. As new data becomes available, this is used to update the MRIO and reduce data uncertainty. EXIOBASE 3rx is built with this in mind, and principally follows the same pipeline as EXIOBASE 3 that has been updated numerous times since its first launch in 2016.

5.1.2 Alternatives to inverting matrices

Previous versions of EXIOBASE had an MRIO system where calculations could be handled by normal desktop computers. When RoW regions were disaggregated for EXIOBASE 3rx, carrying out operations such as inverting an A-matrix of size 42 800 by 42 800 became too large to handle using the programming language MATLAB without using supercomputers or similar. This was handled in two different ways in the thesis. In paper I the emissions embodied in bilateral trade (EEBT) approach was applied. This is a widely used approach in the MRIO field the last 10-15 years, where the traded parts of impacts are calculated using monetary bilateral trade statistics (described in Peters, 2007, Peters, 2008). In paper III a network-based approach (Rodrigues et al., 2016) was applied that gives a good estimate of the inverted A-matrix, and is computationally much less demanding.

The EEBT approach has limitations in terms of applications, as imported goods that are used for intermediate production and later used is exported to a different country for final demand cannot be calculated. However, the EEBT approach is suitable for estimating total impacts embodied in imports and exports of nations (see Peters (2007) for a thorough discussion of this). In paper I, land use embodied in trade results were compared using two differently estimated databases to show the benefit of the added regional detail in EXIOBASE 3rx. The land footprints are calculated using the EEBT approach, and these can somewhat deviate from corresponding footprints using the conventional A-matrix inversion. The advantages of the EEBT approach are that it is more accessible, comprehensible, and is less time consuming to implement. The network approach, though arguably less intuitive and more time-consuming to implement has as broad application area and gives a good estimate of the full MRIO approach. A third alternative is using supercomputers that are powerful enough to do the full A-matrix inversion. This approach requires the least implementation time and is the most intuitive for researchers familiar with IO analysis, but availability of supercomputers is a limitation for users.

5.1.3 Lag in published raw data

Strongly contributing to the historically limited policy relevance of MRIO is the lag in publishing raw data used for building the MRIOs. IO tables and auxiliary raw data are often published some years after the actual flow or transaction occurs. The first version of EXIOBASE 3 (Stadler et al., 2018) contains data including 2011. For EXIOBASE 3rx the time series has been expanded to 2015, a lag of five years compared to the time of publishing. In EXIOBASE 3 (version 3.8) published in November 2020 (Stadler et al., 2020) the issue has been resolved by using auxiliary trade and macro-economic data and the International Monetary Fund expectations to expand the time series up until 2022. This represents a development where MRIOs are less dependent on national statistical offices to publish IO tables and on organizations to publish auxiliary data. Instead MRIO developers can use source data such as company data directly to imitate the assembly process of national IO tables when needed. EXIOBASE already makes use of auxiliary datasets (e.g. IEA and FAOSTAT) to support creating the national supply and use tables but has yet to use company data in the production pipeline.

5.2 Further work

5.2.1 Environmental extensions

Priority of further work should be to add other socioeconomic and environmental extensions to EXIOBASE 3rx. This is important not only to extend the application of EXIOBASE 3rx to other types of environmental studies, but also to continue identifying hotspots of sectoral and regional aggregation errors for other environmental indicators.

Some of the extensions can more easily be added than others. Biodiversity impacts of land use can after the work in this thesis easily formally be added to the database as part of a characterization matrix equivalent to the one processed for EXIOBASE 3. GHG emissions should be the next priority both due to the increasing future relevance of GHG emissions to policy making and due to being the historically most studied environmental indicator in IO studies (Hoekstra, 2010). In addition, carbon footprint value chains need unraveling to mitigation climate change. A much smaller share of global PB GHG emissions occur in RoW regions than the equivalent share for natural land (Stadler et al., 2014), while the impact embodied in trade of the global total is similar (Peters and Hertwich, 2008a) or a bit lower (Hou et al., 2020) than that of land use at about one quarter of global impacts. Studies using a high regional resolution (Our World in Data, 2021, Wiebe and Yamano, 2016) show that the link between GHG emissions and affluence is stronger (affluent countries rank highest) than the link between affluence and land use and biodiversity footprints, but also less affluent countries such as Brunei, Estonia and Trinidad and Tobago (Our World in Data, 2021) and Israel (Wiebe and Yamano, 2016) rank high on carbon footprint per capita. Linking to the work in this thesis but using EXIOBASE 3rx with GHG emission extensions would augment the MRIO policy relevance for climate change in several ways. Further work on GHG emissions after added to EXIOBASE 3rx could explore value chains to uncover carbon footprint hotspots and linking this to trade data similar to paper III. A demand system for all 214 countries could establish the connection between affluence and GHG emissions and build on the findings of previous studies. Is there a clear positive correlation, or is the picture more complex like for land use and biodiversity footprint as shown in this thesis?

Adding GHG emissions also has relevance for biodiversity impacts. The contribution of GHG emissions to biodiversity impacts can be significant and globally contributes to about half of the impacts compared to land use (Wilting et al., 2017). A recent study (Arneth et al., 2020) finds that proposed future biodiversity targets risk being severely compromised due to climate change, and calls for climate change-related risks to be addressed explicitly in biodiversity targets. Understanding the contributions of different causes of biodiversity loss and their underlying drivers will be increasingly important as climate change progresses.

Some improvements in linking LC-impact and EXIOBASE 3rx for land use-induced biodiversity footprint analysis stand out. First, the total land area compiled in the satellite accounts of EXIOBASE 3rx is larger than total land area in LC-impact, even after excluding land with low use intensity. This was handled in the analysis by using relative changes instead of reporting absolute biodiversity impact values. The causes of this difference could be that land use data with low intensity is included in EXIOBASE 3rx but not in LC-impact or that the LC-impact characterization factors of biodiversity impact from land use are overestimated if land use with low biodiversity impacts spread over a large area are excluded from the characterization factors. The LC-impact characterization factors are given relative to the natural state prior to human impact which could be different from the total land use in EXIOBASE 3rx. The characterization factors also reflect an increase in the risk of extinction, not an instantaneous biodiversity loss (Verones et al., 2020). After the discrepancies are identified and adjustments are made, the next step should be a full integration of LC-impact characterization factors into EXIOBASE 3rx linking directly to industrial activities instead of through intermediate land use accounts, which would simplify analyses on biodiversity footprints.

A recent study by Cabernard and Pfister (2021) offers an alternative approach to achieving high regional detail for EXIOBASE 3. Here they integrate regional information from Eora26 to disaggregate RoW regions in EXIOBASE 3 and apply the new MRIO (named R-MRIO) to study a wide range of environmental impacts. After new environmental extensions are added to EXIOBASE 3rx, an important task is to compare results from EXIOBASE r3x and R-MRIO to assess uncertainty and identify future development steps for EXIOBASE.

5.2.2 A demand system applied to EXIOBASE 3rx

To further strengthen modeling of the links between drivers through pressures and to impacts in DPSIR (Figure 1) the analysis in paper II and paper III could be combined by integrating a demand system to EXIOBASE 3rx. The income elasticities of biodiversity footprint for example do not adjust for consumption shifts due to price changes. This would require price data, which in paper II was gathered from EXIOBASE 3 that has this readily processed. By processing price data for all regions in EXIOBASE 3rx, the analysis in paper II could be applied to the biodiversity impact analysis in paper III to estimate the income effect on future biodiversity footprints, while the income effect on GHG emissions in paper II could be expanded to 214 regions. This would signify an important improvement to the contributions of this thesis.

5.2.3 Sectoral resolution

There is also further potential for improvement in covering drivers and pressures through increased sectoral resolution in MRIOs. Lack of sectoral detail has been identified as a key limitation for MRIO analysis in general (Lenzen et al., 2013, Krey et al., 2014), and particularly so for MRIO land use studies (Bruckner et al., 2015, Weinzettel et al., 2013, Steen-Olsen et al., 2012) as mentioned in chapter 2. However, exactly which sectors should be disaggregated depends on the direction of development of the database. If EXIOBASE 3rx is to be used as a tool for a broad range of analyses like the previous EXIOBASE versions, numerous sectors might need to be disaggregated. Carbon footprint analyses suffer from lack of detail in the electricity, energy, and transportation sectors, while material footprint analyses require a higher level of detail in the primary material extraction and subsequent processing sectors. As an alternative, EXIOBASE 3rx development could focus on selected environmental extensions such as land, biodiversity, and GHG emissions. This narrows down the sectors relevant for disaggregation to some degree. However, insight into consumer preferences (paper II) might require consumer-relevant sectors such as food, transportation and tourism that stand out in terms of income elasticities to be further disaggregated. The work in this thesis might therefore in total require increased resolution in food, agriculture, forestry, transportation, tourism, and some of the service sectors. This again requires processing, extrapolation and balancing of raw data.

As mentioned in chapter 2, EXIOBASE was built specifically for environmental analyses and used a principle of avoiding aggregation of heterogeneous environmental accounts. However, environmental accounts are aggregated in EXIOBASE as well. An example is land use data that is provided on a fine product level in the raw data, such as the cropland data gathered from FAOSTAT (FAOSTAT, 2020). This is in EXIOBASE 3rx aggregated to 21 different economic sectors (see supporting information of paper I). The raw crops data from FAOSTAT consists of almost 200 different crops, and the total number of sectors in EXIOBASE 3rx would nearly double by keeping these accounts separate only considering cropland data. The MRIO system might consist of over 1000 sectors if the non-aggregation principle is followed for all environmental accounts, and the benefit is more than outweighed by the enormous amounts of work needed to develop such a database. Still there is potential for future work to investigate this. Specifically, this should involve identifying key sub-sectors that should be separate due to heterogeneous environmental multipliers. Perhaps a handful of sub-sectors like this are found for cropland, and similar for other environmental satellite accounts. This could become an iterative process that is evaluated each time new environmental accounts are added to EXIOBASE and would further improve the accuracy of results.

5.2.4 How detailed should an MRIO be?

Although there is still untapped potential in increased resolution in all domains (sectors, regions, years, and extensions) there perhaps is a limit to the need for adding increased detail. For example, adding a very specific crop that only grows and is consumed domestically in one small Pacific island to the harmonized sectoral classification in EXIOBASE 3rx might not warrant the additional data processing for an analysis on the carbon footprint of a Nordic country. Instead, maybe the role of the MRIO developer should be to provide supporting for the regions in the MRIO at the level of detail provided by the national statistics of that region (like the approach in Eora). The MRIO developer would then create a database structure where supporting data could easily be linked to the MRIO through concordances or balancing/reconciliation procedures and similar. The supporting data could consist of expenditure data for different consumer types (e.g. income levels as in Ivanova and Wood (2020)) or highly disaggregate IO tables both in terms of sectors and regions within a country. A researcher performing an analysis on a specific phenomenon in a specific country can then do so with the supporting data and procedures to link to the MRIO, at the same time as the MRIO developer saves time by not having to integrate the supporting data into the MRIO for all regions, data that might not exist for the other regions represented in the MRIO. The global MRIO lab (Lenzen et al., 2017) is a tool that represents a development in the direction sketched out here.

5.2.5 Improved modeling of changes in consumption and consumer behavior

Arguably the largest opportunities for further work is found in increased understanding of drivers and the role of consumer behavior in environmental impact mitigation. Here I outline a few key pieces of future developments in this area.

The work in paper II is the first step towards fully integrating a demand system into an MRIO. A future full integration will allow studying the ripple effects in the economy resulting from price changes, changes in taxes, trade changes etc. and also capture important feedbacks such as rebound effects resulting from price or efficiency changes (see e.g. Brännlund et al., 2007). In the modelling of lifestyle changes for Norwegian households in paper IV, initial carbon footprint reductions were significantly curtailed due to rebound effects and including such effects can constitute a crucial part in accurately modeling consumer behavior.

The model in paper II has the necessary components for a full integration into the MRIO. An integration could be achieved by the use of the Leontief price model as in Mongelli et al. (2010) or by combining an IO model and a computable general equilibrium model as in Sommer and Kratena (2017).

Relating to this is the circular flow of income in the economy which is not included in a demand system. This circular flow can be explained in the following steps (Mainar-Causapé et al., 2018) starting at the approach in paper II. The changes in consumption patterns influence production in the economy which again affects how producers employ factors from e.g. households. Employment generates income to households, and changes in employment therefore again modifies the consumption patterns.

Extending the MRIO model with social accounting matrices (SAMs) offers a solution to accounting for such a circularity. This can be used to analyze social and economic policy better than the IO model by providing insight into the role of people and social institutions in the economy (Miller and Blair, 2009). In the environmental footprints literature SAMs have been used to determine whether changes in CO_2-emissions can be attributed to levels of income, patterns of consumption, or to general decisions about consumption (Duarte et al., 2010), to study the effect of income redistribution on environmental impacts (Lenzen and Schaeffer, 2004), or combined with structural path analysis to further analyze the transmission channels of carbon emissions in the economy (Li et al., 2018).

Another key component is the role of consumer behavior. A first step here could be to disaggregate the household consumption matrix into different categories of consumers. In the outlook into IO analysis for the next 25 years (Dietzenbacher et al., 2013), disaggregation of household final demand into income or consumption categories was identified as a key future development in the field. Now that we have started the eighth of the 25 years, none of the MRIOs available have yet succeeded at this, despite the recent findings suggesting that the difference environmental impacts within countries is as important to unveil as across countries (see chapter 2). The main obstacle to achieve this is the lack of available data, and this has caused analyses on for example the environmental impacts by different income quantiles to be restricted to single regions with the necessary data available (see e.g. Steen-Olsen et al., 2016), but recently progress has been made to undertake such studies on a multiregional level, such as for 26 European countries (Ivanova and Wood, 2020). Achieving this for regionally detailed MRIOs should be pursued since a key to mitigating environmental impacts and at the same time achieving targets for equality and living withing our planetary boundaries might lie in the countries that rank highest on income inequality. Measured in terms of the Gini index (The world Bank, 2021), these are countries such as Namibia, Suriname, Zambia and Sao Tome and Principe which are all covered in EXIOBASE 3rx, but often not in other MRIOs.

A more ambitious development in consumer behavior is to address the limitations of demand models. These models assume homogeneous, non-interacting and rational consumers that have perfect knowledge about the market and base their consumption decisions on rational behavior to maximize their own long-term profit. These assumptions are easily shown not to hold, and increasingly so in recent years with the emergence of single agents with vast power to influence other consumers through e.g. social media platforms. For example engagement in social media brand communities has been shown to increase expenditures and user-generated content has been found to have a stronger influence on consumer demand than market generated content (Goh et al., 2013). Furthermore, the use of humor and emotion was found to lead to higher levels of consumer engagement than informative content like prices and deals (Lee et al., 2018). There is clearly a need for a method that can consider the effects of such interactions between different agents such as consumers and businesses. One such method is agent-based modeling (ABM).

In agent-based modeling (ABM), agents (e.g. consumers) are represented as individual entities that act and interact according to agent states, and often simple rules of behavior (Axtell, 2000) and the limitations of demand systems as described above are overcome (Farmer and Foley, 2009). ABM is rapidly being applied to multiple research fields, and has in environmental analyses been applied to study for example consumer energy choices (Rai and Henry, 2016), landcover change (Evans and Kelley, 2004, Murray-Rust et al., 2014), climate policy (Gerst et al., 2013), and how food security decision-making affects water use and GHG emissions (Namany et al., 2020). However, within the industrial ecology field, agent-based models are not commonly used despite untapped potential to do so (Axtell et al., 2001, Janssen, 2005). The analysis in paper II can be expanded with elements from ABM in several ways. Agents might for example change consumption choices when they observe the consequences of climate change as the years progress. Perhaps some agents have an inherent motivation to reduce their own carbon footprint, while others do not see the link between their own consumption and climate change at all. If people had full access to their own carbon footprint, some agents could be modeled to be motivated by having a lower carbon footprint than their neighbor. Perhaps trends like switching to a vegetarian diet or slow travel or local travel will continue to increase in popularity. In addition, influence from other agents or social media could be incorporated in the consumption behavior. Targeted online advertisement based on purchase history affecting consumption decisions (the issue is discussed e.g. in Xu et al., 2015) or promotion of specific products by agents with a large number of followers in social media are examples of such aspects.

A possible modeling framework incorporating ABM is given in Figure 4 where the demand system and MRIO database is given in the top half of the figure. Instead of having consumer preferences being fed directly back into the MRIO to calculate carbon footprint, the preferences go through an ABM (lower half of the figure).

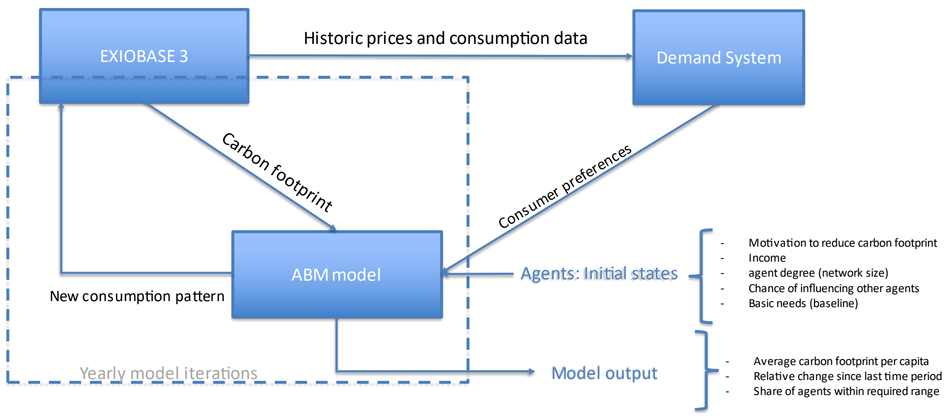

Figure 4: Demand model extended with elements from ABM (own work)

The heterogeneous agents are informed about their own carbon footprint and agents interact and are influenced by other agents and targeted advertisement as outlined above. The agents are heterogeneous in attributes such as income, the size of their network, chance of influencing other agents, and basic needs that the consumption must satisfy. Based on a set of given (often simple) behavioral rules, the agents interact and the consumption pattern from the demand system changes. This is then fed back into the MRIO where carbon footprint is calculated, and information on agents' carbon footprint, and the share of agents who have lowered their carbon footprint within the requirements of global warming targets can be fed back out to the agents. This "query of the population" as named by Axtell et al. (2001) can again influence agents' consumption decisions in the next model iteration (year).

In conclusion, including elements from ABM to improve modeling of consumer behavior and SAMs to include the circular flow of income are improvements that would strengthen the analysis of how consumption-side actions can contribute to reduced environmental impacts and the effects these actions will have on the economic system.

5.2.6 Needed changes to reach environmental targets

A relatively unexplored research area in this thesis is to study from a top-down perspective which changes might be necessary to live within our planetary boundaries. Paper IV is an example of such an analysis where an optimization routine was applied to study the modifications in household consumption needed to stay within the 2°C target of global warming. By using the income elasticities of demand from paper II to model household preferences, this analysis can be expanded globally. The contributions of this thesis to consumer preferences and increased regional detail in MRIO analysis enables a range of analyses on which consumption changes are needed to stay within the limits of our planetary boundaries (Rockström et al., 2009) along with studies on the associated costs or sacrifices of these changes for the consumers. Expanding on the analysis in paper IV, as more environmental extensions are added to EXIOBASE 3rx, a similar approach, but with multiple constraints reflecting the planetary boundaries can be applied. The regional detail in EXIOBASE 3rx can then be used to better reflect which countries and which consumers should bear the responsibility for the largest environmental impact reductions, and which should still be allowed to develop, and hence should be less constrained in their environmental impact reduction responsibility.

Environmental impact mitigation potential from changing consumer preferences (paper II), imposed consumption changes (paper IV), or a bottom-up perspective with elements from ABM are just some examples out of a vast range of demand-side options that could be explored. Much is yet to be done to improve modeling the links between environmental drivers, pressures, and impacts. MRIO analysis can through further developments better model these links, and hereby guide demand-side policy making by pinpointing exactly which actions contribute to environmental impact mitigation and thus assist in focusing efforts to overcome the challenges we face ahead.

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Appendix A Paper I

Bjelle, E. L., Többen, J., Stadler, K., Kastner, T., Theurl, M. C., Erb, K. H., Steen-Olsen K., Wiebe K. S., & Wood, R. (2020). Adding country resolution to EXIOBASE: impacts on land use embodied in trade. Journal of economic structures, 9(1), 1-25.

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Adding country resolution to EXIOBASE: impacts on land use embodied in trade

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Abstract

Multiregional input–output (MRIO) databases are used to analyze the impact of resource use and environmental impacts along global supply chains. To accurately account for pressures and impacts that are highly concentrated in specific sectors or regions of the world, such as agricultural and land-use-related impacts, MRIO databases are being fueled by increasingly more detailed data. To date no MRIO database exists which couples a high level of harmonized sector detail with high country resolution. Currently available databases either aggregate minor countries into rest-of-the-world (WIOD and EXIOBASE 3), or the high country resolution is achieved at the cost of non-harmonized or lower sectoral detail (Eora, OECD-ICIO or the GTAP-MRIO). This aggregation can cause potentially significant differences in environmental and socioeconomic impact calculations. In this paper, we describe the development of an EXIOBASE 3 variant that expands regional coverage from 49 regions to 214 countries, while keeping the high and harmonized sectoral detail. We show the relevance of disaggregation for land-use accounting. Previous rest-of-the-world regions supply one-third of global land, which is used to produce a large range of different products under very different levels of productivity. We find that the aggregation of regions leads to a difference in the balance of land embodied in trade of up to 6% and a difference of land embodied in imports of up to 68% for individual countries and up to 600% for land-use-relevant sectors. Whilst the database can still be considered experimental, it is expected to increase the accuracy of estimates for environmental footprint studies of the original EXIOBASE countries, and provides the first estimates for the countries in the previous rest-of-the world.

Keywords: Multiregional input–output analysis, EXIOBASE, Land use embodied in trade, Country resolution, Rest-of-the-world regions, Regional aggregation, Land footprints

1 Introduction

From the early developments of domestic input–output analysis starting with Leontief (1936), the scope has broadened, both to account for trade relationships across economies (Leontief and Strout 1963) and to extend the framework to enable the attribution of social and environmental impacts, domestic and abroad, to economic activities (Leontief 1970; Miller and Blair 2009). Multiregional input–output (MRIO) models have been widely used in carbon footprint calculations as they provide an appropriate methodological framework for calculations at the national, international and global level (Wiedmann 2009b). In later years, MRIO applications have extended to a wide range of footprint analyses, such as material (Wiedmann et al. 2015; Ivanova et al. 2016; Bruckner et al. 2012; Wiebe et al. 2012), land (Ivanova et al. 2016; Steen-Olsen et al. 2012; Weinzettel et al. 2013), biodiversity (Verones et al. 2017; Lenzen et al. 2012; Wilting et al. 2017, Többen et al. 2018; Marques et al. 2019), labor (Alsamawi et al. 2014a; Simas et al. 2014), income inequality (Alsamawi et al. 2014b) and energy (Wiedmann 2009a; Owen et al. 2017).

The strength of MRIO analysis as a methodology for environmental impact assessment is its ability to trace the impacts of products through the whole supply chain and attribute the impacts at different stages of production to final consumers (Moran and Wood 2014). This enables MRIO analysis to trace increasingly fragmented international supply chains across primary, secondary and tertiary producers, to give a more complete picture of the impacts of final consumption of nations, in comparison to biophysical accounting methods purely based on physical data (Bruckner et al. 2015). A drawback of MRIO analysis in environmental impact studies is the lacking resolution to trace specific products and/or materials (Schaffartzik et al. 2015) or differentiate production technologies in detail. In addition, the efforts to harmonize sectoral and regional data and satellite accounts may require additional aggregation that can compromise the accuracy of environmental and socioeconomic results (Steen-Olsen et al. 2014; Lenzen 2011).

Today several global MRIO databases exist, such as Eora (Lenzen et al. 2013), WIOD (Timmer et al. 2015), GTAP-MRIO (Aguiar et al. 2016), the OECD-ICIO (Yamano and Webb 2018), and EXIOBASE (Tukker et al. 2013). Ideally, a global MRIO is as detailed as possible on both the product/industry resolution as well as on the number of explicitly represented countries. In addition, the ideal MRIO should be available as a consistent long and up-to-date time series and provide detailed socioeconomic and environmental extensions (Tukker and Dietzenbacher 2013). In order to have a consistent database between different world regions, MRIO developers necessarily need to deal with aggregations of extensions, regions and sectors into a standardized classification system (Lenzen 2011). Due to lack of easily available data for many countries, the approach sometimes used to reach global coverage is by estimating "rest-of-the world regions" (RoW), which typically consist of the remaining countries that are not explicitly covered in the database. In EXIOBASE and WIOD, RoW regions comprise over one-third of the world population and 33–44% of global land use, and the aggregation of countries into regions can potentially underestimate impacts embodied in trade, in particular for highly localized pressures such as land use (Stadler et al. 2014).

Discrepancies in environmental impact results across MRIOs are well-documented (Giljum et al. 2019; Owen et al. 2014, 2016; Wieland et al. 2018) and hamper the policy uptake of MRIO results (Moran and Wood 2014; Peters 2007). The robustness of MRIO compared to other methods for estimating sector-specific environmental impacts such as for land use is disputed in the literature. For instance, Schaffartzik et al. (2015) compared biophysical methods and MRIO studies on land use and found a high correlation in regional results for various land use types per capita, except for a few outliers. On the other hand, when trying to interpret MRIO results in comparison to physical trade results, Kastner et al. (2014) found that China is a major net importer of cropland products and embodied cropland in MRIO studies, while physical trade analyses show the opposite. Hubacek and Feng (2016) argue that part of this discrepancy in results between analyses based on MRIO and physical trade balances can be attributed to the differencing system boundaries and conceptual differences, and thus the methods tackle different research questions. Bruckner et al. (2015) summarize the conceptual challenges of using MRIO for attributing land use impacts, especially where aggregation is performed due to lack of product detail (Weinzettel et al. 2014) and regional detail (Stadler et al. 2014). In terms of robustness of impact assessment results from MRIOs, Su et al. (2010) find that around 40 sectors are sufficient to avoid large uncertainties in CO_2 emissions embodied in exports. Comparing the impacts embodied in exports by disaggregating the SUTs of EXIOBASE at a detail of 59 sectors versus 129 sectors, Wood et al. (2014) found differences in the order of maximum 5% for labor and compensation of employees, while CO_2 impacts differed up to 50%. Steen-Olsen et al. (2014) further investigated the effect of sector aggregation on CO_2 multipliers (kg CO^2/\$) in different MRIO databases. Similar to Wood et al. (2014), they found that aggregating sectors of different MRIOs to 17 sectors significantly changed the CO_2 multipliers, and that the multiplier errors increased with increased sectoral detail in the original database. Similarity in economic input structures among sectors did not imply similarity in terms of emission profiles. This advocates for high sectoral detail despite the potentially much larger compilation effort when building MRIOs. This view is supported by Lenzen (2011) who proposed that aggregating environmental extensions to sectors is a large source of uncertainty as they can be highly heterogeneous. Consequently, Lenzen (2011) proposed disaggregating input–output structures to match the detail of the environmental extensions as the best option for estimating input–output multipliers and reducing uncertainties.

The effects of regional aggregation in MRIOs were studied by Bouwmeester and Oosterhaven (2013). Using EXIOBASE, they find large deviations in regional CO_2 footprints (up to 22%) and water use (up to 84%) when aggregating 43 regions to four broad regions and one rest-of-the-world region. Su and Ang (2010) find that energy-related CO_2 emissions are highly dependent on regional aggregation when using an MRIO of China, comparing China as a single region versus split into eight regions. Nevertheless, an earlier paper by Miller and Shao (1990) using an US MRIO model suggests that regional aggregation leads to smaller uncertainties than sectoral aggregation. In part, this is supported by de Koning et al. (2015) who found the aggregation of extensions to be more important than regional and sectoral aggregation for absolute material footprints. Although, due to a significant share of global material extraction in the global south, a more detailed regional coverage of this region in EXIOBASE has been called for by Wiebe et al. (2019). The study of regional aggregation effects due to the RoW aggregation by Stadler et al. (2014) showed that the RoW regions' share of global land use (33–44% of the global total) are much larger than the equivalent share of global warming potential (17–22%). Furthermore, Stadler et al. (2014) found that 38% of global land exports originate in the RoW regions, underlining the need for a higher country resolution to reduce uncertainties in estimating land use embodied in trade.

In terms of available MRIO databases, EXIOBASE has the highest consistent sector resolution of the available MRIO databases, but is limited in regional resolution. Eora has high country coverage and higher sector detail for some counties, but as the level of detail varies from region to region, this complicates the between-region comparison of impacts on a sectoral level. For example, Eora has only one sector aggregating all agricultural, forestry and fishing activities for most countries in the world. The GTAP-MRIO probably has the best compromise of sectoral resolution (57 sectors) and country (140 regions), but is currently not available as a time series, and has limited sectoral resolution outside the agricultural and food sectors. Ideally, there would be a MRIO database with high sector resolution, individual country coverage and a full time-series.

The aim of this paper is to describe the steps towards such an improved MRIO, by increasing the country resolution of EXIOBASE 3 to explicitly including all domestic economies registered in the UN main aggregates database (214 countries, see below).

We use this extended EXIOBASE (named EXIOBASE 3rx) to show the relevance of additional regional disaggregation to estimate land use embodied in trade. We study the degree of regional aggregation errors on both a regional and on a harmonized and detailed product level.

In the following method section, we describe the development of EXIOBASE 3rx and present its methodological building blocks, describe the processing of land use extensions, and the method for comparing the two databases with different regional resolution. In the result section, we present land footprints and explore the degree of regional aggregation errors for land use embodied in trade. To isolate the effect of regional aggregation on land use, we compare an EXIOBASE version where the MRIO structure is pre-aggregated (aggregation of IO data before calculation of coefficients and results), referred to from now on as the aggregated database, with EXIOBASE 3rx, where the land use results of the full detailed database are aggregated to 49 regions. The implication of this work is further picked up in the next section, where we discuss our results for both MRIO development and the use of MRIO for land use studies now and in the future.

2 Methods

2.1 Building EXIOBASE 3rx

The approach to building the monetary supply–use tables for EXIOBASE 3rx (Fig. 1) closely follows previous approaches establishing EXIOBASE 3 and EXIOBASE 2 (Wood et al. 2015, Stadler et al. 2018). Deviations from the EXIOBASE 3 workflow can be found in Additional file 1: S1. In EXIOBASE 3, the economic structures of 44 regions are available in the form of (aggregate) supply–use tables (SUTs). These SUTs are both disaggregated and balanced to product, industry, and trade data. From the SUTs, a trade-linking procedure (Wood et al. 2015) and application of an IO construct (Majeau-Bettez et al. 2014) is applied to obtain square MRIO tables. In order to estimate the SUTs for the RoW regions in EXIOBASE2 and 3, global average coefficient data was reconciled with product output, industry and trade data (see Stadler et al. (2014) for more information). EXIOBASE 3 adds top-level constraints of macroeconomic data to ensure consistency between regions and over time at a highly aggregate level.

EXIOBASE 3 had a strong European focus (28 EU member states, 16 major economies) and 5 RoW regions (RoW Asia and Pacific, RoW Europe, RoW Africa, RoW America, RoW Middle East). In this work, we extend the procedure used in estimating RoW

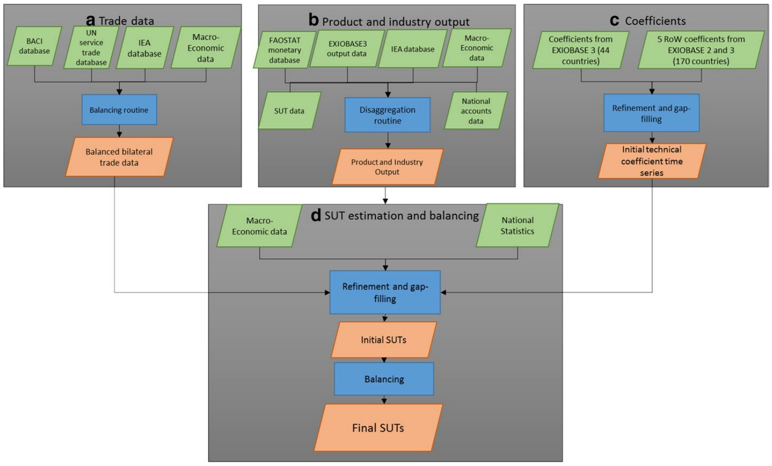

Fig. 1 EXIOBASE 3rx: compilation steps for monetary supply use tables. Approach based on figure in Stadler et al. (2018)

regions in EXIOBASE 3, but apply it to individual countries in order to expand the number of regions from originally 49 to 214 (Additional file 2). As SUT data are not commonly available for the countries in the RoW regions, we follow the regional approach where we use proxy data in the form of generic estimates of coefficients of the supply (i.e., market share relationships) and use matrices (intermediate use and final demand coefficients) to give an initial estimate of the product/industry transactions. The coefficients are then reconciled to globally balanced estimates of trade data, estimates of product outputs for every country and macroeconomic data on value added, taxes, exports, imports, final consumption and gross capital formation (for an overview of regional data sources, see Additional file 1: S2). The macroeconomic data serve as the top-level data towards which all the other data are balanced. The number of countries is based on the available macroeconomic data from the UN National Main Aggregates Database (United Nations 2018a). Additionally, we estimate land use extensions for all 214 countries (more info in Additional file 1: S11).

2.2 Trade estimates and reconciliation

In order to process the country-specific trade data, we combine data from three data sources when compiling the trade estimates. The BACI database is the main data source (balanced product trade data based on the UN Comtrade database, for more information see Gaulier and Zignago (2010)), while the UN services trade database (United Nations. 2018b) and the IEA database (International Energy Agency 2018) provide data for services and energy products/services, respectively. Re-exports are estimated in the same way as EXIOBASE 2 and 3 (based on SUT data for re-exports where available, and extrapolated based on Comtrade data).

After compiling the initial estimate of the trade data, this is reconciled against the top-level macroeconomic trade data in current price obtained from the UN National Accounts Main Aggregates Database. Here, we replace the quadratic programming approach with an information theoretical approach. We minimize cross-entropy (CE), also known as Kullback–Leibler Divergence (Kullback and Leibler 1951), between the final trade flows of product i from country r to country s, p_i^{rs}, and their initial estimate q_i^{rs}, subject to constraints requiring that total export and import values from the UN National Main Aggregates Database, EX^r and IM^s, are met. In addition to the constraint that total exports by country and product are less than gross output, $x_{\mathrm{max_i}}^r$. For the general methodology, see Golan and Vogel (2000). As in Többen and Schröder (2018), we implement the computationally much more efficient unconstrained dual of the minimal cross-entropy problem. In the dual version, the cross-entropy model takes the form

$$\begin{aligned}\max_{\lambda} D = &\sum^{r} \lambda_1^r EX^r + \sum^{s} \lambda_2^s IM^s + \sum_{i}^{r} \left(\lambda_{\mathrm{max}_i}^r - \lambda_{\mathrm{min}_i}^r x_{\mathrm{max}_i}^r\right) \\ &- \sum_{i}^{rs} q_i^{rs} \exp\left\{\lambda_1^r + \lambda_2^s + \lambda_{\mathrm{max}_i}^r - \lambda_{\mathrm{min}_i}^r\right\} \\ &- \sum_{i}^{r} \lambda_{\mathrm{max}_i}^r x_{\mathrm{max}_i}^r - \sum_{i}^{r} \lambda_{\mathrm{min}_i}^r x_{\mathrm{min}_i}^r,\end{aligned} \tag{1}$$

where λ_1^r and λ_2^s are Lagrangian multipliers referring to the equality constraints. Following the approach of Kazama and Tsujii (2005), the inequality constraints are formulated as lower and upper bounds with $\lambda_{\mathrm{max}_i}^r$ and $\lambda_{\mathrm{min}_i}^r$ being the Lagrangians and $x_{\mathrm{max}_i}^r$ and $x_{\mathrm{min}_i}^r$ being the bounds. In this application, the lower bounds are equal to zero, whereas the upper bounds are equal to gross output by country and product.

From the Lagrangians maximizing D, the final trade flows can be computed by

$$p_i^{rs} = \frac{q_i^{rs} \exp\left\{\lambda_1^r + \lambda_2^s + \lambda_{\mathrm{max}_i}^r - \lambda_{\mathrm{min}_i}^r\right\}}{\sum_i^{rs} q_i^{rs} \exp\left\{\lambda_1^r + \lambda_2^s + \lambda_{\mathrm{max}_i}^r - \lambda_{\mathrm{min}_i}^r\right\}}. \tag{2}$$

2.3 Estimating product output

Product output estimates were processed in EXIOBASE 3 (Stadler et al. 2018) and combines data from several national account databases, FAOSTAT (2014), IEA energy balances (IEA 2015) and product output from EXIOBASE 2 (for more information see Additional file 1: S1 and S9 in Stadler et al. (2018)). The main difference is that for EXIOBASE 3rx we process the raw data on an individual country level also for all former RoW countries. In the next step, these data sources served to disaggregate the UN macroeconomic industry output data (United Nations. 2018a), which consists of gross value added from seven aggregated industries. By applying a concordance matrix between the seven UN industries and the 163 EXIOBASE industries (Additional file 1: S3) and by assigning a quality index to the different data sources based on their closeness to raw data, the routine disaggregates the UN industry data. The disaggregation is based on the values in the chosen raw data source. The result is product output at the level of the 163 industries and 200 products of EXIOBASE. In general, this procedure should give reasonable estimates for agricultural, food and energy products, whilst missing detailed country-specific data on manufactured products and services.

2.4 Initial estimates of the input–output structure

For the 44 countries that exist in EXIOBASE 3, the coefficients are used directly as initial estimates in EXIOBASE 3rx. For each of the 170 RoW countries, we use the coefficients from the respective RoW region from EXIOBASE 3. If EXIOBASE 3 coefficients caused balancing problems—such as conflicting constraints between the initial estimate of the SUT and the top-level macroeconomic data, we used EXIOBASE 2 coefficients instead.

2.5 Balancing supply–use tables

The monetary SUT balancing routine applies an algorithm similar to the approach in Stadler et al. (2018) using a quadratic programming target function. One important difference here is that, due to lack of data on a detailed country level, taxes, trade and transport margins are not estimated as explicit layers in our approach. Hence, our system is an MRIO in basic pricing only. The results are monetary SUTs estimated for every country and year independently for a time series from 1995 to 2015 for 214 countries. The balancing routine was unable to find a solution for a few countries, about 3.3% of all cases through the time series. See an overview in Additional file 1: S5 of the unbalanced countries.

2.6 Converting from monetary SUTs to IO tables

To go from individual SUTs to analytical IOTs, we stop at the step before creating fully detailed multiregional input–output tables (see Peters et al. 2011), and instead aim for trade-linked IOTs. This gives us the possibility to apply bilateral trade approaches rather than full MRIO approaches (Peters 2008, and see below). Due to the approach outlined above (balancing trade first, and not changing it in the SUT balancing), we ensure that the final SUTs are globally consistent (i.e., that imports and exports match for trading partners). The result is hence a fully trade-linked SUT system. In the final step, SUTs were converted to IO tables using the procedure described in EUROSTAT (2008). The industry technology construct is applied to deal with co-production. Using this approach, we avoid the problem of negative coefficients that could be faced when applying, e.g., the commodity technology construct (Jansen and Raa 1990). The choice of producing trade-linked IO tables rather than fully compiled MRIO tables (as per EXIOBASE3) was due to the significantly lower loading and running time, and does not constitute a loss of data (we had no additional data to inform the trade relationships). Normal desktop computers are not able to handle the memory requirements of a fully complied MRIO system of the size of EXIOBASE 3rx, but can easily handle the trade-linked system. Because of the trade proportionality assumption over the import use estimates, if a full MRIO system is desired, either the approach of Peters et al. (2011) could be followed if no memory constraints exist, or topological transformation of the data could be applied as explained in Rodrigues et al. (2016).

2.7 Compiling the land use data

To obtain land use data at the sectoral resolution of EXIOBASE, we followed a two-step procedure: First, we created spatially explicit maps for major land cover types based on publicly available state-of-the-art datasets. The data were harmonized following a closed-budget mapping approach (Erb et al. 2007), i.e., the sum of all layers will add up to 100% or the available land area for each specific grid cell. In a second step, we utilized information from census statistics (FAOSTAT) to further disaggregate the data to closely match the EXIOBASE sector classification (in table format). See Additional file 1: S11 for a detailed description of establishing the land use dataset.

The land use extensions comprise 207 countries, which cover most of the countries in EXIOBASE 3rx. For the remaining seven countries, mainly Island states like Palau and Nauru, we use the land area variable from FAOSTAT (2019) to estimate the land use accounts of the missing countries. We first choose a country (country A) with existing land use data and geographical proximity to the country with missing data (country B). Next, the land use extensions of country B are estimated by scaling the data of country A based on the land area variable of country B relative to that of country A. Next, we remap the land use data into EXIOBASE 3rx format. Here, we follow the same procedure as in EXIOBASE 3, and therefore refer the reader to S6 of Stadler et al. (2018). The resulting 40 land use extensions consist of land used by the EXIOBASE 3rx production sectors (**F**) and land directly allocated to households (**F_hh**).

2.8 Estimating land footprints

Due to the large size of EXIOBASE 3rx (e.g., the coefficient matrix (**A**) has $42{,}800 \times 42{,}800$ data points), most of the arrays are saved in a sparse format in MATLAB to reduce disk storage requirements. The sparse format database for one year is approximately 60 megabytes.

We used the emissions embodied in bilateral trade (EEBT) approach (Peters 2007, 2008) to do land use calculations using EXIOBASE 3rx rather than calculating impacts from the MRIO system directly. The main difference is that we do not account for intermediate demand of imports that go to industries to produce exports. Hence, a limitation is that imports that are used for intermediate production, that later end up as exported goods are not accounted for. However, as we are studying aggregate land embodied in trade, and not that resulting from a particular final demand, the EEBT approach is suitable as discussed in Peters (2007). The basic principles of the EEBT approach are explained in S12. Stadler et al. (2014)'s additional information explains the EEBT approach in detail.

2.9 Analyzing the effect of regional aggregation

To enable comparison of the pre-aggregated database and EXIOBASE 3rx for land use results, we aggregate the inter-industry flow matrix (**Z**), the final demand matrix (**Y**), the total land use of production (**F**), and land directly allocated to households (**F_hh**) to 49 regions using a regional bridging (Additional file 2). Next, we calculate the coefficient matrix (**A**) and the land use multipliers (**S)** per monetary unit. We refer to this as the aggregated database from now on. Note that we do not compare land use results of EXIOBASE 3rx and EXIOBASE 3 directly as it would be difficult to distinguish the effect of regional disaggregation to effects arising from other changes (see Additional file 1: S1 for an overview of the differences in workflows between the databases). Two of the most prominent changes to the workflow are the mentioned updated trade processing and reconciliation, and re-processed and more detailed land use extensions. In addition, the land use dataset was newly established specifically for EXIOBASE 3rx.

For comparing the land embodied in trade between the EXIOBASE 3rx and the aggregated database, we define the aggregation error as the sum of the absolute difference of the traded land in question:

$$\in = \sum_{s=1}^{n} \left(\left| T_{q,r,p_{\mathrm{EXIO3rx}}} - T_{q,r,p_{\mathrm{Agg}}} \right| \right), \tag{3}$$

where T is a three-dimensional array of land embodied in imports or exports with dimensions imports/exports (q) by trade partner (r) by product (p). s corresponds to the summed-over dimension(s) and n is the number of data points in the summed-over dimension(s). n varies according to the type of aggregation error in question. We examine aggregation errors of imports and exports of products, between regions, and specific product–region combinations. Hence, for, e.g., the product aggregation error of imports, we sum over q, r—exporting and importing countries. Similarly, for the aggregation error of exports of specific goods originating in specific countries, we sum over r—importing countries. Note that we exclude intra-RoW trade in EXIOBASE 3rx aggregated to 49 regions for the sake of comparison with the aggregated database, where intra-RoW trade is part of domestic demand.

"Aggregation error" refers to the difference in results between those from one input–output table and those from a pure aggregation of the same input–output table prior to calculations (as per literature, e.g., Gibbons et al. (1982)). It must be noted that input–output tables are always estimates of actual transactions and the more disaggregated an input–output table is (especially in the case at hand where there is very poor statistical coverage of some countries) the higher the level of uncertainty of these transactions. Most literature (e.g., Lenzen (2011)) point to the benefit of disaggregation for reducing the uncertainty of footprint calculations, but we do not explore that here. As such, it must be remembered that uncertainty related to disaggregation, and the concept of aggregation error are related, but different concepts. We expect, but cannot measure whether the accuracy of our results will increase by disaggregating EXIOBASE3, whilst we can measure the aggregation error between the disaggregated database and a pure of aggregation of the same database.

Using Eq. 3 we define the aggregation error score $\in_s$ as the aggregation error divided by the export/imports of the region, product or product–region combination in the 49 region version of EXIOBASE 3rx:

$$\in_s = \frac{\in}{T_{q,r,p_{\mathrm{EXIO3rx}}}}. \tag{4}$$

3 Results

The results of the construction process for EXIOBASE 3rx are available at https://doi.org/10.5281/zenodo.2654460. Country SUTs are available as well as IOTs and land extensions. Furthermore, in Additional file 3 we provide compiled production, consumption and trade-related results for land use. Here, we proceed with an analysis of these results, and the differences introduced by regional disaggregation.

Table 1 Percentage of intra-RoW region exports for year 2015

% of exports within region		Rank export partners
RoW Asia and Pacific	22.2	1
RoW Europe	8.6	2
RoW Middle East	15.4	1
RoW America	26.2	1
RoW Africa	11.9	2

3.1 Trade comparisons

The added regional detail changes the trade structure of EXIOBASE 3rx compared to the aggregated database and EXIOBASE 3. In EXIOBASE 3, intra-RoW trade flows are treated as “domestic” flows, while they are treated as inter-country trade flows in EXIOBASE 3rx. In 2015 intra-RoW trade (as classified in EXIOBASE 3) is the largest or second largest export destination of each continental region (Table 1).

This has relevance to the regional disaggregation of EXIOBASE 3 for footprint analyses both for the countries within the RoW region and for the trade partners importing from the RoW region. In the former case a footprint resulting from a demand for an imported good from, e.g., Thailand to the Philippines would be treated as domestic in EXIOBASE 3 with the land use (or emission) intensity equal to the RoW region, while in EXIOBASE 3rx the footprint is treated as imports using the land use intensity of Thailand, which can lead to highly differing results as discussed in the introduction. In the latter case, a final demand of imports from a RoW region with destination in a region outside the RoW region will in both EXIOBASE 3 and EXIOBASE 3rx be treated as an import, but the emission intensity will differ. In EXIOBASE 3 the RoW land use intensity of production is used, while in EXIOBASE 3rx the land use intensity of production of the region now disaggregated from the RoW region forms the basis of the footprint.

3.2 Land footprints

The cropland footprints per capita for all 214 regions in 2015 are presented in Fig. 2 (see Additional file 1: S10 for figures on other land use types and Additional file 3 for per capita footprints for individual land use types and aggregated across all land use types). Monaco has the largest cropland footprint per capita (24,700 m^2/cap) followed by Luxembourg (19,100 m^2/cap) and the United Arab Emirates (9 100 m^2/cap). The lowest footprints are found in Timor-Leste (257 m^2/cap), Bermuda (336 m^2/cap), and Zanzibar (353 m^2/cap). Large economies such as the United States (3620 m^2/cap), Russia (5250 m^2/cap), Germany (3260 m^2/cap) and France (3330 m^2/cap) have cropland footprints per capita well above the global average of 2130 m^2/cap, while those of China (1710 m^2/cap) and India (1260 m^2/cap) are below the global average. In general, the highest per capita footprints are in Europe, the Middle East, Eastern and Northwestern parts of Asia and a few scattered African countries. The import share of total cropland consumed highly varies between countries (see Additional file 3). With countries in the Middle East, some island states and Eastern parts of Asia, having import shares of 100%, while particularly several African countries import less than 5% of the land area needed

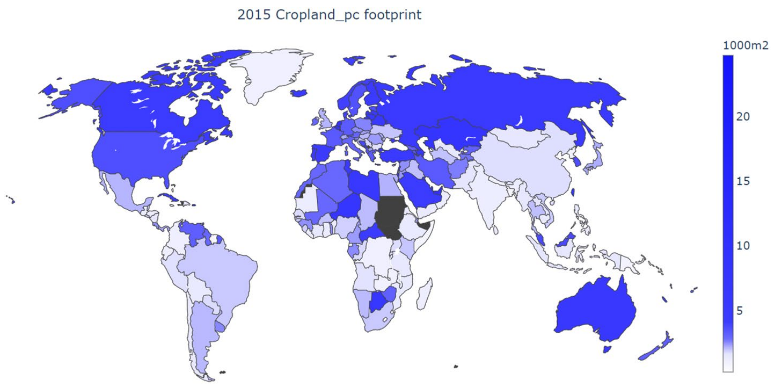

Fig. 2 Map of cropland footprints per capita for year 2015 for 214 countries. Unbalanced countries in dark gray (Comoros, Haiti, Liechtenstein, South Sudan and Sudan)

to satisfy their cropland consumption. For EXIOBASE 3rx, the global import share of cropland consumption increased from 20.9% in 1995 to 42.7% in 2015.

The global consumption-based per capita forest footprint is 3650 m^2, with the largest values found for Finland (68,100 m^2) and New Caledonia (49,300 m^2), and smallest for Palestine (82.4 m^2) and Yemen (146 m^2). The global imported share of total forest consumption is 36.0%. The global per capita grazing land footprint is 3650 m^2 with an import share of 21.3%. Mongolia (1,34,000 m^2) and Botswana (97,500 m^2) have the highest values and North Korea (99.5 m^2) and Bangladesh (113 m^2) have the lowest per capita values. The British Virgin Islands (1650 m^2) and Australia (1500 m^2) have the highest per capita infrastructure footprints, well above the global average of 185 m^2. The total land use summed across all land types has grown by 1.6% from 1995 to 2015. On a per capita basis, global land use has decreased from 15 600 m^2 ha/capita to 12 300 m^2/capita (27%) from 1995 to 2015. This is driven by a moderate decrease in consumption-based land use in populous countries such as India, Brazil and the United States, and a stronger decrease in several African countries. Increases in countries such as China, Germany and the Netherlands partly offset the effect.

Overall there is a factor of 2.20 increase of land embodied in trade from 1995 to 2015. This increase is driven by a growth in exports from geographically large countries such as Russia, Australia and Brazil. China has largely single-handedly driven the global increase in imported land, from 2.3% of the global total in 1995 to 27.4% in 2015. At the same time, the global share of imported land has decreased particularly for Japan (9.5% in 1995 and 3.6% in 2015) and the United States (11.5% in 1995 and 8.4% in 2015).

3.3 Comparison of regional disaggregation

EXIOBASE 3rx shows global land embodied in trade as 25.8% of global land use, compared to 24.2% in the aggregated database (Table 2) (For equivalent results for all countries in EXIOBASE 3rx, see Additional file 1: S13.) Comparing country-specific trade balances of land for the databases, there is consistency in which countries are net

Table 2 Land area use from production, consumption, exports as share of production, imports as share of consumption, and the balance of land area embodied in trade (BLET) for EXIOBASE 3rx aggregated to 49 regions and the aggregated database for year 2015 (adapted from Peters and Hertwich 2008)

Region	EXIOBASE 3RX					Aggregated database				
	Production (km^2)	Consumption (km^2)	Exports %	Imports %	BLET %	Consumption (km^2)	Exports %	Imports %	BLET %	BLET difference
Austria	80,300	119,000	48.6	65.4	−16.8	120,000	48.6	65.7	−17.0	0.2
Belgium	30,600	227,000	66.6	95.5	−28.9	199,000	66.6	94.9	−28.3	−0.6
Bulgaria	110,000	75,100	44.7	19.4	25.3	76,300	44.7	20.6	24.1	1.2
Cyprus	9000	9980	38.6	44.7	−6.0	10,300	38.6	46.1	−7.5	1.5
Czech Republic	78,800	88,000	49.1	54.5	−5.4	88,800	49.1	54.9	−5.8	0.4
Germany	355,000	796,000	37.3	72.0	−34.7	813,000	37.3	72.6	−35.3	0.6
Denmark	43,300	72,300	56.0	73.6	−17.6	73,500	56.0	74.1	−18.0	0.4
Estonia	43,200	21,300	77.3	53.9	23.3	21,100	77.3	53.5	23.8	−0.4
Spain	499,000	517,000	39.9	42.0	−2.1	545,000	39.9	44.9	−5.0	2.9
Finland	284,000	467,000	35.5	60.7	−25.2	466,000	35.5	60.7	−25.1	−0.1
France	588,000	837,000	32.8	52.8	−20.0	815,000	32.8	51.5	−18.8	−1.2
Greece	126,000	134,000	32.6	36.4	−3.7	133,000	32.6	36.0	−3.4	−0.3
Croatia	54,800	53,700	20.2	18.6	1.6	54,400	20.2	19.7	0.6	1.0
Hungary	92,100	73,700	52.8	41.1	11.8	72,900	52.8	40.4	12.5	−0.7
Ireland	70,200	63,300	75.2	72.5	2.7	67,800	75.2	74.3	0.9	1.8
Italy	290,000	571,000	24.3	61.5	−37.2	566,000	24.3	61.2	−36.9	−0.3
Lithuania	64,100	57,500	57.0	52.0	5.0	52,700	57.0	47.7	9.3	−4.3
Luxembourg	2500	26,800	75.6	97.7	−22.1	26,600	75.6	97.7	−22.1	0.0
Latvia	64,200	43,300	79.5	69.6	9.9	40,300	79.5	67.3	12.2	−2.3
Malta	238	3800	26.0	95.4	−69.4	5300	26.0	96.7	−70.7	1.3
Netherlands	35,700	336,000	69.9	96.8	−26.9	371,000	69.9	97.1	−27.2	0.3
Poland	310,000	310,000	36.8	36.8	0.0	307,000	36.8	36.1	0.7	−0.7
Portugal	88,700	183,000	37.5	69.7	−32.2	166,000	37.5	66.6	−29.2	−3.0
Romania	236,000	183,000	36.2	17.7	18.5	186,000	36.2	18.9	17.3	1.2
Sweden	394,000	424,000	38.5	42.9	−4.5	431,000	38.5	43.8	−5.4	0.9
Slovenia	20,300	24,400	49.7	58.0	−8.3	23,100	49.7	55.7	−6.0	−2.3

Table 2 (continued)

Region	EXIOBASE 3RX					Aggregated database				
	Production (km²)	Consumption (km²)	Exports %	Imports %	BLET %	Consumption (km²)	Exports %	Imports %	BLET %	BLET difference
Slovakia	48,900	37,600	69.4	60.2	9.2	38,700	69.4	61.4	8.0	1.2
United Kingdom	248,000	515,000	22.0	62.3	−40.4	581,000	22.0	66.6	−44.6	4.3
United States	7,740,000	7,840,000	23.9	24.8	−1.0	8,030,000	23.9	26.6	−2.7	1.8
Japan	410,000	1,220,000	5.0	68.2	−63.1	1,360,000	5.0	71.5	−66.4	3.3
China	6,990,000	12,300,000	15.8	51.9	−36.2	12,100,000	15.8	51.4	−35.6	−0.6
Canada	3,410,000	2,700,000	29.7	11.0	18.7	2,710,000	29.7	11.4	18.3	0.5
South Korea	105,000	719,000	11.7	87.1	−75.4	754,000	11.7	87.7	−76.1	0.6
Brazil	6,950,000	5,810,000	19.4	3.5	15.9	5,750,000	19.4	2.5	16.9	−1.0
India	3,070,000	3,390,000	9.4	18.1	−8.7	3,430,000	9.4	19.1	−9.7	1.0
Mexico	1,910,000	1,710,000	26.2	17.5	8.7	1,710,000	26.2	17.9	8.3	0.4
Russia	10,200,000	7,110,000	33.6	4.9	28.7	7,000,000	33.6	3.5	30.1	−1.5
Australia	4,870,000	1,800,000	64.9	5.1	59.8	1,860,000	64.9	8.3	56.6	3.2
Switzerland	36,000	72,600	49.4	74.9	−25.5	79,200	49.4	77.0	−27.6	2.1
Turkey	761,000	971,000	13.1	31.9	−18.8	959,000	13.1	31.0	−18.0	−0.8
Taiwan	35,800	1,230,000	48.6	98.5	−49.9	990,000	48.6	98.1	−49.5	−0.4
Norway	262,000	209,000	47.6	34.3	13.3	207,000	47.6	33.6	14.0	−0.7
Indonesia	1,810,000	2,160,000	16.1	29.6	−13.6	2,200,000	16.1	31.1	−15.0	1.5
South Africa	1,190,000	952,000	28.7	10.5	18.2	935,000	28.7	8.9	19.8	−1.6
RoW Asia and Pacific	8,810,000	8,820,000	21.8	21.9	0.0	8,460,000	21.8	18.6	3.2	−3.3
RoW America	8,120,000	7,240,000	24.0	14.8	9.2	7,470,000	15.7	8.4	7.2	1.9
RoW Europe	1,090,000	711,000	46.3	17.8	28.5	770,000	37.7	11.9	25.7	2.8
RoW Africa	17,200,000	14,800,000	19.4	6.7	12.7	14,900,000	16.6	3.6	13.0	−0.3
RoW Middle East	1,110,000	2,280,000	26.6	64.4	−37.8	2,280,000	15.0	58.7	−43.7	5.9
Total	90,300,000	90,300,000	25.8	25.8	0.0	90,300,000	24.2	24.2	0.0	0.0

BLET is the export share out of total consumption minus the import share out of total consumption. BLET difference is the percentage difference in BLET between the databases importers and exporters, but there is a difference of up to 5.9% in the balance of land embodied in trade between the databases.

The top 20 products (global aggregation of results across all countries) ranked according to aggregation error of land embodied in imports are displayed in Table 3. Remembering that the impacts embodied in imports originating in the non-RoW regions are identical in the aggregated and disaggregated database, these results reflect the effect of disaggregation purely of the EXIOBASE 3 RoW regions. The land embodied in imports associated with “Products of forestry, logging and related services (02)” is the single largest product group, with 66,10,000 km^2 or 30.2% of total global land use embodied in imports. This product group is somewhat susceptible to regional aggregation error, with a summed difference between the aggregated and disaggregated database of 6,60,000 km^2 or 19.4% of the total aggregation error observed between the models. In contrast, for “Meat animals nec” and “Hotel and restaurant services (05) “the share of land use embodied in exports is only in the range of 1–2%, but the aggregation error of the product relative to the flow (shown by the “error score”) is much higher at 64% and 95% of the value of the estimated flow, respectively. This suggests a large degree of uncertainty due to regional aggregation in the aggregated database. The last column of Table 3 shows that the aggregation can change the value of the flow by a factor of over five (“Copper ores and Concentrates”) where the value in the aggregated database is 17% of the corresponding value in EXIOBASE 3rx.

The aggregation error for land embodied in imports for regions sorted by regional error score (Table 4) shows that the countries with the largest scores, such as Australia and Malta, have a low share of global imports, although the net effect of the aggregation error for the countries is significant. Countries with a low import share out of total consumption of land, such as Russia, Brazil and Australia (Table 2) have the largest aggregation errors. In addition, these countries stand out with a high proportion of land originating in EXIOBASE 3 RoW regions. A large share of the regional aggregation error is centered in Asia due to Taiwan and Japan having relatively larger aggregation error shares than land import shares, combined with China dominating land imports (although the aggregation error is relatively lower).

Digging deeper into the land embodied in imports by also showing the traded product (Additional file 1: Table S1), we find that the six largest product- and region-specific aggregation errors are due to imports for Taiwan, China and India. Together, they make up about 19% of global aggregation error of land embodied in imports. Asian countries dominate the top 20 list. We also notice that certain items, such as imports of “Hotel and restaurant services (55)” to China and “Meat animals nec” to Japan have significant aggregation error scores. The net effect of the aggregation can change results by up to an order of magnitude (“Chinese imports of Hotel and restaurant services (55)”).

By also including the origin region of the imported good, the concentration of the aggregation error around Asian regions and “Products of forestry, logging and related services (02)” becomes even more apparent (Additional file 1: S8). The total global aggregation error is concentrated on a few flows, with the top 20 contributors to the error summing up to 25% of the global total error. 12 of the top 20 flows are imports originating in RoW Asia.

Table 3 Top 20 product aggregation error of land embodied in imports (2015)

Product	Total land area of flow (km^2)	Share of global land area (km^2), %	Aggregation error (km^2)	Error score (ε)	Share of total aggregation error, %	Difference between databases (100% is equal to no difference), %
Products of forestry, logging and related services (02)	6,610,000	30.2	660,000	0.10	19.4	95
Oil seeds	1,770,000	8.1	251,000	0.14	7.4	95
Hotel and restaurant services (55)	223,000	1.0	209,000	0.93	6.1	159
Meat animals nec	327,000	1.5	208,000	0.64	6.1	126
Wood and products of wood and cork (except furniture); articles of straw and plaiting materials (20)	1,150,000	5.3	135,000	0.12	4.0	92
Products of meat cattle	1,810,000	8.3	127,000	0.07	3.7	98
Food products nec	762,000	3.5	118,000	0.15	3.5	108
Chemicals nec	406,000	1.9	117,000	0.29	3.4	96
Vegetables, fruit, nuts	643,000	2.9	104,000	0.16	3.1	106
Wheat	1,020,000	4.7	104,000	0.10	3.0	91
Copper ores and concentrates	98,800	0.5	93,300	0.94	2.7	17
Cereal grains nec	755,000	3.5	78,400	0.10	2.3	93
Other business services (74)	55,100	0.3	52,500	0.95	1.5	151
Crops nec	374,000	1.7	51,200	0.14	1.5	98
Real estate services (70)	38,200	0.2	50,500	1.32	1.5	181
Cattle	1,510,000	6.9	48,800	0.03	1.4	101
Crude petroleum and services related to crude oil extraction, excluding surveying	103,000	0.5	44,300	0.43	1.3	94
Dairy products	529,000	2.4	40,600	0.08	1.2	99
Furniture; other manufactured goods n.e.c. (36)	233,000	1.1	39,600	0.17	1.2	113
Construction work (45)	53,600	0.2	39,100	0.73	1.1	147

Ranked according to percentage of total product aggregation error. The error score is relative to the total value of the specific flow of imports. The share of total aggregation error refers to the aggregation error summed across all flows (i.e., global). The difference between databases shows the value of the flow in the aggregated database compared to that in EXIOBASE 3rx

Table 4 Land embodied in imports and aggregation error of 49 regions (2015)

Region	Total land area of flow (km^2)	Share of global land area (km^2), %	Aggregation error (km^2)	Error score (ε)	Share of total aggregation error, %	Difference between databases (100 is equal to no difference), %
AU	92,300	0.4	67,400	0.73	2.0	168
MT	3620	0.0	2050	0.57	0.1	141
BR	203,000	0.9	83,100	0.41	2.4	70
RU	350,000	1.6	143,000	0.41	4.2	69
FR	442,000	2.0	161,000	0.37	4.7	95
ZA	99,900	0.5	35,600	0.36	1.0	84
CH	54,400	0.2	18,000	0.33	0.5	112
GB	321,000	1.5	100,000	0.31	2.9	121
HR	10,000	0.0	3010	0.30	0.1	107
IN	614,000	2.8	183,000	0.30	5.4	107
ES	217,000	1.0	63,400	0.29	1.9	113
RO	32,300	0.1	9200	0.28	0.3	108
PT	127,000	0.6	34,900	0.27	1.0	87
LU	26,200	0.1	7030	0.27	0.2	99
BE	217,000	1.0	57,600	0.27	1.7	87
SI	14,200	0.1	3740	0.26	0.1	91
GR	48,600	0.2	12,700	0.26	0.4	99
TW	1,210,000	5.6	315,000	0.26	9.2	80
NO	71,700	0.3	16,900	0.24	0.5	97
TR	310,000	1.4	72,500	0.23	2.1	96
DK	53,200	0.2	12,200	0.23	0.4	102
LT	29,900	0.1	6730	0.23	0.2	84
NL	325,000	1.5	71,600	0.22	2.1	111
IT	351,000	1.6	75,200	0.21	2.2	99
DE	573,000	2.6	112,000	0.19	3.3	103
JP	834,000	3.8	160,000	0.19	4.7	117
IE	45,900	0.2	7890	0.17	0.2	110
HU	30,300	0.1	4930	0.16	0.1	97
WM	1,350,000	6.2	213,000	0.16	6.2	99
BG	14,600	0.1	2210	0.15	0.1	108
PL	114,000	0.5	16,800	0.15	0.5	97
WE	100,000	0.5	14,600	0.15	0.4	92
CY	4460	0.0	636	0.14	0.0	106
AT	78,000	0.4	10,900	0.14	0.3	101
US	1,950,000	8.9	252,000	0.13	7.4	110
KR	626,000	2.9	76,700	0.12	2.3	106
LV	30,200	0.1	3530	0.12	0.1	90
ID	639,000	2.9	73,800	0.12	2.2	107
CZ	48,000	0.2	5400	0.11	0.2	102
CN	6,360,000	29.1	677,000	0.11	19.8	98
EE	11,500	0.1	1180	0.10	0.0	98
SK	22,600	0.1	2280	0.10	0.1	105
SE	182,000	0.8	16,400	0.09	0.5	104
WF	530,000	2.4	46,700	0.09	1.4	100
CA	296,000	1.4	23,700	0.08	0.7	105
WA	1,580,000	7.3	100,000	0.06	2.9	100
MX	298,000	1.4	14,200	0.05	0.4	103
FI	284,000	1.3	5690	0.02	0.2	100
WL	622,000	2.8	12,200	0.02	0.4	101

Table 4 (continued)

Sorted by aggregation error score. The error score is relative to the total value of the specific flow of imports. The share of total aggregation error refers to the aggregation error summed across all flows (i.e., global). The difference between databases shows the value of the flow in the aggregated database compared to that in EXIOBASE 3rx

4 Discussion

4.1 Hotspots for aggregation errors of land embodied in trade

Countries such as China show sharp trends of rapid increases in imports in the later years, and as such also become the main importers of traded land (see Additional file 3). Results show that there is a need for the integration and calculation of a high level of regional detail in these countries' trade partners to avoid regional aggregation errors. We find that the import aggregation errors of Asian countries such as China, India, Taiwan and Japan make up a large share of the global total error (Table 4). Although RoW Asia contributes to only 7.2% of global exported land, the contribution to the export aggregation error is 47.9% (Additional file 1: S8).

The effect of regional aggregation on land embodied in trade by products shows a large concentration of both land embodied in trade and aggregation errors around a handful of products (Table 3). The products are mostly part of the forestry and agricultural sectors, with a few outliers in the service sectors such as "Hotels and restaurant services (55)", "Other business services (74)" and "Real estate services (70)". These outliers are characterized by low shares of total land embodied in trade, but relatively larger shares of aggregation errors. The same is the case for some of the more disparate products groups (those in the not elsewhere classified groups). These later results indicate the need for also more detailed sectoral resolution (see below).

The regions and products prone to aggregation errors depend on the year chosen. We chose to present results for 2015 in this paper, as this is the most recently available data in EXIOBASE 3rx. A look into the aggregation errors summed together across the whole time series (Additional file 1: S8, and S9 for 2015) reveals that 37.4% of the export aggregation error now comes from RoW Africa (27.1% in 2015), while RoW Asia is responsible for 45.6% of the global total (47.9% in 2015). The import aggregation errors for regions show the same trends, except for Portugal that now ranks third when sorting by regions. The products most heavily affected by the aggregation throughout the time series show similar trends to the equivalent 2015 result, but even more concentrated around products of forestry, logging and related services (02) which accounts for 25.9% of the total aggregation error across the full time series (19.4% in 2015). Including the origin and destination of imports reveals that the top four flows, making up 12% of the total aggregation error, are "Products of forestry, logging and related services (02)" from RoW Africa to China, Portugal, India and France.

Compared to other works, Kastner et al. (2014) found that MRIO studies on cropland embodied in Chinese trade diverged from studies using other methods. We find that China's balance of land embodied in trade for all land types (Table 2) did not significantly differ between the two levels of regional aggregation. Despite not finding an aggregation effect, we find a significant change in China's balance of cropland embodied in trade from 1995 to 2015 (Additional file 1: S6). From 1995 to 2000 China was a net exporter of cropland, while from 2001 to 2015 there is a shift to becoming a net importer and increasingly so as we approach present time. Although our results use monetary values for the trade allocation, while studies using other methods typically use physical properties, the time trend we find should be interesting for future research looking at the deviations in results between methods.

Given that a few countries import a large share of globally traded land, we find it is particularly important to have their trading partners represented as individual regions in MRIOs. Similarly, key exporting regions not currently included, such as Argentina, should be represented, and large countries (such as China) can even be split into sub-regions as suggested by Su and Ang (2010) to minimize aggregation errors.

4.2 Challenges and limitations

The inclusion of 214 countries in a single database comes with a trade-off in terms of raw data availability and uncertainty. Whilst country-specific land use, production, and trade data are used (for an overview of the regional data availability in the raw data, see Additional file 1: S2), a lot of data estimation is undertaken, especially for the countries not originally in the EXIOBASE dataset. For the 44 countries originally in the EXIOBASE 3 dataset, it would be expected that the additional disaggregation of the rest-of-the-world regions would improve accuracy. However, for the remaining countries, it must be expected that the uncertainty of individual country estimates are high. Especially when disaggregating small (and trade-exposed) countries the expectation of accuracy is low. It is common in all input–output studies (and all statistical data) to find a declining relationship between accuracy and volume (whether expressed as GDP, output, or key coefficients) (see for example (Lenzen et al. 2010, Karstensen et al. 2015, Wood et al. 2019)) for one reason because of the laws of error propagation (Imbeault-Tétreault et al. 2013). Whilst further work could see the replacement of generic data with more country-specific data, it is still likely that the uncertainty levels of individual countries in the disaggregated database will be high, and it is anticipated that the further development of single-country national account consistent procedures are further developed in order to undertake county specific analysis (see, e.g., Edens et al. (2015); Palm et al. (2019); Hambÿe et al. (2018)).

In terms of empirical validation of results as presented, there are sudden jumps in per capita land footprint results, particularly for small economies such as Aruba, San Marino, Bermuda, the Cayman Islands and the British Virgin Islands (as can be seen in Additional file 1: S6). In addition to being small economies, several of these countries heavily rely on imports with import shares in the range of 95–98% of the total consumption-based land footprints, except for the British Virgin Islands and the Cayman Islands where this value is 43.0% and 50.7%, respectively (see Additional file 1: S13). When there is a jump in land footprint, we do note that that there are sudden changes in the import structure for the specific years (see https://oec.world/en/ (Simoes and Hidalgo 2011) for a visualization of trade data). Aruba has a drastic increase in imports of cattle from Sudan (2010), Bermuda and the British Virgin Islands import crude petroleum from Kazakhstan (2000–2003), San Marino imports raw fur skins from Russia (2006), while the Cayman Islands import soybeans from Paraguay (2001–2007). Drastic increases in imports of these specific products from countries with high use of land area per monetary output, combined with high import shares drastically change the per capita footprint of these countries using the EEBT approach. The EEBT approach however, does not allow us to determine whether these imports are used for domestic consumption, or intermediate production that is later used for exports and therefore should not be counted in that country's consumption-based footprints.

In terms of data reconciliation issues, most of the challenges in building EXIOBASE 3rx were related to the SUT balancing where there were contradictions between the initial estimates and the macroeconomic data. Several of these issues were resolved by changing options in the balancing routine that increased the accepted level of deviation (which was set to a cap in the balancing) from the initial estimated SUTs. If this did not work, we used initial technical coefficient estimates from EXIOBASE 2. In several of the remaining unbalanced cases (Additional file 1: S5), the issue is negative value added from the macroeconomic data specifically for International Standard Industrial Classification C and E from the UN National Main Aggregates Database. Resolving this issue is a work in progress. There are a total of 151 cases with a non-optimal solution in the SUT balancing over the time series (3 cases for year 2015). Data for these cases are set to zero and sum up to 0.15% of global GDP through the time series, hence it should not significantly influence the overall results. To resolve the balancing issues would require more detailed and reliable raw data, which again would manifest in the balancing routine deviating less from the initial estimated SUTs.

Setting the unbalanced countries to zero lead to a slight imbalance in land footprint results (see Table 2). This is one of several ways of dealing with such imbalances. In Eora, this has been handled by compiling the unbalanced regions in a Rest-of-the-world region (Lenzen et al. 2013). As setting the values of the environmental extensions matrix (**F**) to zero for an unbalanced country A means neglecting the land use embodied in imports of a country B from country A, there is a slight underreporting of land use in EXIOBASE 3rx. In 2015, Puerto Rico and the Dominican Republic are the countries whose total land footprints are affected the most by this, with an underreported footprint of 0.86%. For the aggregated database this effect has different distributional impacts as it affects all countries that import from the RoW region that country A is aggregated to. In addition, it affects the domestic part of the RoW region's footprint as there is not a one-to-one relationship between the output of country A and the land use per unit of output (**S**). RoW America's land footprint is affected heaviest by this with a change of 0.25%. In the 49-region version of EXIOBASE 3rx, the change is largest in Latvia (0.08%). Resolving the issue with unbalanced regions in EXIOBASE 3rx is a work in progress.

Using the EEBT approach, we do not distinguish between intermediate and final use of traded products. The approach fits with the scope of this paper as we look at the land embodied in aggregated imports and exports. The EEBT approach is also argued to be more relevant for global trade-related policy (Peters 2007). However, when allocating impacts to categories of final demand, the EEBT approach will give different results compared to the Leontief approach due to different allocation of impacts, although the global total impact is the same. For a country, imported goods that are used for intermediate production, and later exported are in the EEBT approach accounted as part of the imported footprint, while in the MRIO approach, they are not. The implications of this are discussed in Peters (2007). The extent of the difference between the two approaches is unexplored in this paper, although previous studies indicate that this difference could be significant (Su and Ang 2011).

In terms of land use data, other types of area use such as ocean are sometimes included in land use studies (e.g., Weinzettel et al. (2013)). This could alter the regional results, the land embodied in trade, and most likely the hotspots for large aggregation errors, through, e.g. consumption of fish (Weinzettel et al. 2013). It is important to be aware that the effects due to regional aggregation are sensitive to the types of land included in the study. Similarly, the picture would likely look different in terms of regions and sectors sensitive to aggregation errors when studying other types of environmental impacts. For example de Koning et al. (2015) found that regional aggregation had small effects on overall carbon and material footprints. Bouwmeester and Oosterhaven (2013) on the other hand find large, and what they refer to as unacceptable aggregation errors for particularly water use, but also for CO_2 emissions, although their regional aggregation is more drastic with aggregating 43 regions to five and two regions. The deviating conclusions on the effect of regional aggregation in other papers suggest that there is still need for further research on both the underlying causes of differences in these results, as well as identifying regions that are sensitive to aggregation errors. Although de Koning et al. (2015) look at different indicators, our findings coincide in the sense that when looking at the footprint of a country, the net effect of a regional aggregation is not drastic, but when exploring products traded and trade partners in more detail we find large effects of aggregation. This could also manifest in larger deviations when aggregating to very few regions, as in Bouwmeester and Oosterhaven (2013).

4.3 Further work

The results at hand are the first published results using EXIOBASE 3rx. We restrict our scope to the effect of regional aggregation of land use embodied in trade. However, with the limitations related to the EEBT approach and unbalanced countries in mind, there is still unexplored potential in using the database for land use studies in its current form. Firstly, there are multiple land use extensions available, which allows for studying different land types embodied in trade. Secondly, land use embodied in trade can be studied on a sectoral level as the database includes 200 products harmonized across all regions. Thirdly, the database is a time series from 1995 to 2015 which allows for studying the drivers of land use in form of panel regressions or similar methods. This creates opportunities for following up literature findings that suggest some degree of correlation between income and land use (Weinzettel et al. 2013; Ivanova et al. 2016). Panel regression studies using MRIO time series data also enable predictions into the future, which could help overcome the retrospective scope that is identified as a limitation of MRIO studies, which again could increase policy relevance (Axtell et al. 2001).

Currently only land extensions are processed for EXIOBASE 3rx. However, adding other environmental extensions to the database is a work in progress. More immediately, we chose land use as it is a simple and key indicator of agricultural related impacts. The application of biodiversity characterization factors (Verones et al. 2017) and net-primary productivity (Kastner et al. 2015; Weinzettel et al. 2019) are simple extensions to obtain more policy-relevant work. Furthermore, the correlation (Silva Simas et al. 2017) of land use with other agricultural impacts such as blue water consumption (Lutter et al. 2016) and eutrophication (Hamilton et al. 2018) gives a good basis for further extension.

Regarding resolution, the sectoral resolution in EXIOBASE is one of the most detailed in the available MRIOs (Steen-Olsen et al. 2014). However, despite the comparably high sectoral resolution of EXIOBASE 3rx, the sectoral resolution is a main point of criticism and source of error of land use studies using MRIO (Bruckner et al. 2015; Weinzettel et al. 2013; Steen-Olsen et al. 2012). Disaggregation of sectors is argued by Weinzettel et al. (2014) to be an important future development of MRIOs, and can replace the hybrid approaches applied to overcome this limitation today. Already we are seeing the linking of detailed FAO production and use data to both aggregated and disaggregated MRIO tables (Weinzettel et al. 2019) and even the construction of country-specific physical input–output tables (Bruckner et al. 2019).

In terms of methods, there is further work on expanding the cross-entropy model (Többen and Schröder 2018) used for reconciling the bilateral trade data with main aggregates of national accounts and estimates of product output, first, to the balancing of the SUTs and, later, to the simultaneous reconciliation of bilateral trade, SUTs and the physical extensions. The main challenges for the practical implementation of such a concept are the computational requirements due to the enormous size of the database (see the method section for a brief overview of the size of EXIOBASE 3rx). However, recent theoretical work on topological transformations (Rodrigues et al. 2016) and maximum entropy models to reconcile data in physical and monetary units simultaneously (Többen 2017) constitute first theoretical steps to solve this issue.

5 Conclusion

With divergence in environmental results between MRIOs hampering the policy relevance of MRIO studies, it is important to both develop more detailed models, and to get a systematic understanding about the underlying sources of these differences. We have developed a regional extension of EXIOBASE 3 called EXIOBASE 3rx and studied the effect of regional aggregation on land use embodied in trade by comparing results to an aggregated version of the same database consisting of 49 regions. Whilst the disaggregated database is experimental in that a lot of structural economic data are estimated, country-specific data on agricultural and resource output, as well as trade are included. We find that the regional aggregation error for land use embodied in imports on a sectoral level is highly concentrated on sectors with high biomass demand, such as forestry, meat from animals, wood products and hotels and restaurant services. The effect on regions shows that the balance of land embodied in trade differs with up to 6% between the aggregate database and EXIOBASE 3rx, while the net aggregation error of land embodied in imports for some of the 49 EXIOBASE regions differ up to 68% between the databases. The largest absolute aggregation errors for land embodied in imports are found for Asian imports particularly originating in RoW Asia and RoW Africa.

Our findings have two important implications regarding the use of MRIOs for land use studies. Firstly, regions in Asia and Africa should be represented in detail, and higher sectoral disaggregation is necessary for a handful of key sectors. Secondly, we suggest that MRIO developers are aware of the potentially significant effects of regional aggregation and build MRIOs that find the right balance between number of regions and sectors for their studies, while at the same time acknowledging the potential uncertainty introduced by assumptions aimed at closing data gaps in raw data. Further research is needed to identify key sectors and regions vulnerable to aggregation errors. If these are found to converge across environmental and socioeconomic extensions, MRIO systems can be built that find the right level of detail without becoming unnecessarily large. We believe that this is an important step in finding the sources of intra-MRIO result discrepancies and could increase the policy uptake of MRIO studies.

Supplementary information

Supplementary information accompanies this paper at https://doi.org/10.1186/s40008-020-0182-y.

Additional file 1. Supplementary material.

Additional file 2. Concordance matrices for regions, land use types and industries.

Additional file 3. Land use time series results (1995–2015).

Abbreviations
EEBT: Emissions embodied in bilateral trade; MRIO: Multiregional input output; RoW: Rest of the world; SUT: Supply–use table.

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Authors' contributions
ELB, KS, RW and JT built the database. MT, TK and KHE processed the land use accounts. ELB and KSO adjusted the land use accounts to fit with the database format. ELB and KSW processed land use results. ELB wrote the manuscript with important contributions from all co-authors. All authors read and approved the final manuscript.

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Availability of data and materials
The database generated and analyzed during the current study are available in the EXIOBASE 3rx repository, https://zenodo.org/deposit/2654460.
Most of the raw data used to build EXIOBASE 3rx, as referred to in the manuscript, is publically available at the repositories listed in the list of references.
The land use dataset is available in an aggregate format in the EXIOBASE 3rx repository. The full dataset is available from the corresponding authors (MT, TK and KHE) on reasonable request.

Competing interests
The authors declare that they have no competing interests.

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Appendix B Paper II

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Future changes in consumption: The income effect on greenhouse gas emissions

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A B S T R A C T

The scale and patterns of household consumption are important determinants of environmental impacts. Whilst affluence has been shown to have a strong correlation with environmental impact, they do not necessarily grow at the same rate. Given the apparent contradiction between the sustainable development goals of economic growth and environmental protection, it is important to understand the effect of rising affluence and concurrent changing consumption patterns on future environmental impacts. Here we develop an econometric demand model based on the data available from a global multiregional input-output dataset. We model future household consumption following scenarios of population and GDP growth for 49 individual regions. The greenhouse gas (GHG) emissions resulting from the future household demand is then explored both with and without consideration of the change in expenditure over time on different consumption categories. Compared to a baseline scenario where final demand grows in line with the 2011 average consumption pattern up until 2030, we find that changing consumer preferences with increasing affluence has a small negative effect on global cumulative GHG emissions. The differences are more profound on both a regional and a product level. For the demand model scenario, we find the largest decrease in GHG emissions for the BRICS and other developing countries, while emissions in North America and the EU remain unchanged. Decreased spending and resulting emissions on food are cancelled out by increased spending and emissions on transportation. Despite relatively small global differences between the scenarios, the regional and sectoral wedges indicate that there is a large untapped potential in environmental policies and lifestyle changes that can complement the technological transition towards a low-emitting society.

1. Introduction

Households in particularly wealthy countries are causing environmental pressures due to their high demand for goods and services. Globally, households represent about two-thirds of the demand for raw materials and land as well as the waste flows mobilized by production activities, and their attendant environmental loads (Munksgaard et al., 2000, Weber and Matthews, 2008, Steinberger and Roberts 2010, Ivanova et al., 2016). Technology improvements and changes in production are expected to play vital roles in mitigating climate change, but an increasing number of studies suggest that avoiding environmental degradation will not be possible without significant contributions from the consumption side (van Sluisveld et al., 2016, Dietz et al., 2009, Creutzig et al., 2018, Intergovernmental Panel on Climate Change, 2019). Sustainable consumption is part of the UN Sustainable Development Goals (SDG12[1]) and can be achieved by either shifting

Abbreviations: ABM, Agent-based modelling; AIDS, Almost ideal demand system; BRICS, Brazil, Russia, India, China and South Africa; CES, Consumer expenditure survey; CF, Carbon footprint; GHG, Greenhouse gas; GME, Generalized maximum entropy; IIA, Information inaccuracy; MRIO, Multiregional input-output; PADS, Perhaps adequate demand system; QUAIDS, Quadratic Almost ideal demand system; RMSE, Root mean squared error; RoW, Rest-of-the-world.

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[1] http://www.un.org/sustainabledevelopment/sustainable-consumption-production/

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the pattern of consumption or lowering total consumption. Several studies suggest that there is a large untapped potential for climate change mitigation in consumption side changes (Dietz et al., 2009, Girod et al., 2014, Vita et al., 2019, Lekve Bjelle et al., 2018, Wynes and Nicholas, 2017, Moran et al., 2018) and that some policies aimed at consumer choices have the benefit of low implementation costs (Allcott and Mullainathan 2010).

Due to the ability to allocate indirect environmental impacts to the final consumption activities they serve, environmental extended multi-regional input-output (MRIO) models are useful for ranking types of consumption in terms of total environmental impacts, thus potentially allowing prioritization of areas with the greatest improvement potential with respect to sustainable consumption (Lorek and Spangenberg, 2001, Tukker et al., 2006). In addition to the common carbon footprint, MRIO models are being applied to study a wide range of other environmental impacts, such as smog formation, acidification and eutrophication (Kerkhof et al., 2009b, Hamilton et al., 2018), material use (Muñoz et al., 2009, Bruckner et al., 2012), water use (Mekonnen and Hoekstra, 2012), land use (Ivanova et al., 2016), solid waste (Tisserant et al., 2017) and the Ecological Footprint (Wiedmann et al., 2006).

There are several cross-sectional studies that investigate the relationship between income and demand for products and the associated environmental impact of consumption for a single country and year (Wier et al., 2001, Weber and Matthews, 2008, Kerkhof et al., 2009b, Duarte et al., 2010, Steen-Olsen et al., 2016). Kerkhof et al. (2009a) find that for the UK and the Netherlands, per capita GHG emission is higher than for Sweden and Norway. However, the GHG intensity of consumption decreases with increasing affluence in the Netherlands and the UK but grow in Sweden and Norway. Levinson and O'Brien (2015) found that richer households in the US are responsible for more pollution, but with an income elasticity of less than one. They conclude that the observation of decreasing pollution per dollar of expenditure with rising income comes from both lower consumption per additional dollar earned and the fact that households consume goods that pollute less in 2012 than 1984. In a cross-country analysis, Hertwich and Peters (2009) show that services have the highest expenditure elasticity, while having one of the lowest GHG emission elasticities. This indicates that changes in consumption patterns are important to consider for rebound type calculations which concern the environmental implications of re-spending of savings from either technological improvements or reduced consumption on particular goods (Lekve Bjelle et al., 2018, Thiesen et al., 2008, Tukker et al., 2013).

1.1. Towards combined MRIO-demand systems

Growing affluence brings about both increases in consumption and changes in consumption patterns, as spending does not increase uniformly across all products. This effect was first noticed by Engel in 1895 who observed that the share of expenditure on food decreases with increasing income in a given population (Engel's Law) (Engel 1895, Chakrabarty and Hildenbrand 2016). The relationship between changes in consumption patterns with changing income are typically shown using income elasticities or Engel curves. The income elasticity measures the percentage change in demand given a change in income and correspond to linear Engel curves that graphically show the relationship between levels of demand and income. The existence of linear Engel curves across all goods and services is highly unlikely (Blundell and Ray, 1984, Banks et al., 1997), particularly for cross-sectional data (Blundell and Ray, 1984) and implies that goods are not permitted to be luxuries at some income levels and and necessities at others (Banks et al., 1997).

In the 1950s and onwards came models of complete demand systems that describe consumer behavior by specifying both Engel curves and effects of changes in prices consistent with utility maximization (Banks et al., 1997) and represent the decision process faced by a rational representative consumer (Deaton and Muellbauer, 1980). Some of the most prominent models are the Linear Expenditure System (Stone 1954), the Quadratic Demand System (Pollak and Wales, 1978), the Almost Ideal Demand System (Deaton and Muellbauer, 1980), the Quadratic Almost Ideal Demand System (Banks et al., 1997) and the Perhaps Adequate Demand System (PADS) (Almon 1998).

Implementation of demand systems in micro-economic analysis is now common, and they are also used in macro-economic models that consider technological change in the economy integrated with changes in consumption, investments and government expenditure (e.g. Sommer and Kratena, 2017). Several macro-econometric input-output models that estimate environmental impacts under different scenarios exist today, such as E3ME (Barker 1999), GINFORS (Lutz et al., 2009, Distelkamp and Meyer, 2019, Meyer and Ahlert, 2019, Wiebe 2016) and the World Trade Model combined with MRIO (Duchin and Levine 2016). These models focus on the impact of future changes in trade patterns, technology, future impacts under different scenarios of taxations, or a top-down approach where they investigate how future emission targets can be met. Importantly, they are able to include the modelling of macro-economic feedbacks (price effects, economies of scale, etc.) between producers and consumers, however, it then becomes difficult to isolate the impact of specific agents (such as households), due to the endogeneity of modelled change.

Using, such approaches, Kim et al. (2015) studied the impact of future changes in demographic variables (income and age) on consumption patterns, but only for a single region and without considering associated environmental impact. They did this by integrating an almost ideal demand system (AIDS) model based on consumer expenditure survey (CES) data into a regional input-output model. Mongelli et al. (2010) used data from a CES to compute their AIDS model to model sustainable consumption. Their motivation was to extend IO models with a more accurate representation of household demand to study the response of household consumption to policy interventions. Although their paper focuses on the methodological linking between IO databases and CES data, they include a scenario on the emission effects of a CO_2 tax levied on industries. After running the IO calculations, the consumers are then faced with a price change and a change in final expenditure which are modelled using the demand system. In a slightly different vein of research, but ignoring endogenous feedbacks, Wiebe et al. (2018) estimate climate change scenarios in a forward-looking version of EXIOBASE, where future consumption changes were estimated by the use of a demand system, in addition to including scenarios of future technological changes that were determined by exogenous estimates of change.

None of these approaches, however, isolate the effect that future growth in income will have on changing consumption patterns and associated carbon footprints. The work of Sommer and Kratena (2017) probably comes closest, but it focuses on the cross-sectional distribution (by quintile) and related carbon footprints for Europe. Hence in order to better understand the relation between the dynamics of household demand and embodied emissions at the global scale, we link a demand system model with multiregional input-output data. We use this to estimate the effect of increasing income on changes in consumption patterns for 49 regions from the EXIOBASE dataset (Section 2). We then compare the GHG emissions of two scenarios of future consumption (Section 3). The scenarios are driven by increasing affluence and population but differ in the way demand for goods and services grows. The 'static' scenario distributes expenditures according to the 2011 products' share of expenditure, while the Quadratic Almost Ideal Demand System (QUAIDS) scenario uses regression results to forecast demand for products. We calculate the direct and indirect GHG emissions associated with household consumption assuming 2011-constant emission multipliers and constant economic structure, thus isolating the effect of shifting consumption patterns. We supply a framework for global comparison of the effect of affluence on environmental impacts that can be used as a guide to policy makers to lower future emissions from household consumption and provides possibilities for analyses beyond what is explored in this paper. We aim at increased understanding of how changed affluence may affect future emissions globally.

2. Methods

2.1. EXIOBASE database

EXIOBASE is an MRIO database with environmental and socioeconomic extensions. Version 3 of the database used in this article consists of 44 countries and 5 rest-of-the-world (RoW) regions at a level of 163 industries and 200 products. EXIOBASE 3 provides a time series of MRSUT from 1995 to 2011, from which symmetric product-by-product MRIO tables are formed. For a more detailed description of the database and its sources we refer the reader to Wood et al. (2015), and Stadler et al. (2018). GHG emissions available in EXIOBASE allocated to industrial sector and final products were used in this work, covering six major greenhouse gases (CO_2, CH_4, N_2O, SF_6, HFCs and PFCs), and using the IPCC, 2007 Global Warming Potential (GWP) 100 metric.

Total household consumption data in basic pricing was retrieved from the household consumption vector in EXIOBASE 3, including both imported and domestically demanded goods. The current price household expenditure data was first aggregated by collapsing imported and domestically consumed goods. Next, the expenditure data was deflated using the product-level deflators described in Stadler et al. (2018) with base year in 2011. Both the current price expenditure data and the deflated expenditure data were then aggregated to the 15 product groups of the demand system, and price indices were estimated as the current price expenditure divided by the deflated expenditure. Expenditure shares were extracted from the current price expenditure data.

As EXIOBASE has a high product resolution of 200 products, there are products with no household consumption, in some or all regions of the database. Particularly, we found only 42 sectors in EXIOBASE 3 with non-zero household expenditure data for all years and regions. Zero expenditure can cause problems in the estimations of demand systems (Blundell and Robin 1999, Bardazzi and Barnabani, 2001). When projecting demand, such low or zero expenditures can cause unrealistic shifts in consumption patterns. These shifts can be amplified for emissions if observed for product groups with particularly high carbon intensities per monetary unit. Hence, we performed the analysis at a level of 15 product groups (see S1 for the product concordance), after several iterations of the product aggregations to avoid low expenditure shares and unrealistic projected expenditure due to large jumps in historic sectoral data. We set the lower limit for historic expenditure shares at 0.3% to avoid the mentioned problems caused by low shares. Our product resolution is at the upper end of what we found in the demand system literature.

2.2. Estimating demand systems

Demand systems estimate absolute values of consumption (e.g. PADS) or household budget shares (e.g. AIDS) through prices of goods, household income and a price index. Some models also include some form of time trend (e.g. PADS) or a quadratic income term (e.g. QUAIDS). These models are often expanded with demographic variables such age or household size. Different constraints from demand theory are put on the parameters. In the most widely used demand system, AIDS (Deaton and Muellbauer, 1980), these include the adding up constraint (the sum of all budget shares add up to one), homogeneity of degree zero in prices and total expenditure taken together, and Slutsky symmetry.

We estimate the Quadratic Almost Ideal Demand System due to its ability to allow for non-linear Engel curves through a quadratic income term. Non-linear Engel curves have been proven to exist for certain commodities (Banks et al., 1997). They allow the representation of goods as luxuries or necessities at different expenditure levels. We choose the QUAIDS model given our large range of income levels, and our focus on the changing nature of consumption in comparison to income for a range of carbon intensive goods such as transport, food and housing, which can be seen as both necessities and luxuries at different income levels. In S11 we plot Engel curves for selected key regions. Non-linear curves can be observed across several of the product groups, and particularly for “restaurants and hotels”, “clothing”, “tobacco and beverages”, and the housing and food product groups. In addition to the quadratic income term, we include country-specific intercepts. The number of observations per product group in the demand system is yearly data (17 years) for the 49 regions of EXIOBASE.

The QUAIDS specification is given by:

$$w_{itc} = \alpha_{ic} + \sum_{j=1}^{n} \zeta_{ij} \ln p_{jtc} + \beta_i \ln\left(\frac{Y_{tc}}{P_{tc}}\right) + \frac{\gamma_i}{\prod_{j=1}^{n} p_{jtc}^{\beta_j}} * \lfloor ln\left(\frac{Y_{tc}}{P_{tc}}\right)\rfloor^2 + \varepsilon_{itc} \quad (1)$$

The notation is as follows:

- i, j (Product groups)
- n (Number of product groups)
- c (Country index)
- t (Time index)
- P (Stone price index)
- $\alpha, \gamma, \beta, \zeta$ (Regression coefficients)
- Y (Total expenditure per capita)
- w (Budget share)
- p (Prices)
- ε (Error term)

P is usually given by the Translog price index (Cranfield et al., 2003), but can be linearly approximated by the Stone price index (Deaton and Muellbauer, 1980), which is what we do here as well. This approximation is applied also for QUAIDS (Jones and Mazzi, 1996, Mittal 2010).

The usual restrictions on additivity, symmetry and homogeneity are applied as constraints in the model (see Eqs. (8)–(10)).

Following the approach in Banks et al. (1997) the income and price elasticities are calculated by first differentiating Eq. (1) with respect to $ln\,\overline{Y_c}$ and $ln\,\overline{p_{jc}}$ respectively, where $\overline{Y_c} = \frac{1}{yrs} * \sum_{t=1}^{yrs} Y_{tc}$

$$\overline{p_{jc}} = \frac{1}{yrs} * \sum_{t=1}^{yrs} p_{jct}$$

yrs is the number of years.

$$u_{ic} = \beta_i + \frac{2\gamma_i}{b(p)_c} \lfloor ln\left(\frac{\overline{Y_c}}{\overline{P_c}}\right)\rfloor \quad (2)$$

$$u_{ijc} = \zeta_{ij} - u_i\left(\alpha_{jc} + \sum_{k=1}^{n} \zeta_{jk} \ln p_{kc}\right) - \frac{\gamma_i \beta_i}{b(\boldsymbol{p})_c} \lfloor ln\left(\frac{\overline{Y_c}}{\overline{P_c}}\right)\rfloor^2 \quad (3)$$

Where $b(\boldsymbol{p})_c = \prod_{j=1}^{n}\left[\overline{p_{jc}}^{\beta_j}\right]$ and $\overline{P_c} = \frac{1}{yrs} * \sum_{t=1}^{yrs} P_{tc.}$

The income elasticities are then given by:

$$e_{ic} = \frac{u_{ic}}{\overline{w_{ic}}} \quad (4)$$

Where $\overline{w_{ic}} = \frac{1}{yrs} * \sum_{t=1}^{yrs} w_{itc}$

And the uncompensated price elasticities are given by:

$$e^{u}_{ijc} = \frac{u_{ijc}}{\overline{w_{ic}}} - \delta_{ij} \quad (5)$$

Where δ_{ij} is the Kronecker delta.

Demand systems typically violate standard assumptions required for OLS being BLUE (best linear unbiased estimator) and, therefore, in these cases, require specific estimation strategies. For this reason we use the single-stage Generalized Maximum Entropy (GME) estimator developed in Golan et al. (2001), which is shown to be robust, consistent and efficient even under non-normal errors and correlated independent variables.

In the QUAIDS model, the estimates of the parameters α_{ic}, ζ_{ij}, β_i and γ_i are found by solving the non-linear program:

$$\begin{aligned} \max S\left(\pi_{\alpha_{ic}}^{m}, \pi_{\zeta_{ij}}^{m}, \pi_{\beta_i}^{m}, \pi_{\gamma_i}^{m}, \varphi_{itc}^{n}\right) &= -\sum\nolimits_{ic}^{m} \pi_{\alpha_{ic}}^{m} \ \ln \pi_{\alpha_{ic}}^{m} - \sum\nolimits_{ij}^{m} \pi_{\zeta_{ij}}^{m} \ \ln \pi_{\zeta_{ij}}^{m} \\ &\quad - \sum\nolimits_{i}^{m} \pi_{\beta_i}^{m} \ \ln \pi_{\beta_i}^{m} - \sum\nolimits_{i}^{m} \pi_{\gamma_i}^{m} \ \ln \pi_{\gamma_i}^{m} \\ &\quad - \sum\nolimits_{itc}^{n} \varphi_{itc}^{n} \ \ln \varphi_{itc}^{n} \end{aligned} \tag{6}$$

s.t.

$$\begin{aligned} w_{itc} &= \sum\nolimits_{ic}^{m} \pi_{\alpha_{ic}}^{m} z_{\alpha_{ic}}^{m} + \sum\nolimits_{ij}^{m} \pi_{\zeta_{ij}}^{m} z_{\zeta_{ij}}^{m} \ \ln p_{jtc} + \sum\nolimits_{i}^{m} \pi_{\beta_i}^{m} z_{\beta_i}^{m} \ \ln\left(\frac{Y_{tc}}{P_{tc}}\right) \\ &\quad + \frac{\sum_i^m \pi_{\gamma_i}^{m} z_{\gamma_i}^{m}}{\prod_{j=1}^{n} p_{jtc}^{\left(\sum_i^m \pi_{\beta_i}^{m} z_{\beta_i}^{m}\right)}} * \left\lfloor \ln\left(\frac{Y_{tc}}{P_{tc}}\right) \right\rfloor^2 + \sum\nolimits_{itc}^{n} \varphi_{itc}^{n} \sigma_{itc}^{n} \end{aligned} \tag{7}$$

$$\sum_{i=1}^{n} \pi_{\alpha_{ic}}^{m} z_{\alpha_{ic}}^{m} = 1 \tag{8}$$

$$\sum_{i=1}^{n} \pi_{\beta_i}^{m} z_{\beta_i}^{m} = \sum_{i=1}^{n} \pi_{\zeta_{ij}}^{m} z_{\zeta_{ij}}^{m} = \sum_{i=1}^{n} \pi_{\gamma_i}^{m} z_{\gamma_i}^{m} = 0 \tag{9}$$

$$\pi_{\zeta_{ij}}^{m} z_{\zeta_{ij}}^{m} = \pi_{\zeta_{ji}}^{m} z_{\zeta_{ji}}^{m} \tag{10}$$

$$\sum\nolimits^{m} \pi_{\alpha_{ic}}^{m} = 1 \tag{11}$$

$$\sum\nolimits^{m} \pi_{\beta_i}^{m} = 1 \tag{12}$$

$$\sum\nolimits^{m} \pi_{\gamma_i}^{m} = 1 \tag{13}$$

$$\sum\nolimits^{m} \pi_{\zeta_{ij}}^{m} = 1 \tag{14}$$

$$\sum\nolimits^{n} \varphi_{itc}^{n} = 1 \tag{15}$$

In the reparametrized version of the QUAIDS Eq. (1), the parameters α_{ic}, ζ_{ij}, β_i and γ_i are replaced by linear combinations of M supports $z_{\alpha ic}^{m}$, $z_{\beta i}^{m}$, $z_{\zeta ij}^{m}$, and $z_{\gamma i}^{m}$, which are discrete points that span uniform intervals, symmetrical around zero that contain all possible values the parameters can take, and weights to be estimated that add up to one, $\pi_{\alpha ic}^{m}$, $\pi_{\zeta ij}^{m}$, $\pi_{\beta i}^{m}$, and $\pi_{\gamma i}^{m}$. Likewise, the error terms ε_{itc} are replaced by a linear combination of the supports σ_{itc}^{n} and weights φ_{itc}^{n}. We follow the approach of Golan et al. (2001) and define $M = 3$ supports for each parameter, namely lower and upper bounds and zero. According to the principle of maximum entropy, maximizing (6) yields the most uniform weights that are consistent with the empirical model subject to the condition that they constitute proper probabilities (i.e. add up to one).

The non-linear program (6) is implemented in GAMS and solved using the non-linear solver CONOPT. The supports for each parameter of the demand system are specified such that their value exceeds the

Table 1
Parameter values for the QUAIDS model. Values marked in green are significant at level v = 0.05 with degrees of freedom = (yrs ∗ nC) − 1: and critical value $t_{crit,\,0.05} = 1.963$. yrs and nC are the number of years and regions in the input data respectively.

	Vegetables, fruit, nuts, rice and crops	Fish, Meat and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity and other fuels	Furniture, Household goods and services	Health, education, insurance and social security	Transport services and fuels nec	Railway, air and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor Vehicles	Miscellaneous goods and services	β	γ
Vegetables, fruit, nuts, rice and crops	-0.006	0.002	0.001	0.010	0.005	-0.008	-0.003	0.001	-0.004	0.001	0.000	0.003	0.005	0.003	-0.011	-0.036	0.008
Fish, Meat and dairy	0.002	0.007	0.004	-0.003	-0.001	0.011	0.007	-0.002	-0.006	0.003	-0.001	-0.011	0.003	0.001	-0.013	-0.023	0.001
Tobacco and beverages	0.001	0.004	0.006	-0.004	-0.007	-0.017	0.011	-0.007	-0.002	-0.006	0.002	0.009	0.004	-0.015	0.019	-0.002	-0.001
Food nec	0.010	-0.003	-0.004	0.009	0.001	0.010	-0.012	0.001	0.009	0.001	-0.003	0.003	-0.017	0.009	-0.017	-0.017	0.000
Clothing	0.005	-0.001	-0.007	0.001	-0.008	-0.025	0.006	0.008	0.000	0.001	-0.005	0.001	-0.004	0.011	0.015	0.006	-0.003
Housing, real estate, water, gas, electricity and other fuels	-0.008	0.011	-0.017	0.010	-0.025	0.049	-0.012	0.011	-0.001	-0.008	0.015	-0.029	-0.004	-0.001	0.009	-0.003	0.002
Furniture, Household goods and services	-0.003	0.007	0.011	-0.012	0.006	-0.012	0.005	-0.007	-0.004	0.000	0.001	0.002	0.009	-0.011	0.006	0.006	-0.002
Health, education, insurance and social security	0.001	-0.002	-0.007	0.001	0.008	0.011	-0.007	0.013	-0.001	0.004	-0.008	0.001	-0.018	-0.003	0.007	0.005	0.000
Transport services and fuels nec	-0.004	-0.006	-0.002	0.009	0.000	-0.001	-0.004	-0.001	-0.002	0.003	-0.004	0.007	0.001	0.011	-0.008	0.008	0.001
Railway, air and other transportation services	0.001	0.003	-0.006	0.001	0.001	-0.008	0.000	0.004	0.003	0.004	0.003	0.002	-0.008	0.007	-0.006	0.004	-0.001
Communication services	0.000	-0.001	0.002	-0.003	-0.005	0.015	0.001	-0.008	-0.004	0.003	-0.002	0.000	0.008	0.001	-0.007	0.007	0.002
Recreation and culture	0.003	-0.011	0.009	0.003	0.001	-0.029	0.002	0.001	0.007	0.002	0.000	-0.003	-0.003	-0.007	0.023	0.006	-0.001
Restaurants and hotels	0.005	0.003	0.004	-0.017	-0.004	-0.004	0.009	-0.018	0.001	-0.008	0.008	-0.003	0.018	0.001	0.005	0.013	0.001
Motor Vehicles	0.003	0.001	-0.015	0.009	0.011	-0.001	-0.011	-0.003	0.011	0.007	0.001	-0.007	0.001	0.005	-0.012	0.014	-0.003
Miscellaneous goods and services	-0.011	-0.013	0.019	-0.017	0.015	0.009	0.006	0.007	-0.008	-0.006	-0.007	0.023	0.005	-0.012	-0.009	0.012	-0.004

Table 2
Income elasticities for the 49 regions and 15 products. Top and bottom three values per region marked in green and red colors respectively.

	Vegetables, fruit, nuts, rice and crops	Fish, Meat and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity and other fuels	Furniture, Household goods and services	Health, education, insurance and social security	Transport services and fuels nec	Railway, air and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor Vehicles	Miscellaneous goods and services
AT	1.4	0.5	0.4	0.6	0.8	1.0	0.9	1.1	1.2	1.0	1.4	1.0	1.1	0.9	0.9
BE	1.2	0.7	0.5	0.8	0.8	1.0	0.9	1.1	1.2	1.0	1.4	1.0	1.3	1.0	0.9
BG	0.2	0.8	0.9	0.8	1.1	1.0	1.1	1.2	1.2	1.0	1.1	1.2	1.3	1.7	1.2
CY	0.7	0.7	0.6	0.6	0.8	1.0	0.9	1.1	1.3	1.0	1.3	1.0	1.1	1.0	1.0
CZ	0.5	0.8	0.7	0.8	1.0	1.0	1.0	1.1	1.2	1.1	1.3	1.1	1.2	1.1	1.0
DE	1.4	0.6	0.4	0.7	0.8	1.0	0.9	1.1	1.4	1.0	1.4	1.0	1.3	1.0	0.9
DK	1.5	0.6	0.3	0.7	0.7	1.0	0.9	1.1	1.3	1.0	1.4	1.0	1.4	0.9	0.9
EE	0.2	0.8	0.4	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.2	1.3	1.1
ES	1.0	0.7	0.3	0.7	0.8	1.0	0.9	1.1	1.4	1.0	1.5	1.0	1.1	1.0	0.9
FI	1.2	0.7	-0.4	0.7	0.8	1.0	0.9	1.1	1.3	1.0	1.4	1.0	1.2	0.9	0.9
FR	1.2	0.7	0.5	0.6	0.8	1.0	0.9	1.1	1.4	1.0	1.4	1.0	1.3	1.0	0.9
GR	1.0	0.7	0.1	0.6	0.8	1.0	0.9	1.1	1.4	1.0	1.6	1.0	1.1	1.0	1.0
HR	0.5	0.8	0.8	0.7	1.0	1.0	1.0	1.2	1.5	1.2	1.3	1.1	1.3	1.1	1.0
HU	0.4	0.8	0.7	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.2	1.1	1.1
IE	1.5	0.6	0.8	0.7	0.8	1.0	0.8	1.1	1.2	1.0	1.4	1.0	1.1	0.9	0.9
IT	1.2	0.7	0.3	0.7	0.9	1.0	0.9	1.1	1.3	1.0	1.5	1.0	1.2	0.9	0.9
LT	0.7	0.8	0.9	0.8	1.0	1.0	1.0	1.2	1.2	1.0	1.3	1.1	1.3	1.1	1.0
LU	1.3	0.3	0.5	0.5	0.7	1.0	0.9	1.1	1.3	1.0	1.6	1.0	1.2	0.9	0.9
LV	0.5	0.8	0.6	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.3	1.2	1.1
MT	0.8	0.8	0.5	0.7	0.9	1.0	1.0	1.1	1.2	1.0	1.2	1.0	1.3	1.0	1.0
NL	1.3	0.6	0.4	0.7	0.8	1.0	0.9	1.1	1.2	1.0	1.3	1.0	1.4	0.9	0.9
PL	0.6	0.8	0.5	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.3	1.2	1.0
PT	0.9	0.8	0.6	0.7	0.9	1.0	0.9	1.1	1.4	1.0	1.3	1.0	1.1	1.0	1.0
RO	0.7	0.8	0.9	0.9	1.1	1.0	1.1	1.2	1.3	1.1	1.2	1.3	1.2	1.3	1.1
SE	1.5	0.6	-0.4	0.6	0.6	1.0	0.9	1.1	1.3	1.0	1.4	1.0	1.3	0.9	0.9
SI	0.8	0.8	0.3	0.6	0.9	1.0	1.0	1.1	1.2	1.1	1.3	1.0	1.2	1.0	1.0
SK	0.7	0.7	0.7	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.3	1.1	1.3	1.2	1.0
GB	1.6	0.6	0.0	0.5	0.7	1.0	0.9	1.1	1.5	1.0	1.5	1.0	1.1	0.9	0.9
US	2.4	0.1	0.6	0.5	0.5	1.0	0.8	1.0	1.6	1.0	1.5	1.0	1.2	0.9	0.9
JP	1.4	0.5	0.8	0.6	0.6	1.0	0.8	1.1	1.4	1.0	1.4	1.0	1.1	0.9	0.9
CN	0.7	0.8	1.0	0.8	1.2	1.0	1.3	1.0	1.4	1.2	1.3	1.5	1.2	1.8	1.1
CA	1.5	0.4	0.7	0.6	0.6	1.0	0.9	1.1	1.4	1.0	1.6	1.0	1.2	0.9	1.0
KR	0.8	0.5	0.7	0.7	0.9	1.0	0.9	1.0	1.4	1.0	1.2	1.0	1.2	1.1	1.0

BR	0.3	0.6	0.8	0.7	1.0	1.0	1.0	1.1	1.2	1.1	2.3	1.1	1.2	1.2	1.0
IN	0.7	0.6	1.0	0.9	1.2	0.9	1.5	1.1	1.2	1.1	1.2	1.9	1.3	2.1	1.2
MX	0.2	0.6	0.9	0.8	1.0	1.0	1.0	1.1	1.3	1.0	1.3	1.1	1.2	1.1	1.0
RU	0.6	0.8	0.9	0.8	1.1	1.0	1.1	1.1	1.3	1.1	1.1	1.2	1.7	1.9	1.1
AU	1.2	0.4	0.7	0.6	0.7	1.0	0.9	1.1	1.5	1.0	1.4	1.0	1.2	1.0	0.9
CH	2.0	-0.7	0.6	0.5	0.5	1.0	0.8	1.0	1.8	1.0	1.5	0.9	1.2	0.8	0.9
TR	0.8	0.1	0.8	0.9	1.0	1.0	1.0	1.2	1.4	1.0	1.3	1.1	1.3	1.3	1.1
TW	0.8	0.6	0.8	0.5	0.8	1.0	0.9	1.0	1.4	1.0	1.2	1.0	1.2	1.0	1.0
NO	1.5	0.6	0.7	0.6	0.7	1.0	0.9	1.1	1.2	1.0	1.4	1.0	1.2	0.9	0.9
ID	0.7	0.8	1.0	0.8	1.3	1.0	1.2	1.2	1.1	1.1	1.2	1.2	1.1	1.3	1.3
ZA	0.1	0.6	0.9	0.8	1.1	1.0	1.1	1.0	1.3	1.0	1.2	1.3	1.3	1.2	1.1
WA	-0.1	0.3	0.9	0.7	1.2	1.0	1.2	1.0	1.2	1.1	1.1	1.2	1.2	1.3	1.1
WL	0.3	0.5	0.8	0.7	1.1	1.0	1.0	1.0	1.4	1.1	1.2	1.1	1.2	1.2	1.1
WE	0.1	0.4	0.9	0.7	1.2	1.0	1.1	1.0	1.3	1.1	1.2	1.1	1.1	1.4	1.1
WF	0.1	0.5	1.0	0.8	1.3	1.0	1.2	1.1	1.2	1.2	1.1	1.2	1.1	1.4	1.2
WM	0.3	0.5	0.9	0.7	1.1	1.0	1.1	1.1	1.3	1.1	1.2	1.1	1.2	1.2	1.1

estimates of the corresponding parameter typically found in empirical applications by several orders of magnitude.

The ζ, β, and γ parameters from Eq. (1) are presented in Table 1 (All elasticities and regression coefficients are available in S10).

The *t*-tests on regression coefficients in the full QUAIDS model show that 216 out of 225 (96%) of the ζ_{ij}, all 15 of the β_i, and 14 out of 15 (93%) of the γ_i are significantly different from zero.

The estimated income elasticities are displayed in Table 2.)

The elasticities show clear trends of which products are necessities and luxuries, indicated by the number of red and green values per column. "Communication services", "Transport services and fuels nec", and "restaurants and hotels" are luxury goods, while "food nec", "fish, meat, and dairy" and "tobacco and beverages" are necessities. Interestingly, "vegetables, fruit, nuts, rice, and crops" and "clothing" show a clear distinction of being necessities in developing regions and luxuries in developed regions.

All own-price elasticities are negative (Table 3) and hence the concavity of the underlying expenditure function is fulfilled.

"Vegetables, fruit, nuts, rice, and crops", "clothing" and "miscellaneous goods and services" stand out as product groups that are sensitive to increasing prices, while consumption of "tobacco and beverages" and "restaurants and hotels" are affected less by a price increase. Regional differences are apparent for "housing, real estate, water, gas, electricity and other fuels", where consumption is less affected by a price increase in developing regions than developed ones.

2.3. Statistical tests

We assess the QUAIDS model's goodness of fit by estimating the information inaccuracy (IIA) for the demand system and root mean squared error (RMSE) measures by region, product and for the whole demand system equivalent to the approach in Cranfield et al. (2003). Furthermore, as shown in Golan et al. (2001), the GME estimator is consistent and asymptotically normal. Hence, we perform t-tests on the regression coefficients to test whether they are significantly different from zero. For the goodness of fit measures and t-tests we compare the QUAIDS model with nested models that include different variations of the regression coefficients in Eq. (1). We also compute the log-likelihood ratio statistic to test the significance of the quadratic income term in Eq. (1). For a full overview of the model comparisons, and the calculations of the statistical measures, see S9.

As a justification for using the QUAIDS versus the AIDS specification, we tested the significance of the quadratic income term by checking the log-likelihood ratio statistic (S9 eq. S17) against the critical value in the χ^2-distribution. We find that the quadratic term is significant at level $v = 0.01$ (see S9 for calculation steps and test values). The IIA and system-wide RMSE results show that the full QUIADS model performs best, which corresponds well with the equivalent findings in Cranfield et al. (2003). For the product-wise RMSE, the full QUAIDS model performs best (9 of 15 cases), while the model where the price terms (ζ_{ij}) are restricted to zero and the model with the quadratic income term (γ_i) restricted to zero perform second best of all the models (best in 2 out of 15 cases each). For regional RMSE, the full QUAIDS model again performs best (15 out of 49 cases). Second are the model with the quadratic income term (γ_i) removed and the model with all terms except the intercept (α_{ic}) restricted to zero (best in 6 out of 49 cases each). From this we conclude that allowing for non-linear Engel curves overall improves the model performance, with a few exceptions in some regions. The good performance for some products using the specification without price terms (price terms set to zero) can be related to the uncertainty in the price information used in EXIOBASE 3, which is gathered from several different data sources (Stadler et al., 2018).

2.4. Forecasting total household demand/expenditure

Based on the regression results, scenarios of changes in consumption are constructed consistent with exogenous scenarios of population growth and affluence growth. Projections of population are based on the Medium Variant projection from the 2015 Revision of population projections made by the United Nations (UN, 2015). The population projections for 230 countries are available, and were aggregated according to the EXIOBASE region definition, from which population growth rates are calculated.

Table 3
Own-price elasticities for the 49 regions and 15 products. Top and bottom three values per region marked in green and red colors respectively.

	Vegetables, fruit, nuts, rice and crops	Fish, Meat and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity and other fuels	Furniture, Household goods and services	Health, education, insurance and social security	Transport services and fuels nec	Railway, air and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor Vehicles	Miscellaneous goods and services
AT	-1.27	-0.78	-0.61	-0.77	-1.20	-0.82	-0.90	-0.82	-1.04	-0.92	-1.06	-1.06	-0.88	-0.91	-1.11
BE	-1.22	-0.84	-0.62	-0.85	-1.19	-0.83	-0.87	-0.86	-1.04	-0.76	-1.06	-1.07	-0.71	-0.93	-1.09
BG	-1.15	-0.91	-0.85	-0.89	-1.20	-0.83	-0.86	-0.63	-1.05	-0.95	-1.04	-1.09	-0.62	-0.68	-1.19
CY	-1.40	-0.86	-0.68	-0.79	-1.28	-0.79	-0.86	-0.84	-1.05	-0.95	-1.05	-1.09	-0.90	-0.90	-1.13
CZ	-1.17	-0.89	-0.67	-0.87	-1.18	-0.84	-0.90	-0.67	-1.04	-0.87	-1.06	-1.07	-0.75	-0.89	-1.11
DE	-1.33	-0.82	-0.58	-0.80	-1.21	-0.84	-0.89	-0.85	-1.05	-0.90	-1.06	-1.06	-0.74	-0.94	-1.08
DK	-1.24	-0.82	-0.52	-0.83	-1.24	-0.86	-0.88	-0.84	-1.04	-0.84	-1.06	-1.05	-0.63	-0.88	-1.06
EE	-1.22	-0.92	-0.33	-0.88	-1.16	-0.83	-0.89	-0.68	-1.05	-0.92	-1.05	-1.06	-0.76	-0.78	-1.13
ES	-1.18	-0.84	-0.44	-0.84	-1.26	-0.79	-0.85	-0.78	-1.05	-0.87	-1.07	-1.05	-0.93	-0.92	-1.12
FI	-1.25	-0.86	-0.02	-0.83	-1.26	-0.86	-0.87	-0.79	-1.04	-0.90	-1.06	-1.05	-0.77	-0.88	-1.10
FR	-1.21	-0.87	-0.66	-0.77	-1.25	-0.85	-0.88	-0.82	-1.05	-0.91	-1.06	-1.06	-0.75	-0.94	-1.09
GR	-1.13	-0.87	-0.35	-0.78	-1.19	-0.81	-0.79	-0.85	-1.06	-0.93	-1.09	-1.06	-0.90	-0.82	-1.08
HR	-1.13	-0.91	-0.75	-0.80	-1.15	-0.84	-0.94	-0.63	-1.09	-0.75	-1.07	-1.05	-0.69	-0.90	-1.10
HU	-1.16	-0.90	-0.67	-0.87	-1.21	-0.80	-0.89	-0.78	-1.06	-0.90	-1.05	-1.06	-0.76	-0.92	-1.11
IE	-1.41	-0.83	-0.83	-0.82	-1.24	-0.81	-0.82	-0.83	-1.04	-0.93	-1.05	-1.05	-0.87	-0.83	-1.09
IT	-1.14	-0.86	-0.53	-0.79	-1.10	-0.81	-0.92	-0.74	-1.05	-0.88	-1.07	-1.07	-0.85	-0.92	-1.10
LT	-1.07	-0.91	-0.85	-0.86	-1.18	-0.79	-0.91	-0.66	-1.05	-0.93	-1.06	-1.09	-0.69	-0.88	-1.12
LU	-1.11	-0.67	-0.70	-0.68	-1.24	-0.86	-0.88	-0.78	-1.04	-0.87	-1.07	-1.08	-0.81	-0.93	-1.07
LV	-1.11	-0.90	-0.52	-0.89	-1.19	-0.82	-0.88	-0.75	-1.05	-0.92	-1.05	-1.05	-0.67	-0.89	-1.16
MT	-1.17	-0.89	-0.59	-0.83	-1.14	-0.76	-0.93	-0.75	-1.04	-0.94	-1.04	-1.06	-0.66	-0.91	-1.10
NL	-1.23	-0.79	-0.57	-0.84	-1.21	-0.83	-0.87	-0.89	-1.04	-0.88	-1.05	-1.06	-0.66	-0.90	-1.08
PL	-1.12	-0.91	-0.42	-0.88	-1.23	-0.83	-0.89	-0.72	-1.05	-0.90	-1.05	-1.10	-0.62	-0.87	-1.09
PT	-1.18	-0.88	-0.64	-0.82	-1.11	-0.75	-0.90	-0.85	-1.06	-0.86	-1.05	-1.08	-0.87	-0.94	-1.11
RO	-1.06	-0.92	-0.78	-0.91	-1.21	-0.81	-0.88	-0.61	-1.06	-0.93	-1.06	-1.21	-0.76	-0.87	-1.20
SE	-1.33	-0.83	-0.07	-0.78	-1.35	-0.86	-0.86	-0.83	-1.05	-0.90	-1.05	-1.04	-0.69	-0.89	-1.07
SI	-1.16	-0.89	-0.42	-0.77	-1.18	-0.82	-0.91	-0.82	-1.04	-0.84	-1.06	-1.05	-0.80	-0.93	-1.14
SK	-1.09	-0.88	-0.64	-0.86	-1.14	-0.83	-0.91	-0.70	-1.05	-0.91	-1.06	-1.07	-0.65	-0.87	-1.10
GB	-1.34	-0.79	-0.33	-0.73	-1.25	-0.83	-0.88	-0.82	-1.07	-0.93	-1.06	-1.05	-0.90	-0.92	-1.10
US	-1.49	-0.56	-0.73	-0.68	-1.35	-0.80	-0.83	-0.95	-1.07	-0.81	-1.06	-1.04	-0.79	-0.89	-1.06
JP	-1.21	-0.74	-0.83	-0.77	-1.32	-0.82	-0.83	-0.86	-1.05	-0.92	-1.05	-1.05	-0.88	-0.89	-1.10
CN	-1.00	-0.91	-0.49	-0.86	-1.16	-0.68	-0.86	-0.88	-1.11	-0.86	-1.13	-1.18	-0.77	-0.83	-1.09
CA	-1.35	-0.74	-0.82	-0.75	-1.34	-0.83	-0.88	-0.88	-1.06	-0.83	-1.07	-1.04	-0.78	-0.92	-1.06
KR	-1.13	-0.80	-0.74	-0.80	-1.22	-0.74	-0.76	-0.93	-1.06	-0.93	-1.04	-1.05	-0.84	-0.81	-1.10

BR	-1.18	-0.85	-0.75	-0.80	-1.16	-0.64	-0.83	-0.88	-1.04	-0.91	-1.24	-1.06	-0.73	-0.88	-1.04
IN	-0.99	-0.86	-0.78	-0.92	-1.14	-0.65	-0.79	-0.85	-1.08	-0.94	-1.17	-1.30	-0.54	-0.82	-1.13
MX	-1.26	-0.85	-0.84	-0.90	-1.31	-0.77	-0.85	-0.75	-1.06	-0.97	-1.06	-1.09	-0.77	-0.93	-1.08
RU	-1.05	-0.91	-0.91	-0.90	-1.19	-0.72	-0.84	-0.74	-1.07	-0.93	-1.04	-1.10	-0.08	-0.63	-1.07
AU	-1.20	-0.74	-0.82	-0.74	-1.26	-0.82	-0.87	-0.88	-1.07	-0.95	-1.06	-1.04	-0.78	-0.92	-1.08
CH	-1.25	-0.22	-0.77	-0.71	-1.31	-0.84	-0.85	-0.94	-1.08	-0.90	-1.06	-1.14	-0.82	-0.83	-1.06
TR	-1.05	-0.66	-0.75	-0.91	-1.09	-0.78	-0.89	-0.52	-1.07	-0.97	-1.06	-1.12	-0.70	-0.81	-1.12
TW	-1.15	-0.83	-0.78	-0.69	-1.43	-0.80	-0.87	-0.90	-1.06	-0.93	-1.05	-1.06	-0.81	-0.91	-1.08
NO	-1.22	-0.81	-0.77	-0.78	-1.27	-0.83	-0.89	-0.77	-1.03	-0.93	-1.05	-1.05	-0.82	-0.91	-1.10
ID	-1.01	-0.91	-0.88	-0.84	-1.31	-0.57	-0.88	-0.62	-1.04	-0.94	-1.07	-1.09	-0.89	-0.94	-1.18
ZA	-1.17	-0.84	-0.89	-0.88	-1.17	-0.77	-0.88	-0.92	-1.06	-0.95	-1.06	-1.17	-0.66	-0.92	-1.18
WA	-1.15	-0.78	-0.72	-0.83	-1.17	-0.74	-0.88	-0.89	-1.06	-0.89	-1.03	-1.07	-0.79	-0.92	-1.08
WL	-1.14	-0.83	-0.76	-0.82	-1.23	-0.76	-0.90	-0.91	-1.07	-0.88	-1.05	-1.05	-0.80	-0.92	-1.08
WE	-1.12	-0.80	-0.77	-0.84	-1.25	-0.79	-0.89	-0.89	-1.07	-0.88	-1.06	-1.07	-0.83	-0.89	-1.08
WF	-1.09	-0.85	-0.81	-0.85	-1.22	-0.74	-0.90	-0.87	-1.07	-0.89	-1.05	-1.07	-0.83	-0.93	-1.09
WM	-1.13	-0.82	-0.76	-0.82	-1.21	-0.79	-0.88	-0.88	-1.05	-0.90	-1.06	-1.06	-0.80	-0.92	-1.08

We model growth in affluence using the projections of economic indicators from the International Energy Agency's Energy Technology Perspectives, IEA ETP (IEA, 2015).[2] It provides long-term compound growth rate projections of GDP for the World, OECD countries, Non-OECD countries, ASEAN, Brazil, China, European Union, India, Mexico, Russia, South Africa and the United States (see S6). For the years up to 2022, the IMF medium term forecast has been used for the all regions in EXIOBASE. For the years after, the relative distance between the region's growth rate in 2022 and the average annual growth rate of the corresponding region in the IEA ETP data for the years 2020–2030 has been used.

GDP is a measure of the output of a country but does not fully represents that country's consumption as it includes exports and excludes imports. Therefore, we estimate household consumption development relative to GDP using simple ordinary least squares regressions (S5). In a last step, we apply the obtained growth rates in future consumption to the consumption data of 2011 from EXIOBASE 3 to ensure consistency with historic data when projecting into the future.

2.5. Calculating scenarios of GHG emissions based on forecasted demand

Impacts (I) of changing population (P), affluence (A) and technological change (T) on the environment are often modelled using the IPAT concept (Ehrlich and Holdren, 1971). Here we focus only on the effect of changes in affluence on consumption and through this, the impact on the environment. In the static scenario, we assume no changes in household preferences by projecting the 2011 EXIOBASE expenditure shares. In the QUAIDS scenario we estimate the QUAIDS model (Eq. (1)) to calculate the projected expenditure shares. Note that all scenarios are based on the same forecasted population and expenditure. To isolate the effect of changing consumption structure on environmental impacts, we use 2011 Leontief multipliers (which show impact per unit of final consumption) for all projections. These product-specific multipliers are calculated to include direct household emissions (by product) as well as the indirect emissions via the Leontief inverse as is common in the calculation of carbon footprints (Ivanova et al., 2016). Therefore, our scenarios are purely based on the sensitivity of different ways to attribute increasing consumption to categories of products: no technological change, price responses, divestment from fossil fuels or energy efficiency improvements are considered.

For calculating total environmental impacts of household consumption, we firstly estimate the 2011 multiplier for each country c of the model individually to include both indirect emissions and direct household emissions (see below for nomenclature):

$$\mathbf{q_c}^{2011} = \left[\left(\mathbf{b}*((\mathbf{S}*\mathbf{L})+\mathbf{S_{hh}})*\widehat{\mathbf{y}^{mr}_{hh,c}}\right)*\mathbf{G}\right]*\left(\widehat{\mathbf{y}^{mr}_{hh,c}*\mathbf{G}}\right)^{-1} \tag{16}$$

Whilst the equation looks complex compared to a conventional multiplier calculation, it is simply keeping the detail on products consumed by households for the region of consumption, and creates weighted average multipliers of goods consumed by that region – that is, it aggregates the multi-regional dimension of the multipliers. Hence Eq. (16) shows a diagonalization of the footprint calculation in order to maintain the product disaggregation, followed by an aggregation of the footprint, before division by the expenditure on each product group (also aggregated to remove the regional dimension). Eq. (16) also includes intensities for household emissions (such as household use of a vehicle) which are obtained by dividing the fuel use emissions of a certain good by the expenditure on that good.

We then estimate the carbon footprint[3] for different countries c and years t using the projections of per-capita expenditure Y_{tc} from the GDP regressions (Section 2.4) and estimated household budget shares w_{tc} from the demand model (Section 2.2) as:

$$\mathbf{e_{tc}} = \left(\mathbf{q_c}^{2011}*\widehat{\mathbf{w_{tc}}}*Y_{tc}\right)*pop_{tc} \tag{17}$$

[2] https://www.iea.org/etp/etpmodel/assumptions/

[3] The carbon footprint (CF) is the weighted sum of GHG emissions according to their global warming potential. From the result section and onwards, results are shown as carbon footprints, not the individual GHGs. The terms CF and GHG are both used but refer to the same unit of measurement.

Letting nG, nC and nS represent the number of GHGs, regions, and sectors respectively, in EXIOBASE, whilst nAggS represents the 15 product groups used in the demand model, the nomenclature is:

$\mathbf{e_{tc}}$ vector of total environmental carbon footprint by product for each country *c* and year *t* [1 x nAggS]

b vector of characterization factors linking the global warming potential of different GHGs to carbon footprint in CO_2-equivalents [1 x nG]

S matrix of GHG emission per unit of production [nG x nC*nS]

L Leontief inverse matrix [nC*nS x nC*nS]

shh vector of GHG emission per unit of household expenditure directly emitted by households. [nG x nC*nS]

G Binary aggregation matrix to aggregate both the region of production of goods as well as from the EXIOBASE classification to the 15 sectors used in the demand model [nC*nS x nAggS]

$\mathbf{y}_{hh,c}^{mr}$ vector of household consumption from EXIOBASE (showing goods produced in any region, but consumed in country *c*) [nC*nS x 1]

$\mathbf{q_c}^{2011}$ vector of GHG multipliers (emissions per unit of final expenditure) based on the Leontief production function for 2011 in country *c*, aggregated to nAggS products consumed in the country. [1 x nAggS]

pop_{tc} the population projection for year t and region c [1 × 1]

The "hat" means diagonalization of a vector.

This derivation implies that elements in Eq. (17) change according to the population and affluence projections, as well as the difference in w_{tc} between the scenarios we investigate (QUAIDS and static), while $\mathbf{q_c}^{2011}$ remains unchanged. Furthermore, the traded expenditure of $\mathbf{y}_{hh,c}^{mr}$ and the shares of sub-products contained in the same product group in the QUAIDS model remain equal to the 2011 values in the projections. Further analysis on these points is in the discussion. More details about MRIO methods and calculations can be found in S7.

In the future scenarios the new total expenditure per region obtained from the exogeneous projections is applied to Eq. (1) with prices assumed to be constant (i.e. equal to 2011 prices = 1 for future years). Then the carbon footprints are calculated in Eq. (17) The modelling steps described in the sections above are illustrated in Fig. 1.

3. Results

The income elasticities for the 15 products in Table 2 are presented in Fig. 2 according to the expenditure per capita of each of the 49 regions (bubble size) and the global average elasticity weighted by each region's share of global expenditure in 2011 (black horizontal lines).

The difference between developing and developed regions for certain product groups discussed under Table 2 become evident for additional product groups such as "motor vehicles" and "furniture and household goods". The degree of variance between regional elasticities highly varies. "Vegetables, fruit, nuts, rice and crops" has the highest variation between 0.1 (RoW Asia) and 2.4 (USA). The preference for "health, education, insurance, and social security" is quite uniform between 1.0 (USA) and 1.2 (Turkey). "Housing, real estate, water, gas, electricity and other fuels" is even less elastic with values between 0.9 (India) and 1.0 (USA). The highest global weighted average elasticity is found for "transport services and fuels nec" (1.4) and is the results of large elasticities for regions contributing to a large share of the global total expenditure such as the US (1.6), Great Britain (1.5) and China (1.4). "Fish, meat, and dairy" has the lowest global weighted average elasticity value (0.6) with countries such as Switzerland (−0.7) and USA (0.1) contributing to the low value.

When ranking the top and bottom three regional elasticities per product group, some regions show consistently more extreme elasticities than others. The US has bottom three elasticities for seven of the product groups, and top three elasticities for two product groups. India has five product groups that rank in the top three and one in the bottom three. China has one bottom three elasticity and four top three ones. Switzerland has two top three elasticities and six bottom three ones. RoW Africa has three top three elasticities and one ranking in the bottom three.

Future population, expenditure per capita, and the GHG intensity of consumption for six aggregate regions (See S1 for regional aggregation) are displayed in Fig. 3.

Population is expected to increase by over 30% for the RoW region, with more moderate growth in the other regions, and even decline in Rest of EU by 2030 (Fig. 3A). The BRICS (Brazil, Russia, India, China and South Africa) and RoW have the highest expected growth in expenditure per capita. The already affluent regions EU15 + NO, North America, and other OECD have lower expected expenditure growth at 10–15% over 2011 values (Fig. 3B). The GHG intensity of consumption (Fig. 3C) increases the most for Other OECD and BRICS, while it remains constant or slightly decreases for RoW and EU15 + NO.

Fig. 4 shows the forecasted GHG emissions per capita (Fig. 4A) for the static scenario (dashed lines) and the QUAIDS scenarios (solid lines), and cumulative total emissions (Fig. 4B) for six aggregate regions for the QUAIDS scenario compared to the static scenario.

The largest relative difference in emissions between the scenarios are in the RoW and the BRICS regions, where the QUAIDS scenario results in lower emissions than the static scenario. These two regions also have the lowest emissions per capita. The QUAIDS scenario results in a cumulative 1% lower GHG emissions compared to the static scenario by 2030 globally (Fig. 4B). The differences in cumulative emissions in the populous BRICS and RoW are 1.5–2% lower in the QUAIDS scenario, which largely explains the cumulative lower global emissions in the QUAIDS scenario. The causes of these declining trend in emissions are further explored in Fig. 5 and Fig. 6.

Fig. 5 shows the relative difference in GHG emissions of the QUAIDS scenario compared to the static scenario per product group.

Globally (global expenditure and GHG emissions in S3) there is relatively higher demand and resulting GHG emissions[4] of particularly "Railway-, air-, and other transportation services" in the QUAIDS scenario. Demand and emissions for "vegetables, fruit, nuts, rice and crops" and "fish, meat and dairy" is however about 20% lower than in the static scenario. The direction of the graphs directly follows the trends observed in Fig. 2, and thus the GHG emissions (and expenditure shown in S4) are increasing for "communication services" and "transport services and fuels nec" that have income elasticities above unity in all regions. Compared to the static scenario, "transport services and fuels nec" is the product group with the largest increase in RoW Other OECD, and Rest of EU, while "communication services" increase the most in BRICS in the QUAIDS scenario. Similarly, income elasticities lower than unity in almost all of the 49 regions lead to decreasing GHG emissions in all aggregate regions for "tobacco and beverages" and "fish, meat, and dairy". In the QUAIDS scenario compared to the static scenario. The highly varying trends in income elasticities for "vegetables, fruit, nuts, rice, and crops" observed in Fig. 2 results in highly differing trends in future GHG emissions between regions in the QUAIDS scenario. While the GHG emissions are lower in RoW, BRICS, and Rest of EU, it is the product group that sees GHG emissions increase the most in North America and EU15 + NO in the QUAIDS scenario relative to the static scenario. Globally however, "vegetables, fruit, nuts, rice, and crops" is the product group with the largest decrease in both expenditure and emissions in QUAIDS compared with the static scenario, suggesting that the large populations in particularly BRICS and RoW more than cancels out the increasing trends observed for EU15 + NO and North America. The contribution of different product groups is further explored in Fig. 6 which shows

[4] Note that on a global and aggregated regional level, the observed difference between the expenditure graph (S3) and the GHG emission graph (Figure 5) for a particular product group is purely due to the fact that the sum of all household expenditure in a particular region differs between regions. For a single region, a 1% increase in expenditure on a specific product group will always correspond to a 1% increase in GHG emissions for that product group.

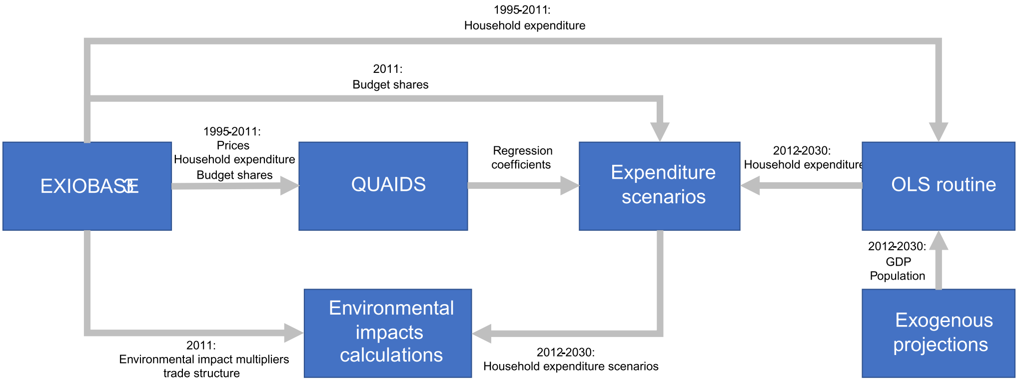

Fig. 1. Overview of the model.

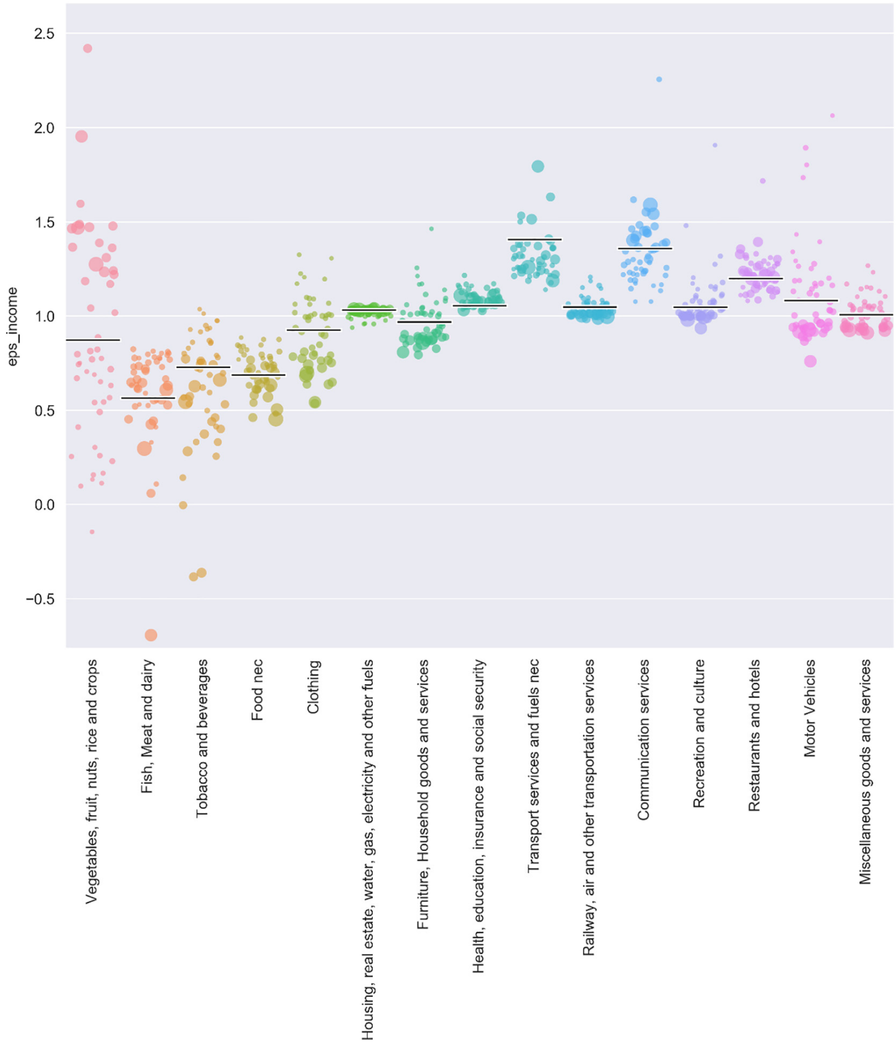

Fig. 2. Value of income elasticities (vertical axis) for the 15 product groups (horizontal axis) and the 49 regions with bubble sizes representing the 2011 expenditure/cap value of each region. The global average elasticity weighted by regional share of global expenditure in 2011 is indicated by black horizontal lines for each product group.

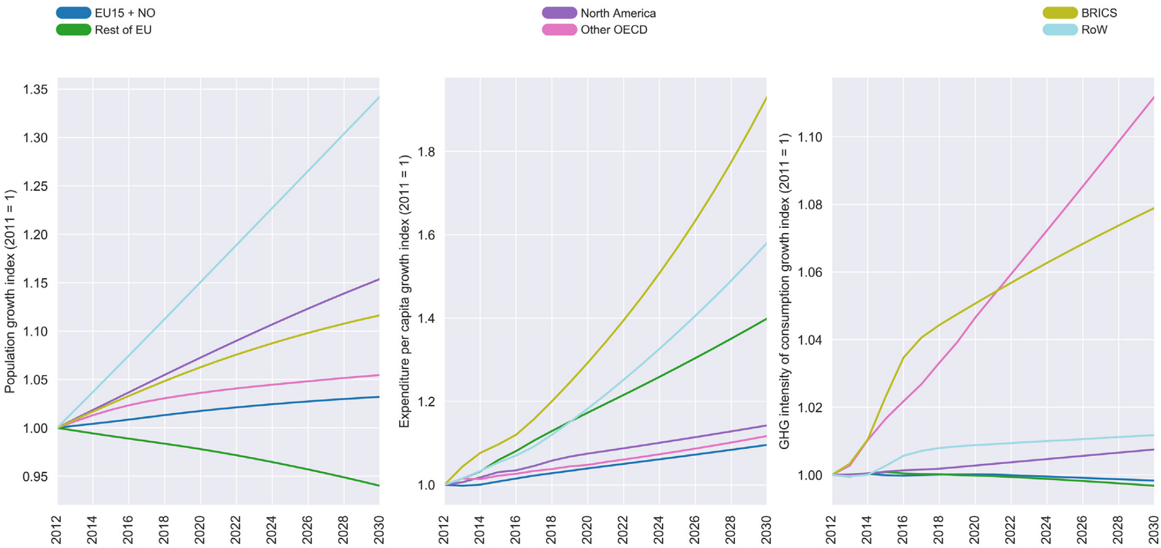

Fig. 3. Evolution of future (A - left) population, (B - middle) expenditure/cap and (C - right) GHG intensity of consumption for the QUAIDS scenario.

the relative contribution of product groups to total emissions in 2030 for the six regions and the 15 product groups used as input to the demand system.

Although the relative difference in GHG emissions between the scenarios is large for e.g. "Transport services and fuels nec" in the BRICS and RoW regions, the contribution to total GHG emissions is quite small. On the other hand, in both RoW and BRICS the decrease in emissions from "vegetables, fruit, nuts, rice, and crops" and "fish, meat, and dairy" is substantial in the QUAIDS scenario relative to the static scenario. This decrease is significant in explaining the declining trend in emissions observed for these regions in Fig. 4B. For North America and EU15, the relative increase in emissions in QUAIDS compared to the static scenario for "vegetables, fruit, nuts, rice, and crops" has small absolute effects on total emissions due to small budget shares in 2011. Overall, the lower emissions from the food product groups in these two regions are cancelled out by higher emissions in the transportation product groups. For all regions, "housing, real estate, water, gas electricity and other fuels" is the largest contributor to emissions. This product group is the most inelastic to changes in expenditure levels (see Fig. 2), observed through small changes in absolute emissions between the scenarios for all regions.

Country and product comparisons for employment, water consumption, material extraction, energy use and land use are available in S2. We find that the QUAIDS scenario results in lower impacts in all regions in four out of these five categories. Only energy use is higher in the static scenario. The largest deviations between the two scenarios are again found for the RoW and BRICS regions, and all regions show the same trend within each product group (i.e. lower impacts for all regions in four out of the five impact categories except for energy use).

We suggest policy recommendations in the form of focal areas of household consumption with the aim of lowering household carbon footprint (CF) based on the outcome of the projections in the QUAIDS scenario Table 4. We investigate the CF share and the CF intensity per monetary unit in 2012 compared to the CF share and intensity of an average product group in the same year. In addition, we look at the changes in household demand in 2030 relative to that in 2012. Hence, a high increase in demand by 2030 combined with a high GHG intensity and share is an indication of important focal areas for lowering consumption-based emissions.

The expected increase in affluence for the developing RoW and BRICS regions are clearly seen with sharp increases in demand per capita from 2012 to 2030 for most product groups (for equivalent country-specific results, see S8). Policies for reducing household emissions in these regions should focus on the "housing, real estate, water, gas, electricity, and other fuels" product group, but also "transport services and fuels nec" and "food nec" due to high GHG intensity and sharp increases in future demand. In North America, demand per capita is expected to increase for all product groups, but the development is most critical regarding emissions from "transport services and fuels nec" with sharp increases in demand, high GHG intensity and high GHG shares. The second product group to focus on in North America is "housing, real estate, water, gas, electricity and other fuels", but this product group has a somewhat lower GHG intensity. These two product groups are essential also in EU15 + NO. Although the expected demand increase is not as high as in North America, the high CF share and intensity indicates that they are key to reducing household impacts. For EU15 + NO and Other OECD there is an expected decrease in demand per capita for some of the product groups, particularly for the food product groups as the previous results (Fig. 5 and Fig. 6) also indicate.

4. Discussion

4.1. Policy implications

Understanding and projecting possible futures is one of the most important tasks in sustainability science and policies as stated in the IPCC Fifth Assessment Report (Edenhofer et al. 2014) and the Shared Socio economic Pathways (Riahi et al., 2017). Given the rise in global wealth, and the strong correlation between wealth and emissions, it is fundamental to understand the potential changes in consumption and its effects on global emissions. Households contribute to the majority (60%) of global GHG emissions (Ivanova et al., 2016), which underlines the importance of understanding how households in countries in different stages of development change their consumption habits as their income changes. We complement the existing forecasting tools by only focusing on the impact of future household preferences on GHG emissions using historic expenditure data from EXIOBASE 3.

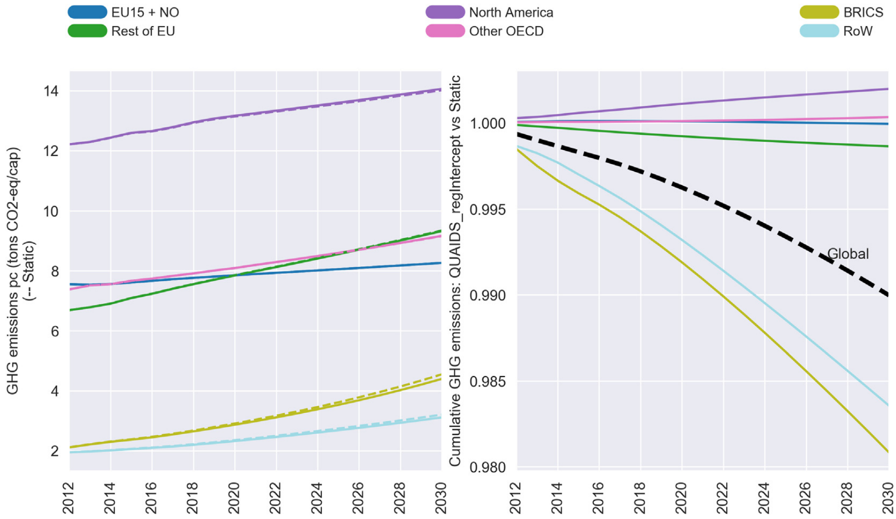

Fig. 4. A (left): Future GHG emissions per capita for the static scenario (dashed lines) and the QUAIDS scenario (solid lines). B (right): Relative deviation from the static scenario (equal to one) for cumulative GHG emissions from 2011 per region for the QUAIDS scenario. Global emissions in dashed lines.

On a global level (see S3), we find a clear tendency towards lower demand and associated impacts for the food product groups in the QUAIDS scenario. Lower-than-unity elasticities for food has strong support in the literature (see e.g. Seale Jr. et al. (2003), Almon (1998), (Muhammad et al., 2011)). Like Almon (1998), we find strong income effects on expenditure for transport, communication, and restaurants and hotels (Fig. 2). The "housing, real estate, water, gas, electricity and other fuels" and "transport services and fuels nec" product groups alone make up about 50% of the global household carbon footprint in 2012 (S3), but add up to less than 30% of household expenditure in 2012, which indicates a high emission multiplier per monetary unit as verified in S3. This contrasts with "health, education, insurance, and social security", which makes up 13% of expenditure in 2012, but only 4% of emissions. The "transport services and fuels nec" product group globally have high income elasticities, while "housing, real estate, water, gas, electricity, and other fuels" behaves like a normal good with an income elasticity around one (see Fig. 2, Fig. 5 and S3), which also has support in the literature (Muhammad et al., 2011). The emission intensities of the three food product groups are all among the highest five out of the 15 product groups globally in 2012 (S3). The combination of low income elasticities and significant share of total household GHG emissions (21%) makes these the main drivers for lower global GHG emissions in the QUAIDS scenario compared to the static scenario. The product group that contributes most to lower relative emissions in the QUAIDS scenario is "vegetables, fruit, nuts, rice and crops".

Our results indicate that accounting for household preferences for products in emission forecasting can have a negative impact on cumulative GHG emissions of up to 2% by 2030 for some of the aggregate regions (Fig. 4) and up to 4% for the individual regions of EXIOBASE (S8). Considering these results, we argue that regional-specific policies aimed towards household consumption can be an important contribution in mitigating global warming. In Table 4 and S8 we provide a guide for policy makers on areas of prioritizing based on our results for the six aggregate regions and each of the 49 regions respectively. The cumulative emissions by 2030 (Fig. 4) shows that the difference in total emissions for developed regions is minimal between the scenarios, while the largest relative decrease in emissions is found in developing regions. From S8 we see that the largest relative cumulative decreases compared to the static scenario are found in India (95.8%), RoW Asia (97.0%) and RoW Africa (98.1%).

Given the rapid changing technology of the last decades, we expect a decrease in the GHG emission intensity of most consumption categories. These technology improvements will have differing effects on the GHG intensity of consumption for different product groups. The electricity sector is in general considered a sector that is relatively easy to decarbonize compared to other sectors, and one which is expected to play a vital role in climate change mitigation (de Sisternes et al., 2016). The transport sector is expected to be more difficult to decarbonize (Kriegler et al., 2014). The same holds for the food sector, which is less dependent on energy and therefore expected to benefit less from the energy transition. Such "hard-to-abate" sectors depend on efficiency improvements or demand side changes to achieve emission reductions. Our results indicate that the relative contribution of food consumption to total emissions is less prominent in the future, which indicates some decarbonization on the demand side. In contrast, the transport sector is expected to have a more significant contribution to total emissions in most countries when considering household preferences (S8). As efficiency improvements, particularly in the energy sector, are susceptible to rebound effects (Sakai et al., 2018, Sorrell, 2014), demand side changes are likely to play a much more prominent role in climate change mitigation in the future.

Our results shed light on the untapped potential of environmental taxation (OECD 2015). Countries that enforce higher environmental taxation as share of GDP, such as Denmark and the Netherlands (OECD 2019) are indeed among the countries in which we have seen the largest decrease in carbon footprint per capita throughout the time series of EXIOBASE (S8). Our results on consumer preferences combined with environmental intensities provide a suitable tool for predicting the effectiveness of environmental taxation which will have different distributional impacts when applied to different goods. Taxes applied for example to domestic heating and electricity are typically found to be regressive, while transport-related taxes are found to be less regressive or even progressive (Milne and Andersen, 2012). Knowledge about this could direct taxation towards largest emission reductions without burdening low-income households (Milne and Andersen, 2012).

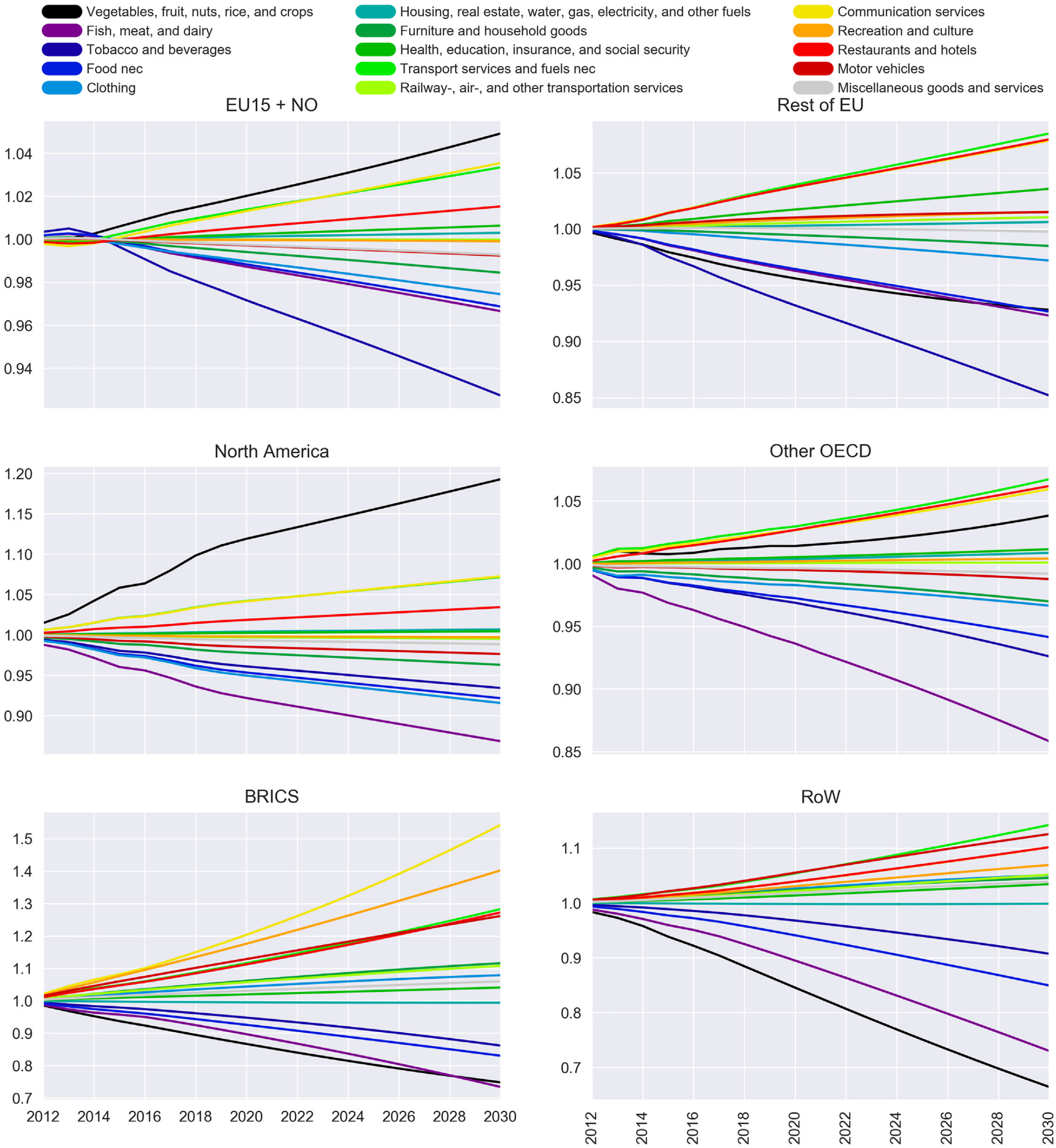

Fig. 5. Comparison of GHG emissions for the QUAIDS scenario relative to the static scenario for six regions and 15 product groups.

4.2. Limitations and future developments

The principal aim of this paper was to study the impact of income changes on consumption, and how this will translate to change in carbon footprints. To isolate this effect, we assume that economic structure and technology will not change in the future, even with respect to the changing demand from the demand system (i.e. we use Leontief production functions). It is well known that Leontief production functions are a gross simplification for modelling long-term changes in the economy, but our principal aim here is to isolate the income effect on consumption, rather than the broader economic response. In order to model the full macro-economic ramifications of demand-side and technological changes, a complete macro-economic model would be needed (e.g. GINFORS (Lutz et al., 2009) and E3ME (Barker 1999)), but it would

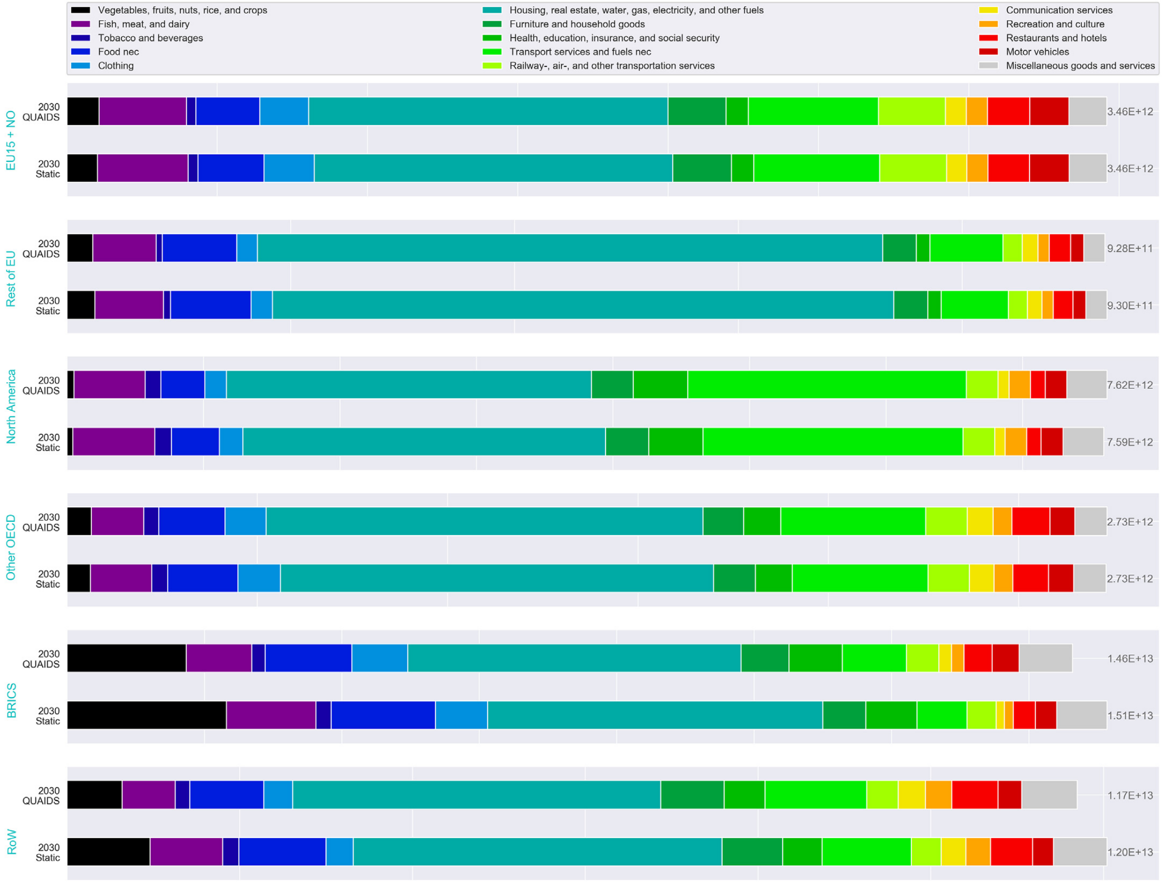

Fig. 6. Contribution to total GHG emissions for 15 product groups by six aggregate regions for the QUAIDS scenario and the static scenario.

then not be possible to isolate the income-consumption effect directly. In reality, several structural changes will occur in the economy over the time-horizon that we model, and assuming that these tend to lower the carbon intensity of production, it would be expected that Leontief multipliers based on future IO tables would be considerably lower (depending on how successful international policy is) than today.

Although it is outside the scope of our study, the price and income elasticities estimated from the demand system provide possibilities for analyses beyond what we have shown in this paper, such as to study how households distribute money saved due to efficiency gains, cheaper renewable energy or consumption changes across goods and services (Freire-González 2011, Thomas and Azevedo, 2013, Font Vivanco et al., 2014, Grabs, 2015, Chitnis and Sorrell, 2015).

For stronger analyses on income inequality, an important future improvement to the IO and the System of National Accounts framework is to add more household detail. The OECD already started this discussion (Fesseau et al., 2013, Fesseau and Mattonetti, 2013). Reconciling household budget surveys and national accounts data is challenging and a potential source of uncertainty per se (Robilliard and Robinson, 2003). However, there is still potential in adding resolution to the sector for understanding distributional issues related to the environment. This could be achieved by splitting household consumption into income quantiles as was done in Sommer and Kratena (2017). A further step could be to incorporate Social Accounting Matrices into IO models. These enable studying the complete cycle of income, from consumption to income generation and re-spending, and allow for a better understanding of the interactions between social and environmental aspects (Lenzen and Schaeffer, 2004).

At least two points are relevant to discuss in relation to the projection of future household expenditure. First, we assume that a change in income is equivalent to a change in expenditure, implicitly assuming household saving patterns are similar in the projections as in 2011. The consumption-savings decision has been frequently discussed in the demand system literature (see e.g. Lluch (1973)) and is something that could be explored further. However, as we are not analyzing different types of consumers, but rather the average consumer in each region over time, it is reasonable to assume that over the time period (2011–2030) income and expenditure are similar, although they might differ from one year to the next. Second, when projecting expenditure from diverse regions, there are likely to be inter-regional differences in terms of collective service provision and governmental spending. Countries with provision of social services would likely require lower household spending. This in turn can affect the projected expenditure as an observed lower preference for a good with rising household income can be the result of increased provision of social services rather than decreased preference for that good. This is particularly a concern when using time series data, as governmental policies regarding social services likely changes with time.

Table 4
Policy recommendations for six regions based on the 2030 projections from the QUAIDS scenario.

	Vegetables, fruit, nuts, rice, and crops	Fish, meat, and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity, and other fuels	Furniture and household goods	Health, education, insurance, and social security	Transport services and fuels nec	Railway-, air-, and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor vehicles	Miscellaneous goods and services
EU15 + NO															
CF share	- -	+	- - -	-	-	+++	-	- -	++	-	- -	- -	-	-	-
CF intensity	+	+	-	+	+	+	+	- -	+++	+	- -	- -	- -	-	- -
Demand pc	+	+	-	+	+	+	+	+	+	+	+	+	+	+	+
Rest of EU															
CF share	- -	-	- - -	+	- -	+++	- -	- - -	-	- -	- - -	- - -	- -	- - -	- -
CF intensity	+	+	-	+	-	+++	-	- -	+++	-	- -	- -	- -	- -	- -
Demand pc	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
North America															
CF share	- - -	+	- - -	-	- -	+++	-	-	+++	- -	- - -	- -	- - -	- -	-
CF intensity	- -	+++	- -	-	-	-	-	- - -	+++	+	- - -	- -	- - -	- -	- - -
Demand pc	++	+	+	+	+	++	+	++	++	++	++	++	++	++	++
Other OECD															
CF share	- -	-	- -	+	-	+++	-	-	+++	-	- -	- -	- -	- -	-
CF intensity	+	++	-	+	+	+	+	- -	+++	-	- -	- -	- - -	-	- -
Demand pc	+	-	-	+	+	+	+	+	+	+	+	+	-	-	+
BRICS															
CF share	++	++	- - -	+	-	+++	-	-	-	- -	- - -	- - -	- -	- -	-
CF intensity	++	++	-	+	-	+++	+	- -	++	-	-	- -	- -	-	- -
Demand pc	+++	+	++	++	+++	+++	+++	+++	+++	+++	+++	++	+++	+++	+++
RoW															
CF share	+	+	- - -	+	- -	+++	-	-	+	- -	- -	- -	-	- -	-
CF intensity	++	++	-	+	-	++	+	- -	+++	-	- -	-	- -	- -	- -
Demand pc	++	++	++	++	+++	+++	+++	+++	+++	+++	+++	+++	+++	+++	+++

The + and – symbols represent the relative difference compared to a baseline. For the GHG share, the baseline is the emissions share for an average product group in 2012, which is compared to the emission shares of the other product groups in 2012. The GHG intensity baseline is the emission intensity (kg CO^2-eq) per monetary unit of an average product group in 2012, which is compared to the GHG intensity of the other product groups in 2012. For the demand per capita, the baseline is 2012, and this is compared to the 2030 per capita demand. The signs correspond to the following relative changes compared to the baseline:
-, 50–100%
- - , 25–50%
- - -, 0–25%
+, 0–50% increase
+ +, 50–100% increase
+ + + larger than 100% increase

We aggregate the sectors of EXIOBASE into 15 product groups. The reasoning behind this is discussed in Section 2.1. Another reason relates to the underlying MRIO data. Creating an MRIO database involves making assumption, and balancing and interpolating data, particularly for the RoW regions where data availability is limited. Thus, MRIO household expenditure data necessarily deviates from actual expenditure data. By aggregating household expenditure to the level chosen in this paper, we avoid jumps in data points from year to year that could be a result of these mechanisms.

There is a variety of ways to forecast future consumption, all of which come with a set of limitations and assumptions. Beside the challenges related to using household consumption data from IO models, there are limitations related to the demand model used in this paper. Demand models assume homogenous, non-interacting and rational consumers, a criticism of neoclassical economic models in general (Axtell et al., 2001, Veblen 1898, Colander et al., 2004). A possible way to overcome this is to include elements of e.g. agent-based modelling (ABM). In ABM, these limitations are overcome by letting individual, autonomous agents interact. These interactions are determined on the basis of the agents' states and rules of behavior (Axtell 2000), which can for example be based on microdata from consumer expenditure surveys. This approach also enables the inclusion of consumers taking environmental considerations into their consumption decisions.

5. Conclusion

In this work we looked at the specific contribution that the income effect will have on global GHG emissions, everything else being equal.

We forecasted household consumption to 2030 in two different scenarios based on expenditure data from an MRIO database (EXIOBASE) in the period 1995–2011. In the first static scenario, consumption is forecasted using the 2011 household consumption shares of 15 aggregated product groups. In the second (QUAIDS) scenario, we use a demand system to incorporate changes in household preferences as their income changes. By applying population and GDP per capita projections, we compare the resulting GHG emissions up until 2030 to isolate the effect of income changes. Globally, we find a small 1% reduction in cumulative GHG emissions of the QUAIDS scenario compared to the static scenario. This result is mainly driven by lower emissions in the BRICS and rest-of-the-world regions. On a product level, we find lower emissions from particularly food product groups in developing countries, while emissions related to transport and services contribute to higher emissions in the QUAIDS scenario.

To further develop MRIO databases as a tool for studying future emissions from household consumption, we call for two areas of improvement. The first is a disaggregation of the household consumption vector, at least into income quantiles, which would facilitate analyses of income inequality as well as the distributional effects of the implementation of policy instruments such as environmental taxation. The second relates to disaggregation of sectors and regions. A greater detail of household consumption-relevant sectors, such as food and transport would improve the representation of household preferences in demand system analyses. A disaggregation of regions would reduce uncertainty in emissions embodied in traded goods due to high variability in GHG emission intensities among different countries aggregated in the same region.

Although there is a slight optimism in lower emissions when considering household preferences as income changes, the overall effect is limited. As a guide to policy makers we provide focal areas to reduce emissions from household consumption for 49 regions. Given that the ease of decarbonization highly differs between sectors, such a guide can be an important tool in the undoubtedly challenging decision-making faced with mitigating emission in the years to come.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105114.

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Appendix C Paper III

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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 eitherPDF (Koslowski 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; Koslowski 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 (Koslowski et al., 2020), and by specific analysis on the effects of consumption (Marquardt et al. (2019). Although Koslowski 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; Koslowski 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:

$$\mathbf{E} = \mathbf{SLY} \tag{1}$$

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. km^2/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:

$$\mathbf{E} = \mathbf{S}\left(\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \mathbf{A}^4 + \ldots\right)\mathbf{Y} \tag{2}$$

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:

$$\mathbf{E} = \mathbf{S}\hat{\mathbf{x}} \tag{3}$$

$\hat{\mathbf{x}}$**:** 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).

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

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

$$CF_{u,j} = \frac{\frac{P_{lost,u,j} \cdot b_{i,j}}{B_{i,j}} \cdot VS_{u,j}}{N \cdot P_{u,world} \cdot VS_{u,world}} \tag{5}$$

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/m^2) 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/m^2) with land use data (m^2/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 ($\mathbf{S_l}$) for EXIOBASE 3rx are given in km^2/Million Euro, while the LC-IMPACT global biodiversity loss characterization factors (**CF**) are in PDF/m^2. To arrive at biodiversity loss intensities ($\mathbf{S_b}$), the total land use associated with production in each sector and country of EXIOBASE 3rx ($\mathbf{F_b}$) 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:

$$\mathbf{S_b} = \frac{\mathbf{10^6 * (F_l * CF)}}{\mathbf{x}} \tag{6}$$

$\mathbf{F_l}$: 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 $\boldsymbol{S}$ with $\boldsymbol{S_b}$. 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:

$$D = \frac{bf_t / bf_{1995}}{GDP_t / GDP_{1995}} \tag{7}$$

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:

$$ln(bf_{ct}) = \alpha_c + \beta_0 + \beta_1(lnGDPpc_{ct}) + \beta_2(lnyield_{ct}) + \epsilon_{ct} \tag{8}$$

α: Time-invariant unobserved heterogeneity (country-fixed effects)
β_0, β_1, β_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%).

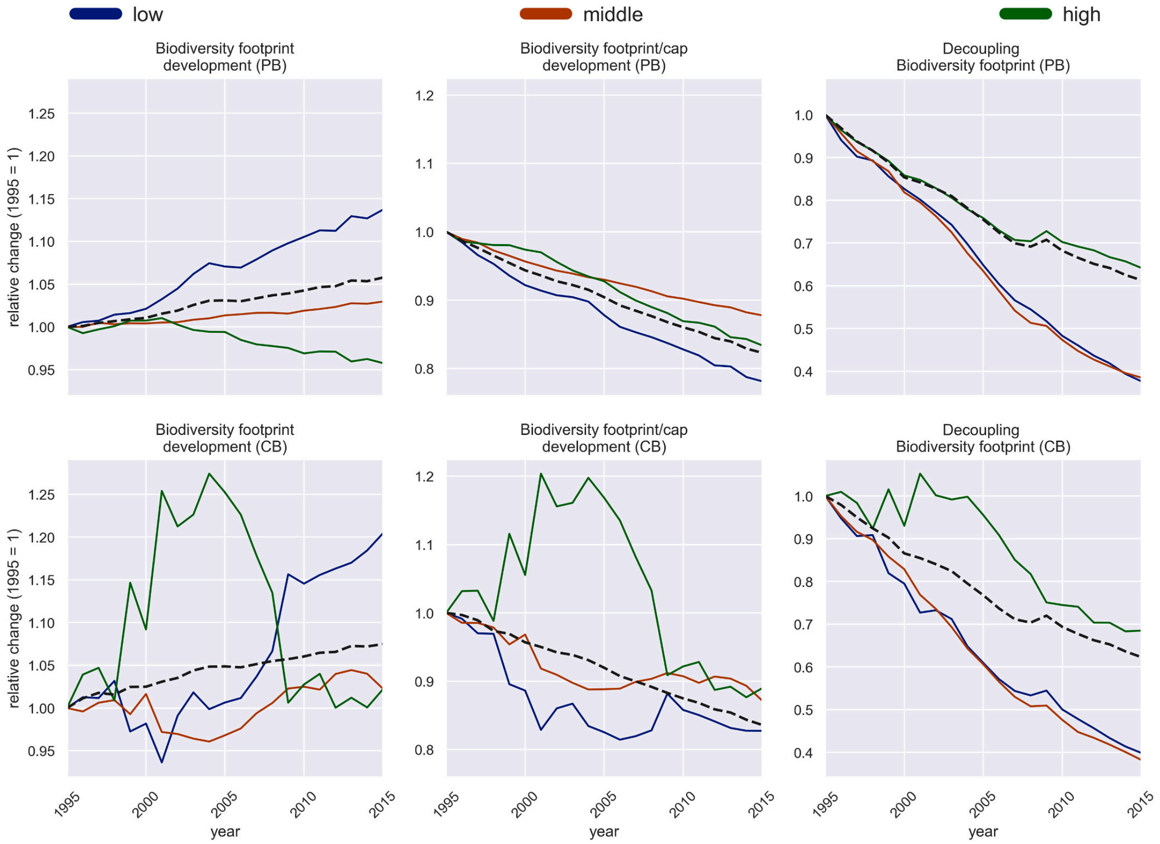

Fig. 1. Footprints development, total (left) and per capita (middle), as well as decoupling of biodiversity impacts from GDP (right) for PB (top row) and CB (bottom row) accounts. Values are relative to 1995. The colors represent the regions grouped by income quantile. CB: Consumption-based, PB: production-based.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

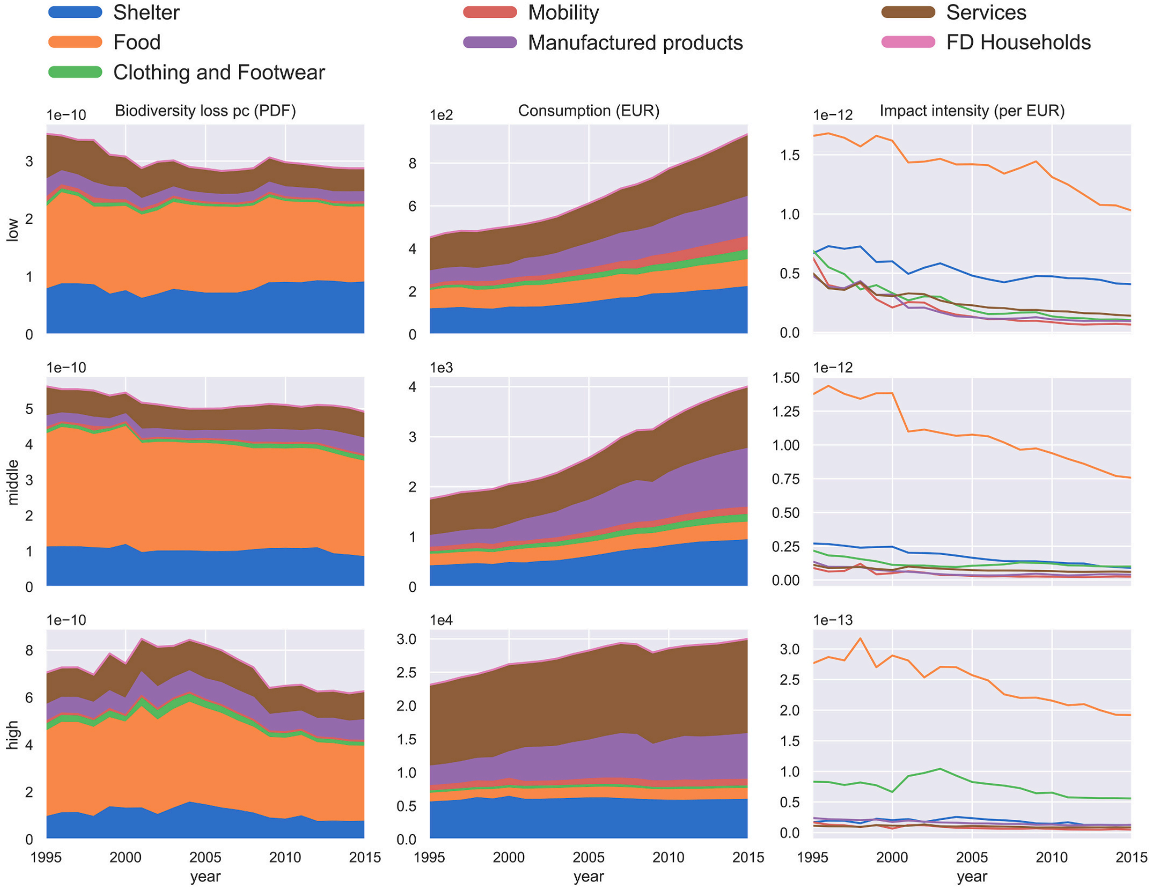

Fig. 2. Biodiversity footprint, consumption, and footprint intensities (PDF/EUR) for six consumption groups and the three income groups.

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 (SI7), 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 (SI4), 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-

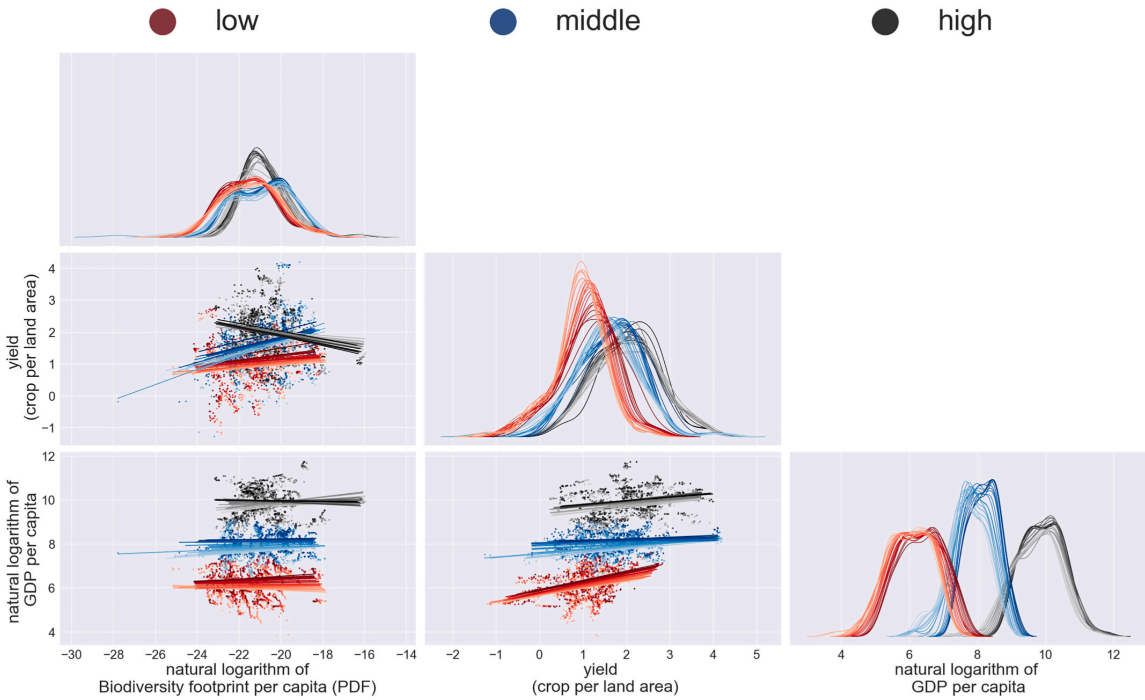

Fig. 3. Scatter plots of individual countries with linear regression model fits (off-diagonal) and kernel density estimation (diagonal): Natural logarithms of GDP per capita (in 2005 constant Euros), biodiversity footprint per capita (in PDFs), and efficiency (crop per land area). Years are represented 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 (***)**	**1.02 (**)**	**1.37 (**)**	**1.25 (**)**	**1.94 (***)**	**1.34 (***)**	**1.3 (***)**
	(0.48 1.88)	*(0.16 1.87)*	*(0.05 2.69)*	*(0.16 2.35)*	*(1.2 2.69)*	*(0.62 2.07)*	*(0.63 1.97)*
middle	**0.92 (*)**	**0.3 ()**	**0.56 ()**	**0.46 ()**	**0.98 (**)**	**0.77 ()**	**0.62 ()**
	(−0.13 1.96)	*(−0.53 1.13)*	*(−0.54 1.66)*	*(−0.55 1.48)*	*(0.12 1.85)*	*(−0.78 2.33)*	*(−0.37 1.6)*
low	**0.14 ()**	**−0.31 (**)**	**0.19 ()**	**0.14 ()**	**0.38 (**)**	**−0.05 ()**	**−0.0 ()**
	(−0.1 0.38)	*(−0.56–0.05)*	*(−0.13 0.5)*	*(−0.3 0.59)*	*(0.05 0.7)*	*(−0.34 0.24)*	*(−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 an (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 EXIOABSE 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 Morecroft, 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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Appendix D Paper IV

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Climate change mitigation potential of Norwegian households and the rebound effect

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An increasing number of studies show that efficiency improvements alone will not be sufficient to attain the substantial emission reductions needed to mitigate global warming to a target of 2 °C. Consumption side changes are likely to be needed to achieve sufficient emission reductions. The United Nations emphasize the importance of developed countries taking the lead in lowering emissions to achieve the sustainable development goals. This paper assess to what extent Norwegian households can lower their carbon footprint consistent with territorial emission reductions towards the 2 °C target of global warming through implementing a set of behavioral actions. We evaluate the efficacy of the set of actions both initially and after considering rebound effects. A multiregional environmentally extended input-output database is linked with the Norwegian consumer expenditure survey to analyze both average and marginal expenditure per unit of increased income. Further, linear programming is applied to examine the changes needed by households to reach different emission reduction targets. We find that households implementing the full set of actions without re-spending can obtain a 58% decrease in their carbon footprint. When accounting for the effect of re-spending, this reduction drops to 24–35%, which is not within the requirements of the 2 °C target. The optimization analysis suggests households can achieve reductions up to 45% by restricting re-spending to specific goods and services. This indicates that curbing the rebound effect is key to achieving real reductions in household carbon footprints. We show that changing consumption patterns can significantly contribute to lowering anthropogenic greenhouse gas emissions without compromising the level of economic activity.

1. Introduction

The Intergovernmental Panel on Climate Change report of 2014 states that a 40–70% reduction in anthropogenic GHG emissions between 2010 and 2050 are needed to limit global warming to 2 °C above pre-industrial levels (Pachauri et al., 2014). The recent Paris Agreement calls for signatories to pursue efforts towards the even more ambitious goal of 1.5 °C to significantly reduce the risks and impacts of climate change. Recent studies show that it is becoming increasingly difficult to attain these goals through technical solutions alone (van Sluisveld et al., 2016). Historically, technological improvements have not outweighed the growth in impacts due to increased consumption (Wood, 2009). This underlines the need for a broader set of mitigation options, including on the consumption side (Davis and Caldeira, 2010).

A key challenge to limiting anthropogenic GHG emissions is to combine eco-efficiency on the production side with consumer efficiency on the consumption side (Throne-Holst et al., 2007). The 12. Sustainable development goal of the United Nations "ensure sustainable consumption and production patterns" makes the link explicit (United Nations, 2015). Optimal benefits are historically not achieved because the environmental gains from cleaner production (efficiency improvements and innovations) are offset by demand side aspects such as population growth and increased consumption and standards of living (Clark, 2007). Little agreement on strategies to approach sustainable consumption, such as focusing on eco-efficiency versus sufficiency measures and greening of markets versus awareness raising have further delayed progress in sustainable development (Mont and Plepys, 2008). Strategies to realize this potential includes "reasonable" consumption through changing consumption patterns complemented by "reasonable" production strategies (Kronenberg, 2007) and interfering more with consumer choices and markets, instead of a pure focus on greening

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Abbreviations

APP	Absolute purchasing power
CF	Carbon footprint
COICOP	Classification of Individual Consumption According to Purpose
GHG	Greenhouse gas
GWP	Global warming potential
ICEV	Internal combustion engine vehicle
IPCC	Intergovernmental Panel on Climate Change
MDF	Medium-density fiberboard
MPC	Marginal propensity to consume
MRIO	Multiregional input-output
NOK	Norwegian krone
pkm	Passenger-kilometer
RPP	Relative purchasing power
SCP	Sustainable consumption and production

production and products (Tukker et al., 2008).

Consumers have two options to reduce consumption-driven greenhouse gas (GHG) emissions. The first is to reduce overall consumption, which several studies find to be an important step in climate change mitigation (Garnaut, 2008; Ivanova et al., 2016; Stern, 2007), but which often has negative effects on economic growth (Silva Simas et al., 2017). The second option is to shift the pattern of consumption towards goods and services that are less GHG emission intensive (Throne-Holst et al., 2007). Some studies find that the contribution to climate mitigation of such changes in consumption patterns can be significant. Gardner and Stern (2008) found energy savings in the range of 30–58% studying the impacts of lifestyle change. Druckman and Jackson (2010) report 37% lower GHG emissions in a reduced consumption scenario, while Alfredsson (2004) found a 30% reduction in CO_2 by adopting a “green” consumption pattern.

However, it is often not realistic to consider lifestyle changes without regarding impacts on the household budget. If households for example reduce their car travel to lower their environmental impact, this will both reduce costs and GHG emissions. However, rebounds occur when consumers *re-spend*[1] this saved money from driving less on a vacation by airplane to a faraway destination. This produces additional GHG emissions that offset the initial emission reductions. This mechanism is known as the rebound effect, first described by Jevons (1866) and later by Saunders (1992) and the Khazzoom-Brookes Postulate which states that increased energy efficiency leads to increased energy consumption. The rebound effect has been seen in practice in car-free households in Vienna (Ornetzeder et al., 2008).

Rebound effects can arise either from efficiency improvements that make a good or service cheaper or from changing the pattern of consumption leading to lower costs, known as sufficiency strategies. There are three main types of rebound effects; direct (re-spending on the same good or service as the one where money is saved), indirect (re-spending on other goods and services) and various macroeconomic effects (how the effect of the efficiency improvement or changed consumption distributes throughout the economy) (Greening et al., 2000).

Since Jevons (1866), researchers have known that efficiency improvements are subject to rebound effects. However, recent studies have shown that sufficiency strategies also are subject to rebound effects (Figge et al., 2014). In the discussions of a transition to a circular economy, overcoming rebound effects of efficiency and sufficiency strategies is pointed out as a key challenge (Ghisellini et al., 2016). If rebound effects are not overcome, the last resort is to reduce economic activity on the macro level (Figge et al., 2014).

Previous rebound effect studies often analyze the impacts of one or a few behavioral actions, rather than lifestyle changes. Grabs (2015) found GHG emission rebound effects of 49% from changing to a vegetarian diet. Briceno et al. (2005) found indirect rebound effects of 42–49% from car-sharing schemes. Chitnis et al. (2013) found direct and indirect rebound effects in the range of 5–15% from energy efficiency improvements by UK households. Font Vivanco et al. (2014) found rebound effects in the range of 3–5% when changing from a conventional car to a plug-in hybrid electric passenger car. Chitnis and Sorrell (2015) found combined direct and indirect rebound effects of energy efficiency improvements by UK households to be 41%, 48% and 78% for measures involving domestic gas use, electricity use and vehicle fuel use respectively.

Studies on rebound effects from complete lifestyle changes are less common. Chitnis et al. (2014) found combined direct and indirect rebound effects of 15–35% for different combinations of household actions. Rebound effects were lowest for measures affecting domestic energy use and largest for reducing food waste. Druckman et al. (2011) found combined indirect and direct rebound effects from three efficiency measures to be 34%, which dropped to 12% when restricting re-spending to goods and services with low GHG intensities. Alfredsson (2004) found CO_2 rebound effects of 238% for “green” food consumption, 12% for “green” travel and 19% for “green” housing. An overall “green” consumption pattern resulted in 14% rebound using a “green” re-spending scenario. Murray (2013) found effects in the range of 9–12% for combined sufficiency measures concerning vehicle fuel and household electricity.

This paper investigates consumption side changes as a complementary strategy to efforts to decarbonize the production side to achieve sufficient emission reductions. We assess to what extent households can contribute to CF (carbon footprint) reductions on the scale of what is needed to keep to the 2 °C target of global warming. The 2 °C target is translated to a required per-capita emissions reduction of 40% for Norway (Norwegian Ministry of Climate and Environment, 2015). An equivalent per-capita reduction from the consumption side is then taken (to cover the fact that a large proportion of Norway's CF is embodied in imports). A set of actions is suggested that reduce GHG emissions in line with this target. Only consumption side changes are considered here, whereas (as discussed above), these will need to complement production side changes. We build on existing work as well as novel linear programming approaches to develop a framework to investigate rebound effects of different scenarios of fully re-spending the savings (Section 2). We explore differences between average and marginal spending patterns, as well as a constrained “green” spending pattern. We then calculate the possible reduction in household CF when including rebound effects and relate results to methodological choices of the analysis (Sections 3 and 4), before concluding and assessing the implications of the results in the final section.

2. Methods

2.1. Norwegian carbon footprints

The CF is calculated using the input-output framework developed by Wassily Leontief in the 1930s (Leontief, 1936). A basic

[1] Full *re-spending* in this paper relates to first implementing a behavior that saves money, and then spending an equivalent amount of money on one or several alternative goods or services.

input-output model consists of a system of linear equations, where each equation describes the distribution of an industry's product throughout the economy. It considers flows of products from industrial sectors (producers) to other sectors (consumers), and thus describes the composition of inputs required by a particular industry to produce its output (Miller and Blair, 2009). For a derivation of the input-output framework, see S2. The framework has been applied extensively to looking at CFs of domestic consumers (Wood and Dey, 2009).

Total (direct + indirect) emissions per unit of expenditure, called emission multipliers, were obtained using the multiregional environmentally extended input-output database EXIOBASEv2, which includes information on 48 regions and 200 products for the reference year 2007 (Wood et al., 2015). The database provides high detail on greenhouse gas emission intensive products (Wood et al., 2014). All major forms of greenhouse gas emissions (CO_2, CH_4, N_2O and SF_6 using IPCC emission factors (Solomon et al., 2007)) are included. EXIOBASE provides emission estimates for each sector in each region as well as for direct emissions by households. The number of Norwegian households was obtained from Statistics Norway (2014).

In this work we further utilize spending pattern data by consumer group from the Norwegian Consumer Expenditure Survey of 2012 (Statistics Norway, 2013). Both handling of under-reporting and conversion of the data from COICOP (Classification of Individual Consumption According to Purpose) classification to the EXIOBASEv2 classification and pricing was dealt with using the framework of Steen-Olsen et al. (2016).

2.2. Cost and emission savings of household actions

After screening the Norwegian household CF, we assess the GHG reduction potential and the direct economic impacts of 34 household actions. The base scenario is the average Norwegian household's current pattern of consumption. A literature survey is used to obtain the needed data on each action in sufficient detail. GHG emissions and direct economic impacts of the actions are calculated by comparing a current type of consumption behavior to an environmentally better performing alternative, before scaling up to yearly savings per household. Where the literature presents relative savings from actions, absolute savings are calculated based on the current average consumption in EXIOBASEv2. The 34 actions are distributed among seven sectors of household consumption: transport, shelter, food, clothing, furniture, paper and plastic (see S1 for detailed calculations and data sources). Consumer price indices and exchange rate data (Statistics Norway, 2015) are used to convert to 2007 costs in Norwegian *kroner*[2] (NOK), and further to basic prices for later connection to the input-output modelling in the rebound framework (S2 and Section 2.4).

2.3. Adjusting for double counting

Since some of the actions cover the same household activities, the degree to which actions overlap must be evaluated to determine the cumulative effects of implementing several actions simultaneously. This potential double counting is accounted for by introducing an actions-activity matrix (S3). In this matrix, we for example distribute travels within a specific distance range among six transport modes to cover the total yearly distance traveled. Net savings in emissions and costs are multiplied by the number of units available for each activity to obtain the total cost and emission reduction structure of that combination of actions. The actions-activity matrix serves as the basis for further calculations, but it enables several other scenarios.

2.4. Rebound effect framework

The rebound effect framework builds on the assessment of the Norwegian household footprint, but integrates the household actions and the rebound effects. We look purely at Norwegian consumption irrespective of region of origin by aggregating across exporting regions and dividing by product level expenditure to give weighted emission multipliers per unit demand for the 200 products detailed in EXIOBASE (see S2 in supporting information).

The relative environmental rebound effect (Druckman et al., 2011) is defined as:

$$\textit{rebound effect} = \frac{(\textit{potential savings} - \textit{actual savings})}{\textit{Potential savings}}$$

A redefinition of this is:
Δh = Expected reduction in GHG emissions.
Δg = GHG emissions associated with re-spending.
This gives the actual emission reduction: $\Delta h - \Delta g$.
The rebound effect (re) is then

$$re = \frac{\Delta h - (\Delta h - \Delta g)}{\Delta h} = \frac{\Delta g}{\Delta h} \tag{1}$$

where Δh is determined based on literature findings (S1 and Section 2.2).

For Δg direct emissions from households (f_{hh}) are added to the weighted multiregional emission multipliers for Norwegian consumption from EXIOBASEv2 (see S2 in supporting information) to give emission multipliers m_{tot} that include both direct and indirect emissions per unit of expenditure.

Full re-spending of the saved money according to different scenarios (y_{re}) is then:

$$y_{re} = \sum_{1}^{34} (y_{sav} * B * q) * y_{sp} \tag{2}$$

y_{sav} is the direct financial savings from the 34 actions not adjusted for double counting.B is the matrix adjusting for double counting.q is the vector of total number of units per action.y_{sp} is the scenario of re-spending.

Re-added GHG emissions (Δg) due to re-spending are then given as:

$$\Delta g = m_{tot} * y_{re} \tag{3}$$

Finally, Δg from Eq. (3) is inserted into Eq. (1) to calculate the rebound effect

$$re = \frac{\Delta g}{\Delta h} = \frac{m_{tot} * y_{re}}{\Delta h} \tag{4}$$

2.5. Spending patterns

After finding rebound effects using the framework above, the next step is to look into the development of the re-spending scenarios (y_{re}) to assess the impact of re-spending on rebound effects. We examine three scenarios: average, marginal and green re-spending. While the average and marginal approaches are common in the literature, the green scenario is developed for this study.

[2] In 2007, 1 € was equivalent to around 8.02 NOK.

2.5.1. Average

The average spending pattern is the shares of total consumption for each product group converted to the EXIOBASE classification. All savings are re-spent across products in the same proportions as the current average household expenditure.

2.5.2. Marginal

In the marginal scenario, it is assumed that households change their spending pattern towards that of higher income groups as income increases.

There are multiple approaches to calculating marginal spending patterns (Font Vivanco et al., 2014). Our approach builds on Thiesen et al. (2008) who comparted consumption patterns across income brackets using cross-sectional data. We obtain detailed data on household consumption patterns (COICOP Level 2 classification) broken down into six income brackets consisting of income deciles 1, 2-3, 4-5, 6-7, 8-9, and 10 (Statistics Norway, 2013). This is used to calculate a weighted average distribution of an incremental increase in income.

The marginal propensity to consume (MPC) from one income group to the adjacent one is found as:

$$\mathrm{MPC}_{n,i} = \frac{\partial \mathrm{Q}_i}{\partial \mathrm{i}} = \frac{\mathrm{Q}_{i_{n+1}} - \mathrm{Q}_{i_n}}{\mathrm{i}_{n+1} - \mathrm{i}_n} \tag{5}$$

In Eq. (5), i_n is the average income of income group n, while Q_i is demand for product group i. This gives the marginal propensity to consume product i when moving from income group n to income group $n+1$.

Next, the relative purchasing power of each of the six income groups is calculated:

$$\mathrm{rpp}_n = \frac{\mathrm{app}_n}{\sum_{i=1}^{6} \mathrm{app}_i} \tag{6}$$

app_n is the absolute purchasing power of income group n.rpp_n is the relative purchasing power of income group n.

The weighted relative purchasing power (rppw_n) when moving from one income group to the adjacent one is then:

$$\mathrm{rppw}_n = 0.5{*}\mathrm{rpp}_n + 0.5{*}\mathrm{rpp}_{n+1} \tag{7}$$

Eq. (7) is used for all income groups, except the lowest and highest which are assigned a weighting factor of one as these income groups are counted only once.

Finally, the marginal spending pattern is given as:

$$\mathrm{msp}_i = \sum_{i=1}^{5} (\mathrm{MPC}_{n,i}{*}\mathrm{rppw}_n) \tag{8}$$

where msp_i is the marginal spending on product group i.

2.5.3. Green

We further develop the green spending pattern based on the marginal spending pattern. The idea is that environmentally aware households avoid re-spending on goods and services with high emission multipliers. Selected goods and services eliminated from additional spending in this pattern have a combination of large GHG intensity and a large share of total consumption (selected commodities in S4). Shares of the deducted product groups are reallocated to the remaining groups as:

$$\mathrm{a}_{i_G} = \mathrm{a}_{i_M} + \left(\frac{\mathrm{a}_{i_M}}{1 - \sum_{j=1}^{d} \mathrm{a}_{j_M}} \right) {*} \sum_{j=1}^{d} \mathrm{a}_{j_M} \tag{9}$$

a_{i_G} is the relative share of product i in the green consumption vector. a_{i_M} is the relative share of product i in the marginal consumption vector. a_{j_M} is the relative share of product j (deducted product) in the marginal consumption vector. *d is the* number of deducted product groups.

2.6. Optimizing pattern of re-spending

We introduce optimization methods in the analysis to investigate the potential of altering the pattern of re-spending. This enables studying the degree to which households must adapt their re-spending to achieve different reductions in their CF. Linear programming finds an optimal solution that minimizes or maximizes an objective function, subject to one or several linear constraints. These constraints can be limitations on materials or factor resources, such as capital or labor. Several multiregional input-output (MRIO) studies within the input-output field use linear programming techniques, but usually employed for choice of technology. Examples are the World Trade Model that determines world prices, scarcity rents, and international trade flows based on comparative advantage in a world economy, described in Duchin (2005) and further developed to include bilateral trade in Hammer Strømman and Duchin (2006). The World Trade Model with Bilateral Trade builds on the logic of comparative advantage (Duchin and Levine, 2015). This often leads to complete specialization in production as the optimal solution, which is considered an important limitation of linear programming (Ten Raa and Shestalova, 2015).

In comparison to that work, we are interested in seeing whether it is possible to look at linear programming from a consumption basis. Whilst earlier works study possibilities for alternate technologies, or substitution at the industry level, this analysis is purely limited to what households can do in terms of spending patterns. As such, we are interested in what mixture of spending will yield optimal environmental effects. Whilst the realization of an «optimal spending pattern» is subject to many constraints about basic versus discretionary spending, as well as localized requirements by households, the goal is to use linear programming to inform the scale and rate of possible change. In the setup of the linear program (S6.1), we start with the marginal re-spending scenario as a default and then impose stepwise restrictions on the minimum overall CF savings tolerated. The objective function is set to minimize the change in re-spending compared to the default.

3. Results

To identify areas of large potential reductions in the CF of the average Norwegian household, we look into updating the work of Steen-Olsen et al. (2016) who ranked the goods and services according to largest consumption share, GHG emissions, and emission multipliers. Consumption data is from the Norwegian Consumer Survey of 2012 (Statistics Norway, 2013), while emission multipliers and GHG emissions are calculated by Steen-Olsen et al. (2016).

Several of the consumption groups with the highest emission multipliers include fuel or passenger transport consumption. A combination of high emission multiplier and large share of total consumption results in a large CF. However, some consumption with relative high expenditure shares have lower than expected CFs. An example is electricity that accounts for 3% of total spending, but is not included in the top 10 CF groups. This is likely due to a low

Table 1
Top 10 products groups by emission multipliers, total spending and carbon footprint for Norwegian household consumption.

Top 10 emission multipliers COICOP level 3 (2007)	
Product Group	Top 10 emission multipliers (gCO_2-eq/NOK)
0734 Passenger transport by sea and inland waterway	486
0722 Fuels and lubricants for personal transport equipment	333
0453 Liquid fuels	223
0454 Solid fuels	161
0733 Passenger transport by air	118
0611 Pharmaceutical products	113
0613 Therapeutic appliances and equipment	95
0713 Bicycles	95
0612 Other medical products	90
0431 Materials for the maintenance and repair of the dwelling	87
Top 10 household spending COICOP level 3 (2007)	
Product Group	**Percent of total**
0421 Imputed rentals of owner-occupiers	12%
0711 Motor Cars	8%
0431 Materials for the maintenance and repair of the dwelling	4%
0312 Garments	4%
0451 Electricity	3%
0722 Fuels and lubricants for personal transport equipment	3%
1111 Restaurants, cafés and the like	2%
0112 Meat	2%
0411 Actual rentals paid by tenants	2%
0511 Furniture and furnishings	2%
Top 10 CF COICOP level 3 (2007)	
Product Group	**Percent of total**
0722 Fuels and lubricants for personal transport equipment	19%
0711 Motor Cars	8%
0431 Materials for the maintenance and repair of the dwelling	7%
0421 Imputed rentals of owner-occupiers	5%
0312 Garments	3%
0960 Package holidays	2%
0734 Passenger transport by sea and inland waterway	2%
0112 Meat	2%
0511 Furniture and furnishings	2%
0611 Pharmaceutical products	2%

emission multiplier, since electricity consumed in Norway is largely hydropower-based.

3.1. Household actions

Table 2 shows the 34 actions chosen to reduce the household CF, as well as corresponding GHG emission and cost savings potential from implementing each action individually (for calculations see S1). In Table 2 savings are shown for actions individually, disregarding potential double counting issues.

Comparing Table 2 with Table 1, several interesting trends appear. Large CF reductions for the transport actions are as expected based on large consumption shares and large emission multipliers for transport related consumption. Food and shelter actions also result in large CF reductions, but the reduction potential of shelter actions is more a result of large share of total expenditure than that of the food actions. Garments have in Table 1 the fifth highest CF. However, most of the clothing actions do not contribute to large CF reductions, indicating that the CF of garments is a result of a high household budget share. Reducing business flights (one per month) results in the largest cost reduction, however it ranks fourth in largest GHG emission savings.

3.2. Spending patterns

Comparing the three approaches to calculating spending patterns (Table 3) indicates how Norwegian households spend money when income rises (average to marginal) and how households who which to lower their CF could spend their money (marginal/average to green).

The decrease in spending on particularly shelter (category 04) and the increase in transport (category 07) from the average to the marginal scenario indicates a low and a high income elasticity of demand respectively for these consumption groups. The large shares on miscellaneous goods and services and food in the green scenario are due to constraining re-expenditure on products within the other more environmentally impacting categories. The miscellaneous goods and services category contains amongst others insurance, financial services, personal care and social protection (United Nations Statistics Division, 2016).

3.3. Rebound effects for individual actions

The GHG emission savings including rebound effect in absolute values (Table 2) are given as $((1-\%\,re)*original\ GHG\ savings\ )$. The green spending pattern achieves the best results in reducing GHG emissions when including rebound. Actions with negative rebound effects are a result of a cost increase of implementing the action. Hertwich (2005) calls this a spillover of environmental behavior, where environmentally aware households implement other types of beneficial behavior, such as spending additional income on more expensive organic food. Actions that backfire (over 100% rebound) do so because of a high ratio of saved expenditures to reduced emissions. However, these in general have low initial GHG emission savings, resulting in small effects in absolute terms.

The set of actions includes both demand shifts (e.g. buying an

Table 2
Household actions with according GHG emission and financial savings from implementing each action individually including rebound effects of different spending pattern scenarios (discussed in Section 3.3).

Household Actions	Savings in NOK (2007 Prices)	GHG savings (kg CO_2-eq)	Rebound Effects		
			Marginal	Average	Green
Switch to budget electric car	32,885	3685	62%	48%	42%
Switch to top of the line electric car	−23,233	2760	−58%	−45%	−40%
No trips by car under 3 km	688	150	32%	25%	22%
Only bus transport	14,312	4863	20%	16%	14%
Car-pooling for work under 10 km	474	103	32%	25%	22%
Only train transport	14,312	4973	20%	15%	14%
Walk instead of train (9.4 km)	12,030	183	456%	353%	311%
Reduce business flights (one per month)	71,344	3112	159%	123%	108%
Eliminate long-distance flight for vacation	8202	2629	22%	17%	15%
Reducing indoor temperature by 1 °C	472	92	35%	27%	24%
Space and water heating	920	1333	5%	4%	3%
Appliances and other	−843	174	−34%	−26%	−23%
Green Diet	11,853	1854	38%	29%	26%
Eliminating food waste	17,384	1020	100%	78%	68%
Organic Green diet	−23,706	2039	−68%	−53%	−47%
Other measures (organic, local, composting)	−15,804	695	−134%	−103%	−91%
Eco-efficiency across supply chain	0	57	0%	0%	0%
Design for durability	−1649	107	−90%	−70%	−62%
Market shift to more synthetic fibers	330	6	348%	269%	237%
Clean clothing less	660	36	107%	83%	73%
Wash at lower temperature	660	20	199%	154%	136%
Increase size of washing and drying loads	330	20	99%	77%	68%
Use the tumble dryer less	660	15	253%	196%	173%
Dispose less - reuse more	989	10	597%	461%	407%
Start closed loop recycling of synthetic fibers	0	13	0%	0%	0%
Dispose less - recycle more	0	7	0%	0%	0%
Reduce clothing purchases by 20%	6597	279	139%	108%	95%
Average of changing 6 pieces of furniture	−3070	96	−223%	−172%	−152%
Increase lifetime by 20%	2333	116	119%	92%	81%
Buy furniture with 20% recycled MDF	−1166	73	−94%	−73%	−64%
Eliminating unsolicited mail	0	39	0%	0%	0%
Reduced printing	246	17	104%	80%	71%
e-papers and e-books	1970	26	525%	405%	358%
Reducing plastic waste by 30%	191	14	95%	73%	65%

Table 3
Comparing spending patterns (COICOP Level 1 classification).

Product Groups	Average	Marginal	Green
01 Food and non-alcoholic beverages	12%	11%	18%
02 Alcoholic beverages and tobacco	3%	1%	1%
03 Clothing and footwear	5%	8%	1%
04 Housing, water, electricity, gas and other fuels	31%	24%	9%
05 Furnishings, household equipment and routine household maintenance	6%	7%	11%
06 Health	3%	1%	3%
07 Transport	19%	24%	8%
08 Communication	2%	1%	3%
09 Recreation and culture	10%	11%	9%
10 Education	0%	0%	0%
11 Restaurants and hotels	4%	4%	6%
12 Miscellaneous goods and services	6%	8%	30%

electric car) and reduced consumption (e.g. reducing indoor temperature by 1 °C). The aim is to exclude technological improvements not currently available to the consumer. Possible exceptions to this are some actions within the clothing sector that require changes on the production side, such as eco-efficiency across the supply chain.

3.4. Cumulative rebound effects

Relative and absolute CF reductions for the three re-spending scenarios are found using the actions-activity matrix that adjusts for double counting (Table 4).

Transport, shelter and food actions result in the largest CF reductions. Implementing the combined transport actions have large rebound in all re-spending scenarios because of large financial cost reductions. There is no rebound of the combined shelter actions, since financial costs add to close to zero. CF reductions of the furniture actions are enhanced since these come with a cost increase.

The decrease in CF reduction from before re-spending (58%) to after re-spending (24–35%) underlines the importance of including rebound effects. The goal of reducing anthropogenic GHG

Table 4
Sectoral and total rebound results and GHG emission savings including rebound adjusted for double counting.

Household Actions	Original GHG savings (kg CO_2-eq)	Rebound effect in percent		
		Marginal	Average	Green
Transport	9847	83%	64%	57%
Shelter	1383	0%	0%	0%
Food	3587	16%	13%	11%
Clothing	569	89%	69%	61%
Furniture	284	−51%	−39%	−35%
Paper	81	190%	147%	129%
Plastic	14	95%	73%	65%
Total of all actions combined	**15,766**	**59%**	**46%**	**40%**
Original CF of households	**27,170**			
Reduction in CF	**58%**	**24%**	**32%**	**35%**

emissions by 40% (10.9 tons CO_2-eq per household) is not achieved with this set of actions when including rebound effects. However, households can achieve further reductions through changing, adding or eliminating actions. Such scenarios can be explored by using optimization approaches.

3.5. Optimization of re-spending

In the final part of the assessment, we use linear programming to explore how the rebound effect can be reduced through changes in re-spending patterns. We impose stepwise restrictions on the minimum overall CF savings tolerated, starting from the default marginal re-spending pattern (24% overall CF reduction) and moving towards the theoretical maximum (58% reduction, equal to no re-spending) (Fig. 1). The objective is to achieve specific emission reductions while minimizing the change in the consumption pattern. Whilst linear programming approaches give only indicative results, as determined by the extent of the constraints applied, they do allow for visualizing the scale of change required.

The results show that households can achieve up to 35–45% CF reductions with moderate changes in their pattern of re-spending. Strict re-spending on goods and services with low GHG intensities for reductions above 35–45% makes the practical implementation of this re-spending questionable. This is seen by the rapid increase in the change in pattern of consumption for reduction targets over 40% (S6.4). The total financial savings is about 150,000 NOK, or about 35% of total expenditures (Statistics Norway, 2013). Although requiring careful re-spending considerations, changing only 35% of total expenditure seems feasible.

The increased re-spending on “Housing, water, electricity, gas, and other fuels” for large CF reductions is different from the green spending pattern (Table 3) that showed an increase in consumption on “Miscellaneous goods and services” and a decrease in “Housing, water, electricity, gas, and other fuels”. However, since the linear program's objective is to minimize change in consumption compared to the marginal scenario, consumption will not simply move towards consumption groups with the lowest emission multipliers. Instead, it will choose consumption groups with a combination of large consumption shares and low emission multipliers. A disaggregation into 25 consumption groups reveals a heavy move towards “Shelter: Electricity” for larger CF reductions (S6.3), which could be considered an anomaly for Norway in the international context because of the low-carbon electricity mix. The emission multiplier of electricity by hydro is actually the fourth lowest of all 200 product groups for final consumption expenditure by Norwegian households in EXIOBASEv2 (S7). A second analysis available in the SI, that excludes the impact of margins on different products, instead shows a shift to services rather than electricity (S6.5). The message is the same however – there are radical shifts in consumption patterns at around 40% reduction.

4. Discussion

Most of the scenarios in this paper show CF reductions that are not within the minimum 40% reduction in anthropogenic GHG emissions needed to stay within the 2 °C target of global warming. Only scenarios of moderate to large changes in household consumption show CF reductions above this. However, the potential reductions are larger when including future efficiency improvements in production and optimal collaboration between producers, consumers and policy makers. It is also important to consider that the household CF tells only part of the story on the demand side. Similar large reductions in emissions related to government and capital consumption are also required.

4.1. Re-spending

Further CF reductions can be achieved by relaxing the constraint of total re-expenditure and including technological improvements. Considering less than total re-spending could have negative effects on economic growth through deferred or reduced overall consumption. Deferred consumption have potential negative short-term consequences, while reduced overall consumption can of course, lead to recession or “de-growth”. The implications of this is not considered in the scope of this work.

The green re-spending scenario does not consider whether the goods and services eliminated from re-spending are basic or discretionary. Purchasing an electric car might for example be incompatible with eliminating re-spending on electricity from sources such as coal, gas, and biomass and waste, unless replaced with electricity from other sources. However, the re-spending affects only 35% of total household expenditure.

4.2. Rebound effects

The large number of actions should indicate that the rebound effects of 40–59% are less sensitive to changing, eliminating, or adding actions. These results are, however, generally higher than those found in other similar studies. Druckman et al. (2011) found effects of 12–34%. However, in the 12% scenario all re-spending was in the least GHG intensive category. This is a stricter re-spending than the green re-spending scenario. Of other similar studies, Alfredsson (2004) found rebound effects of 14% for an average re-spending scenario, Murray (2013) found effects of 12–14% for a marginal re-spending scenario, while Chitnis et al. (2014) found effects of 15% from combined efficiency measures and 35% from

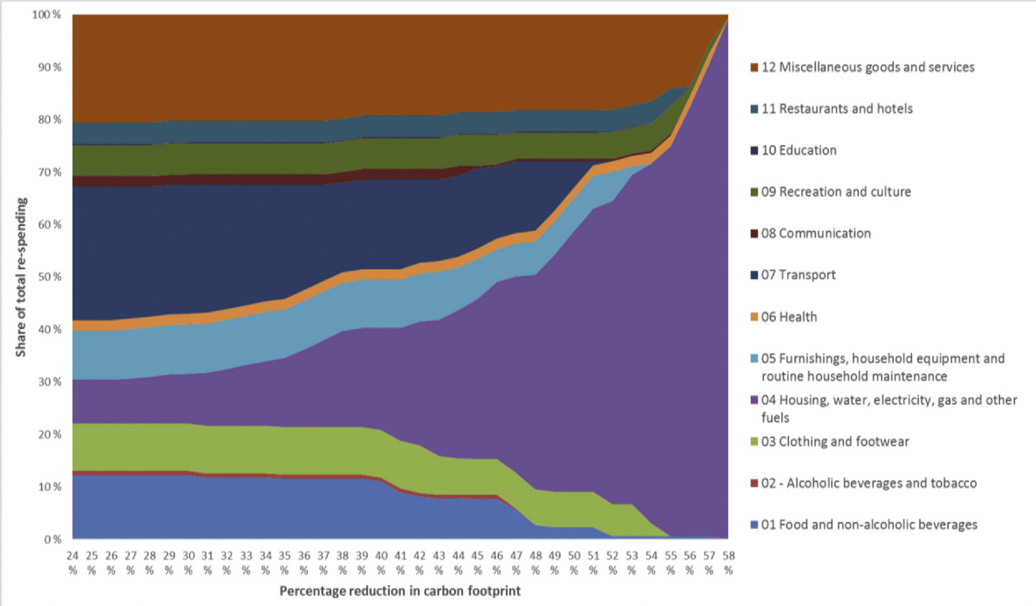

Fig. 1. Pattern of re-spending for different CF reduction targets (COICOP level 1).

combined sufficiency measures. However, in these three studies households implement only a handful of actions, making rebound results dependent on the choice of actions. Our results are however comparable to those in Freire-González (2011) with rebound effects of 56–65%, but that study only looks at rebound effects from energy efficiency improvements in the use of energy in the household.

Rebound effects are primarily indirect as the scenarios include re-spending across most goods and services. However, as re-spending on the same good or service as that of the behavioral action is included, a small portion of the total is direct rebound. Disaggregating types of rebound effects is outside the scope of this study.

Considering the validity of the different re-spending scenarios is important. The large cost decrease of 150,000 NOK from the current lifestyle change, justifies the use of the marginal pattern of re-spending. If households continue on a similar consumption pattern as before the lifestyle change, the average re-spending could be a good choice. However, assuming that households take CF considerations into their choice of re-spending, the green re-spending scenario is plausible.

Large-scale implementation of the suggested lifestyle change can drive production side changes through shifting demand. This potential demand-shift needs attention (Alcott, 2008). The idea behind restricting the analysis to consumption side changes is not to ignore the modifications on the production side, but rather to allow household changes to drive production side changes that generate further GHG emission reductions.

4.3. Optimization

Electricity by hydro had an unrealistically large share of re-spending found in the optimization results. The focus should rather be to re-spend saved money on goods and services that are both fulfilling and have low emission multipliers. Consumption groups that could provide both environmental and personal benefits include education services, printed matter, and recorded media, as well as recreational, cultural, and sporting services.

Under the assumption of stable or even increased consumption levels, households should focus their re-spending on higher quality goods and services, such as organic food or durable electronic products to curb the rebound effect as these goods have low emission multipliers.

4.4. Limitations and uncertainties

Practical difficulties in implementing the suggested lifestyle change because of considerations like infrastructure, urban versus rural area and access to appliances and products (e.g. organic food or special types of furniture) are likely. This is particularly relevant for actions requiring access to specific transport modes. As such, the current setup fits a scenario of multiple households implementing the actions, as relatively low shares are assigned to bus and train transport for the travel distances.

One return business flight per month per person at a first glance seems overestimated. However, it should rather be interpreted as an example of how frequent flying affects the household CF. The flight distance used for this action is rather short, so one or several long-distance flights within a year are comparable to the GHG emissions and costs associated with multiple return business flights. In Norway, air transport now accounts for almost half of all work related travels (Denstadli and Rideng, 2012). Exact data on air transport per person in Norway were scarce, but Denstadli and Rideng (2012) suggest Norwegians travel 0.4 trips per person by plane per month.

The optimization approach is highly stylistic in changing the pattern of re-spending to reduce the household CF, and does not consider household intuition of the GHG intensities of goods and services. The objective of minimizing absolute change in consumption pattern compared to the marginal scenario is quite abstract. Further research could focus on measures that are more intuitive, such as the behavioral costs associated with achieving GHG emission reduction targets.

The purpose of the actions-activity matrix is to account for double counting; however, complete elimination is unlikely. Double counting related to the transport actions involving daily travel is accounted for by setting a limit to the total distance travelled within each distance range. Other actions are however, more entangled. Eliminating food waste for example depends on the diet choice. Here, the original scenario is used as a reference, but the food waste will depend on the choice of diet. Buying furniture with 20% recycled MDF (medium-density fiberboard) follows a similar argument as it depends on the type and lifetime of the furniture. Some actions in the clothing sector, and reading e-newspapers and e-books are linked to the mitigation potential of “appliances and others”. However, we believe that these instances of double counting should not change the results significantly.

5. Conclusion

This study examines the potential CF reduction of changing household consumption. We propose an ambitious lifestyle change consisting of 34 behavioral actions and investigate to what extent the average Norwegian household can achieve sufficient reductions in their CF in line with a 2 °C target of global warming, and what impact rebound effects will have. Implementing the lifestyle change would imply considerable behavioral changes, but most of these also equate to substantial financial savings. Under the assumption that total expenditure levels stay unchanged, how households re-spend these savings is crucial to the overall CF reduction. The analysis includes the common average and marginal scenarios of re-spending, implementing a green re-spending scenario, as well as finding required re-spending to meet different reduction scenarios using linear programming. An initial reduction of 58% in household CF dropped to 24–35% for the re-spending scenarios when including rebound effects. To lower the rebound effect, households should eliminate re-spending on goods and services with high GHG intensities. Given the importance of the pattern of re-spending, the linear programming approach shows that CF reductions of 35–45% can be achievable without massive changes in expenditure habits. Particularly, households should curtail re-spending on goods and services associated with fossil fuel use, such as mobility, and production processes demanding heavy use of resources, such as clothing and certain manufactured products. For emission reductions within the 40% official reduction target of the Norwegian government by 2030, re-spending must largely shift towards services associated with a low GHG intensity.

If we are to limit global warming to the 2 °C target, action is needed now rather than later. We should not rely entirely on future technology improvements to do the job, but complement them with changes on the consumption side. To acquire sufficient CF reductions before re-spending, changes are not limited to consumption of products associated with high GHG intensity per unit of expenditure. Since the ratio of the average GHG intensity associated with the lifestyle change compared to that of the re-spending determines the rebound effect, a comprehensive consumption change will necessarily result in larger absolute rebound than small changes. The rebound results in this study are therefore large compared to other similar studies.

Ignoring the rebound effect is equivalent to assuming decreased total expenditure, which could severely compromise economic activity. This calls for a larger focus on rebound effects and factors that determine re-spending in discussions on sustainable development and the transition to a circular economy.

Further research on the willingness and behavioral costs of implementing different actions that reduce CF could provide understanding of the best ways to reduce CF on the consumption side. Studying the effect of investment instead of total re-spending can give useful insight to ways of curtailing the rebound effect.

Large-scale implementation of the set of actions can drive production changes through shifting demand towards goods and services associated with low GHG intensities. The production side can respond to this demand shift by production of environmentally better performing products, leading to further emission reductions. Further studies on how lifestyle changes and production side changes can benefit from influencing each other to lower GHG emissions will offer increased understanding on how to achieve the emission reductions needed to reach the 2 °C target of global warming.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2017.10.089.

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