Going global to local: achieving agri-food sustainability from a spatially explicit input-output analysis perspective

Sun, Z.

Going global to local: achieving agri-food sustainability from a spatially explicit input-output analysis perspective

Zhongxiao Sun

孙中孝

Going global to local: achieving agri-food sustainability from a spatially explicit input-output analysis perspective

PhD Thesis Leiden University, The Netherlands

Cover design:	Cai Huang
Cover icons:	www.nounproject.com
Printing:	www.proefschriften.nl
ISBN:	978-90-5191-999-8

Going global to local: achieving agri-food sustainability from a spatially explicit input-output analysis perspective

Proefschrift

ter verkrijging van

de graad van doctor aan de Universiteit Leiden,

op gezag van rector magnificus prof.dr.ir. H. Bijl,

volgens besluit van het college voor promoties

te verdedigen op dinsdag 1 juni 2021

klokke 10.00 uur

door

Zhongxiao Sun

geboren te Zaozhuang city, Shandong province, China

in 1991

Promotor:	Prof. dr. A. Tukker (Universiteit Leiden)
Copromotor:	Dr. P.A. Behrens (Universiteit Leiden)
	Dr. L.A. Scherer (Universiteit Leiden)
Promotiecommissie:	Prof.dr.ir. P.M. van Bodegom (Universiteit Leiden)
	Prof.dr.ing. J.W. Erisman (Universiteit Leiden)
	Prof. dr. R. Wood (Norwegian University of Science and Technology)
	Prof. dr. M. Huijbregts (Radboud UMC Nijmegen)
	Dr. N.A. Soudzilovskaia (Universiteit Leiden)
	Dr. J.M. Mogollón (Universiteit Leiden)

Table of Contents

Going global to local: achieving agri-food sustainability from a spatially explicit input-output analysis perspective 1

Going global to local: achieving agri-food sustainability from a spatially explicit input-output analysis perspective 3

Abbreviations 7

1 General Introduction 9

1.1 Background 9

1.2 The heterogeneity of social and environmental impacts, especially in food systems 11

1.3 Global spatially-explicit multi-regional input-output analysis 12

1.4 Priorities in sustainable development – a focus on agriculture 13

1.5 Aims and research questions 13

1.6 Outline of this thesis 14

2 Going global to local: connecting top-down accounting and local impacts, a methodological review of spatially explicit input-output approaches 16

2.1 Introduction 16

2.2 An expanding field 18

2.3 Methodological and spatial categories 19

2.4 Options for enhancing spatial and sectoral resolution 25

2.5 Addressing uncertainties 31

2.6 Integration with other environmental 32

2.7 Outlook 33

2.8 Acknowledgements 33

2.9 Supporting Information Available 33

3 Linking Global Crop and Livestock Consumption to Local Production Hotspots 34

3.1 Introduction 34

3.2 Materials and Methods 36

3.3 Results 39

3.4 Discussion 43

3.5 Data statement 45

4 Land use in key biodiversity areas disproportionately threatens global biodiversity 46

4.1 Introduction 46

4.2 Results 47

4.3 Discussion 55

4.4 Conclusion 57

4.5 Materials and Methods 57
5 A double carbon dividend from dietary change in high-income nations 61
5.1 Introduction 61
5.2 Carbon sequestration and emission reduction potentials from dietary change 62
5.3 The role of animal products in the carbon cycle 65
5.4 Carbon mitigation potentials for items not included in the EAT-Lancet diet. 66
5.5 Implications for natural climate solutions 68
5.6 Methods 70
6 General Discussion 74
6.1 Answers to the research questions 74
6.2 Limitations and future research – ways forward for SMRIO 76
6.3 Policy implications 79
7 References 81
8 Appendix 111
8.1 Supporting information to chapter 2 111
8.2 Supporting information to chapter 3 122
8.3 Supporting information to chapter 4 143
8.4 Supporting information to chapter 5 148
Summary 156
Samenvatting 159
Acknowledgements 163
List of publications 164
Curriculum vitae 165

Abbreviations

AGBC	Above Ground Biomass Carbon
AIDA	Italian company information and business intelligence
AIM/CGE	Asia-Pacific Integrated Model/Computable General Equilibrium
AMNE	Analytical Activity of Multinational Enterprises
BGBC	Below Ground Biomass Carbon
CDR	Carbon Dioxide Removal
CES	Consumer Expenditure Surveys
CFs	Characterization Factors
CO_2e	Carbon Dioxide equivalent
COICOP	Classification of Individual Consumption by Purpose
cSAR	countryside Species–Area Relationship
DEHM	Danish Eulerian Hemispheric Model
EDGAR	European Commission’s in-house Emissions Database for Global Atmospheric Research
EEIO	Environmentally Extended Input-Output
ESA CCI-LC	European Space Agency Climate Change Initiative-Land Cover
FABIO	Food and Agriculture Biomass Input-Output
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
GCAD	Global Cropland Area Database
GCAM	Global Change Analysis Model
GEOS	Goddard Earth Observing System
GGCMI	Global Gridded Crop Model Intercomparison
GHG	Greenhouse Gas
GISMO	Global Integrated Sustainability MOdel
GLOBIO	GLObal BIOdiversity model for policy support
GLOFRIS	Global Flood Risk with IMAGE Scenarios
GMRIO	Global Multi-Regional Input-Output
GRIP	Global Roads Inventory Project
GTAP	Global Trade Analysis Project
HYDE	History Database of the Global Environment
IAMs	Integrated Assessment Models
ICIO	Inter-Country Input-Output
IELab	Industrial Ecology virtual Laboratory
IFA	International Fertilizer Association
IMAGE	Integrated Model to Assess the Global Environment
IoT	Internet of Things
IPBES	Intergovernmental Science–Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change

ISA	Integrated Sustainability Analysis
KBAs	Key Biodiversity Areas
LPJmL	Lund-Potsdam-Jena managed Land
LQs	Location Quotients
LULCC	Land Use Land Cover Change
MESSAGE	Model for Energy Supply System Alternatives and their General Environmental Impacts
Mha	Million Hectares
MODIS	Moderate Resolution Imaging Spectroradiometer
MRIO	Multi-Regional Input-Output
NRMSD	Normalized Root Mean Square Deviation
OECD	Organisation for Economic Co-operation and Development
PNV	Potential Natural Vegetation
POPs	Persistent Organic Pollutants
PREDICTS	Projecting Responses of Ecological Diversity In Changing Terrestrial Systems
REIM	Regional Econometric Input–output Model
REMIND	REgional Model of Investment and Development
SABI	Survey data from enterprises
SAR	Species–Area Relationship
SCA	Smeared Concentration Approximation
SDGs	Sustainable Development Goals
SIO	Spatially explicit Input-Output
SMRIO	Spatially explicit Multi-Regional Input-Output
SOC	Soil Organic Carbon
SPAM	Spatial Production Allocation Model
TEC	Trade by Enterprise Characteristics
UNEP	United Nations Environmental Program
WIOD	World Input-Output Database
ZCTAs	Zip Code Tabulation Areas

1.

Chapter 1.
General Introduction

1 General Introduction

1.1 Background

In an era of increasing globalization, supply chains have become tightly interconnected and complex[1]. Given the depth of integration and the importance of international trade in sometimes helping to improve resource efficiencies, facilitating socio-economic development, and promoting human welfare, today's complex supply chains have been called the lifeblood of the global economy [2]. This is especially true in the food system where international trade plays a critical role in safeguarding nutrient and food security [3,4]. Indeed, globally traded food calories have more than doubled since the 1980s, and around one-fourth of global food production is traded on international markets [5,6]. Increasing linkages among trade partners could help mitigate climatic impacts on local food production and have knock-on impacts for reducing hunger risk and improving the resilience of the food supply chain [4,7,8].

However, international trade has not only revolutionized the way that commodities are produced, exchanged, and consumed, but has also altered the sites and scale of social and environmental impacts[1]. Depending on the indicator considered, between 10% -70% of environmental pressures (e.g. land use and greenhouse gas (GHG) emissions) or impacts (e.g. biodiversity loss) are embodied in international trade. That is, the consumption of a product in one location can lead to environmental pressures across supply chains geographically located across many distant locations on the planet [1]. The social and environmental impacts embodied in international trade have been increasing with globalization. For example, CO_2 emissions from fossil fuel embodied in the global supply chain increased from 5 Gt in 1995 to 10 Gt in 2011, and the share of embodied carbon accounting for total carbon emission increased from 27% in 1995 to 37% in 2011 [9]. Similarly, agricultural production embodied in international trade has been increasing due to globalization. For example, the area of cropland embodied in the global supply chain increased from 178 Mha in 1987 to 272 Mha in 2008, accounting for 15% and 21% of the total global cropland area respectively [10]. The amount of cropland embodied in trade increased further to 350 Mha in 2016 [11].

Affluence is a primary driver of social and environmental impacts along international supply chains [1,12–14]. While organizations such as the United Nations Environmental Program (UNEP) advocates a decoupling of economic growth from environmental impacts [15], high-income countries have been displacing environmental impacts to middle- and low-income countries [1,14,16]. Such displacement often increases overall social and environmental impacts because production in middle- and low-income nations is more environmentally intensive and faces fewer regulations[1]. Consumers, who ultimately drive economic demand and hence global trade, generally show a greater desire to reduce environmental and social impacts locally rather than distant impacts through the supply chain [14]. For example, Europe restored territorial forests by 9% (~ 13 Mha) while outsourcing 11 Mha deforestation due to crop displacement from 1990 to 2014 [17]. Furthermore, the outsourced deforestation is located in climate-vulnerable regions with incomparable biodiversity and carbon stocks [17–19].

It is important to understand how consumption and production are linked via supply chains, and how final consumption drives social and environmental impacts of production processes in these value chains. In the last 15 years, Global Multi-Regional Input-Output (GMRIO) tables have become an important tool to map such relations between production and consumption[20]. In short, a (national) input-output table divides a national economy into numerous economic sectors. A consumer demand is met by a set of production relationships between sectors which ultimately require primary natural resources. Such tables are typically available at the national level from National Statistical Institutes. By combining tables from different countries, and using the information on imports and exports by sector, a GMRIO table can be constructed that maps global value chains in the form of transactions between different economic sectors and different countries, including actors responsible for final demand. If the primary resource use and emissions are calculated for each economic sector by country, then these can be added to the GMRIO table as so-called environmental extensions. The result is an Environmentally Extended (EE) GMRIO model. Such EE GMRIO models can trace environmental impacts associated with production and consumption of commodities, following the full downstream and upstream value chain [20] (see Box 1 for more details). These GMRIO tables play a critical role in analyzing social and environmental impacts embodied in international trade [20].

Box 1. An introduction to GMRIO analysis

A global multi-regional input-output (GMRIO) table provides the input-output relationships of economic sectors within and between nations [20]. They can take two different forms: product-by-product or industry-by-industry. Product-by-product tables divide the economy into multiple products, describing the amount of a product used to produce each product regardless of the industry [21]. Similarly, industry-by-industry tables divide the economy into multiple industries, describing input-output relationships of industries irrespective of the product. The following chapters employ product-by-product tables. Adding environmental pressures (e.g. primary resource extraction, land use, water use, emissions) due to production to each economic sector generates an Environmentally Extended GMIRO (EE GMIRO) table [20]. The structure of an EE GMRIO table is illustrated below in product-by-product format. The figure shows that every product links with environmental pressures associated with its production and these pressures are then embodied in economic flows via the transaction matrix. For example, soybeans produced in Brazil, which are exported to feed cattle in China, which are then exported to South Korea for final consumption in the form of beef. The production of each intermediate product from each different country results in environmental pressures (e.g. carbon emissions) that in turn cause environmental impacts (e.g. biodiversity loss) along the supply chain. EE GMRIO can estimate all pressures related to beef consumption (a consumption-based footprint). The example is only for one product, but GMRIOs cover in a similar way all product and service categories traded between economic sectors and nations.

The structure of the global economy as depicted by a GMRIO table is shown in Figure 1.1 for a product-by-product table. In a monetary product-by-product GMRIO table, the interdependencies (i.e. input requirements per unit of output) between products and regions are expressed as a matrix (known as transaction matrix, technical coefficients matrix or matrix $\boldsymbol{A}$ in Figure 1.1). The A matrix describes the direct input-output relationship or production recipe between products and nations where products can be regarded as inputs to produce other products. However, since the products used to produce another product themselves have a production recipe, the total requirements of all upstream production has to be computed. This is calculated by a solution called the Leontief inverse matrix given by $L = (I - A)^{-1}$.

The EE GMRIO approach inherits an economic consistency from the GMRIO approach, which means direct environmental pressures generated from production cannot be "lost" in the calculation along the global supply chain [20]. The total pressures due to production shown in an EE GMRIO, by definition are equal to the total environmental footprints of consumption. Given its consistency, EE GMRIO tables are widely used to trace environmental pressures embodied in the global supply chain.

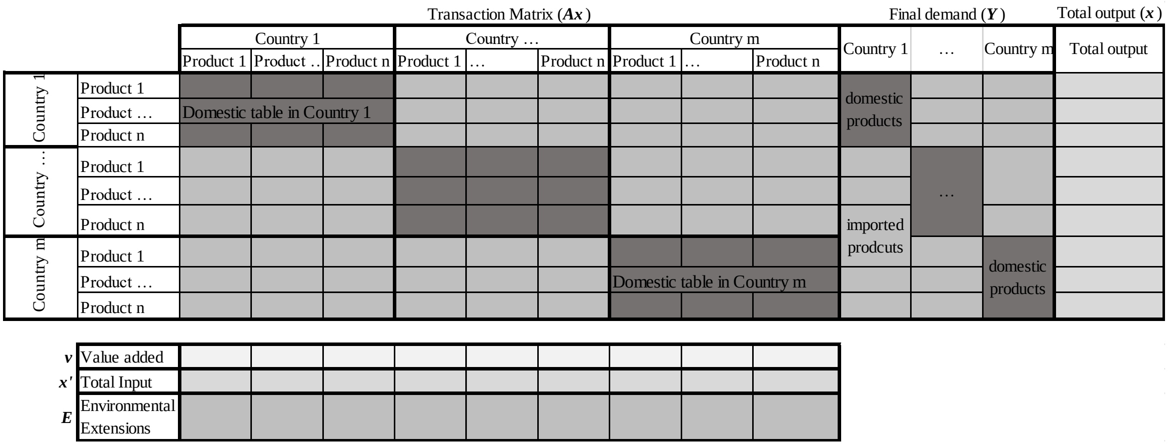

Figure 1.1. The structure of an EE GMRIO table. The transaction matrix is given by A, the final demand (the consumption of goods and services by different sectors of society) by F, the extension row vectors to the bottom of the table by E. The latter can describe economic extensions such as the value added required to produce a product, social extensions such as the hours of labor required, or environmental extensions such as emissions.

1.2 The heterogeneity of social and environmental impacts, especially in food systems

The number of EE GMRIO studies has been increasing rapidly in recent years, resulting in many country-level social and environmental footprint assessments[1]. They have focused on many different social and environmental pressures and impacts, including climate change (e.g. CO_2, N_2O, CH_4), air pollution (e.g. $PM_{2.5}$, PM_{10}, NO_x, SO_2), biodiversity loss, and employment [1]. However, as indicated, GMRIO tables are usually only available at country level and represent the average information of an economic sector for a country. The implication is that while the GMRIO approach is capable of calculating footprints of consumption, the hotspots contributing to these footprints at best can be identified at the level of sectors in a specific country. However, local social and environmental impacts of the same sector can be spatially very heterogeneous. This issue is prominent in some large countries (e.g. the US, Brazil, and China). In addition, drivers of environmental pressures from both a production and consumption perspective can be spatially concentrated. This is due the fact that different human production and consumption activities are often concentrated in specific geographical areas. For example, more than 90% of the Chinese population and most production and consumption activities of Chinese people concentrate on the east of Heihe-Tengchong Line (also known as Hu Huanyong-Line), which only accounts for 40% of China's area. Overall only 1% of China's land area accounted for three-quarters of carbon emissions driven by global consumption in China [22].

The need for spatially explicit assessments is particularly relevant for the agri-food system. The type of agricultural production in a specific area is determined by a variety of biophysical (e.g. climate conditions, land topography, and soil property) and socioeconomic variables (irrigation, population density, access to market, and cultural convention) [23]. For example, more than 90% of global oil palm is planted in Indonesia and Malaysia in relation to the specific climatic conditions in these countries [24]. In addition, there is also huge spatial heterogeneity of agricultural production and associated social and environmental impacts within a nation. For example, the US contributes to about 40% of global soybean and corn production, with 85% of this production being located in the "Corn Belt" [25]. However, agricultural production is commonly shown at provincial or country-level administrative units, which masks local diversity and spatial patterns [26].

With the development of remote sensing technologies and hyperspectral image-processing methods, an increasing number of high-resolution global land cover maps are available (e.g. Copernicus Global Land Service [27], GlobeLand30 [28], ESA-CCI-LC [29], MODIS [30], Global Food Security-Support Analysis Data[31]). These datasets are widely used to study local social and environmental impacts associated with crop and livestock production. The results of such analyses show that social and environmental impacts due to local production are spatially heterogeneous [32]. At the same time, production- and consumption-based analysis with traditional GMRIO tables misses this spatial heterogeneity, since they usually cover rather aggregated economic sectors (including agricultural sectors) with average data for whole countries.

1.3 Global spatially-explicit multi-regional input-output analysis

To trace the pathways of local social and environmental impacts along international supply chains or to identify local impact hotspots driven by global consumption, a new approach is emerging: global spatially-explicit multi-regional input-output analysis (SMRIO). There are three main options in which the spatial resolution of GMRIO models can be increased. The three options are related to the three main matrices pictured in Box 1 (***E, A, and F)***:

- Spatially explicit environmental or social extensions. That is, a spatially explicit picture is provided of the resources, emissions or land use related to production within a specific economic sector (represented by matrix ***E****).*
- Spatially explicit final demand. That is, a spatially explicit picture of the consumption of households, businesses or governments in different locations is provided, representing for example the consumption baskets of cities vs rural consumers (represented by matrix ***F***).
- Spatially explicit transaction matrices (represented by matrix ***A***). Such matrices describe value chain linkages between production and consumption activities at a high spatial resolution (and usually require information on points 1 and 2 above, too. We make this differentiation, since some SMRIO approaches just give spatially explicit information on production, or consumption, without making the transaction matrix spatially explicit).

The data requirements, already significant in the classic GMRIO approach, would be overwhelming if the approach was to include all three aspects. A more tractable approach would be to exclude points 2 and particularly 3. While in principle the intermediate inputs and outputs for a product, as given in the transaction matrix, could differ by location, as a first proxy the assumption could be made that similar production processes have similar, national average inputs and outputs. This reduces the complexity of constructing SMRIOs to combining information from GMRIOs with spatially explicit information of production activities. Such an approach would still help identify local social and environmental impacts hotspots driven by global consumption of goods and services, and which actors are involved in specific supply chains [33,34].

In the domain of agriculture and food there are several datasets that can be used in support of such a SMRIO approach. These include crop-specific land use maps such as EarthStat [35] and the Spatial Production Allocation Model [26]. Another useful dataset is the recently developed Food and Agriculture Biomass Input-Output (FABIO) table[36]. FABIO is an annual table at an unprecedented level of detail in agricultural and forestry products by country, covering 191 countries and 130 agriculture, food, and forestry products from 1986 to 2013 [36]. By linking the national data provided by FABIO to spatially explicit agricultural production maps it becomes possible to develop highly product- and location-specific details of social and environmental pressures associated with agricultural production and consumption along the international supply chain [36]. While a limitation of FABIO is that it does not cover the total economy, compared to existing GMRIOs it gives an unprecedented detail in transactions related to agriculture, food and forestry products.

1.4 Priorities in sustainable development – a focus on agriculture

The agricultural system currently occupies ~43% of global ice- and desert-free land. The food system is a major driver of biodiversity loss[37]. This is a critical issue since the earth is entering a sixth mass extinction. That is, current species extinction rates are 100-1000 times higher than the background extinction rate [38,39]. Around 25% of all species face extinction within decades, and the species extinction rate may even accelerate without any further increase in the drivers of biodiversity loss [40,41]. Around 26% of human GHG emissions are created along the global food supply chain, predominately via direct agricultural production (e.g. fertilizer use and enteric fermentation of ruminants) and indirect via land-use change (e.g. deforestation) [42]. Most GHG emissions from the food system are related to the production and consumption of animal products. For example, about one-third of global cereal production (which accounts for 40% of global cropland) is used to feed livestock [43]. This is somewhat unsurprising when we consider that the energy feed-to-food conversion efficiency of animal products is low and varies from 3% for beef to 17% for eggs within animal products [44]. In addition, consumption of animal products, especially unprocessed red meat and processed meat, increases the risk of some diseases (e.g. cancer, cardiovascular disease, diabetes, and stroke) [45,46].

Next to these significant environmental pressures we are seeing increasing concerns related to food security around the world. Yield growth has been slowing or even stagnating; average global crop yields for the 174 crops covered in FAOSTAT increased by 56% in the first stage of the Green Revolution (from 1965 to 1985), but only 20% in the post-Green Revolution (from 1985 to 2005)[47,48]. The world is off-track to achieve targets related to food security and the number of hungry and malnourished people has been increasing in past years [49]. Furthermore, agricultural production caused numerous serious social and environmental impacts because the present agricultural system is resource- and labor-intensive and consuming a large amount of natural capital [37].

On top of these issues, food systems are also highly spatially heterogeneous globally. Few studies have investigated local agricultural production and associated social and environmental impacts along the global supply chain. There are exceptions, for example studies that map local freshwater pressure driven by global consumption, but these are at a rather coarse spatial resolution (e.g. basin level) and discern just a few agricultural sectors[50]. One of the reasons is that the agricultural sectors are highly aggregated in the present GMRIO tables. Therefore, we chose the food and agricultural system as a focus in this thesis. We build an SMRIO framework to examine three key issues in sustainable food production in the following chapters—food security, biodiversity loss driven by global land use, and the carbon emission and sequestration implications of dietary changes. Each of these issues relates to different drivers and pressures or problems in the production stage, and requires hence a somewhat different approach in the SMRIO analysis.

1.5 Aims and research questions

This thesis investigates the global SMRIO method and its use in assessing environmental pressures and impacts. The thesis uses the food system as an application area, given the fact that food consumption is a driver of major environmental issues, such as biodiversity loss and carbon emissions. The analysis of such problems related to the agri-food system can benefit greatly from a spatially explicit approach. The overall research question is:

How can spatially explicit multi-regional input-output approaches be used to evaluate sustainability in the global agri-food system?

This main research question is addressed via the following sub-questions discussed in the following chapters (see Figure 1):

Question 1: What is the current status of spatially explicit input-output analyses? (Chapter 2)

Question 2: What are the local production hotspots of crops and livestock driven by global consumption and how does this impact food security through trade? (Chapter 3)

Question 3: How does land use driven by final consumption affect global biodiversity within key biodiversity areas? (Chapter 4)

Question 4: What are the global interactions between carbon emissions and carbon sequestration driven by diets and diet changes in high-income nations? (Chapter 5)

1.6 Outline of this thesis

This thesis is composed of 6 chapters. This chapter gives a general introduction, and Chapters 2 to 5 address the above research questions. Chapter 6 summarizes and synthesizes the main findings of this thesis, and discusses limitations. In short, the principal content of each chapter is as follows:

Chapter 1 introduces recent developments in the assessment of social and environmental impacts embodied in international trade based on GMRIO analysis, and shows that GMRIOs overlook spatial heterogeneity of such pressures and impacts at local scale. It shows that SMRIO is an approach that can overcome this limitation, and that spatially explicit analyses are particularly relevant for the agri-food system. It also identifies three priorities (food security, biodiversity, climate change), which are applied to case studies in the following chapters.

Chapter 2 reviews the state of the art of spatially explicit input-output analyses, diagnoses the mechanisms connecting global consumption with local environmental impacts and identifies research gaps. It proposes a theoretical framework of the global spatially explicit multi-regional input-output approach by analyzing previous studies and provides methodological support to the following chapters.

Chapter 3 explores the importance of primary crop hotspots in international trade and food security. It uses the road network to allocate between domestic consumption and export, identifies hotspots (the most significant regions for production) for primary crops and livestock driven by international consumption, and compares per-capita primary crop and livestock consumption with an illustrative target safe operating space for every nation.

Chapter 4 assesses global biodiversity loss caused by anthropogenic land use within key biodiversity areas (KBAs) driven by final consumption. The assessment is performed by combining the Food and Agriculture Biomass Input-Output (FABIO) and EXIOBASE input-output databases with spatially explicit agricultural production maps. The biodiversity loss calculation is based on the land use area driven by global consumption and characterization factors (i.e. global species-equivalents potentially lost per area of land use) under different land use types and intensities.

Chapter 5 estimates a 'double dividend' of reduced GHG pressures by dietary changes in high-income countries from both (1) reduced direct agricultural production emissions and (2) carbon sequestration via land sparing whereby agricultural lands can revert to other uses.

Chapter 6 answers research questions, discusses broader insights, provides some policy implications, and provides recommendations for the development of spatially explicit input-output analysis.

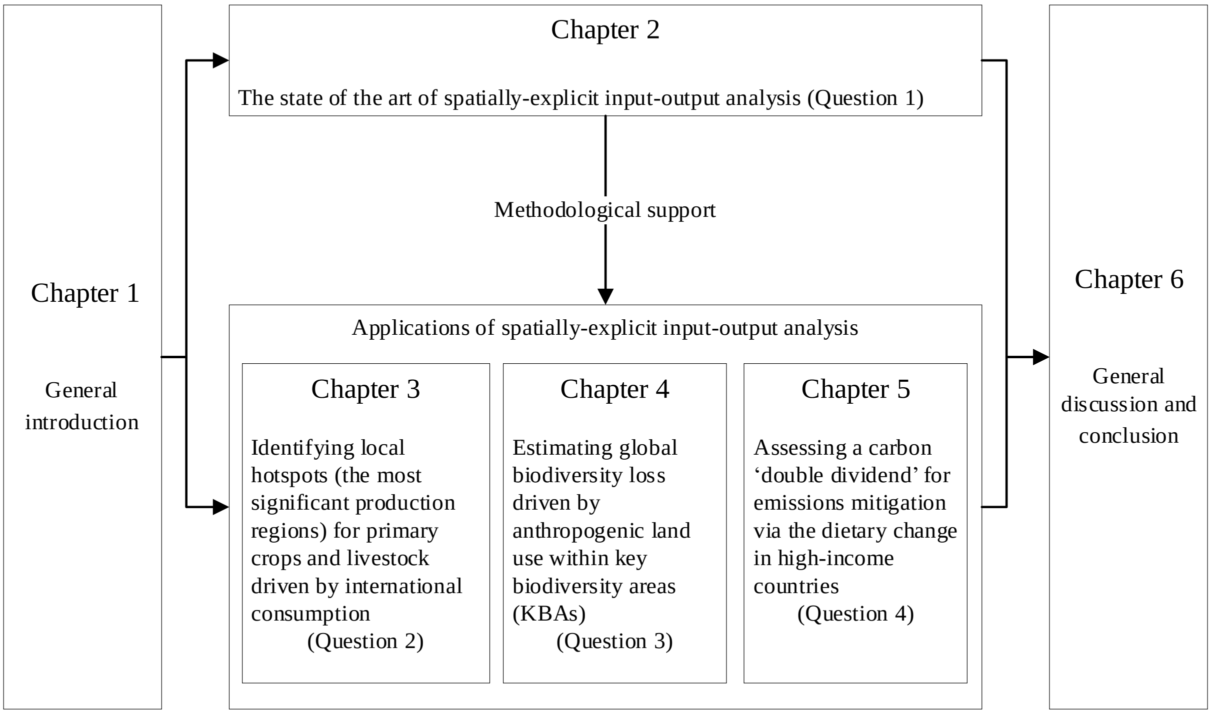

Figure 1.2. Outline of this thesis.

2.

Chapter 2.
Going global to local: connecting top-down accounting and local impacts, a methodological review of spatially explicit input-output approaches

2 Going global to local: connecting top-down accounting and local impacts, a methodological review of spatially explicit input-output approaches [1]

Abstract

Environmentally Extended Input-Output databases (EEIOs) provide an effective tool for assessing environmental impacts around the world. These databases have yielded many scientific and policy relevant insights, especially through the national accounting of impacts embodied in trade. However, most approaches average out the spatial variation in different factors, usually at the level of the nation, but sometimes at the subnational level. It is a natural next step to connect trade with local environmental impacts and local consumption. Due to investments in earth observation many new datasets are now available, offering a huge potential for coupling environmental datasets with economic models such as Multi-Region Input-Output (MRIO) models. A key tool for linking these scales are Spatially explicit Input-Output (SIO) models, which provide both demand and supply perspectives by linking producers and consumers. Here we define an SIO model as a model having a resolution greater than the underlying input-output transaction matrix. Given the increasing interest in this approach, we present a timely review of the methods used, insights gained, and limitations of various approaches for integrating spatial data in input-output modelling. We highlight the evolution of these approaches, and review the methodological approaches used in SIO models so far. We investigate the temporal and spatial resolution of such approaches and analyze the general advantages and limitations of the modelling framework. Finally, we make suggestions for the future development of SIO models.

2.1 Introduction

Environmentally-Extended Input-Output (EEIO) models have been widely applied and have been used to link production and consumption while accounting for the direct and indirect relationships between different economic activities [1,51,52]. Prominent consumption based studies include analyses of air emissions [53–55], waste generation [56], water use [57], land use [58], and biodiversity loss [59] around the world [60]. Part of the popularity of EEIO databases (EEIOs) is due to the steady increase in the level of environmental impacts embodied in trade [1,52]. Additionally, since these models connect producer and consumer through supply chains [61] (which are often complex), it is possible to investigate policy interventions from production-based [62–64], consumption-based [51,65], income-based [66,67], and other, in betweenness-based perspectives [68].

Currently, the vast majority of EEIO applications are based on results at the national level. This is acceptable for well-mixed, global environmental stressors such as greenhouse gases, and for broader investigations on a national level, but it limits the usefulness of models for stressors which have highly local impacts, and for nexus investigations which examine the interaction and interdependence of several resources. Particular examples of these types of stressor include water use, land use, biodiversity, water pollution, and local air pollution (such as SO_2, NO_x, $PM_{2.5}$, PM_{10}). Given this, there has been a recent trend to link EEIOs with global environmental maps and databases by disaggregating modelled or directly measured production activity by sector [69–73].

Maps and databases of environmental impacts or stressors are typically generated from observations by monitoring stations [74] and satellite remote sensing measurements [75]. They can

[1] This chapter has been published as: Sun, Z., Tukker, A. and Behrens, P., 2018. Going global to local: connecting top-down accounting and local impacts, a methodological review of spatially explicit input–output approaches. Environmental science & technology, 53(3), pp.1048-1062.

also be modelled by using spatially explicit simulations that often use direct observations as model boundary conditions [71,76]. Monitoring stations collect environmental information *in situ*, with common examples including air quality ($PM_{2.5}$, PM_{10}, O_3, SO_2, CO, NO_2) (for example see: http://aqicn.org), soil quality [77], and water quality [78]. Remote sensing aims to measure environmental impacts from a distance, including land use [30,76], water [79], air quality [75], and biodiversity [80]. Remote sensing may include ground-, sky-, or space-based observation. The spatial distribution of environmental impacts derived from these methods can be very accurate and are often available over time. For example, fixed monitoring stations record in real time, while satellite imagery products for air quality and land use are generally updated annually [29,75]. Most efforts are carried out by governmental, public research institutions, or some private research groups. However, there is always a balance between large-scale, continuous modelling, and the scientific resources available to make such global assessments. In response, researchers have also used spatially explicit simulation models to estimate the spatial distribution of environmental impacts at higher temporal or spatial resolutions. Such examples include: the global dynamic vegetation model LPJmL (Lund-Potsdam-Jena managed Land) [81]; the global freshwater model WaterGAP [82], the dynamical atmospheric Sulphur transport model DEHM [83]; a variant of this model DEHM-POP to depict transport of persistent organic pollutants (POPs) [83]; and a historic model of environmental impacts (HYDE) to simulate land use and land cover change over time [84]. These examples depict environmental issues caused by local production, but they do not connect local environmental impacts with consumption from other regions. Additionally, they do not contain enough sectoral information to provide information on policy impacts.

What we have described so far is the estimation of environmental impacts from a supply perspective, that is, in the production of materials for good and services. These data can be connected to the consumer in several different ways. We focus on input-output models in this review, but there are other methodologies for assessing consumption-side impacts using process-based methods to identify spatially explicit environmental impacts [85]. For example, Hoekstra and Mekonnen et al. estimated the spatial distribution of global water footprints (blue, green, and grey water footprints) using a grid-based dynamic water balance model, calculating virtual water flow from water embodied in the direct consumption of agricultural and industrial commodities [86,87]. This approach describes the embodied impacts through direct consumption of commodities between two regions, but they omit the complex supply-chain relationships between different sectors and different regions.

With the increasing availability of spatially explicit environmental data disaggregated by sector, there have been several efforts to take EEIO analysis to the local level. As yet these approaches are disparate and spread across the literature. Given the likely similarities of approaches, the diversity of environmental and resource assessments, and the possible utility of such approaches, we provide a critical review of the approaches so far, limitations, and future opportunities.

We start by highlighting recent efforts in SIO modelling and we categorize these analyses by the form of disaggregation used in the input-output model. We then provide an overview of spatial data sources and their resolution. The need to balance spatial resolution with policy recommendations is addressed. We discuss the potential for uncertainty analysis in SIO investigations and the possibility for further incorporation with other environmental models. Finally, we highlight the major obstacles going forward in developing, utilizing, and extending SIO models.

2.2 An expanding field

Although the term *spatially explicit* implies a variety of meanings, there is no uniform definition. Here we define it as involving a result where the spatial information available from a study is at a spatial scale greater than the available IO (input-output) data itself. Studies such as Wang et al.[88], Ridoutt et al. [89] , Wilting et al. [90], and Verones et al.[91], average results to the national level, and would fall under the category of input-output modelling not SIO since spatial information is not available. Multi-region input-output tables at the regional level, such as those using Chinese provincial data also do not conform to the definition above since the IO table is already at the spatial scale of the region. These regional MRIOs have been previously been reviewed in Ploszaj et al [92] . Ploszaj et al found 42 articles using subnational input-output papers based on data from 15 countries between 1980 and 2013. We omit these studies from the review herein.

Interest in incorporating spatially explicit information into EEIO is a relatively new development, with fast growth since 2014 (see Figure 2.1, and the Supporting Information for how the literature was selected). However, James et al. provided the first methodological approach in 1985, by integrating an input-output model with an air pollution dispersion model [93]. It focused on a small region (the Hunter Region, Australia) and traced the spatial diffusion of sulphur oxide and fluoride emissions from location-specific production sites given by the regional authority as part of the New South Wales Clean Air Act. These emissions were calculated based on the output from specific production sites and emission coefficients from a regional input-output table. They assumed the same emission coefficient for the specific site as the corresponding sectors in the input-output table [93]. This early approach showed that the spatial distribution of emissions varied with the level of regional economic development.

It subsequently took 20 years for the next publication of an SIO study, probably due to the limited availability of spatial datasets with adequate sectoral resolution along with the limitations of computing power. From 2010, there has been a large increase in the number of spatially explicit studies. These studies use a variety of different methods and approaches, and analyze a number of different environmental pressures. We are currently in a period of exponentially increasing citation counts for SIO papers, especially from 2013 onwards. This is likely to continue with increasing dataset availability and the fast development of SIO approaches.

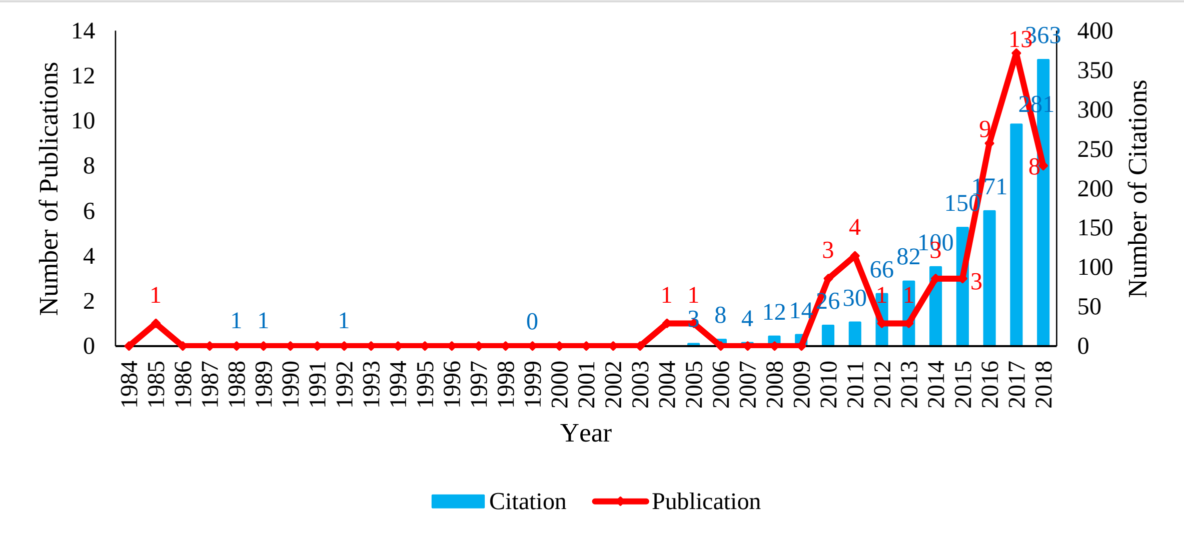

Figure 2.1 Number of published papers and their citations using SIO approaches

2.3 Methodological and spatial categories

Methodological categories: In total, we identify ten distinct methodological approaches for linking spatially explicit data to input-output databases (please see Supporting Information for qualitative and mathematical descriptions of each). We then classify these further based on the structure of Environmentally Extended Input-Output (EEIO) databases. The canonical structure for an EEIO database is a matrix for environmental extensions by sector and region, a final demand matrix by sector and region, and a transaction matrix where sectors purchase the output from other sectors to produce goods for final demand. We further classify the 10 methods to 3 categories based on the matrices to which the spatial disaggregation is applied (the studies falling into each category are shown in Table 2.1). The categories are enumerated as:

Category 1:Disaggregation in environmental extensions. Here, environmental extensions are disaggregated by mapping the environmental impacts between the production sectors in the input output model and impacts identified spatially from the spatial databases. The result is a spatially explicit mapping of consumption-based footprints. In this category, analysis mainly focuses on hotspot assessment, which can be driven by a specific country, region, or sector. Examples of spatial databases that can be used in this way include: WaterGAP [70] for fresh water use and consumption; emissions data from EDGAR [69] giving greenhouse gas (CH4, CO2, N2O), air pollution (BC, CO, NH3, NOx, PM10, PM2.5, SO2), and toxic pollutants (Mercury); the IUCN red list which provides details on threatened species [72,73]; and, Aqueduct Global Maps which maps water stress [94]. The connection between the spatial database and IO tables is usually made by assuming proportionality between impacts. That is, the demand for products in an IO table is assumed to be proportionally distributed to the production information in the spatially explicit database. Some studies have then aggregated these impacts or stressors to the national or regional level to build a set of new environmental extensions for the IO model first, and then used the same spatial information to allocate consumption-based impacts into grid cells [95,96]. Others use the existing source data for the environmental extensions provided by the IO datasets to calculate consumption-based impacts, and use spatial information to disaggregate to a finer scale [97].

Some studies then perform additional analyses to model the diffusion of a pollutant based on the consumption footprint. Typically, these studies use an input-output model to calculate the volume of emissions from a region and then apply a physical model to simulate the spatial diffusion of emissions (which may also include an atmospheric chemistry model) [98–103]. For example, the approach (Method 7 in the supporting information) has been used to investigate the human health impact in China driven by the overseas consumption of Chinese products (this also required the use of a health impact model) [104].

Category 2: Disaggregation in final demand. Here the final demand matrix is disaggregated using regional statistics. These statistics can be derived from household or enterprise surveys or from local purchasing data such as electricity bills [105–107]. This disaggregation is then used as a stimulus vector whereby the disaggregated matrix is used instead of the total national final demand (and the traditional Leontief analysis is performed). Note that this approach still uses the original national (or multi-regional) input-output transaction matrix and environmental extensions to trace upstream environmental impacts. Instead of finding spatially explicit hotspots in production driven by overseas and domestic consumption (as in Category 1), this approach is used to show the environmental footprints of consumption across regions, for example the differences in the environmental impacts of consumers in different subnational areas [108,109]. For example, Method 6 (see supporting information) was used to show spatially explicit consumption footprints in the EU[105,110]. First, the product classifications used in consumer expenditure surveys (CES) were mapped to the sectors available in the MRIO

EXIOBASE using concordance matricies at the country level. Then this combined CES-MRIO model was used to calculate subnational environmental impacts according to household consumption across the EU.

Category 3: Disaggregation in the transaction matrix. Here the transaction matrix is disaggregated, which by definition requires the spatial disaggregation of final demand and environmental extensions also [111,112]. As previously stated, this category requires the construction of an entirely new IO table in all IO elements, which does not conform to our definition above, and has been reviewed elsewhere [92] . As we will discuss later in this paper, data limitations preclude doing this for every analysis. Often we have limited information on the structure of value chains linking spatially separated production and production consumptions. Therefore, we focus mainly on Categories 1 and 2 and reflect on the further development of Category 3 studies in the discussion.

Table 2.1 Categories of SIO linked with the methods and data sources applied

Category	Example spatial database or model used	Methods	References
Disaggregation in environmental extensions	The WaterGAP model	Methods 1 & 2: Identifying hotspots	50,113
	EDGAR emissions data		95,96
	Extent-of-occurrence, from IUCN red list and BirdLife datasets		114
	Aqueduct Global Maps for water stress	Method 3: Integrating a process-based model with an input-output model	97
	IFA hazardous substance database	Method 4: Integrating an MRIO model with production location information	115
	Survey data from enterprises (SABI, Sistema de análisis de balances ibéricos: base de datos)		116
	Location of volcanic eruptions and ash volume (Auckland Volcanic Field, from Geology of the Auckland urban area)	Method 5: Quantitative risk assessment of economic output reduction due to final-demand perturbations.	117
	GEOS-Chem chemical transport model	Method 7 & 8 : Integrating an MRIO model with an air pollution dispersion model.	98–104
	Pollutant dispersion models (Smeared Concentration Approximation (SCA))		93
	Spatially explicit econometric model (spatial Regional Econometric Input–output Model (REIM))	Method 9: Integrating an econometric model with an MRIO model	118

	GIS methods and approaches	Method 10: Integrating an MRIO model with, for example, spatial interpolation	119–122
Disaggregation in final demand	Local statistical data	Method 6: Integrating an MRIO model with demand-side subnational information.	123–125
	Consumer Expenditures Survey (CES) data		107,108,134–142,126–133
	Enterprise survey data (Italian company information and business intelligence (AIDA))		106
	Zip code tabulation (U.S. zip code tabulation areas (ZCTAs))		107,143,144
	Gridded population		107
	Purchasing power index		107
Disaggregation in the transaction matrix	Disaggregation all matrices via Non-survey methods (such as location quotients (LQs), gravity models, behavior-based models, neural networks), survey methods, or hybrid methods		145–149

Spatial categories: Summarizing Categories 1 and 2, the inclusion or development of spatially explicit data in the literature arises from: 1) synthesis and incorporation of spatial environmental extensions data with EEIO (23 of the 48 articles evaluated), and 2) tracing environmental footprints using subnational stimulus vector in final demand (25 of the 48 evaluated, see supporting information). We found no papers belonging to Category 3 – papers coming closest to this represented sub-national MRIO tables at e.g. provincial level, which as discussed above we do not see as disaggregated transaction matrices at a high spatial detail but rather special cases of regular multi-country IO tables. The spatial resolution varies to a large extent both between and within categories.

Studies falling in **Category 1** used a total of 20 different spatial databases or models to trace spatial hotspots driven by consumption. These databases originate from different sources; some databases are based on remote sensing observations. For example, Moran et al. apply IUCN red list and BirdLife data, whose species-specific habitat loss is estimated from remote sensing and traces species threat driven by consumption [114]. Others use data from WaterGAP [50,113] and EDGAR [95,96], or point measurements of impacts, such as the location of volcanic eruptions [117], power plants [93], and spatial maps of national enterprises [106,116]. Based on these databases and models, researchers have explored issues including water consumption [50,113,131], nitrogen and phosphorus loading [115], biodiversity loss [96], volcanic eruption risk [117], energy consumption [129], greenhouses gas emissions (CO_2, CH_4) [95,122,130], and other air pollution emissions (NO_x, SO_2, PM_{10}, $PM_{2.5}$) [96,102]. The highest spatial resolution used was $0.5^\circ \times 0.5^\circ$ for water consumption and $0.1^\circ \times 0.1^\circ$ for greenhouse gas emission and air pollution. All studies are at the temporal resolution of a year and range from 1970 to 2008.

Studies falling in **Category 2** used 42 different databases to identify environmental impact footprints at local consumption level. These databases are mainly from Consumer Expenditures Survey (CES) (26 European countries, plus US, Austria, and Canada) according to the international COICOP (Classification of Individual Consumption by Purpose) division. For example, Ivanova, et al., build EU27 subnational household environmental footprints (carbon, land, water, organic materials, non-organic materials) based on CES databases of every country (except Croatia, Netherlands, and Sweden) [105]. Additionally, other databases source from national statistics (such as, Australian Land Use Mapping Program, the National Pollutant Inventory, and the Australian Business Register; U.S. zip code tabulation areas (ZCTAs)) [131,143], commercial enterprise information (e.g., Italian company information and business intelligence (AIDA))) [106], *in situ* questionnaire survey data [138,142], and regional purchasing power and gridded population data [107]. These researches explores environmental impacts footprints, including greenhouse gas emission [105,126], water and land [105,108], which map to the consumption-based side of IO analysis. The highest spatial resolution mapped carbon footprints into 250 m based on GHS-POP gridded population model [107], and US household carbon footprints at zip code tabulation areas (ZCTAs). Most studies are at the temporal resolution of a year and range from 1990 to 2015, and even some researches project to 2050 [144].

Studies falling into **Category 3** would give spatially explicit information on production processes and related extensions, spatially explicit information on consumption patterns, with transaction matrices matching this spatial and sectoral disaggregation. The disaggregation of transaction matrices is a clear bottleneck. All existing work uses non-survey approaches or suffers from other crucial limitations, as illustrated by work on subnational MRIO tables (e.g. Australia [150], China [112], Japan [151], Indonesia [146], Spain [152] and Germany [149]), the Industrial Ecology Virtual Laboratory (IELab) [89,111,146] and the Transparent Supply Chains for Sustainable Economies (Trase.earth) project [109,153,154]. The IELab [89,111,150,155] includes a lot of detailed regional data (especially for Australia), from which customized input-output models can be developed based on a specific research question, but it cannot provide a input-output database including all sectors and regions due to a lack of computing power (one approach could result in over 5 petabytes of data, and impractical computation times)[111]. Trase.earth [109,153,154] focuses on constructing trade flows at finer scale (see Method 11 described in the Supporting Information), disaggregating producers on a finer scale, but consumers still at national level. None of these examples use directly-measured data or survey-based data for estimating spatially explicit transaction matrices. This is natural due to the expense of ad-hoc surveys for interregional trade data [111] . Claims such as ‘city X consumes Y beef from pixel Z’ by necessity requires estimates of highly estimated and modelled flows. We have found no work yet that solves this problem and hence do not discuss this category further in this section.

We classify studies into 5 further spatial categories: global, regional, national, subnational regional, and city, depending on the resolution of the final result. Table 2.2 shows a breakdown of the spatial scale and environmental impacts for different studies in the literature. We then discuss the major highlights from studies at each of these scales and their policy relevance.

Table 2.2 Studies analyzing social or environmental impacts at different spatial scales

Spatial scale	Category 1	Category 2
Global	Air pollution (SO_2, NO_x, and PM_{10}, $PM_{2.5}$, BC, CO)[96,98,102,104] Greenhouse gases (CO_2, CH_4)[95] Biodiversity [114] Water [50,97,113]	Greenhouse gases (CO_2)[107]

	Grey water [115]	
Macro Regional		Carbon (EU27; 19 cities around the Mediterranean)[105,135]
National		Water (UK, Australia)[131]
	Grey water (Spanish)[116]	
	Air pollution (SO_2, NO_x, and $PM_{2.5}$, China) [99,101,103]	
	Atmospheric Mercury (China) [100]	
	Carbon (Japan)[122]	Carbon (Norway, USA. UK. Australia, Estonia, China, Germany)[124,125,139,143,126–128,131,132,134,137,138]
		Natural disasters (earthquakes, floods, landslides)(Italy)[106]
Subnational regional		Ecological footprint (15 cities, Canada)[133]
		Carbon (15 cities, Canada; San Francisco Bay Area in USA, 20 cities in Finland; 24 cities in China; Helsinki Metropolitan Area in Finland)[133,136,140,142,144]
City	Air pollution (Hunter region, Australia)[93]	
	COD (chemical oxygen demand) (Changzhou City, China)[119,120]	
	Volcanic eruptions (Auckland region, New Zealand)[117]	
		Economic loss driven by earthquake (Beijing, China)[123]
	Employment, population (Chicago, USA)[118]	
	Flood (South-Holland, Netherlands)[121]	
		Energy (Sydney, Australia)[129]
		CO_2 (Sydney, Australia; Boston, USA)[130,141]

Global studies: Globalization has served to disconnect commodity consumption with production-related impacts [113]. High-income countries to some extent have improved their local environmental footprints and impacts by outsourcing through the global supply chain [96]. However, these impacts will impact high-income countries as well. For example, along the US West Coast, 3-10% of annual average surface sulfate and 0.5-1.5% of ozone, both of which are deleterious to health, arise from the atmospheric transport of Chinese pollution driven by exports [98]. In another example, Zhang et al., build a global spatial distribution estimate of premature mortality driven by $PM_{2.5}$ in 2007 at 100 km × 100 km resolution, and find that some 411,100 deaths (12% of total premature mortality) are caused by pollutant transport from one location to a more distant location, and 762,400 deaths (22% of total premature mortality) are linked indirectly through the supply chain [104].

A common analysis is the tracing of embodied environmental impacts flowing through global supply chains at the national level. Spatially explicit approaches allow for a greater resolution in assessing local environmental impacts. We illustrate this using two examples: CO_2 emissions, and biodiversity threats. Firstly, at the national level, Davis et al. identified national flows of CO_2 emissions, and identified American imports as having the largest embodied CO_2 flows in 2004 (0.7 Gt net import) [156]. By using the EDGAR database, further work made these flows spatially explicit, showing that US footprints of CO_2, SO_2, NO_x, PM_{10} in 2008 are highly concentrated, with 90% of the footprints located in only 1.6%, 3.1%, 3.6%, 9.9% of the land area, respectively 2008 [95,96]. Similarly, at the national level, Lenzen et al., find that American consumption drives the largest number of biodiversity threats (2424 total threat records, and 995 from net imports) [59]. Further spatially explicit analysis showed that 23.6% of species threats were concentrated on just 5% of global land area, and 60.7% of species threats were concentrated on 5% of the global marine area [114]. The identification of these hotspots may help facilitate global policy responses.

Macro-regional studies: A good example of macro-regional scale applications is the use of European Union data to investigate the spatial variation of environmental impacts driven by consumption. Ivanova et al. introduced a method for calculating carbon footprints, driven by household consumption in 177 regions of the EU27 [105]. They used this approach (described in Method 5 in the supplementary information) to calculate land, water, organic materials, and non-organic materials footprints under different kinds of consumption categories—shelter, food, clothing, mobility, manufactured products, and services [105].

National studies: High-income countries and lower-income countries have different perspectives for environmental impact research. For the UK, a high-income country with relatively large consumption-based impacts, researchers have focused on carbon footprints [126,127] and water footprints [108] at the scale of the local authority. Some researchers go further, attempting to find even higher resolution spatial distributions, for example of the grey footprint of Spain [116] and the carbon footprint in Estonia [128]. Since some atmospheric pollutants have highly local health effects, but can also be transported within the nation, there has been work to model the diffusion of pollutants such as $PM_{2.5}$ and mercury, which also incorporate dynamics of international and interprovincial trade [99–101].

Subnational regional studies: These studies are very useful for interregional management, especially for a large country. For example, by linking census data with input-output models, researchers were able to show that the lowest Canadian per capita carbon footprint was found in metropolitan areas, since they often share goods and services [133]. Another study investigated the opportunities for high-income and low-income consumers to reduce their carbon footprints across California, USA [144], finding that lifestyle modes have a large impact on overall carbon levels.

City studies: Compared with other scales, cities tend to have highly-local measurements of environmental impacts, for example via *in-situ* air or water pollution measurement devices. Researchers have used input-output models and local city data to estimate direct economic losses to cities from natural hazards, including earthquakes [123], volcanic eruptions [117] and floods

[121]. Analysis of the energy requirements of cities at suburban scales has also been made [129,130]. City-based input-output tables are useful for this sort of analysis, and can provide specific support for local decision makers.

Most SIO investigations are on global and national levels. This makes a certain amount of sense since global input-output models (WIOD, Eora, GTAP, EXIOBASE) and national input-output tables (official statistical publications) have been available for some time now, as have large-scale, spatially explicit, global models of environmental stressors and impacts

2.4 Options for enhancing spatial and sectoral resolution

Theoretically, an MRIO framework could provide arbitrary spatial and sectoral resolution if the data and resources are available to those constructing the models. In one sense, at the extreme, a full MRIO model could include all interactions of economic activities for very fine spatial units, for example, 1 m × 1 m. This sort of model would fall under Category 3 above and is the ultimate ideal in developing SIO models (this would involve trillions of data points) because it can reveal all sectoral and spatial heterogeneity.

This approach overcomes the spatial homogeneity assumption, which is an intrinsic shortcoming of input-output models (i.e. that each sector and region has specific environmental impacts across all products produced by that sector and across regions). However, data and computation limitations preclude such an approach for the foreseeable future. SIO models in Category 1 and 2 attempt to gain insights that such an approach might yield without the significant data and computation challenges. There is a large potential for developing these models further. In the following we expand on the opportunities for developments, first from a sectoral perspective, and then from a spatial resolution perspective. We then present some avenues for the development of approaches for Category 3.

Enhancing Category 1, the sectoral and spatial resolution of environmental extensions.

Sectoral resolution: The individual sectors included in analyses are important for further environmental and policy insights beyond the total environmental impact. However, it is difficult to create spatial maps for each sector, especially in the form of grid-cell data. In general, there are a greater variety of spatial data available for primary sectors such as crops [157] and livestock [158] . Primary sectors account for most of the land use, water use, and other environmental impacts resulting from production, so these sectors receive more research attention. Also, the function of land for primary sectors is often unique, so it is generally easier for remote-sensing to identify. In contrast, identifying the distribution of secondary and tertiary sectors is much more challenging. For example, a particular building could be used as a residence, restaurant, school, a company, or several other uses. Many land classification schemes do not include factories, refineries, restaurants etc. It is this underlying inability to specify land use that causes much of the problem. Some environmentally important industries may still be possible to spatially identify, for example, transport and stationary power plants [159]. The phenomenon is especially evident in spatial distribution of carbon emission from EDGAR databases, which have detailed carbon emission for transport sectors, but much more coarse for manufacturing and service sectors [69]. Given this issue, the environmental impacts of most of industries are proportionally allocated into sectors based on their output. For example, for lack of sector-specific data Moran et al. mapped all sectors in an input-output table into 11-13 spatial maps of air pollution and greenhouse gas emission [95,96]. Similarly, for water, in Lutter et al. and Holland et al., WaterGAP consumption data was combined with an MRIO model (EXIOBASE for Lutter et al, and GTAP for Holland et al.), which was relatively straightforward to link in the case of agricultural and electricity sectors, but not directly possible in the manufacturing sectors [50,113]. These difficulties in pinpointing secondary and tertiary sectors are a focus of ongoing research for water and energy modelers [71].

One way to solve this sectoral information problem is to construct a map with a detailed land use classification based on current high-resolution map data, for example, Google Earth or OpenStreet map, which can identify location of secondary and tertiary sectors precisely. It would then be possible to link the sectoral map with spatially explicit environmental models to create more accurate spatial distribution of environmental impacts for more sectors in input-output models. Multi-use buildings will remain a challenge for the foreseeable period; for example, one building may include resident households, restaurants, banks and other service. The phenomenon is particularly prominent in metropolis areas with high-density population and complex industrial structures. While some regions in some datasets have information on building-by-building use, the data is currently too patchy and limited for full integration into input-output models.

Spatial resolution: Compared to subnational statistical data, grid-cell data is not limited to administrative boundaries, and it has the possibility of depicting spatial variation more accurately. But spatial variation still depends on the area of the grid cell. The coarsest resolution used in the 48 papers reviewed this study was 2° lon × 2.5° lat (about 60,500 km^2 at the equator) [98], slightly larger than smaller countries such as Netherlands, Switzerland, Slovakia, and Belgium. While increasing the spatial resolution of databases may be important for SIO models, there is little the input-output practitioner can realistically do about this given that these models often result from large research campaigns, for example NASA Earth Observations (NEO)[160] . For ease of viewing we have presented a non-exhaustive selection of some common spatial databases that have the potential to be used in combination with input-output models in Table 2.3.

A key issue arises when looking at the spatial resolution of Category 1 studies. All the studies in our review use a proportionality assumption in assigning regions for production (which fulfills international demand). That is, all regions of production are treated the same whether products are used domestically or exported. This means that regions which do not have good access to markets and are likely producing goods for local consumption are ‘counted’ as part of the footprint of overseas consumers. Studies have suggested that regions with good transportation services and access to ports are more likely to be regions which export commodities [161,162]. It may be possible to use this fact to apply a first-order correction to which regions may be producing domestically or exporting goods. Regions where road density is highest could be used as the first-priority for export, with the remaining area as the first-priority for domestic production and consumption. Similarly, we can allocate environmental impacts in the same way. In some cases, the subnational trade data is directly available (for example, at the municipal level in Brazil) [163], but is difficult to implement globally due to data limitations.

Table 2.3. Potential spatial information sources to improve SIO models

Environmental impacts	**Databases**	**Sectoral resolution**	**Temporal resolution**	**Spatial resolution**
Land use and land cover	European Space Agency Climate Change Initiative [29,164]	Cropland for crop sectors; grassland for livestock;	Each year, from 1992 to 2015	300 m × 300 m , global

	MODIS land cover [30,76]	forestland for forest products; urban area for manufacturing and service sectors	Each year, data from 2001 to 2012	5'× 5' minute, global
	USGS Global Cropland Area Database (GCAD)[165]	Detailed cropland classification, including wheat, rice, maize, barley, soybean, cotton, orchards, sugarcane, cassava.	2010	1 km × 1 km, global
			2015	30 m × 30 m , global
			Annually 2003 to 2014	250 m × 250 m, Africa
			Annually 2000 to 2015	250 m × 250 m , Australia
			Annually 2001 to 2013	250 m × 250 m , USA
Water	Aqueduct Global Maps [166]	No specific mapping relationship with input-output databases, but can be combined with other spatial information, for example, crop distribution, power plants distribution, to create mapping relationship with input output databases	2010	Shape file by water basin, Global
	12 Global hydrological models (HDTM, Macro-PDM, MPI-HM, GWAVA, VIC, LaD, WaterGAP, PCR-GLOBWB, LPJmL, WASMODM, H08, ISBA-TRIP), details see [167]	Details for agricultural sectors and electricity sectors; difficult to combine with other manufacturing sectors	Varying, from hours to month	Varying, from 0.5° × 0.5° to 2° × 2°, Global
Air pollution, GHG	Emissions Database for Global Atmospheric Research (EDGAR) [69]	Varying from 7 to 28 sectors related to energy consumption.	Annually, 1970 to 2012	0.1° × 0.1°, Global
Pesticides	USGS, Grids of Agricultural Pesticide Use in the Conterminous United States [168]	All detailed crop sectors for input-output tables in US.	1992	1 km × 1 km

Biodiversity	Global Mammal Assessment [169]	Details see [59]	Annually, 2000 to 2050	1 km × 1 km, Global
	IUCN Red List [72]		Annually, 2009 to present	Shape file by hydrological basins for freshwater basins; by taxonomic groups (species) for territorial and marine animals
	BirdLife [73]		Annually, 2007 to present	Shape file by taxonomic groups (species)
Agriculture	Global Gridded Crop Model Intercomparison (GGCMI) [170]	All detailed crop sectors for input output databases.	Annually, 1979 to 2010	0.5° × 0.5°, global
	Spatial Production Allocation Model (SPAM)[171]		2005	5'× 5', global
Soil organic carbon	Food and agricultural organization (FAO) [172]	No specific mapping relationship with input-output databases, but can be combined with other spatial information, for example, crop distribution to create mapping relationship with input-output databases	2017	30"× 30", global
Electricity	US, environmental protection agency, Emissions & Generation Resource Integrated Database (eGRID) (USEPA, 2018)	Power generation sectors in input-output databases	Annually, 1996 to 2016	Point locations, global
	Global Energy Observation (http://globalenergyobservatory.org/)		Annually, 1950 to present	
	Platts (https://www.platts.com/)		Quarterly, from 1998 to present 2017	

Going beyond the data sets provided in the Table 2.3, the increasing number of monitoring stations provided by local authorities, such as those for air and water quality may also provide further data available for analysis [74]

Enhancing Category 2, the sectoral and spatial resolution of final demand.

Sectoral resolution: typically, commodity classification is more detailed than the products or sectors given in input-output models. However, the classification of consumer expenditure surveys is based on direct household consumption in mind, rather than economic sectors like those included in input-output models and so a conversion has to be applied. In addition, most categories within a consumer expenditure survey are food commodities. For example, out of the 183 commodities in the Norwegian database, 66 are food-related, but there are only 26 food related products in 200 products in high sectoral MRIO databases, EXIOBASE [110]. Additionally, surveys cannot distinguish domestically made or imported products consumed by households. Other import parts, such as government consumption expenditure, and gross fixed capital information still lack of research. Blockchain with IoT devices would be a good way to trace these final consumptions in the future [173].

Spatial resolution: From the final demand perspective, the spatial distributions of environmental footprints are generally performed at the local authority level – as described by Method 6 in the supporting information. This is mainly due to the lack of spatial distribution of consumption at any other resolution. Some scholars, for example, Moran, et al., applied global gridded population and local per-capita purchasing power databases to spatialize consumption-based environmental impacts [107]. Beyond that, Big Data methodologies have been suggested by various researchers as the possibility of collecting detailed human activities consumption with geolocation at a very high spatial (as well as sectoral) resolution [174].

Pathways for moving towards Category 3 SIO's.

In an ideal situation, efforts to enhance sectoral and spatial resolution ultimately leads to a Category 3 SIO database. That is, spatially explicit information on production processes and related extensions, spatially explicit information on consumption patterns, with intermediate transaction matrices that match this spatial and sectoral detail. Compiling the intermediate transaction matrix is extremely challenging when compared to compiling spatially explicit extensions or final demand. Some national statistical institutes may have detailed, sectoral, statistical data consistent with international standards [175]. But even in these cases it is extremely challenging to build spatially explicit input-output databases, since it requires a large amount of *in-situ* surveys. As discussed, studies that provide such transaction information generally do so using non-survey methods, leading to highly estimated transaction information.

The most common non-survey method for constructing intraregional input-output models is to compile subnational input-output models and then estimate interregional trade flows separately [145]. However, this approach requires the common assumption that regional production technologies and preferences of customers are similar to the national level [145]. Clearly this introduces uncertainties at the subnational level. Furthermore, interregional trade flows are usually estimated using a gravity model that assumes trade is only related to economic size and geographical distance of the producing and consuming regions [112,176] (other non-survey models, such as entropy and information models, neuronal network models, and behavior-based models can also be used [148]).

From above analysis, we find that most studies concentrate on the global or national level since national input-output models are readily available, and GMRIO models (e.g. EXIOBASE, WIOD, EORA, GTAP) have become increasingly available in recent years. Few studies focus at city level, due to a lack of official data. New technologies based on Big Data approaches and blockchain may offer ways forward in the future. Blockchain is a shared, distributed ledger that protects records from deletion, tampering or revision. Some researchers have used distributed ledgers combined with IoT devices to trace food supply chains, from plantation to processing and to retailers [177]. Similarly, if any commodity is labeled with a unique code, it can be traced using advanced database approaches. Once a complete network of supply chains is constructed, it may be possible to use these data to build a transaction matrix for input-output models. The technology may reduce the cost of collecting transaction data, improve the efficiency and reliability of databases [173], and provide real-time information.

Balancing resolution and policy needs: Ideally, finer spatial and sectoral scales will reveal more spatial heterogeneity in environmental impacts and will be of increasing relevance to policy makers. However, if there are no (reliable) data or reasonable assumptions for downscaling some regions, and attempting to do so might introduce unquantifiable uncertainty. Additionally, there may be cases where the policy need does not require higher-resolution in the first place. From the papers reviewed herein, the resolution of the final result is almost always dependent on external spatial information beyond input-output models. For this reason, papers which fall under Category 2: the disaggregation of final demand, are focused on American, European, and Australian regions since they have more complete local consumption statistics and a high availability of household surveys. It's best if the spatial scale chosen relates to the policy relevance of the environmental impact findings. For example, water pollution is regarded as local environmental impact, but a river will run through many regions and countries, so local and regional water balances need to be considered as well as the linkages to trade through input-output tables [50]. For example, Lutter et al. [50] and Wang et al. [97] study fresh water at the spatial resolution of the water basin, which may be more helpful to inform general, sector-based policies for water extraction and pollution within a region. Conversely, greenhouse gas (GHG) emissions are well-mixed and is an impact suitable for analysis at the national scale. However, identifying the spatial distribution of GHG driven by consumption helps connect consumers with the impacts of their consumption [95]. This is the case for Kanemoto et al. where they develop a hotspot analysis of carbon footprints at a global resolution of $0.1° \times 0.1°$ [95].

A different approach is needed for other types of air pollution such as particulate matter, which is very much a local issue and most often driven by point source emission [96]. In addition, aerosols which remain in the atmosphere for several days, can easily diffuse to other regions [102]. Therefore, locating pollution sources and exploring the spatial distribution of emission diffusion embodied in trade is a more appropriate scale to help consumers participate in abating targeted air pollution. This also requires additional modelling of emission diffusion and a temporal resolution greater than the yearly average as commonly used in studies.

Increasing the spatial resolution of input-output models may also put pressure on increasing the temporal resolution. One of the major drivers of making an IO database spatially explicit is to examine the local impacts of resource availability or pollutant emissions, which can sometimes vary more temporally than spatially. Since input-output databases are annual aggregations of activity, this elides some of the seasonal complexities. For example, the availability for water used in the cooling of thermal power plants vary more through the year than across the nation [178]. Some level of temporal resolution may be possible simply by using time-explicit final demand vectors, however these data will first have to be collected by national or regional bodies. For example, emission transport models need time series data, (hourly, daily, weekly or monthly), since aerosols diffuse to other locations on the order of several days. Temporal issues may also impact uncertainties, a topic to which we turn next.

2.5 Addressing uncertainties

Underlying sources of uncertainty: General uncertainties for input-output models arise from the source statistical data, sector aggregation, and data allocation approaches [65,179–184]. For EEIO models, further issues with source data and assumptions about the density of environmental impacts also contribute to uncertainties [183,184]. SIO analyses add two further, related uncertainties: 1) Uncertainty in spatial databases themselves, and 2) uncertainty from spatial and sectoral aggregation.

With respect to uncertainty in spatial databases, this can vary depending on the type of source. For remote sensing, sensor quality, image generation, and processing techniques will drive uncertainty [185]. In local statistical data, uncertainty will be driven mostly by statistical methods [186]. Finally, for modelling approaches, input data, assumptions, and model methodology will all drive uncertainties. Furthermore, the spatial resolution in environmental impacts will, on its own, result in some uncertainty. For example, the resolution of WaterGAP is 0.5° × 0.5° (about 50 km × 50 km at the equator), implying that water consumption is the same within a 50 km × 50 km region.

Uncertainty will also be introduced when aggregating spatial databases into regions matched with input-output databases, especially at the border between regions. Spatial databases often have to break down spatial information into different sectors, using assumptions which will further drive uncertainty. Often, we can resolve the spatial distribution of primary sectors (e.g. food crops and livestock) and some secondary sectors (large power plants, for example). But as mentioned above, most manufacturing and service sectors remain difficult to locate.

As we will see below, it is often hard to obtain a firm grasp of where the largest uncertainties may arise. In some cases, researchers have found it is likely that more uncertainty arises from additional pollutant modelling and not the input-output models themselves. For example, emission transport and health impact models have been found to have more uncertainty than the underlying input-output model [98,104].

Approaches for estimating uncertainty: Uncertainty analysis for EEIO modelling is already challenging given the diversity of data [187] and the model structure [188]. Approaches have been developed to estimate uncertainties [187,189–191] and perform sensitivity analyses [183,192,193], but there is still a lot more work to do to fully understand uncertainties. Given these existing difficulties, spatially explicit uncertainties add another layer of complexity. Given the variation of possible uncertainties, approaches such as Monte-Carlo simulations can be computationally prohibitive [100,104,107].

Still, some researchers have attempted to clarify uncertainties by narrowing down the number of uncertainties for sensitivity analysis. For example, Lin et al. ran over 10,000 Monte-Carlo simulations [98] for each type of air pollution in their study. Zhang et al. estimate overall uncertainty in SIO models by aggregating 4 sources of uncertainty, including uncertainty from air pollution (via the spatial database), uncertainty in the MRIO model, uncertainty from chemical transport model—GEOS-Chem model using Normalized Root Mean Square Deviation (NRMSD) method, and uncertainty from health impact model [104]. Lenzen et al., simulate standard errors of household factor multipliers, embodied factor multipliers and household expenditure, and then integrate all these parts of standard error into a total standard error estimate of the entire SIO model using Monte-Carlo simulations. In another example, Moran et al., employ a Monte-Carlo approach to build up range of alternative global Lorenz curves for carbon emissions [107]. These methods inherit approaches used in the uncertainty analysis of traditional input-output models [194].

These examples are all based on conventional Monte-Carlo simulations, extracting a large number of samples with assumed distributions, usually normal or log-normal. These simulations require an assumption that the extracted data are independent. Rodrigues et al. use a Bayesian approach to compare the uncertainties of independent sampling such as this [195], and find that this approach underestimates the uncertainty of results [195]. Future uncertainty analysis could expand this concept to include spatial data, since spatial data are often developed by incorporating the same underlying databases as those used in input-output models, resulting in non-independent errors.

2.6 Integration with other environmental models

Future options for SIO models may include integration with other environmental assessment models including technology-rich Integrated Assessment Models (IAMs), such as IMAGE [196], GCAM [197], AIM/CGE [198], MESSAGE [199], REMIND [200]. Generally, IAMs use macroeconomic models to downscale the world spatially into 10-30 aggregated regions [201], after which they are coupled to earth system models or environmental data using spatially explicit models. The environmental impacts are then downscaled to that resolution (Figure 2.2). IAMs have already been integrated with other spatially explicit land use models such as the CLUE-s model [202,203], the Global Land-use Model [204,205], and the Land Use Land Cover Change (LULCC) model [206], and these could be all be combined with input-output approaches. IAMs have also been used to make water demand spatially explicit [207,208]. For example, the LPJmL land model has been used to examine carbon balances [209], the dynamic GLOBIO model for evaluating biodiversity impacts [196], the integration of the GLOFRIS model for estimating impacts of flood risks [196], and the GISMO model for human development [196]. However, IAMs lack physical linkages between capital stock and material flows and they cannot trace the entire supply chain, this means IAMs are generally not able to assess environmental impacts other than on a production-basis. However, input-output models are an effective tool to assess impacts including those impacts embodied in the trade [210].

Generally, input-output models are constructed from historical data and used for historical analysis. Given their structure there are no built-in dynamic mechanisms. Conversely, technology-rich IAMs are used to project different scenarios for industrial structure, final demand, and spatial distribution of environmental impacts, which are the components of input-output models. It would be possible to establish soft links between IAMs and SIOs [210]. IAMs could be used to project components of input-output models needed to provide input-data to perform scenario-based consumption focused accounting [210–212].

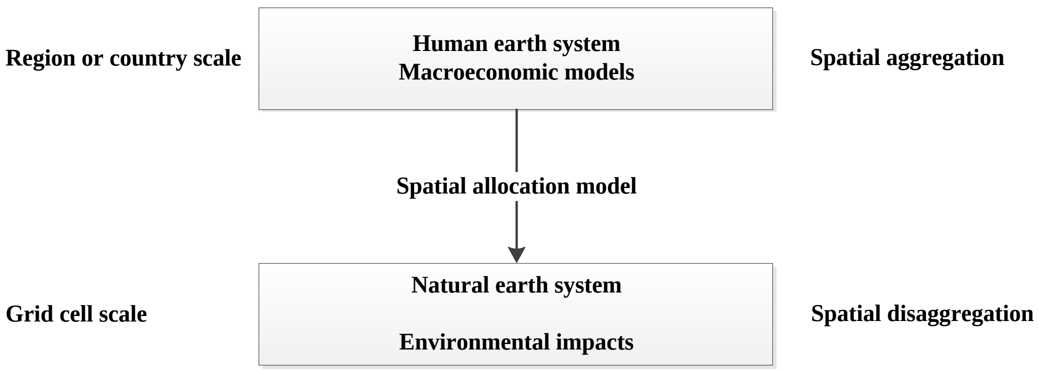

Figure 2.2 Schematic of general structure that integrates macroeconomic models with spatially explicit modes.

2.7 Outlook

Spatially explicit approaches inherit the advantages of EEIO, linking environmental impacts from production to consumption [65], while revealing the spatial variation of local environmental impacts. The recent growth in SIO is not necessarily surprising given the extensive role of globalization in outsourcing production and the associated environmental impacts of goods and services worldwide. Such SIO approaches can allow for a better understanding of the distribution of impacts from consumption, and provide data for targeted consumption-based mitigation measures.

We have critically reviewed recent SIO analyses and provided an overview of their methodologies and strengths. These analyses can be broadly separated into three approaches: 1) spatial disaggregation in environmental extensions, 2) spatial disaggregation in final demand, and 3) construction of a new input-output table with spatially disaggregated transaction matrices. We describe the considerations and issues that are raised when performing these analyses, and have presented an overview of specific findings. We have outlined the main challenges and limitations in present SIO modelling, including: the availability of spatially explicit data of different spatial and sectoral resolutions, the balancing of spatial resolution with research goals and policy advice, and the difficulty in assessing uncertainties. We also discuss the possibility of incorporating SIO modelling with integrated assessment models.

We expect that future efforts will focus on several key areas: as further spatial databases become available with greater sectoral resolution – especially in secondary and tertiary sectors – more options for deeper analysis and linkage with other environmental models will become possible; we see the opportunity of temporal analysis for certain resources, such as water, becoming increasingly tractable; and, studies that combine both demand-side (Category 1) and consumption-side (Category 2) disaggregation will become possible. A major hurdle in building accurate Category 3 input-output models at a high level of spatial detail is the lack of information about intermediate transactions and the structure of the value chains at this level of detail. Issues with uncertainties will likely remain problematic for some time, given the difficulties in assessing input-output model uncertainty even without spatial disaggregation. However, this is a problem which is not specific to input-output modelling, and is faced by many other large-scale environmental model approaches such as IAMs.

2.8 Acknowledgements

Zhongxiao Sun is financially supported by the China Scholarship Council (CSC) (NO. 201706040080). The authors would like to thank three anonymous reviewers and the editor for helpful comments and suggestions for improving this work.

2.9 Supporting Information Available

This information is available free of charge via the Internet at http://pubs.acs.org

3.

Chapter 3.
Linking Global Crop and Livestock Consumption to Local Production Hotspots

3 Linking Global Crop and Livestock Consumption to Local Production Hotspots [2]

Abstract

International trade plays a critical role in global food security, with global consumption having highly localized environmental impacts. It has been difficult to gain insights into these effects due to the diversity of food production, and complexity of supply chains in international trade. We present a Spatially explicit Multi-Regional Input-Output (SMRIO) model which couples primary crops and livestock at a high spatial resolution with a global Multi-Regional Input-Output (MRIO) model. We then identify hotspots (the most significant production regions) for primary crops and livestock driven by international consumption. We present the method and data behind this approach, and provide illustrative case studies for Indonesian palm oil and Brazilian soy and beef production. Regionally, China is the largest primary crop consumer, while the EU28 is the largest livestock consumer. Primary crops and livestock hotspots are highly unequal, and the embodied primary crops and livestock for high-income countries are distributed over larger areas when compared to lower-income countries since high-income countries have more numerous trade links. Identified hotspots could allow for increased cooperation between consumers (high-income countries) and producers (lower-income countries) to improve sustainability programs for global food security.

Keywords: primary crops; animal husbandry; spatially explicit; Multi-Regional Input-Output (MRIO) analysis

3.1 Introduction

Global food security is fundamental for human development with 12 of 17 Sustainable Development Goals (SDGs) having direct relationships with food systems [213]. However, global food security is challenged by increasing global food demand due to both population growth and potential dietary shifts to higher calorie intake and a greater proportion of animal products [214]. Global population doubled from 1950 (2.5 billion) to 1987 (5.1 billion), and tripled by 2018 (7.6 billion) (Figure S 8.6) [215]. Although population growth is slowing, estimates suggest a global population of almost 10 billion by 2050 at a medium variant scenario [215]. To meet this growth, the FAO suggests that cereal, meat, fruit and vegetables, and oil supply need to increase by ~39%-56%, ~29%-55%, ~48%-54%, and ~40%-51% respectively (between 2012 and 2050) [216]. Since the green revolution, increases in crop yield and cropland area have kept pace with increases in global food demand [217]; however, food supply is unevenly distributed [218], and yields have stagnated in recent years [219]. Between 2008 and 2050, four staple crops – wheat, rice, soybean, and maize – are estimated to have annual yield growths of 0.9%, 1.0%, 1.3% and 1.6% respectively [220], half the rate needed to satisfy demand while keeping prices stable [220]. In some regions, yield growth may even stagnate entirely [221]. The projected demand growth may exceed yield growth given these estimations. Following current food production and consumption patterns, environmental impacts are estimated to increase by 50% - 90% from 2010 to 2050 in the absence of technological progress and targeted mitigation measures [222]. To stay within a safe operating space for humanity, we must therefore limit both the inputs and space required for food production [222]. This is because agricultural production requires increasing areas of land [223] and freshwater [224], causing serious environmental impacts, such as eutrophication, soil acidification, ecotoxicity, greenhouse gas emissions, and biodiversity loss [43]. While many studies only focus on crops, we also examine the spatial distribution of livestock. Feed contains a large amount of additives, antibiotics, and antimicrobials, but most of them are not degraded

[2] This chapter has been published as: Sun, Z., Scherer, L., Tukker, A. and Behrens, P., 2020. Linking global crop and livestock consumption to local production hotspots. Global Food Security, 25, p.100323.

in the animal's body. Instead, they are excreted by the livestock and released to the environment [43,225]. As the consequence, these compounds harm environmental and human health by accelerating eutrophication, deteriorating soil contamination, and promoting the spread of drug-resistant pathogens [43,225,226]. Additionally, the fact that about one third of food is lost or wasted embodied in food supply chain from farm to fork exacerbates these burdens [227]. Food loss and waste occurs at every phase from production to final consumption along the food supply chain, and varies for agricultural products at different regions [227]. For example, fruits and vegetables are lost or wasted more than cereals, and lower-income countries have a higher ratio of food loss at the production stage, while higher-income countries have a higher rate of food waste at the consumption stage [227]. On top of these significant challenges, climate change and the increasing frequency of extreme weather events further exacerbate the problems faced by agricultural production [228].

Some countries have gradually given up expanding cropland [229], and have spared cropland to preserve nature [230]. This can result in a shift of the environmental burden related to agricultural production from high-income nations to low- and middle-income nations through trade [231]. Although trade can globally increase resource use efficiency and reduce environmental impacts in some cases [232], the externalities in producing countries are not accounted for in trade. Globalization has led to a spatial disconnect between production and consumption of agricultural products [233]. Growing international trade provides exotic or seasonal agricultural products for consumers year-round [234], improving food supply. The amount of global food trade, as measured in caloric content, has doubled from 1986 to 2009, enough to feed more than 1 billion people. The global food trade as percentage of global food production increased from 15% to 23% [235]. Understanding the role of international trade in food systems is essential in understanding the environmental impacts of global food supply and demand. Previous studies have focused on embodied environmental pressures and impacts, such as land use, water use, greenhouse gas emissions, and biodiversity loss [43]. These studies attribute the environmental responsibility of this supply to the consumers of food [65].

Two prominent examples of shifting environmental burdens through international trade are the export of Brazilian soy and Indonesian palm oil. Increasing global demand for beef, soybean oil, and soybean meal used, to a large extent, to feed livestock and produce biofuels has promoted Brazil to a position as one of the largest exporters of soybean and beef in the world [236]. Brazil is expected to have the largest potential for agricultural expansion within this century [237]. Another high-yielding oil crop, oil palm has been the fastest growing crop in the 21st century [238], driven by increasing demand for high-yielding crops producing refined vegetable oil. Much of this growth has occurred in South Asia, mainly Indonesia, where ~55% of global palm oil production takes place [236]. However, agricultural expansion in tropical regions often comes at the expense of deforestation and the destruction of associated ecosystem services, devastating biodiversity, emitting large amounts of greenhouse gases (GHGs), and disturbing hydrological regulation. In Brazil's case, even though deforestation has been decreasing since 2004, it has seen the largest deforestation of any country worldwide. This is mainly due to agroindustry clearing for pasture and soybeans [237]. Deforestation appears to be worsening in Indonesia, with oil palm expanding at an average rate of 4500 km^2 annually, resulting in an average 1700 km^2 of deforestation per year from 1995 to 2015 [239].

In the past decades, increasing global food consumption was partly achieved by international trade at the expense of the local environment. This led to the global food system losing its resilience by becoming too homogeneous and dependent on continued trade [240]. Therefore, identifying spatial heterogeneity of different consumption patterns and setting a safe target for primary crops and livestock consumption are helpful for guiding more sustainable practices and healthier diets. Consumption-based accounting of primary crops and livestock raises consumer awareness of the original sources of their food and this can facilitate global cooperation between production- and consumption-oriented countries [65]. For example, while impacts of food production are often outsourced from high-income to lower-income nations, high-income nations often have advanced technology and management experience that can be transferred to those lower-income, producing countries. According to our knowledge, there has been no comprehensive assessment of crops and livestock embodied in trade at a high spatial resolution. To fill this gap, we develop a spatially explicit multi-regional input-output model (SMRIO) based on the EXIOBASE input-output model [241], and investigate case studies on Brazilian soybean and cattle, and Indonesian palm oil to show the utility of this approach. Additionally, our work facilitates a more accurate assessment of environmental impacts from agriculture driven by final demand of any region in EXIOBASE, as our spatially explicit primary embodied crops and livestock can easily be combined with environmental intensities.

3.2 Materials and Methods

Here we use a global, environmentally-extended multi-regional input-output (MRIO) model, EXIOBASE, linked to crop and livestock data derived from FAOSTAT, to calculate the consumption of crops and livestock for countries and regions. To avoid double-accounting in the system, we remove primary crops fed to livestock. The choice of livestock over feed for the food-related material footprint is justified by livestock being closer to human food consumption. As such, the information is easier to understand for consumers who usually choose food based on simple and informationally frugal heuristics [242]. We then spatially allocate the consumption-based result of crops and livestock to the grid-level. We do this by using crop and livestock maps (Table 3.1), and by using both road quality and density [161] to distinguish between production likely for export and production for domestic consumption.

Compared with other GMRIOs, EXIOBASE 3 contains the most detailed sectoral and environmental information and covers a long period from 1995 to 2015 [241]. For a detailed comparison, see Tukker and Dietzenbacher (2013). EXIOBASE 3 includes 163 industries, 200 products, 28 EU countries, 16 other major countries, and 5 regions for the rest of the world [241]. In order to construct EXIOBASE 3, a series of underlying databases are needed to estimate bilateral trade flows, including re-exports. Specifically, for re-exports, EXIOBASE 3 uses publicly available data from Comtrade on either re-exports or re-imports at the country level to estimate changes over time in the share of re-exports in total exports from the 2007 base year [241]. Since spatial databases for crops and livestock are available in 2006, we choose this year for EXIOBASE. The database includes 8 crop sectors linking 163 types of crop derived from FAOSTAT (domestic extraction of primary crops, cereals are based on the weight of dry grain, vegetable and fruits are based on the weight of fresh fruit of human consumption, treenuts are based on the weight of nut for sale) with input-output accounts (Table S 8.10). This forms the foundation for analyzing the distribution of crops driven by consumption.

To keep the livestock data consistent with that of spatial databases and comparable between different types of animal, we select related data from FAOSTAT to create 6 livestock satellite accounts to match with EXIOBASE, including cattle, pig, chicken, duck, goat, and sheep (

Table S 8.11). In addition, we use primary livestock products instead of live animals to keep them comparable. The mapping relationship between FAO countries and EXIOBASE countries and regions is shown in

Table S 8.12. Even though aquaculture is becoming more and more important [238], we do not consider it in this paper because of a lack of spatially explicit data for aquaculture.

3.2.1 **The spatial distribution of crops and livestock**

We use spatial crop production data from the Spatial Production Allocation Model (SPAM) version 3.2. SPAM depicts the spatial distribution of 42 types of crop, including variables on production, yield, physical area, and harvest area [157]. SPAM uses the average value of statistical data from 2004 to 2006. In order to match these data with the crop categories available in FAOSTAT, we aggregate *Millet Pearl* and *Millet Small* into *Millet*, and we aggregate *Coffee Arabica* and *Coffee Robusta* into *Coffee* (see Supplementary material).

For livestock data, we use a high-resolution livestock density dataset at 30 × 30 seconds for 2006, including cattle, goat, sheep, pig, chicken, and part of duck [244]. In order to keep the same spatial resolution with road density as described below, we scale this down to 5 × 5 minutes.

3.2.2 **Global Roads Inventory Project (GRIP)**

Previous studies using SMRIO approaches assume proportionality between production volumes and locations [95]. This proportionality means there is no ability to distinguish between regions that produce food for export and regions that consume this food locally. This can be important in regions with both subsistence farming and industrial production in low- and middle-income nations (consider the Indonesian case with a high amount of subsistence consumption yet producing large amounts of palm oil for international markets). To address this and take the literature a step forward, we start from the assumption that agricultural products have better access to markets if there are better transportation services [161,162]. We use data from the Global Roads Inventory Project (GRIP) [161] to allocate the spatial distribution of primary crops and livestock for export. We regard regions where road density is higher than 100 m / km^2 as the first-priority for export, and the remaining area as the first-priority for domestic consumption. We allocate exported primary crops and livestock into the first-priority region for export. If the ratio of actual exports to the production in this region is above one (implying that more is produced for export than currently produced in this region), we allocate the rest of primary crops and livestock for export into the lower-priority region for export (first-priority region for domestic consumption). Similarly, we allocate primary crops and livestock into first-priority regions for domestic consumption, and the rest for domestic consumption is allocated into the second-priority region for domestic consumption (Canada is a special case, please see explanatory note 1 *Special solution for Canada* in the Supplementary material).

Table 3.1. Spatial data employed in this paper

Data	Data source	Resolution
Global distribution of crops (SPAM)	http://mapspam.info/	5 arc minutes
Global distribution of livestock [244]	http://www.livestock.geo-wiki.org	30 arc seconds
Global administrative areas	https://gadm.org/data.html, Version 3.6	vector data
Global Roads Inventory Project (GRIP) [161]	http://www.globio.info/download-grip-dataset	5 arc minutes

3.2.3 **SMRIO analysis**

We use spatial distributions as spatial weights, and allocate consumption-based primary crops and livestock into grid cells with the same proportion of each grid cell accounting for the total amount in a country or region, according to equations 1 and 2, which have been used to allocate carbon emissions [95]. By doing so, we trace the spatial distribution of the production source for crops and livestock to the consumption destination.

$$\boldsymbol{F}^s = \sum_r R^r \frac{\sum_i \boldsymbol{e}_i^r \sum_{jt} \boldsymbol{L}_{ij}^{rt} \boldsymbol{y}_j^{ts}}{\sum_i d_i^r} \tag{1}$$

$$\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1} \tag{2}$$

Where $\boldsymbol{F}^s$ is the spatial distribution of the total consumption of country *s; R^r* is the distribution map of crops or livestock in absolute values in country *r* that produces crops or livestock; e_i^r is the crop or livestock intensity for sector *i* in country *r;* $\boldsymbol{L}$ is the Leontief inverse matrix; $\boldsymbol{I}$ is the identity matrix, and $\boldsymbol{A}$ is the technical coefficient matrix to describe input output relationships between sectors and countries; y_j^{ts} is the final consumption of sector *j* of the country *t* with the last sale to the destination country *s*. d_i^r is the share of sector *i* in country *r.*

3.2.4 **Comparison with tentative targets**

A safe operating space typically relates to environmental impacts (e.g., biodiversity loss) or to emissions as outputs from the anthroposphere (e.g., greenhouse gas emissions) [245], especially from food production [246]. Operationalizing such planetary boundaries is complicated and has not yet been done for most environmental impacts. The most comprehensive assessments exist for carbon emission targets [247,248]. Further tentative boundaries for water and land use have been suggested based on limits of physical availability [60,249]. Bringezu suggested halving (agricultural) resource use compared to the 2000 level to reduce environmental pressures, as human impacts on the planet were already too high in 2000 [250]. These suggested targets for resource use have not been unanimously accepted for several reasons [60]. Most importantly, these targets are not based on an actual assessment of physical limits or levels of unacceptable environmental damage, but are simply based on the assumption that any further increase implies the risk to further aggravate environmental impact beyond acceptable limits. While this objection is undoubtedly true, this approach offers a heuristic for understanding the increasing environmental pressures triggered by food consumption through supply chains. In this case, and in the absence of any updated alternative, we will use the target of keeping the use of primary crops and livestock at the 2000 level for illustrative purposes.

In 2000, primary crops, excluding feed crops, totaled 5.9 Gt, and livestock totaled 0.8 Gt, based on EXIOBASE 3 and FAOSTAT [241,251]. Based on this, we obtain per-capita targets for embodied primary crops and livestock of 0.90 t/capita and 0.12 t/capita in 2006, our year of analysis. These targets are roughly in line with the latest food-specific healthy diet recommendation [252]. The EAT-Lancet Commission recommends 0.4 t/capita/year of plant-based food, and 0.1 t/capita of animal-based food (except for fish) for human direct consumption. If we assume one third of primary crops are consumed directly by humans, one third of primary crops are used to feed livestock [43], and one third of primary crops are wasted, while also one third of livestock are wasted [227], and two thirds of livestock are consumed by humans directly, it requires additional production of 0.4 t/capita/year for primary crops (excluding feed), and 0.05 t/capita/year for livestock. This sums up to almost 0.8 t/capita for primary crops and 0.15 t/capita for livestock, which is similar to 0.9 t/capita for primary crops and 0.12 t/capita used in our study. To investigate the variation of per-capita mass for different nations regarding primary crops, we set 0 to 0.45 t/capita as far below the target, 0.45 t /capita to 0.9 t/capita as below the safe target, 0.9 to 1.8 t/capita as exceeding the target, and >1.8 t/capita as far exceeding the target. For livestock, we set 0 to 0.06 t/capita as far below the target, 0.06 t /capita to 0.12 t/capita as below the safe target, 0.12 to 0.24 t/capita as exceeding the target, and >0.24 t/capita as far exceeding the target.

3.3 Results

3.3.1 Hotspots of primary crops and livestock

As expected, per-capita primary crop and livestock consumption is positively correlated with the per-capita GDP (Figure S 8.7). For example, the highest per-capita crop consumption is found in Luxembourg (8423 kg/capita), 12 times higher than in Indonesia (643 kg/capita). This phenomenon is more significant for livestock with a factor of 30 difference among per-capita total livestock weight, at 845 kg/capita in Ireland compared to 26 kg/capita in Indonesia (Figure S 8.7). In addition, high-income nations have more significant overseas primary crop and livestock hotspots than that of low-income nations (Figure 3.1), because they have a comparative advantage in capital while having more expensive labor and land (Figure S 8.8). This is consistent with previous studies [253,254]. Figure 3.1 depicts primary crop and livestock hotspots driven by the three largest economies: the EU28, the United States (US), and China. The spatial distribution of primary crop and livestock hotspots generally matches.

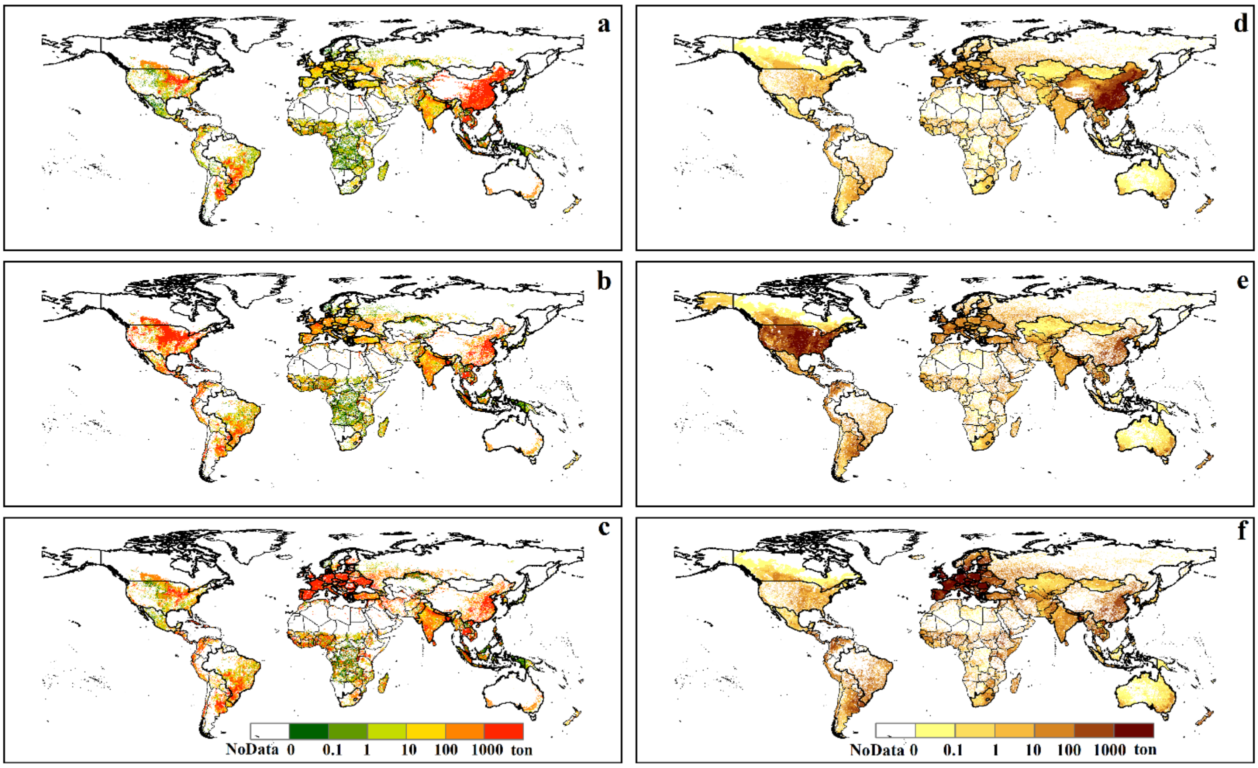

Figure 3.1 Spatial distribution of the primary crop hotspots driven by consumption of China (a), the US (b), and the EU28 (c), and the livestock hotspots driven by consumption of China (d), the US (e) and the EU28 (f).

China is the largest consumer of primary crops, accounting for 18.4% of global primary crop consumption (Figure S 8.9). Figure 3.1 (a) reveals the spatial distribution of primary crops driven by China's consumption. The most significant primary crop hotspots are located in East China, following the so-called 'Hu-line' closely (a geographical line South to North between Heihe in Heilongjiang Province and Tengchong in Yunnan Province). More than 90% of Chinese people live in the east of the "Hu line", an area home to the most intensive cropland in China, including the three great plains of China: the Northeast China Plain, the North China Plain, and the Yangtze Plain.

International crop hotspots driven by Chinese consumption include the Corn Belt in the US, and the Cerrado biome of Brazil, which are a major source of China's soybeans. China is the largest consumer of soybean in the world, accounting for 28.7% of total production. To a large extent this is possible with large amounts of imports, at 32.6% of the global total soybeans imports in the supply chain. The US and Brazil are the largest two contributors to China's soybean consumption with 20.4 Mt and 17.9 Mt, respectively. China is also the largest importer of palm oil with hotspots in Sumatera in Indonesia (the largest exporter of palm oil).

For many other products, the US has larger trade flows. Domestic primary crop hotspots are centered on the well-known Corn Belt. Although it is the largest producer and exporter of cereals, it is the largest importer of global vegetables, tropical fruits, and temperate fruits, accounting for 15.2%, 19.4%, and 13.7% of global imports, respectively. In addition, 43.6% of vegetables, 57.0% of tropical fruits, and 35. 2% of temperate fruits consumed in the US come from abroad. An estimated 15.1% of vegetables and 6.6% of temperate fruits for US final consumption import from China, mainly from the east of China. The US imports 15.3% of its tropical fruit from Mexico, mainly surrounding the Gulf of Mexico; and 7.6% of tropical fruit from Brazil, mainly the Upper Paraná Basin.

Turning to the EU28, large amounts of domestic production of primary crops translates into limited imports. Where imports arise they are generally from the Corn Belt of the US; the Cerrado biome of Brazil; Sumatra and Kalimantan in Indonesia; the east of China; and the Indo-Gangetic Plain in India. The result is consistent with previous studies that the spatial distribution of land and water use for crop production driven by EU consumption [50,223].

Compared with primary crop hotspots, livestock production is driven by domestic rather than foreign consumption. Domestic livestock makes up 88% of EU28 livestock consumption (it is also the largest consumer of livestock at 23.5% of global consumption) (Figure S 8.10). Overseas livestock hotspots of the EU28 are scattered in the east of China,; the south of India, the southeast and southwest of Australia, and the Pampa in South America.

The US imports the largest percentage of livestock, accounting for 12.8%-15.8% of global animal trade flows (all animals summed together). Since the US produces mainly pig, cattle, and chicken, other animals are generally imported. As such 96.2% of goats, 91.9% of sheep, 59.4% of ducks, 28.6% of pigs, 14.7% of cattle, and 11.6% of chickens originate from abroad. A significant pig hotspot is located in the Interior Plains since a large amount of maize and soybean produced in the area provides feed for rearing. Other hotspots are scattered in the east of China, such as the North China Plain, the south of Canada, the southeast of Mexico, the west and north of the Netherlands, the west of the United Kingdom, the south of India, the southeast and southwest of Australia, and the northeast of Spain.

China is the largest consumer of primary crops, it is the third largest consumer of livestock, accounting for 11.0% of global consumption. The livestock hotspot for China is also east of the "Hu-Line", which provides feed for livestock. Other significant hotspots are located in the west of the "Hu-line" and distributed in the top four prairies, namely Hulunbeier Prairie, Xilin Gol Prairie, Erie Prairie, and Nagga Alpine Steppe, which suit the grazing of ruminant animals.

3.3.2 **Consumption of Brazilian soybean and beef and Indonesian palm oil**

To reveal specific issues for regions under pressure, we provide case studies on the role of beef and soybean production in Brazil and palm oil production in Indonesia through international supply chains.

Brazil is a dominant producer of soybeans, accounting for 23.4% of the global production and 30.6% of global exports respectively. Only 4.7% of Brazil's soybean production is used domestically, with 35.7% exported to China, 22.5% exported to the EU28, and 6.0% exported to the USA (Figure 3.2 a, c), both directly and indirectly. Because most of soybeans are consumed by foreign countries, the spatial distribution of soybeans for domestic and overseas consumption is almost identical, and concentrates on its producing regions–the South Atlantic Forest biome, the Cerrado biome, and the South Amazon biome. The result is similar to previous analysis [255]. In contrast, most of cattle is consumed domestically, even though Brazil was the second largest producer of cattle in 2006, exporting 1.23 Mt of beef to the EU28, 0.2 Mt to the US, and 0.1 Mt to China. The major regions for domestic beef consumption concentrate on the Paraná River basin, the Tocantins basin, and along the Atlantic coast in the Atlantic Forest biome, which covers a large amount of pasture suitable for grazing. However, major regions for beef consumption abroad mainly gather in the South of the Paraná River basin and the Atlantic coast in the Atlantic Forest biome, which are the major cattle feeding areas, have a developed transportation network, and are near the Brazilian ports (Google Map, 2018).

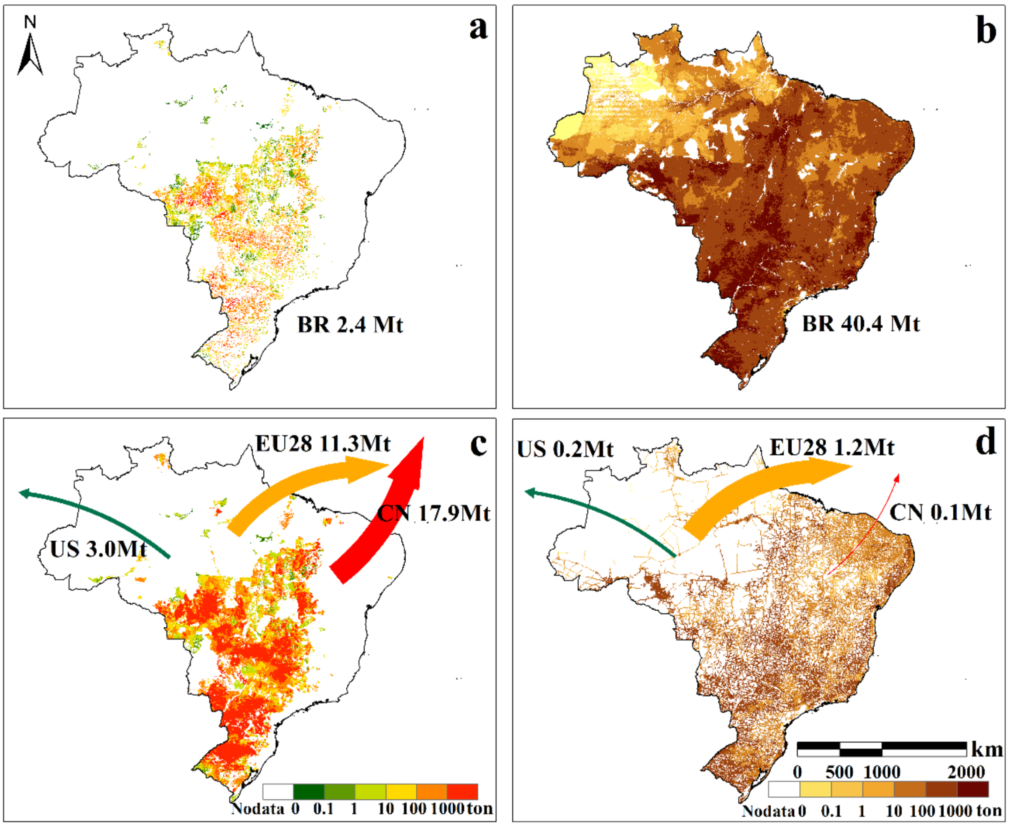

Figure 3.2 Brazilian soybeans and beef for domestic consumption (a, b) and consumption in foreign countries (c, d).

Indonesia, the largest exporter of palm oil, contributes 49.8% to the global exports embodied in the supply chain. However, only 27.6% of palm oil is used for domestic consumption, 13.1% is exported to the EU28, 10.5% is exported to China, and 7.4% is exported to the US (Figure 3.4), both directly and indirectly. Regions for domestic palm oil consumption in Indonesia range from Sumatra to Papua, covering almost all of Indonesia's territory, even though the intensity, palm oil mass per grid cell, gradually decreases. In contrast, regions for overseas palm oil consumption mainly gather in Sumatera and the South of Kalimantan, because most of Indonesian ports locate at the coast around these two islands (Google Map,2018). In addition, one of the most important transportation hubs– Strait of Malacca settles between Sumatra and Malay Peninsula, and it provides a transportation advantage for these two islands.

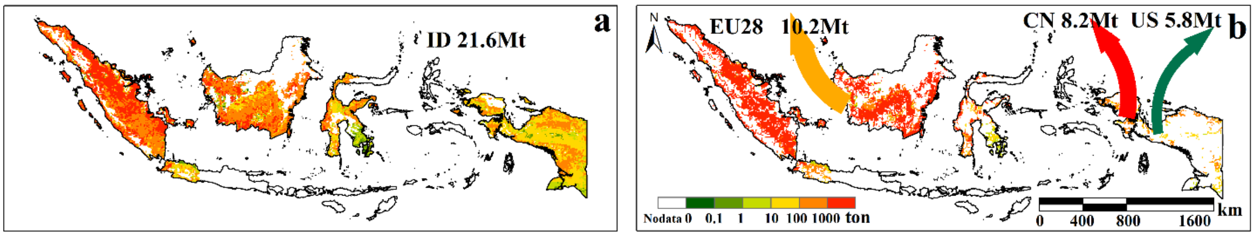

Figure 3.3 Indonesian palm oil for domestic (a) and foreign consumption (b).

3.3.3 **Comparison with tentative targets**

We find that primary crop and livestock consumption in almost all high-income countries (some of them, for example, New Zealand are included in rest-of-the-world regions) is beyond the illustrative target in 2006 (Figure 3.4). Especially some of them, such as Australia, the US, Canada, the United Kingdom, and France, consume more than double the safe threshold. In contrast, the consumption of most low- and middle countries, mainly in Asia, the Middle East, and Africa, which constitute 75% of the global population (including China, India, Indonesia, South Africa, rest of Asia and Oceania, rest of America, rest of Africa, rest of Middle East) is within the safe operating space. The consumption in the rest of Africa and rest of Asia regions, making up 25% of the global population, is even far below the indicative target.

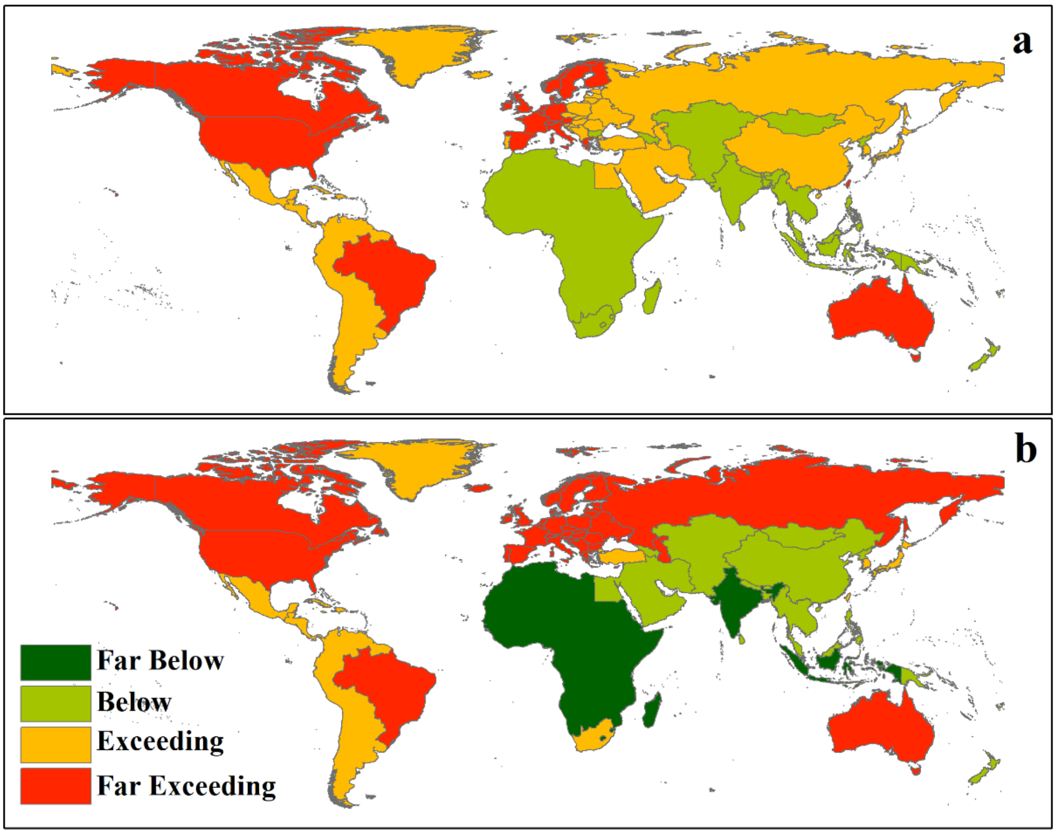

Figure 3.4 Total primary crop (a) and livestock (b) consumption per-capita in comparison with the tentative target of 0.9 and 0.12 ton per-capita in 2006, respectively.

3.4 Discussion

Some studies, for example, the well-known transparent supply chains for sustainable economies (TRASE) project [255], have been tracing global supply chains sub-nationally very well [257]. However, the TRASE project mainly focuses on the environmental and social risks of agricultural expansion of a few commodities (soy, palm oil, sugarcane, cocoa, coffee, timber, and beef) on tropical forest ecosystems, and the SEI-PCS model (Spatially explicit Information on Production to Consumption Systems) mainly focuses on subnational administrative regions [255]. In this paper, we trace the supply chain of more agricultural products, namely 40 crop categories (as available in SPAM except for 2 types due to aggregations) and 6 types of livestock. We identify spatially explicit hotspots at a higher resolution (5 arc min) driven by final consumption by tracing primary crops and livestock embodied in supply chains based on SMRIO analyses. We find that low- and middle-income countries, for example China, have a greater self-sufficiency (here defined as the ratio of production to demand [258]) as opposed to high-income countries, which are associated with larger trade flows. These results indicate that high-income countries outsource a significant amount of the burden from agricultural production, including large amounts of land and water use, to low-income countries with lower production cost. This is consistent with previous research [58,259,260], where the EU28, the US, and Japan are the top outsourcers of cropland, grazing land, and agricultural freshwater. More than 40% of the trade volume of cropland is driven by the EU and the US. Cropland and animal stocks have been decreasing in high-income nations since 1960 [261], and in the future, agricultural production transfer to lower-income countries are expected to continue [262]. In addition, emerging giants, like China and India, will need more food from international markets, putting further pressure on food systems [263]. Most notably, more than 70% of global soybean exports are estimated to flow into China by 2023/2024 [264].

Primary crops and livestock in lower-productivity regions overseas are being consumed at a larger growth rate by richer countries, although the productivity gap between lower-income and high-income countries is shrinking [261]. Regions with lower productivity have cheaper land and labor and have a competitive advantage in terms of low value-added production, especially primary crops. But these regions have less advanced agricultural technologies and lack capital to improve infrastructure (e.g., water efficiency and transportation services among many other improvements). In this paper, we identify spatially explicit hotspots driven by final consumption, which could help decision makers to provide targeted technical and financial support for countries from which they consume primary crops and livestock. This could narrow the yield gap of primary crops and livestock between countries to ensure global food security. This would help in achieving the UN's Sustainable Development Goals (SDGs), such as no poverty (SDG 1) and zero hunger, good health, and well-being (SDG 2). According to the latest published report on the *state of food security and nutrition in the world*, world hunger has started to increase since 2014 after a prolonged decrease, and about 1/9 of the global population (822 million) are undernourished in 2018 [265]. Improving nutrition and providing healthy diets requires long-term efforts and needs global cooperation.

3.4.1 **Limitations**

There are several limitations to this approach. The first is sectoral and spatial homogeneity hypothesis. There are only 8 sectors for primary crops (Table S 8.10) and 6 sectors for livestock

for 44 individual countries and regions, and remaining countries are aggregated into 5 rest of world regions in EXIOBASE.

However, FAOSTAT has the most detailed classification for primary crops (163 types) and livestock (6 types selected) for each country in the world. The sectoral and spatial aggregation leads to some loss of detail [266]. For example, soybean, rapeseed, and palm oil share the same trade structure in EXIOBASE, which impacts the real distribution of soybeans and palm oil driven by final consumption in the EU28, the US, and China.

The second limitation is related to the quality of spatial databases. Robust and high-resolution spatial databases are essential to SMRIO [267]. These spatial databases are created by models, which might have biases. The most obvious is that there is no data on the spatial distribution of ducks in South America and Africa [244]. The situation has slightly improved in the recently updated spatial distribution of livestock [268], but due to the higher temporal mismatch we chose the previous version.

A third limitation relates to the allocation method. We use a road network to allocate the spatial distribution of primary crops and livestock to production for exports and for domestic consumption. While this approach seems to outperform previous analyses, for example of market access [162], it still leads to some biases. Where there are large connected fields coupled with a low population density, and consequently fewer roads, such as in the Northeast China plain, exports might be underrepresented. However, linking trade with transportation is a widely accepted way in studying commodity supply chains at subnational scale. For example, some studies used a spatial cost minimization model (mainly including transportation cost) from production areas to consumption areas to estimate subnational commodity flows [255,269]. Their results provide a good fit with results from this paper, as exemplified by soybeans in Brazil (Figure 3.2, Figure S 8.11).

3.4.2 **Future work**

Agricultural production consumes the vast majority of land and freshwater, and leads to biodiversity loss and other environmental impacts. Identifying local environmental impact hotspots driven through global food consumption is the first step to mitigating local environmental impacts, to keep food production sustainable, and to guarantee global food security. Most present studies on estimating environmental impacts driven by agricultural production use a multiplication of environmental intensities or conversion factors (e.g. environmental impact per ton or ha of a specific crop) with crop-specific harvest areas or production amounts, and animal-specific production amounts(Table 3.2). The methods for getting conversion factors include meta-analyses, simulation models, and expert surveys. Such studies are promising sources for environmental conversion factors, which can be used in future research. By having spatially explicit embodied crops and livestock in combination with environmental conversion factors, we can obtain more accurate environmental impacts driven by final consumption of any given region within EXIOBASE.

Table 3.2. Environmental impact research based on crop and livestock databases.

Environmental impacts	Spatial resolution	Agricultural products	Sources of conversion factors	References
Greenhouse gas (GHG) emissions	national level	crops	International Fertilizer Association (IFA) survey	270
	national level	livestock	Meta-analysis	270
	5 arc min	crops	IPCC tier 1 method; International Fertilizer Association (IFA) survey	271,272
	21500 individuals	13 food groups	LCA and meta-analysis	273

Nitrogen and Phosphorus	5 arc min	crops	International Fertilizer Association (IFA) survey	271,274
Biodiversity	5 arc min	crops and livestock	Meta-analysis	275
Antimicrobials	5 arc min	livestock	Meta-analysis	226
Water	5 arc min	crops	Hydrological model	271,276
	21500 individuals	13 food groups	Water Footprint Network survey	273

3.4.3 **Implications**

Around 11% of the global population are still undernourished (habitual food consumption is insufficient to provide the dietary energy levels that are required to maintain a normal active and healthy life),mainly in Africa and Asia [265]. If only eradicating poverty and other people keep their current consumption level, total primary crop and livestock consumption will exceed the safe operating space. Therefore, it is necessary to reduce consumption in high-income countries to offset the increase in lower-income countries. In addition, sustainable production and consumption of primary crops and livestock play a critical role in achieving other SDGs beyond the elimination of hunger (SDG 2) [277]. The large difference in final consumption of primary crops and livestock between high-income and lower-income countries also indicates social inequality among countries. Besides, agricultural technological changes and the reduction of food loss and waste are huge challenge to maintain sustainable consumption [222]. However, it is difficult to implement target policy, according to previous studies, because they trace food supply chains at the national level. In this paper, we use the SMRIO method to map the spatial relationship from production to consumption of primary crops and livestock. This can help to build targeted cooperation relationships between high-income and lower-income countries to keep agricultural production and consumption sustainable.

3.5 Data statement

Product-specific data and figures are available from the authors upon reasonable request.

4.

Chapter 4.
Land use in key biodiversity areas disproportionately threatens global biodiversity

4 Land use in key biodiversity areas disproportionately threatens global biodiversity[3]

Abstract

Key Biodiversity Areas (KBAs) are critical regions in efforts to preserve global biodiversity. KBAs are identified by their importance to biodiversity rather than their naturalness or legal status. As such, KBAs are often under pressure from human activities. KBAs can encompass many different land use types (e.g. cropland, pastures) and land use intensities. Here we combine a global economic model with spatial mapping to estimate the biodiversity impact of human land use in KBAs. We find that global human land use within KBAs causes disproportionate biodiversity losses. While land use within KBAs accounts for only 7% of total land use, it causes 16% of global plant loss and 12% of global vertebrate loss. The consumption of animal products accounts for more than half of biodiversity loss within KBAs, with housing the second largest at around 10%. Bovine meat is the largest single contributor to this loss at around 31% of total biodiversity loss. In terms of land use, lightly grazed pasture contributes most, accounting for around half of all species loss. This loss is concentrated mainly in middle- and low-income regions with rich biodiversity. International trade is an important driver of loss, accounting for 22-29% of total plant and vertebrate loss. Our comprehensive global, trade-linked analysis provides insights into maintaining the integrity of KBAs and global biodiversity.

Significance

Global land use threatens biodiversity within Key Biodiversity Areas (KBAs). In an interconnected world, the consumption of products such as food in one region can drive biodiversity loss in other, producing regions via the international supply chain. We linked high-resolution global land use and land-use intensity maps with detailed environmental-economic databases to trace biodiversity loss due to land use with different intensities within KBAs. We find a much higher proportional level of biodiversity loss within KBAs than in other areas. In terms of products, animal-based foods drive over half the total biodiversity loss. With respect to land use, pasture with light intensity accounts for half of the total loss. The findings can help to better target KBA conservation efforts.

Keywords

Biodiversity loss, countryside species-area relationship, multi-regional input-output analysis, land use intensity

4.1 Introduction

Biodiversity loss severely alters and threatens ecosystem functioning, and human-driven land use is the largest threat to terrestrial biodiversity [278,279]. This land use has led to a rapid acceleration in the rate of species extinction, far exceeding estimated planetary boundaries [280–282]. The urgency for biodiversity protection is reflected in international agreements, for instance in Sustainable Development Goals (SDGs) 14 and 15 [283] and the elapsed 2020 Aichi Biodiversity Targets [284]. Recent developments in biodiversity protection include the identification of Key Biodiversity Areas (KBAs), sites that significantly contribute to the global persistence of biodiversity [285]. KBAs reflect an increasing appreciation of the complexities required to maintain biodiversity and are identified on the basis of 11 globally standardized threshold-based criteria within five categories: threatened biodiversity, geographically restricted biodiversity, ecological integrity, biological processes, and irreplaceability. Around

[3] This chapter has been submitted to Proceedings of the National Academy of Sciences, as Sun, Z., Behrens, P., Tukker, A., Bruckner, M., and Scherer, L. Land use in key biodiversity areas disproportionately threatens global biodiversity. (submitted to Proceedings of the National Academy of Sciences)

16,000 KBAs have been identified as of 2020 [286] and they are likely to take a more central role in the main framework for identifying future conservation priorities [287–289]. This approach contrasts with other methods that generally address one biome or a group of species, leading to the omission of important biodiversity integrity [290]. Even though KBAs play an important role in biodiversity protection, little is known about the biodiversity loss driven by land use within KBAs.

KBAs encompass regions of human activities and land use. However, it is not only the amount of land use that drives biodiversity loss, but also the intensity of that land use [291,292]. To investigate land use impacts on biodiversity, researchers have used characterization factors (CFs) derived from the countryside Species–Area Relationship (SAR) (see methods) [291,292]. These CFs estimate the potential species extinctions driven by a unit of land use if it remains in its current state over the long term [291,292]. Although land use is a local phenomenon, these CFs also evaluate if a species faces the potential for loss globally and will therefore go extinct [292]. Here we refer to global species-equivalents potentially lost over the long term as *species lost* and use this approach in our analysis [292].

Further, due to increasing levels of globalization, local human land use is often driven by global demand, which enhances the geographic disconnection between producers and consumers as supply chains grow in complexity. For example, biofuels consumed in the EU can drive loss in Indonesia when these fuels are derived from palm oil [293]. Previous estimates have concluded that 25% of global species lost [291] and 30% [294] of global species threats are driven by international trade, a larger proportion than for estimates of several other trade-based displacements such as carbon emissions [295]. The displacement of biodiversity loss is generally from high-income to middle- and low-income nations [296]. As such, assessments of the responsibility for land use in KBAs benefit from taking both a production-based (responsibility is shouldered by the producing nation) and consumption-based (responsibility is shouldered by consumers of products all along the value chain) perspectives.

A previous analysis found that global cropland, even inside protected areas, has large impacts on vertebrate species, but did not include the role of other land uses, impacts on other species or the responsibility of international trade [297]. There have been efforts to map biodiversity loss in trade, for instance Moran et al. (2017) mapped consumption-based global biodiversity loss hotspots, but did not identify biodiversity loss due to a specific driver (e.g. land use) and used highly aggregated sectors for the economic activities driving this loss [296]. Other studies have traced biodiversity loss along the global supply chain for some products back to specific production locations (e.g. the Brazilian Cerrado) but have not examined the global picture [298]. Here we provide a global, trade-linked assessment of biodiversity loss within Key Biodiversity Areas (KBAs). We examine potential global loss of terrestrial species driven by domestic and teleconnected land use both within and outside KBAs (to provide a comparison of activities within and outside KBAs). We do this by building a hybrid model using physical and monetary input-output databases, spatially explicit land use maps, and characterization factors (CFs) of biodiversity loss (see methods for further details).

4.2 Results

4.2.1 **A global picture of biodiversity loss from land use within KBAs**

Overall, we find that human land use within KBAs leads to a total potential loss of 781 terrestrial plant species (hereafter referred to as plants) and 208 terrestrial vertebrate species, including mammals, birds, amphibians, and reptiles (hereafter referred to as vertebrates) (Figure 4.1). The loss accounts for 0.3% of global plant species and 0.7% of global vertebrate species. To put this in perspective, our results suggest that total land use (inside and outside KBAs) causes a potential loss of 5038 plant species and 1765 vertebrate species (Figure S 8.13). While land use within KBAs only accounts for 7% of total land use, it drives 16% of global plant loss and 12% of global vertebrate loss compared to total land use. The biodiversity loss due to land use differs among regions (Figure S 8.14), since different regions have different mixes of land use types, varying land use intensities (we cover minimal, light, and intensive land use patterns here), consume different goods, and have different levels of biodiversity. Light use of pasture within KBAs is the primary driver of biodiversity loss, accounting for a loss of 382 plant species (49% of losses), and 91 vertebrate species (44% of losses). This is because pasture with light use accounts for the largest proportion (50%) of land use within KBAs (Figure S 8.14). Pasture also sometimes displaces species-rich natural ecosystems, such as tropical forests in Latin America [299], thereby causing severe biodiversity loss. The exact mechanism by which cattle grazing influences biodiversity varies depending on location and management practices, but in general, biomass removal, trampling and destruction of root systems, and competition between livestock and wildlife have the largest impacts on reducing biodiversity [299,300].

At a regional level, there are several distinct biodiversity-loss hotspots. Plant loss is highly concentrated across Mexico, the nations of Central America, the Caribbean, Colombia, Venezuela, Madagascar, Southern Europe, South Africa, the south of India, the southwest of China, Southeast Asia, and the southwest and southeast of Australia (Figure 4.1). Vertebrate loss from land use within KBAs is also mainly located in Mexico, the nations of Central America, the Caribbean, Colombia, Venezuela, Madagascar, southern India, and Southeast Asia (Figure 4.1).

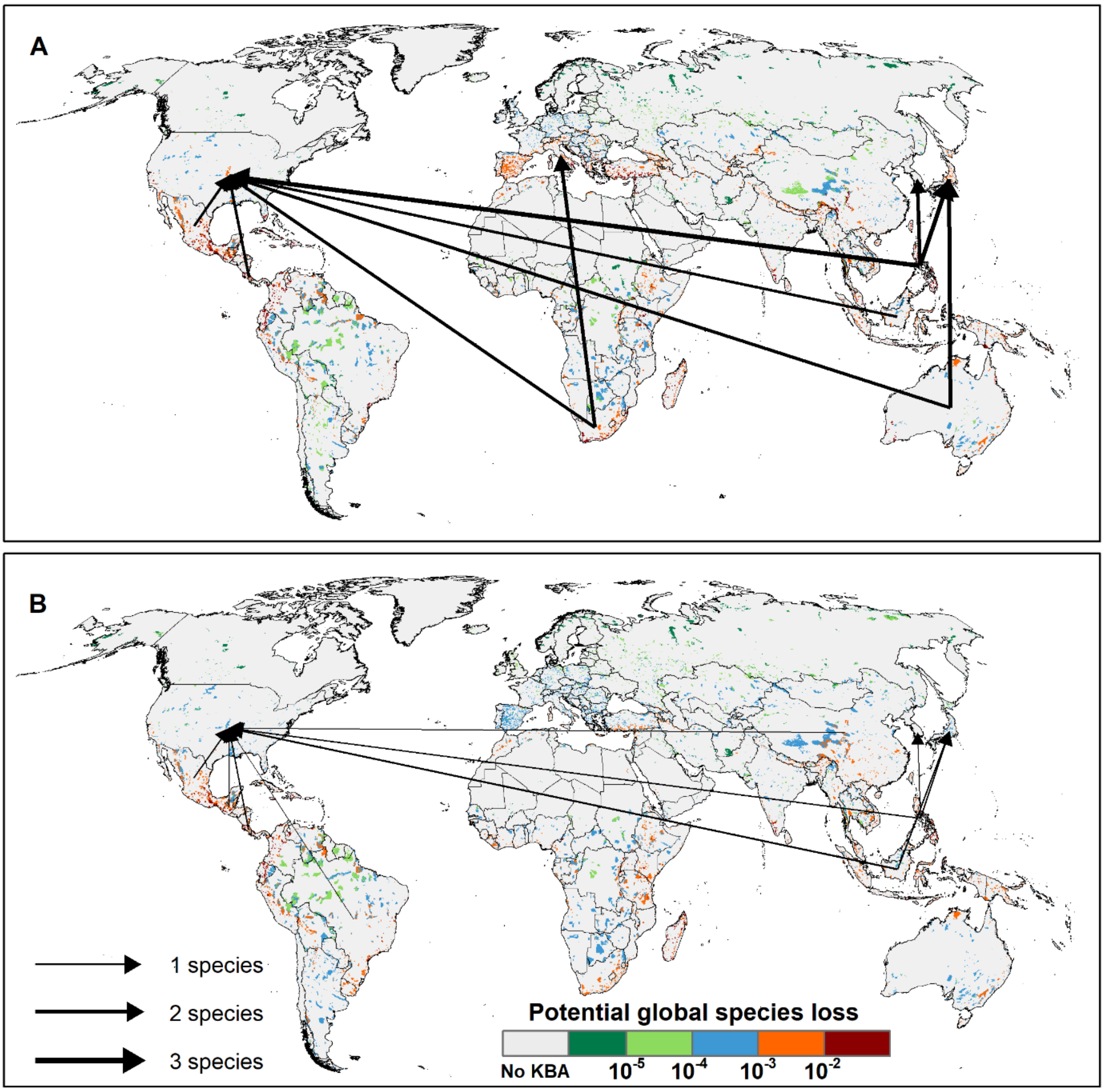

Figure 4.1. Potential global species loss driven by land use within KBAs for A) plants and B) vertebrates (mammals, birds, amphibians, and reptiles). Arrows indicate the top 10 flows of potential global species loss from nations where biodiversity loss occurs (tail of arrow) to final consumers (head of arrow). The width of arrows reflects the value of potential global species loss.

4.2.2 **Biodiversity loss from different land use types with three intensities**

We focus on the results for 15 countries with the largest consumption-based or production-based biodiversity loss from KBAs (Figure 4.2). These top 15 countries account for 62%-73% of total plant or vertebrate loss from either a production or consumption perspective. Consumption-based biodiversity loss from land use within KBAs ranks highest in biodiverse regions, such as South Africa and Madagascar (i.e. mainly as a result of domestic consumption) as well as in areas that import large amounts of loss via trade (e.g. the US). For plant species, South Africa sees the largest loss from a consumption- and production-based perspective (149 and 168 species lost from land use within KBAs, respectively). Pasture with light use is the primary land-use driver in South Africa, contributing to 82% and 80% of consumption- and production-based plant loss, respectively.

São Tomé and Príncipe sees the largest per-capita plant loss from a consumption- and production-based perspective (both 135×10^{-6} per-capita species lost from land use within KBAs). This is almost entirely due to land used for crops at a minimal use intensity. Such a large result is driven by São Tomé and Príncipe's position as an important region for endemic species – 30% of its mammals are endemic – and more than half of its land area being covered by KBAs, a higher share than any other country [301,302]. There is a large drop in per-capita plant loss in the next most prominent country, South Africa, at 3×10^{-6} and 5×10^{-6} per-capita consumption- and production-based species loss, respectively.

Focusing on vertebrate loss, Colombia's teleconnected land use within KBAs drives the largest consumption-based loss (13 species lost), where pasture contributes to 89% of the loss. In contrast, Indonesia sees the largest production-based impacts, with 14 species lost from land use within KBAs. Here, managed and planted forests are the main driver, contributing 61% of the loss. When looking at land use also outside KBAs, Brazil and the US surpass Indonesia and China, causing the largest production- and consumption-based total vertebrate species loss, respectively (Figure S 8.14). Among the top countries (Figure 4.2), Ecuador sees the largest per-capita consumption-based and production-based vertebrate loss (0.7×10^{-6} and 0.8×10^{-6} species lost from land use within KBAs), where pasture with light use accounts for 80% and 79%, respectively.

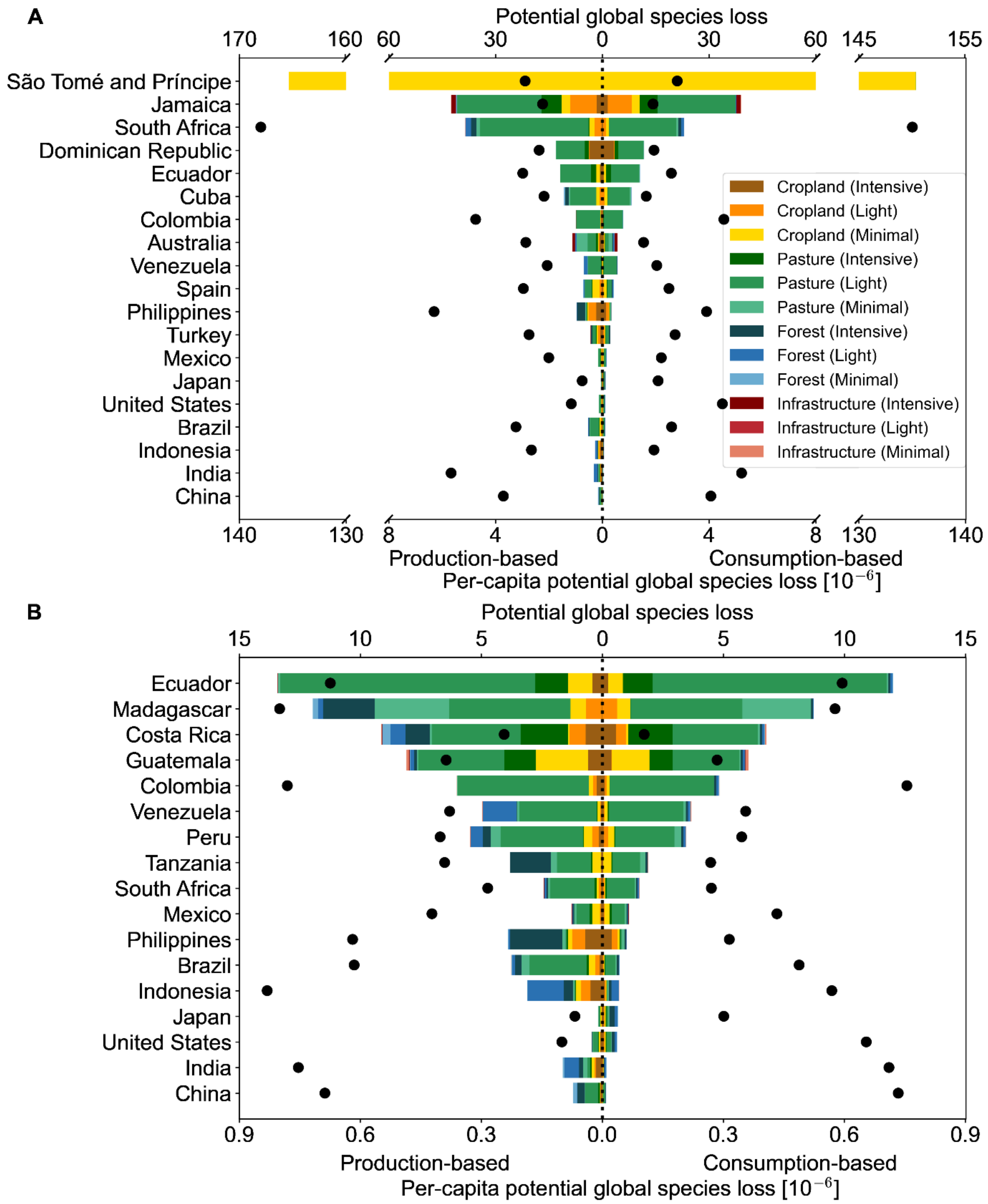

Figure 4.2. Potential global species loss from land use within KBAs for A) plants and B) vertebrates (mammals, birds, amphibians, and reptiles). On each x-axis (bottom and top of figures), the production-based perspective is shown to the left of zero and the consumption-based perspective to the right. The y-axis lists the top 15 countries/regions with the largest consumption-based or production-based biodiversity loss from land use within KBAs at the national level. The bar shows the per-capita value of biodiversity loss within KBAs per land type and land use intensity. The circles show the total national biodiversity loss with a value shown by the upper x-axes on the top of each plot. Forest includes managed and planted forest.

4.2.3 **Biodiversity loss embodied in international trade**

International trade is a major driver of biodiversity loss, contributing around a third of global vertebrate loss and a quarter of plant loss within KBAs (Figure 4.3). To illustrate flows from regions where biodiversity loss occurs to regions which consume the goods produced, we aggregate countries/regions into seven world regions. Western Europe and North America drive the largest biodiversity loss embodied in international trade (Figure 4.3). For instance, 79% of consumption-based plant loss in North America is driven through international markets, mainly from Central and South America (37%), and Asia and Pacific (30%) (Figure 4.3). Similarly, 82% of consumption-based vertebrate loss in Western Europe is embodied in international trade, mainly from Asia and Pacific (33%), Africa (26%), and Central and South America (20%) (Figure 4.3). This is similar to other studies finding that Western Europe and North America were responsible for 69% of biodiversity impacts transferred through international trade [291]. Specifically, the largest flow of plant loss via trade (excluding domestic production and consumption) is from Philippines to the US with 2.4 species lost (from land use within KBAs) (Figure 4.1). In contrast, the largest flow of vertebrate loss through trade is from Indonesia to the US with 1 species lost (Figure 4.1). The US is involved in 7 and 6 of the top 10 trade flows for vertebrates and plants, respectively.

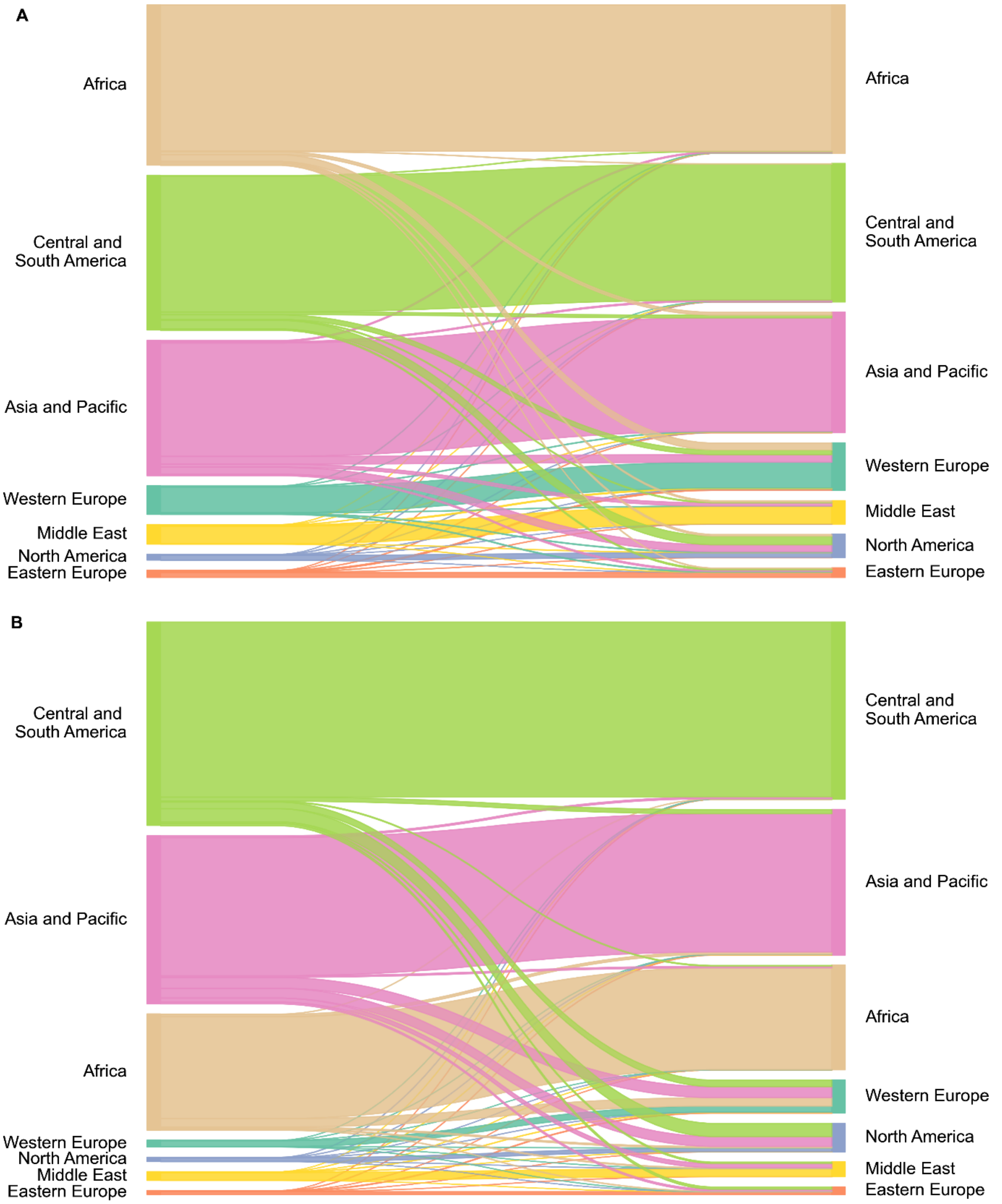

Figure 4.3. Embodied biodiversity loss flows for A) plants, and B) vertebrates (mammals, birds, amphibians, and reptiles) from land use within KBAs. Producing regions are on the left of the figure, consuming regions on the right. Regions are ordered by the magnitude of loss in the consuming region. The width of the flows are proportional to the magnitude of the potential global species loss.

4.2.4 **Biodiversity loss driven by the consumption of products**

Overall, food products contribute 74% of biodiversity loss within KBAs, with the remaining 26% driven by non-food products. Food-driven biodiversity loss is dominated by the consumption of animal products which account for more than half of total biodiversity loss within KBAs, with 408 plants (52%) and 104 vertebrates lost (50%). Within this, the consumption of bovine meat is the largest single contributor to biodiversity loss, with 241 plants lost (31%) and 63 vertebrates lost (30%). The result is consistent with Marques et al. (2019) who found that cattle farming was the largest driver of bird species loss from 2000 to 2011 [291]. Since they did not consider land use intensity, we can further clarify that this is more due to the extent of cattle farming than its intensity compared to other land uses. In addition, feeding livestock uses large areas of land. For example, 60% of land use within KBAs is pasture which is used for livestock ranching. Further, around 30% of cropland within KBAs is used to feed livestock.

The next largest product category is housing which includes all built infrastructure (e.g. roads), with 61 plants lost (8%) and 27 vertebrates lost (13%), driven mainly by “Construction work” and “Furniture” sub-categories, both of which heavily rely on forest products. Clothing contributes a further 6%, mainly driven again by pasture for animal products such as leather products. Grains contribute 5% biodiversity loss, which is proportionally much smaller than the around 16% land used as cropland within KBAs.

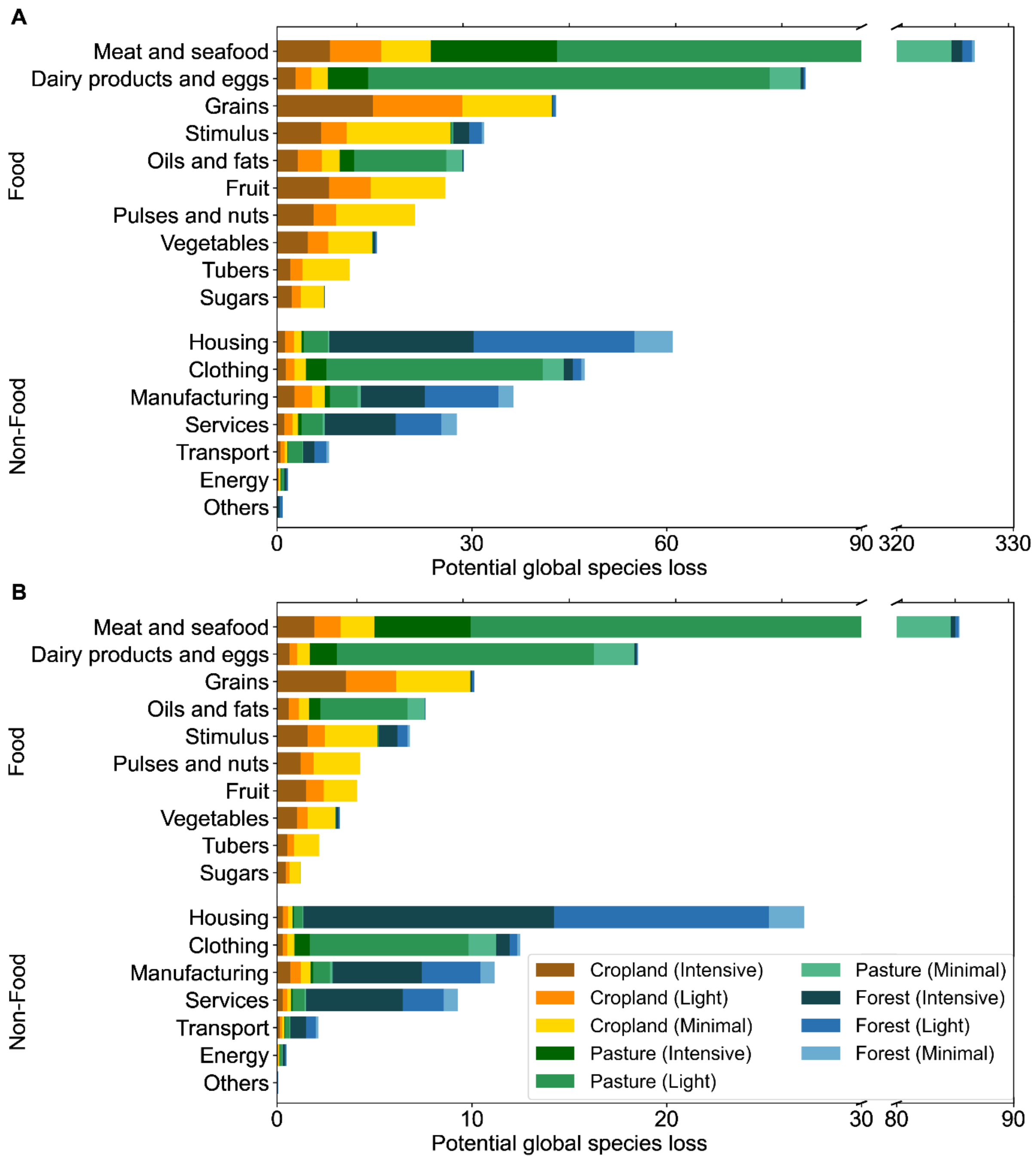

Figure 4.4. Potential global species loss due to specific product consumption from land use within KBAs for A) plants and B) vertebrates (mammals, birds, amphibians, and reptiles). Forest includes managed and planted forest.

4.3 Discussion

We provide a comprehensive overview of global, land-use driven biodiversity loss within and outside KBAs by: 1) using potential global species loss for multiple taxa rather than a single aggregated index [291,303]; 2) considering different land use intensities rather than just one [304]; and, 3) analyzing the effect of international trade on biodiversity loss rather than production-based biodiversity loss [292]. We find that pasture is the largest contributor to biodiversity loss from land use within KBAs with 58% of total plant species loss and 56% of vertebrate species loss (Table S9). Consequently, animal products are the primary drivers of biodiversity loss, in particular bovine meat. Lowering animal product consumption could reduce agricultural expansion and intensification, eventually even leading to land sparing/sharing which could potentially reverse biodiversity declines [305,306].

We estimate a quarter of global plant losses and a third of global vertebrate losses are embodied in international trade. This is slightly higher than previous estimates of 20% based on net primary productivity in biodiversity hotspots [307] and similar to a previous estimate of 25% for global endemic vertebrate loss [308] or 30% for threats to vertebrates [294]. In the international market, high-income nations can outsource land use and the associated biodiversity loss to other middle- and low-income nations that may have lower regulatory standards and higher biodiversity [291,297]. These differences partly drive leakage in biodiversity loss through international trade (analogous to carbon leakage). For example, Europe restored territorial forests by 9% (~ 13 Mha) while outsourcing 11 Mha deforestation due to crop displacement from 1990 to 2014 [17]. This deforestation occurs in many biodiversity-rich regions [17]. These dynamics may change in the future as agricultural development is projected to grow due to rapidly increasing population and per-capita income in tropical and subtropical regions which may result in higher local consumption and lower exports [305]. In addition, economic growth will threaten biodiversity loss by changing consumption patterns (e.g. increasing animal product consumption), especially in rapidly growing regions [291].

It is possible to argue that KBAs are both more and less exploited than neighboring regions. They might be more exploited because they provide more resources, such as food, timber, and fiber [309,310], but also more protected because 56% of global terrestrial KBAs are in protected areas, much higher than the global average level of protected areas (14%) [311]. Protected areas are established to prevent habitat loss and reduce biodiversity decline. Coverage of KBAs by protected areas can be used to measure the progress toward their protection [312]. However, the status of a protected area does not guarantee adequate management [289]. Some protected areas are simply "paper parks" and cover a high prevalence of habitat disturbance such as cropland, thereby, threatening biodiversity. For example, cropland within protected areas causes 18% of total species threats of global cropland [297]. In addition, protected areas can also have little biodiversity conservation value, while KBAs are important for the persistence of biodiversity [289]. Therefore, other metrics to assess progress toward reaching biodiversity protection goals within KBAs are necessary. These may include the relative change of the current value compared with a reference value for different biodiversity and habitat indicators within KBAs [289]. This reference value may be the expected biodiversity in a region if there were little or no human disturbance. These metrics need extensive data from systematic monitoring (e.g. remote sensing, in situ monitoring) and timely update across all KBAs [289].

There are a number of opportunities for future research. Given the dominance of land use for food systems, the first set of opportunities arises from improved agricultural mapping. Advances in remote sensing [313,314] and the use of crowdsourced data [315] may improve the accuracy of crop- and animal-specific maps. In terms of assessing biodiversity loss, improving the resolution of CFs can reduce uncertainties. Although other studies employ this same assumption to study biodiversity loss at a grid cell level [304], it would be an improvement to develop biodiversity CFs in line with the resolution of land use (i.e. 5 arc min in the paper). In addition, biodiversity responses are known to be scale-dependent and can be non-linear (for example, when critical thresholds are reached), making them extremely challenging to incorporate into global models [316]. Further methodological breakthroughs are needed in order to represent these dynamics. Biodiversity is itself diverse and multidimensional (involving genetic, species, ecosystem, functional, structural, cultural and behavioral diversity) [278,306,317,318]. Many species indicators, such as richness, evenness, differentiation, and abundance, have been used to assess biodiversity at multiple scales [278,306,319,320]. However, indicators going beyond the species level are usually applied in case studies and still need an impact assessment method to be developed for the global scale [318]. Even though land use change is the largest single threat to global biodiversity, other threats (e.g. climate change, invasive species, pollution, and overexploitation) can be more important locally, and will induce further global biodiversity loss via their interaction [306,321]. An ongoing challenge is to represent the interaction of these pressures in biodiversity research [306].

4.4 Conclusion

The rising salience of biodiversity loss among policy spheres has led to a deeper integration of biodiversity knowledge between science and policy, with the most prominent example being the Intergovernmental Science–Policy Platform on Biodiversity and Ecosystem Services (IPBES) [322]. Key Biodiversity Areas (KBAs) are likely to become the main regions of focus for biodiversity conservation [289]. We globally assess biodiversity loss driven by human land use within KBAs and across nations in a spatially explicit integrated framework that retains important resolution in the food products which drive 22-29% of plant and vertebrate loss in international trade. We find that human land use within KBAs causes a proportionally high biodiversity loss (i.e. 7% of total land use caused 16% of global plant loss and 12% of global vertebrate loss), which indicates that KBAs, despite their importance, will need increasing policy protection in the future. Pasture with light use, as the most widespread land use type within KBAs, is the largest driver, accounting for around half of all species loss. Our comprehensive assessment can provide guidance for maintaining the integrity of KBAs and global biodiversity.

4.5 Materials and Methods

We assess global biodiversity loss driven by anthropogenic land use within KBAs by combining Multi-Regional Input-Output (MRIO) analysis with spatial analysis. Using MRIO analysis, we link production and associated environmental pressures to consumption anywhere in the world at the national scale. Then we allocate the consumption-based land use of a specific country into grid cells with the help of global land use maps and assign land use intensities. Different land use types and intensities determine the potential biodiversity loss at a location per area of land use, reflected by characterization factors. The biodiversity loss within the boundaries of KBAs can be delineated via this spatially explicit information. In short, we calculate biodiversity loss driven by land use both within KBAs and outside KBAs in order to provide a comparison. We focus on biodiversity loss within KBAs in the results section.

4.5.1 **Modeling framework**

The starting point for quantification of biodiversity loss within KBAs is gridded land use data (see the next section). This enables the calculation of the biodiversity loss per m^2 of land use (using characterization factors, CFs) (Figure S 8.12). While human land use is dominated by agriculture sectors, traditional global MRIO databases have highly aggregated agricultural sectors or regions. This is addressed by using the recently developed Food and Agriculture Biomass Input-Output (FABIO) table, a consistent, balanced, physical input-output database based on FAOSTAT data, covering 191 countries and 128 agriculture, food, and forestry products [323] (excluding non-agricultural sectors). To cover non-agricultural sectors, we build an integrated model framework linking FABIO and EXIOBASE (Figure S 8.12). EXIOBASE v3.6 is a highly detailed, monetary global multi-regional input-output database, including 200 products and 49 countries or regions [324]. EXIOBASE covers non-agricultural sectors in detail and by combining the two MRIO databases we can harness the advantages of both. An *other uses* matrix (A_{other}) links FABIO with EXIOBASE by providing agriculture and forestry biomass inputs in physical units for manufactured products in monetary units. We consider land use for food consumption ($\boldsymbol{y_{FABIO}}$) and non-food consumption ($\boldsymbol{y_{EXIO}}$) separately. To attribute land use to consumers across countries, we use a spatially explicit multi-regional input-output (SMRIO) model [293,325] (equations 1-2).

SMRIO connects the economic sectors in a standard MRIO database with spatially explicit estimates of environmental pressures (e.g. land use) to track a country's final consumption to the location of the embodied environmental pressures [325]. The SMRIO in the study is used to estimate the impact of the demand of a given commodity (e.g., palm oil) in a specific region or country (e.g. the US) through land use in a region or country (e.g. Indonesia) on a species group (e.g. plants). The full model is expressed mathematically as:

$$\boldsymbol{F}^s = \sum_{i,r} R^r \frac{\boldsymbol{e}_i^r \sum_{jt} \boldsymbol{L_A}_{ij}^{rt} \boldsymbol{y}_{FABIO,j}^{ts}}{d_i^r} + \sum_{i,r} R^r \frac{\boldsymbol{e}_i^r \sum_{jt} \boldsymbol{L_B}_{ik}^{ru} \boldsymbol{y}_{EXIO,k}^{uv}}{d_i^r} + \sum_i R^s \frac{\sum_i HH_i^s}{d_i^s} \tag{1}$$

$$\boldsymbol{L} = \begin{pmatrix} (\boldsymbol{I}_{FABIO} - \boldsymbol{A}_{FABIO})^{-1} & (\boldsymbol{I}_{FABIO} - \boldsymbol{A}_{FABIO})^{-1}(\boldsymbol{0} - \boldsymbol{A}_{other})(\boldsymbol{I}_{EXIO} - \boldsymbol{A}_{EXIO})^{-1} \\ \boldsymbol{0} & (\boldsymbol{I}_{EXIO} - \boldsymbol{A}_{EXIO})^{-1} \end{pmatrix} = \begin{pmatrix} \boldsymbol{L_A} & \boldsymbol{L_B} \\ \boldsymbol{0} & \boldsymbol{L_D} \end{pmatrix} \tag{2}$$

where, $\boldsymbol{F^s}$ is the global spatial distribution of environmental impacts driven by final consumption of country *s* for both FABIO and EXIOBASE. R^r defines the spatial distribution, represented in absolute values, of land use in country *r*. e_i^r is the environmental intensity (land use area per unit of output) of product *i* in the producing country *r*. $\boldsymbol{y}^{ts}_{fabio,j}$ indicates the final consumption of FABIO product *j* in country *s* that originates from country *t*, which is the last country exporting to country *s* in FABIO (that is, in a supply chain of four countries producer A, intermediate B, intermediate C, and consumer D, this refers to country C). $\boldsymbol{y}^{uv}_{exio,k}$ indicates the final consumption of EXIOBASE product *k* in country *v* that originates from country *u*, which is the last country exporting to country *u* in the other-uses matrix (i.e. required amount of biomass inputs per Euro of manufactured product) in Fig. S1. Since EXIOBASE has a higher spatial aggregation (with five "rest of world" regions), we assume the same per-capita consumption for FABIO countries, which fall under the five "rest of world" regions in EXIOBASE (see the mapping relationship in Table S5). d^r_i expresses the total land use of product *i* in country *r*. HH^s_i is the infrastructure land which is land that is not attributed to any product of the IO model but directly to final consumption of product *i* in country *s*. Since the matrix of technical coefficients (i.e. input requirements per unit of output) is a block matrix integrating FABIO and EXIOBASE, we can derive the Leontief inverse $\boldsymbol{L}$, via a simplified equation (1) using $\boldsymbol{L_A}$, $\boldsymbol{L_B}$, $\boldsymbol{L_D}$ as the subcomponents of the inverse in equation (2). $\boldsymbol{I_{fabio}}$ is the identity matrix with the same dimension of FABIO, and $\boldsymbol{I_{exio}}$ is the identity matrix with the same dimension of EXIOBASE. $\boldsymbol{A_{fabio}}$ is the technical matrix of FABIO; $\boldsymbol{A_{exio}}$ is the technical matrix of EXIOBASE; $\boldsymbol{A_{other}}$ is the matrix of technical coefficients linking the agricultural products from FABIO to the non-agricultural products in EXIOBASE.

4.5.2 **Product groups**

There are 128 agricultural and forestry commodities in FABIO, and 172 additional product categories are provided by EXIOBASE. We reported detailed product-based biodiversity loss driven by consumption of FABIO and EXIOBASE in Tables S11 and S12 respectively. For ease of inspection, we classified 200 product categories in EXIOBASE into 8 categories (Food, Housing, Transport, Energy, Clothing, Manufacturing, Services, and Other) according to previous work [326]. Food is detailed in FABIO, therefore, we categorized food into 10 groups (Grains, Tubers, Vegetables, Fruit, Pulses and nuts, Meat and seafood, Dairy products and eggs, Oils and fats, Sugars, and Stimulus) similar to former studies [327,328]. For the detailed mapping relationship between product categories and reporting groups, see Tables S6 and S7.

4.5.3 **Land use datasets**

We choose a base year of 2005, which aligns with characterization factors we employ. To keep the geographic data consistent, we aggregate all land use maps to a common resolution of 5 arc min.

Cropland: For national cropland, we use the harvested area of 168 types of primary crops from FAOSTAT in 2005 [329], and aggregate them into FABIO's 62 crop sectors. For the spatial maps of cropland, we use 40 categories covering 168 types of primary crops from FAOSTAT at 5 arc min resolution in 2005, provided by the Spatial Production Allocation Model (SPAM) [330] (see Table S2 for the detailed mapping relationship between FAOSTAT, FABIO, and SPAM crop categories). Specifically, we include the original 42 categories crop maps, but since "Pearl Millet" and "Small Millet" are not split in FAOSTAT, we aggregate them into millet; similarly "Arabica Coffee" and "Robusta Coffee" are not split in FAOSTAT and we aggregate them into coffee. Since FAOSTAT does not report the physical area of crops, we use the ratio of harvested to physical area of crops from SPAM to convert the consumption-based harvested area to the physical area for impact assessment. For national cropland used to produce animal fodder, we use the harvested area derived from FABIO in 2005. However, there is no cropland map of fodder in SPAM. Therefore, we incorporate cropland used to produce animal fodder and calculated it analogously using EarthStat's aggregated fodder maps at 5 arc min resolution in 2000 [331].

Forest: Previous studies tend to overestimate forest use because they consider all reported forest areas without distinguishing between natural forests and managed or planted forests [332]. Therefore, we link our framework to the latest, global forest data at 1 km resolution in 2000 [333]. We assume there are no large changes for the forest map from 2000 to 2005. Although this assumption may not hold for some countries [334]. Overall, this may slightly underestimate the effects of forest loss on biodiversity loss. The map downscales forest areas derived from FAO's Forest Resources Assessment (FRA) into grid cells with two different levels of forest management (Level 1: primary, naturally regrown, and planted forests; Level 2: production, multiple purposes, and other purposes) [333]. First, we use 6 combinations of forest classes and forest uses as forest use for human production and consumption (Table S4) [333]. After summing the forest area used for production (derived from Schulze et al. 2019) in FABIO countries and regions, we allocate the managed and planted forest areas to the sectors "*Wood fuel*", "*Industrial roundwood, coniferous*", and "*Industrial roundwood, non-coniferous*" in FABIO. The allocation uses the share of wood produced by the different sectors in [329]. We then aggregate the forest area map to 5 arc min, which we use as the uniform spatial resolution in this paper.

Pasture: Pasture was represented by a high-resolution (30 seconds) map from 2005 [335]. We excluded non-productive areas (aboveground NPP below 20 g C m^{-2} yr^{-1}) following a previous study [291,336], and capped the pasture at 100% total land-use coverage in each grid cell.

Infrastructure: We use ESA CCI land cover maps (category Urban Areas at 300 m resolution) in 2005. We assume all infrastructure land is used in final demand (i.e., we assume all infrastructure land only takes part in domestic consumption activities and is not involved in international trade), even though some areas are used for manufacturing sectors. Previous work has outlined the challenges for including infrastructure land more comprehensively [337].

Land use intensity: For the land use intensity map, we follow the method provided by Newbold et al. (2015). They map the global land system onto five land use types (we use cropland, pasture, and urban land) with three land use intensities (minimal, light, intense). A detailed definition of land use intensity classes is given in Table S3, and detailed conversion rules between Global Land System data and land use intensity in Table S4. For the definition of forest land use intensity, see Table S4, which itself is based on [333]. The Global Land System mixes different land use types within a grid cell. For our purpose, the land use intensity at a location was judged separately for each land use type.

4.5.4 **Deriving spatially-explicit biodiversity loss related to land use**

To quantify global species loss driven by human land use at different land use intensities, we use the latest characterization factors (CFs) developed by Chaudhary & Brooks (2018). The characterization factors (CFs) allow for an estimation of global potential extinctions driven per unit of land use [292]. The CFs were derived from the countryside Species–Area Relationship (SAR) for regional species loss of 804 terrestrial ecoregions [292]. While the classic SAR approach assumes that species can only persist in their native habitat, the countryside SAR acknowledges that species can also persist to some extent in human-modified habitats. Consequently, the classic SAR overestimates species loss and the countryside SAR provides more realistic estimates [338]. Regional species loss was subsequently multiplied with a vulnerability score of species based on their geographic ranges and threat levels from the IUCN Red List to estimate global species loss [292]. The vulnerability score is 1 if all species within a region are "critically endangered", as assessed by the IUCN Red List, and have their entire range inside that region (i.e. they are strictly endemic to that region). Thus, local land use within KBAs can potentially lead to global species extinctions, especially if the species is endemic and critically endangered. The unit is *global species-equivalents potentially lost* (referred to as species lost).

The CFs consider five taxa (mammals, birds, amphibians, reptiles, and plants) and five land use types (managed forest, plantation, pasture, cropland, and urban) under three intensity levels (minimal, light, and intense) for terrestrial ecoregions [292]. Specifically, each taxon consists of numerous species, including 5,490 mammals, 6,433 amphibians, 9,084 reptiles, 10,104 birds, 321,212 plants [339]. We use average instead of marginal CFs. Marginal CFs apply to marginal changes from the current situation (e.g., one additional m^2 of land use) [339]. In this study, however, we are investigating large changes from natural habitat to the current land use pattern in KBAs or even globally. Because the CFs are at ecoregion scale, we assume that the value of CFs in each pixel is the same for all pixels situated within the ecoregion, as also assumed by Chaudhary et al. (2016). After computing the spatial distribution per unit area of each land use type at different land use intensities driven by final consumption in a given region, we multiply the corresponding CFs with consumption-based land use data to obtain consumption-based global species loss for each taxon equation (3).

$$SL^{s}_{global,g,m,n} = \mathrm{CF}_{global,g,m,n} \times \mathrm{F}^{s}_{m,n} \tag{3}$$

$SL^{s}_{global,g,m,n}$ is the potential global species loss for each taxon g for a different land use type and intensity m in each grid cell n driven by final consumption in country s. $CF_{global,g,m,n}$ is the land occupation CF (species lost per unit land use) for taxon g at a different land use type and intensity m in each grid cell n. $F^{s}_{m,n}$ is the land use for each different land use type and intensity m in each grid cell n driven by final consumption in country s. F is derived from equation 1.

After finding the global distribution of biodiversity loss driven by human consumption, we use KBA boundaries [286] to get the subset of biodiversity loss from land use within KBAs. The consumption-based biodiversity loss is the sum of agriculture related biodiversity loss (from FABIO) and non-agriculture related biodiversity loss (from EXIOBASE).

5.

Chapter 5.
A double carbon dividend from dietary change in high-income nations

5 A double carbon dividend from dietary change in high-income nations [4]

Abstract: A dietary shift from animal-based to plant-based food in high-income nations could reduce greenhouse gas (GHG) emissions from direct agricultural production and increase carbon sequestration if spared land is restored to its antecedent natural vegetation. Changing food behaviours in high-income countries—where these effects would be most pronounced —thus provides an opportunity for a double carbon dividend. We investigate this dividend under a scenario in which national average diets in 54 high-income nations representing 68% of global GDP and 17% of population shift to a planetary health diet, which is committed to the co-development of healthy diets and sustainable food production. Here we show that these dietary changes across high-income nations could reduce direct annual emissions by 0.61 Pg CO2e yr^{-1} while sequestering as much as 115.57 Pg CO2e over the long term. This sequestration represents a significant contribution to limiting GHG concentrations and could potentially fulfil high-income nations' future carbon dioxide removal obligations. Linking land, food, climate and public health policy will be vital to harnessing the opportunities of this double dividend.

5.1 Introduction

Agriculture is a significant human system which has the potential to dictate the rate and depth of climatic change. Current food system emissions may preclude the limiting of climate warming to 1.5 or even 2 degrees Celsius [340], yet simultaneously, radical land use and agricultural management interventions may be crucial strategy for limiting climatic change [341]. Dietary change has been found to be a practical and effective strategy in multiple studies [342,343]. The global food system is responsible for ~13.7 Pg of carbon dioxide equivalent (CO_2e) emissions per year (yr^{-1}) accounting for 26% of anthropogenic greenhouse gas (GHG) emissions[37]. Agricultural production, particularly animal-derived products and land-use change, accounts for the largest proportion of these emissions[344]. Historical livestock emissions are estimated at 5.6 – 7.5 Pg CO_2e yr^{-1} between 1995 and 2005 [345] and western dietary patterns in high-income countries—characterized by a high intake of animal-based products, sugar, and saturated fatty acids—are a major driver of these emissions[46,346,347]. In 2013, for example, per-capita meat consumption in high-income countries was almost six times greater than that in low-income countries[348]. Animal-derived products account for 70% of food-system emissions in high-income countries but only 22% in low-middle-income countries[349]. Attribution of these emissions is complicated by agricultural globalization whereby food consumption in high-income drives overseas carbon emissions through international trade[12]. For example, around one sixth of the EU dietary carbon footprint is comprised of tropical deforestation emissions[19] and in some high-income nations, such as Japan and Luxemburg, imported agricultural carbon emissions are higher than those associated with domestic production[19]. Dietary change in high-income countries, may therein, hold the potential to substantially reduce agricultural emissions around the world—a potential carbon 'dividend'.

Shifting from current dietary patterns in high-income nations to healthier alternatives with few or no animal products could simultaneously spare agricultural land for other uses. While a portion of this land may ultimately be used for various types of development and/or bioenergy, its use for intentional ecosystem restoration – a so-called 'natural climate solution' [341,350] would represent a second, additive carbon dividend of dietary change. In many regions, reverting cropland to its antecedent or 'potential' natural vegetation (PNV) can substantially increase aboveground biomass carbon (AGBC), belowground biomass carbon (BGBC) and soil organic

[4] This chapter is under review with Nature Food, as: Sun, Z., Scherer, L., Tukker, A., Spawn-Lee, S., Bruckner, M., Gibbs, H., and Behrens, P. A double carbon dividend from dietary change in high-income nations

carbon (SOC) stocks [12,351–354] with additional co-benefits for biodiversity [355] and other ecosystem services. Recent studies highlight the large magnitude of this sequestration potential. Global vegetation is believed to currently store less than 50% (450 PgC) of its potential C stock (916 PgC) due to appropriative land use [352]. Likewise, global soils have lost 116 PgC over the course of agricultural history due to C-cycle imbalances imposed by cultivation and other human appropriation [356]. A substantial portion of these carbon stocks could be recovered if land is spared by dietary change and subsequently restored to PNV. However, the extent to which land could be spared has not been comprehensively assessed due, in part, to the complex trade relationships between food producers and consumers[12]. Such relationships are particularly relevant to the land use footprints of high-income nations which import large amounts of food from around the world[5].

We assess the potential for a 'double dividend' for emissions mitigation via dietary change from both (1) reduced direct agricultural production emissions and (2) carbon sequestration via the land sparing whereby agricultural lands can revert to other uses. While linked, these elements play out over two different timeframes: the first—reduced production emissions—influences the sector's annual GHG contribution, while the second—sequestration—often requires decades or even centuries to realise its full potential. We conceptualize the latter effect, below, as a one-time "committed" mass of C that is sequestered over an unspecified period after restoration is initiated (see methods). We use data for the year 2010 from the Food and Agriculture Biomass Input–Output dataset (FABIO) [36] to relate the international final demand for food items with primary agricultural production. A GHG emission dataset linked to FABIO quantifies emissions for each step in the value chain[357]. Agricultural production is mapped to spatially explicit land use, which we linked to the latest harmonized global AGBC and BGBC map[358]; a SOC stock map of the top 100 cm[359]; and a PNV map with AGBC, BGBC, and SOC[352,353]. The result is a spatially explicit multi-regional input-output (SMRIO) model [360,361]. We use the recommendations of the EAT-Lancet Commission as a basis for dietary change in high-income countries[342]. The EAT-Lancet Commission aims to develop human healthy diets and sustainable food production while meeting UN Sustainable Development Goals (SDGs) and climate goals [342]. Such diets are characterized by reduced animal protein consumption and result in lower agricultural land requirements (for detailed recommendations per food group see methods and Supplementary Table 3). For our double dividend scenario, we assume spared land is restored to PNV (see methods and supplementary information) and determine the ensuing carbon sequestration potential as the difference between the carbon stock of PNV and that of current use.

5.2 Carbon sequestration and emission reduction potentials from dietary change

A shift to the EAT-Lancet diet in high-income nations would reduce annual food system emissions by 61.0% or 0.61 Pg CO_2e yr^{-1}. Our estimate is in line with those in the literature[327] (Figure 5.1, Figure S 8.18). About half of this reduction would collectively occur in the US (31.2%), France (6.7%), Australia (6.2%), and Germany (5.0%) (Figure 5.1B). Some large exporting middle- and low-income countries would also see emission reductions via reduced exports of agricultural products to high-income countries. These include India (2.2% of India's emissions from agricultural production), and Brazil (3.0% of Brazil's emissions from agricultural production).

A dietary shift from national average diets to the EAT-Lancet diet across high-income countries would also result in significant opportunities for carbon sequestration. We find that a shift of this nature could spare more than 464.25 million hectares (Mha)—an equivalent area slightly larger than that of the EU. Subsequent committed sequestration over the long term on this land could increase C stocks by 115.57 Pg CO_2e. Spared agricultural land would be comprised of

383.54 Mha pastureland and 80.71 Mha cropland, with major abandonment hotspots expected in the western half of the US, Central Europe, and eastern states of Australia (Figure S 8.19).

Carbon sequestration would be achieved predominately in large countries with large amounts of agricultural production, especially feed crops and pasture. For example, more than a half of the increase in global carbon sequestration would occur in four nations alone: the US (28.0%, 32.33 Pg CO_2e), Australia (9.5%, 11.01 Pg CO_2e), Germany (8.1%, 9.40 Pg CO_2e), and France (6.7%, 7.78 Pg CO_2e), collectively (Figure 5.1A). Regionally, major hotspots for sequestration include the Midwest US, Central Europe, and the eastern states of Australia (Figure 5.1A, Figure S 8.18) where the potential natural vegetation is forest with a high carbon density[352,362]. Australian dietary changes would see the largest per-capita carbon benefit overall at 605.22 Mg CO_2e of sequestration (6 times the average of all high-income countries, see Supplementary Fig.3.), driven largely by a shift away from animal products and restoration of mixed native grassland and native forest [362].

As a percentage of the total sequestration potential of dietary change, 34.1% lies outside of the consuming country (i.e. dietary change in a high-income country influences production in another country)—22.4% would be located in other high-income countries and around 11.7% would be located in middle- and low-income regions (Figure 5.1A, and Figure S 8.18). These latter regions would also be located mainly in countries providing large amounts of agricultural production for high-income nations, such as Brazil (1.50 Pg CO_2e) and Botswana (1.06 Pg CO_2e).

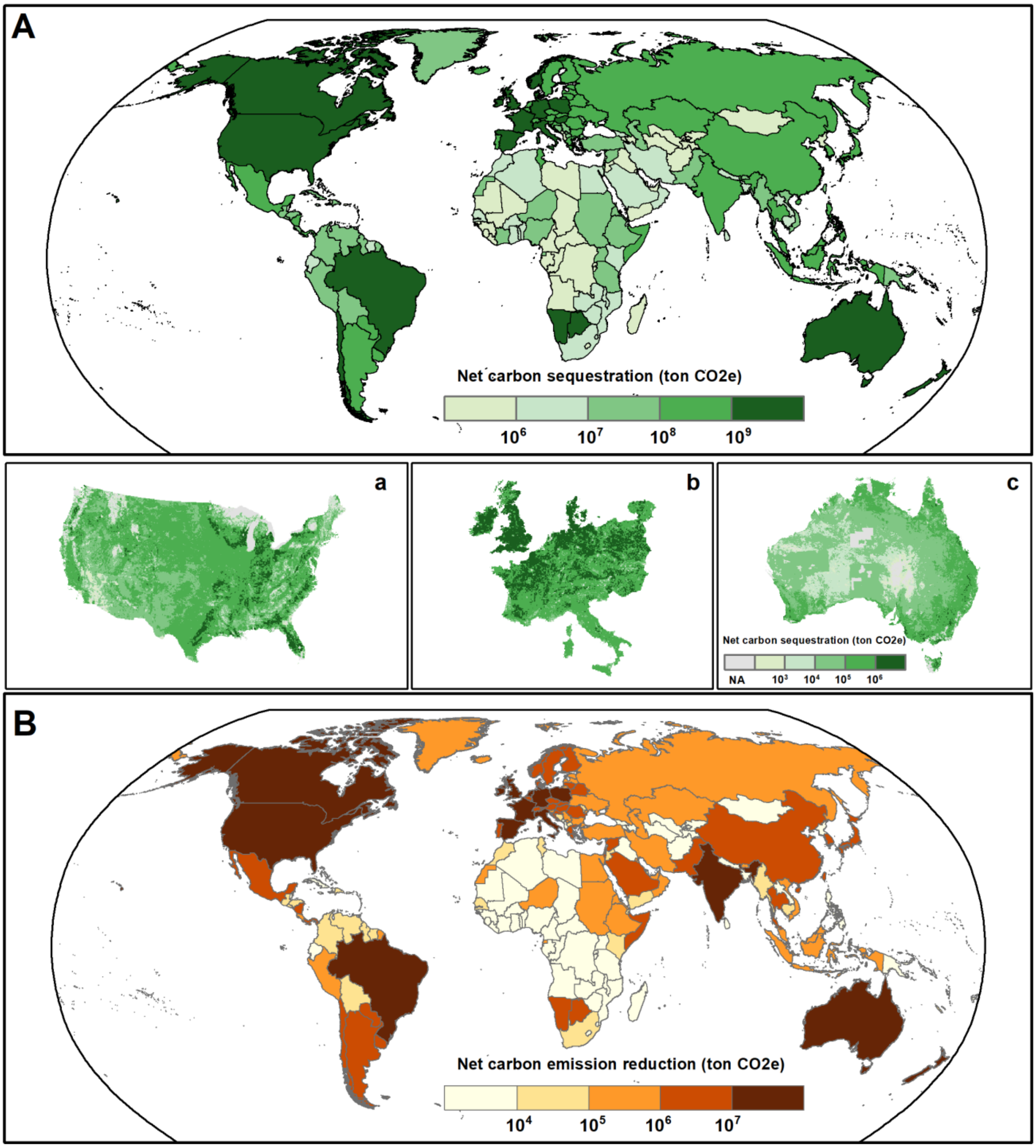

Figure 5.1. Changes in (A) net carbon sequestration (the sum of AGBC, BGBC, SOC), (B) net carbon emissions due to dietary change in high-income countries (shown in Robinson projection). Three major hotspots of carbon sequestration are in the Midwest of the US (a, shown in USA Albers Equal Area Conic projection), central Europe (b, shown in Europe Albers Equal Area Conic projection), and coastal regions in Australia (c, shown in Australian Albers projection). Further maps of the global spatial distribution of changes in these variables are in Figure S 8.19.

5.3 The role of animal products in the carbon cycle

Given the large land requirement and high emission intensity of animal agriculture, a shift away from animal product consumption comprises the largest opportunity for both increased carbon sequestration via land sparing and emission reductions from the food system itself [327,349,362]. Reductions in animal protein consumption would result in 110.54 Pg CO_2e of sequestration over the long term, along with direct annual emission reductions of 0.57 Pg CO_2e yr^{-1} (Figure 5.2). The reduced consumption of dairy products would result in an additional sequestration of 17.32 Pg CO_2e, and emission reductions of 0.01 Pg CO_2e yr^{-1} (Figure 5.2). Land spared by reducing the consumption of animal protein and dairy products could capture and store 128 times the annual GHG emissions from direct agricultural production (1.00 Pg CO_2e yr^{-1}) of food consumed in high-income countries in 2010.

Carbon mitigation due to dietary change depends on both local agricultural production practices and local dietary preferences. Dietary changes in the US and Australia contribute the largest carbon benefits since they are mostly comprised of reductions in animal product consumption (Fig. 2 and Supplementary Fig.5). This is due to the preponderance of grass-fed beef production systems in the US and Australia[349]. We find a different situation in the populous East Asian countries. In South Korea and Japan, the opportunity for carbon sequestration is offset slightly—by 0.48 Pg CO_2e and 0.44 Pg CO_2e due to an expected increase in dairy product consumption under the EAT-Lancet diet recommendations (Figure 5.2 and Figure S 8.19). Given that the current low levels of dairy consumption in East Asia are driven by high levels of lactose intolerance [363] our finding highlights the need for locally appropriate dietary recommendations that consider both public health and environmental outcomes.

The reduction in animal proteins would be offset slightly by an increase in plant-protein production. Increased production of plant-based alternatives would also be needed to satisfy other nutrient demands such as vitamin B12 and Omega-3[364]. Increasing plant proteins and fruit production would result in a small offset—23.52 Pg CO_2e—of the gains made from reducing animal products. The increase in direct emissions from the agriculture sector would be very small, at just 0.008 Pg CO_2e yr^{-1} (Figure 5.2). This is somewhat unsurprising when we consider that the energy feed-to-food conversion efficiency of animal products is low and varies from 3% for beef to 17% for eggs within animal products[44,365]. In addition, the grains fed to livestock (e.g. maize and soybean) could be redirected to human consumption or spared land could be used to produce plant-based products without expanding agricultural land in net (Figure S 8.19).

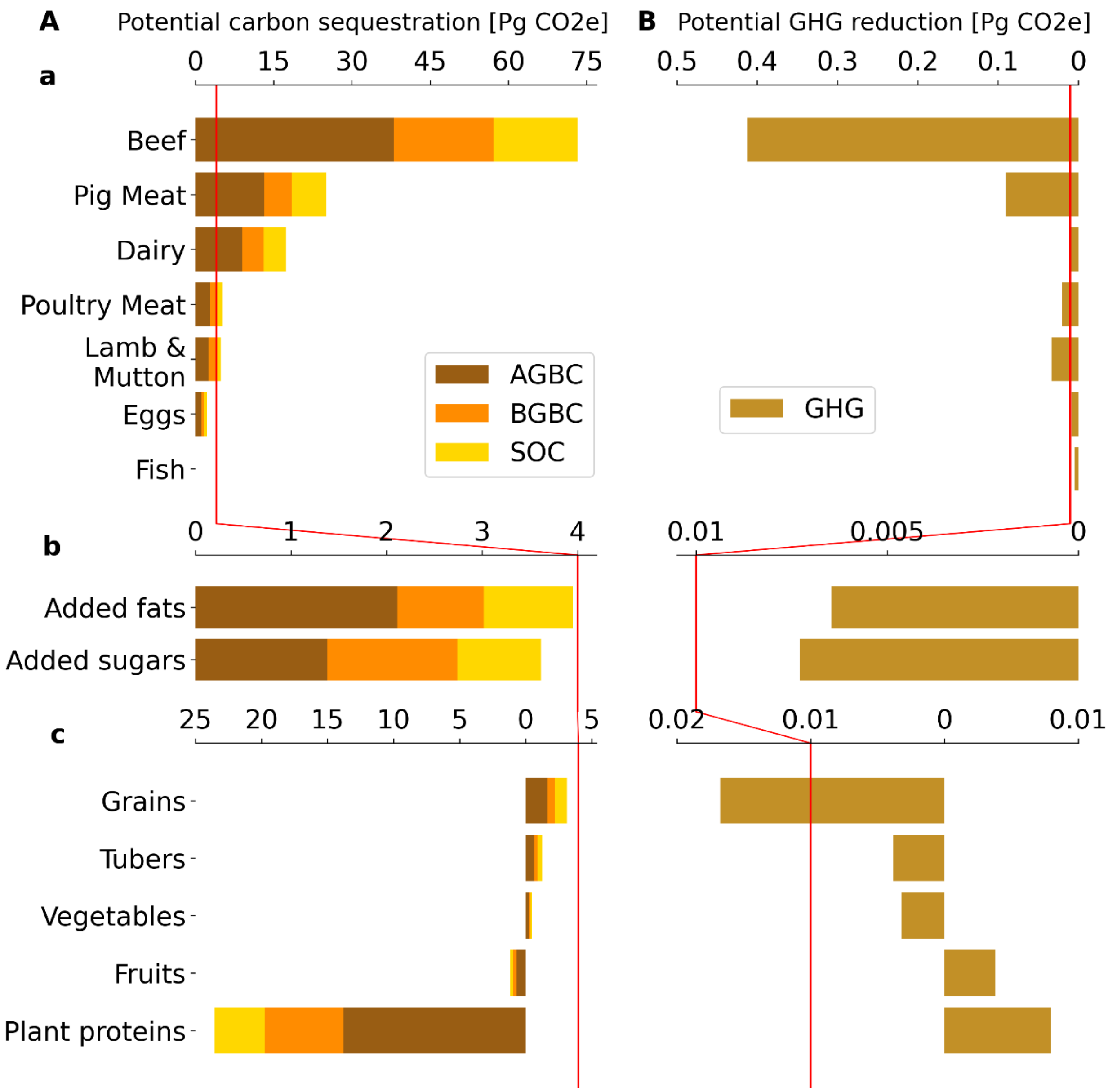

Figure 5.2. Potential carbon sequestration (A) and GHG emission (B) change by food category ((a) Animal products (b) mixed animal- and plant-based products, (c) plant-based products) due to dietary shifts from national average diets to the EAT-Lancet diet in high-income countries. We showed detailed sectors for animal-protein groups given its important role. For detailed reporting group information, see methods and Supplementary Table 2. The potential increase of carbon sequestration means carbon sequestration in potential natural vegetation minus that of current agricultural vegetation. The offset of carbon sequestration means carbon sequestration in potential natural vegetation minus that of increased agricultural vegetation. The left y = 0 in (A) means offset of potential carbon sequestration, and the right of y = 0 in (A) means potential carbon sequestration. The red line in (A) means 4 Pg CO_2e. The carbon reduction of GHG emission means the GHG reduction due to the reduction of food categories, and the offset means the GHG increase due to the increase of food categories The left of y= 0 in (B) means potential GHG reduction, and right panel of y = 0 in (B) means offset of potential GHG reduction. The red line in (B) means 0.01 Pg CO_2e.

5.4 Carbon mitigation potentials for items not included in the EAT-Lancet diet.

There has been little discussion of stimulants (coffee and products, cocoa beans and products, tea including mate), alcoholic beverages (wine, beer, fermented beverages, alcoholic beverages), edible offal, and other meat (e.g. horse, ass, camel, rabbit, game meat) in previous studies, as these were not a focus of the EAT-Lancet diet [327,366]. Although these items only comprise 8.1% of dietary carbon emissions, they represent a non-negligible carbon sequestration opportunity. The cumulative total of these items represents a sequestration opportunity of 27.78 Pg CO_2e (Figure 5.3) or 24.0% of the total sequestration opportunity identified above (Figure 5.1A) if high-income nations cease all consumption of these items.

While others have pointed to opportunities for sustainable intensification by abandoning luxury, low-nutrition crops such as feedstock for alcoholic beverages [367], it would be a significant challenge to model potential reductions. There exist health issues related to stimulant consumption, including a risk of anxiety and depression [368], along with relationships between alcohol consumption and cancer risk[369]—significant reductions in these items would be a controversial cultural topic[370]. Nevertheless, per-capita alcohol consumption of high-income countries, for example, is much higher than that of middle- and low-income countries, and some high-income countries (e.g. in Europe) have been reducing alcohol consumption[371,372].

Since edible offal is a by-products of meat production, it obviously cannot be reduced unilaterally from other meats. However, offal is often wasted in high-income nations due to convention and consumer preference [373]. Decreasing the waste of edible offal in high-income nations is an effective way to reduce overall meat consumption and its associated carbon cost [374]. Finally, if the animal proteins listed in the EAT-Lancet diet were to satisfy human demand, other meat consumption (consumption not listed in the EAT-Lancet diet for meat varieties such as horse, ass, rabbit and others) could be avoided, resulting in a sequestration opportunity of ~10.28 Pg CO_2e (Figure 5.3A).

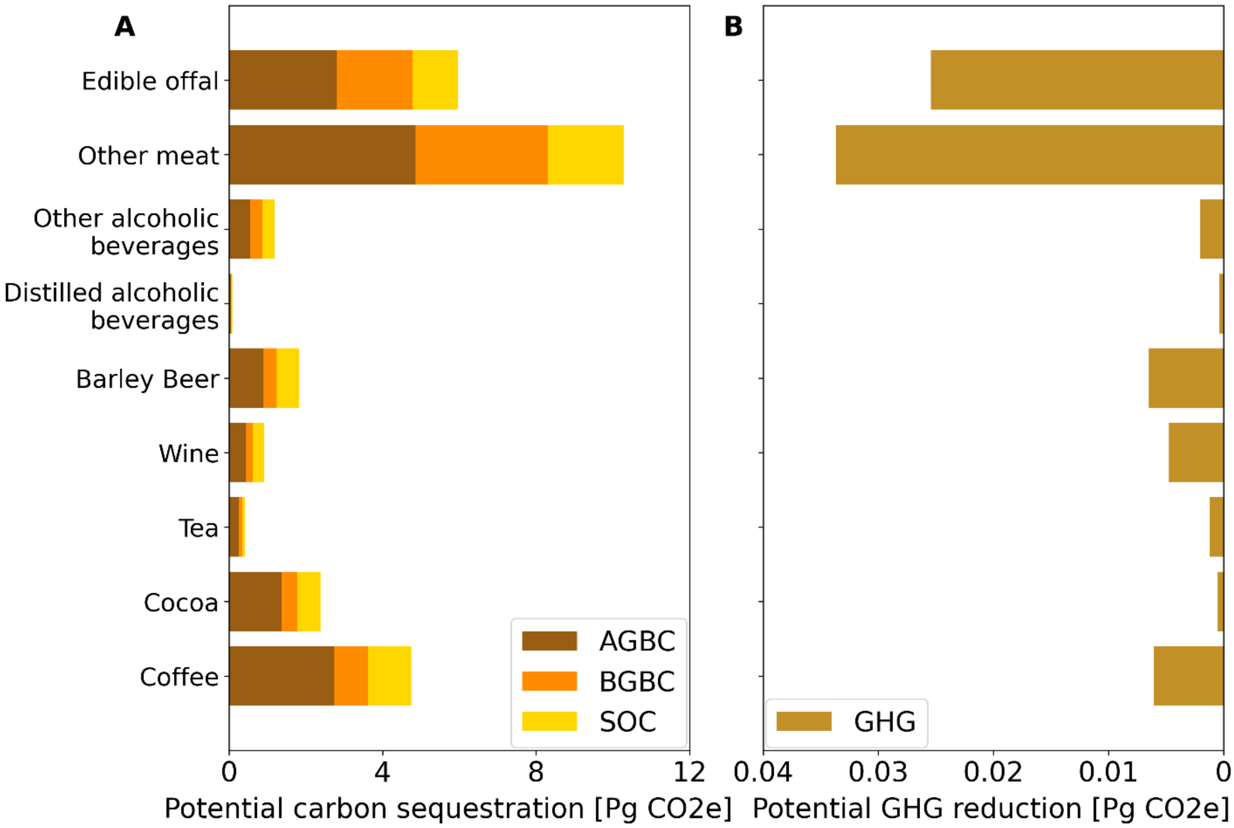

Figure 5.3. Potential carbon sequestration (A) and GHG emission (B) change due to removal of ignored food items in EAT-Lancet diet for high-income countries.

5.5 Implications for natural climate solutions

Emission trajectories as reported by the IPCC 1.5°C special report suggest that limiting global average temperature increase to 1.5°C could require a cumulative carbon dioxide removal (CDR) of 348-1218 Pg CO_2e by 2100, with a 'middle-of-the-road' scenario—one in which societal and technological development follows historical patterns—requiring a ~687 Pg CO_2e reduction[375,376]. As with mitigation efforts under existing international frameworks for 'shared but differentiated responsibilities', there may be highly differentiated CDR targets for high-income countries. Others have allocated global CDR requirements to countries based on responsibility (per-capita production-based carbon emission since 1850), capability (per-capita GDP) and equality (per-capita CDR quotas) principles[376]. Cumulative allocations to the 54 high-income countries we investigate here vary from 84.70 Pg CO_2e to 530.98 Pg CO_2e depending on the allocation principle (ranging from equality to capability respectively), compared to our calculated 115.57 Pg CO_2e CDR by PNV restoration due to dietary change[376]. Our results thus suggest that ecosystem restoration facilitated by dietary change alone could potentially fulfil between 21% and over 100% of these countries' CDR obligations needed to limit warming to 1.5°C.

Uniform adoption of the EAT-Lancet diet across high-income nations would benefit both the global environment and human health in high-income countries[327,366]. Land spared due to dietary change would expand opportunities for the implementation of natural climate solutions, such as regrowth of natural forest which is arguably the single most effective natural climate solution throughout much of the world[341,350,354]. Nevertheless, it would likely be a challenging, long-term, and complex process to restore the agricultural land spared by dietary change. A comprehensive analysis of social acceptance of land sparing is lacking but would likely find that success greatly depends upon local contexts[377]. In our analysis, we assume a scenario in which all spared land is restored to the potential natural vegetation associated with today's climate to delineate the maximum potential[352]. However, this idealized opportunity is likely confounded by more nuanced biophysical and socioeconomic characteristics of various world regions.

Restoration is also just one of many potential end uses for spared land. Competition among end uses inevitably precludes 100% adoption of any one type of land use and strategies are needed to identify ways in which trade-offs among uses can be optimally balanced. For example, from an emissions mitigation perspective some have recently proposed that restoration be prioritized based on the rate and degree to which candidate lands can recover C [378]. Yet, even recovery rates are not a trivial criterion. Many contingencies determine theses rates—e.g. subsequent management, local climate, soil properties, surrounding ecology, etc.—that ultimately influence the efficacy of restoration[379]. Passive restoration, for example, is sometimes desirable as species on spared land can undergo natural succession and recover quickly at no or low cost[379]. Even so, passive restoration may be a less effective means sequestering C than active restoration in systems in which successional dynamics favor the dominance of less productive plant communities [380]. In either case, restoration is a relatively slow process requiring decades or centuries to manifest its full effects. It therein requires a long-term mindset and commitment that may not be politically tenable.

Spared land could also potentially be used for bioenergy cultivation – albeit with different outcomes[379,381]. Traditionally, bioenergy has been regarded as an economically costly strategy for climate change mitigation with a lower efficacy per unit of land use compared to alternatives[341,379,381,382]. However, a recent US case study suggests that the climate mitigation potential of second-generation bioenergy crops (switchgrass) in some US contexts could be 4 to 15 times greater than the sequestration attained by restoring current cropland or pastureland to natural forest and grassland. However, these efficiencies remain contingent upon ensuing improvements to energy crop yields and biofuel conversion technology in addition to carbon capture and storage[383]. Moreover, unlike a return to PNV, the efficacy of bioenergy depends on technological and agricultural development [384,385]; it may depend on, or drive, greater use of agricultural inputs like fertilizer, pesticides, or irrigation; and its effects on biodiversity or other ecosystem services remain unclear but are likely less than those expected from PNV restoration[383].

In addition to natural climate solutions that ensue from the sequestration element of the double dividend, other supplementary natural climate solutions address production emissions. These solutions, including improved nutrient management, cover crops, and biochar (see supplementary information), do not require extra land but instead target emissions reductions from remaining cropland[341,379]. Moreover, their effects are realized quicker (days to years) than those of PNV restoration which may make them more tractable for producers and policy makers. Even so, governance of land use changes implied by both elements of the double dividend will likely require new technological (e.g. remote-sensing monitoring) and financial support (e.g. reforestation and afforestation) [379,386,387].

In order to harness the GHG mitigation potential of dietary change, a holistic social policy that coordinates between food, environment, and public health systems will be needed. Global agricultural subsidies, for example are currently ~\$700 billion yr^{-1}, and result in unsustainable production practices[388,389]. These subsidies could instead be redirected along the lines of environmentally cognizant agricultural practices and healthy diets[388]. Decision-makers could also repurpose taxes and regulations on unhealthy food[389]. High-income countries stand to achieve the largest per-capita carbon reductions by shifting to the EAT-Lancet diet due to the large proportion of their average diet currently devoted to carbon-intensive animal protein consumption[327,362]. While we estimate the magnitude of the potential carbon sequestration benefit due to dietary change in high-income nations, we do not include non-agricultural sectors such as transportation, processing, wholesale and retail, hotel and restaurant food emissions. Further, given the number of datasets integrated into this analysis, uncertainties in these data[352,358] and the model[36] mean that estimates for specific crops in individual nations should be interpreted cautiously. Nevertheless, our analysis sheds light on the indirect ways in which dietary change may offer substantial opportunities for GHG reductions via enhanced natural climate solutions and the deep and complex policy changes upon which they are predicated.

5.6 Methods

In this paper, we employed a Spatially explicit Multi-Regional Input-Output (SMRIO) model to derive carbon emission and carbon sequestration change after a dietary shift from national average diets in the year 2010 to a planetary health diet proposed by the EAT-Lancet Commission in high-income countries[342]. We focus on carbon emissions and sequestration – the latter distinguishing aboveground biomass carbon (AGBC), belowground biomass carbon (BGBC), and soil organic carbon (SOC) of crop and livestock production for human consumption. Carbon emissions and sequestration requires two different timeframes: the reduced production emission influences the sector's annual GHG contribution, while sequestration requires decades or even centuries to realise its full potential. Therefore, we assess a 'double dividend' for emission mitigation from (1) annual reduced direct agricultural production emissions [327] and (2) carbon sequestration via the land sparing over the long term [352,362]. To keep the geographic data consistent, we aggregate all spatial maps to a uniform resolution of 5 arcmin. We outline the construction of the model for each plant type in turn.

5.6.1 Biomass carbon and soil organic carbon in current vegetation

Primary crops and fodder:

We calculated AGBC and BGBC for herbaceous crops and fodder using the approach of Spawn et al. [358] (equations 1 and 2) based on the crop production data at national scale from FAOSTAT [357], to begin with (detailed parameters in Supplementary Table 1, and detailed description see Supplementary Methods). We then allocated AGBC and BGBC into grid cells based on the spatial distribution of the 29 herbaceous crops in SPAM [390] and the fodder crop map in EarthStat [35].

$$AGBC = y\omega(0.451h^{-1} + 1.025c - 0.451) \quad (1)$$

$$BGBC = 0.451yrh^{-1} \quad (2)$$

where y is the production of a specific crop or fodder item (in tons), ω is the dry matter fraction of its harvested biomass, h is its harvest index (fraction of total AGBC collected at harvest), c is the carbon content fraction of its harvested dry mass, and r is the root-to-shoot ratio of the crop (detailed values in Supplementary Table 1). We assume that 2.5% of all harvested biomass is lost between the field and farm gate and that unharvested residue and root mass is composed of 44% carbon (following Wolf et al. [391])

Since some regions saw multiple harvests in a single year, we further determined the harvest frequency (f) of each grid cell by dividing a cell's harvested area by its physical area as reported in SPAM. If f was greater than one, multiple harvests were assumed and AGBC and BGBC were divided by f to ensure that AGBC and BGBC estimates did not exceed the maximum standing biomass density [358].

Woody crops like fruit, nuts, and oil palms were addressed separately and their biomass was assumed to be captured by the harmonized biomass AGBC and BGBC map from Spawn et al. [358]. The AGBC and BGBC were extracted based on the share of the physical area of 11 woody crops in SPAM on the grid cell area. We then allocated the AGBC and BGBC of 11 woody crop groups into individual crops based on the share of AGBC and BGBC calculated in equations 1 and 2 at the national level.

Soil organic carbon (SOC), the carbon remaining in the soil after partial decomposition of any material produced by living organisms, constitutes a primary element of the global carbon cycle through the atmosphere, vegetation, soil, rivers, and the ocean. About 50% of total global SOC (i.e. top 300 cm depth) is stored in the top 100 cm depth, so SOC stock change assessment should be made to at least 100 cm depth [392]. In this paper, we used a soil organic carbon stock map predicted by machine learning ensemble models at 250 meters resolution [359] in the top 100 cm depth. We used the share of the physical area of 40 crops in SPAM and a fodder map from EarthStat to extract the value of SOC, and we then allocated the value into separated crops based on their harvested area in FAOSTAT and SPAM in 2010.

Pastureland

We used the latest year of pastureland for feeding livestock in the year 2010 provided by Sloat et al. [393] and calibrated it based on capping 100% total land-use coverage in each grid cell (see Supplementary Methods). AGBC and BGBC of pasture are from the harmonized biomass carbon map of pasture provided by Spawn et al.[358]. SOC is based on the same dataset as above cropland. We extracted the value of AGBC, BGBC, and SOC based on the percentage of pasture on a grid cell.

5.6.2 **GHG emissions**

The GHG emissions for agricultural production in tonnes of CO_2e yr^{-1} were calculated following the tier 1 methodology of FAOSTAT for the year 2010 [357] applied at the national level rather than the grid cell level (see Supplementary Methods).

5.6.3 **AGBC, BGBC, and SOC of potential natural vegetation**

To calculate the potential additional carbon storage of returning land to natural vegetation, we used the work of Erb et al. [352] and Searchinger et al. [353]. Erb et al. generated a land-use induced biomass stock (AGBC, and BGBC) reduction percentage map based on 42 potential–actual biomass-stock difference maps by combining the seven actual biomass-stock maps with the six potential biomass-stock maps [352]. In addition, Erb et al. adjusted the maps to guarantee the actual biomass stocks would not surpass the potential biomass stocks [352]. We used the AGBC and BGBC maps constructed as above as the actual biomass stocks map, and used a reduction percentage map from Erb et al.[352] to get AGBC and BGBC of potential natural vegetation. For SOC of cropland, we assumed 25% of soil carbon loss in the top 100 cm of soils, consistent with other global studies [353,394,395]. The SOC difference between pastures and its potential natural vegetation remains disputed. We assume no change in SOC for tropical pastures and 10% loss in the temperate pasture, following a previous study [353]. For climate classification, we employed the latest Köppen-Geiger climate classification map at a 5-arcmin resolution [396]. We assumed SOC of pastures in tropical rainforest, tropical monsoon, and tropical savannah stays unchanged, and other zones in the Köppen-Geiger climate classification lose 10%. We used this assumption to calculate SOC of potential natural vegetation.

5.6.4 **Dietary change in high-income countries**

Source data for average national diets were obtained from FAO food balance sheets (FBSs) in 2010 [357]. FBSs are available as calories (kilocalories per person per day) and weights (grams per person per day) [357] which can be used to compute the food-specific energy content (calories per unit food) for each country. We used food supply from FBSs, and did not include stock variation and food loss, because these are not consumed in human diets. The food used in feeding and processing are reflected by the input-output relationship in The Food and Agriculture Biomass Input-Output model (FABIO).

For targeted healthier diets in high-income countries, we chose the food recommendations from the Universal Healthy Reference Diet (EAT-Lancet) which follows the guidelines on healthy diets and sustainable food systems [342,366]. For each country, we aggregated food demand (in grams/capita/day) for each classification of the EAT-Lancet diet (for the detailed mapping relationship between FABIO sectors and EAT-Lancet classification, see Supplementary Table 2), calculated the energy content (kilocalories/capita/day) in each classification, adjusted the energy intake for each classification to conform with the recommendation of EAT-Lancet, and adjusted all energy intake to 2500 kcal/capita/day similar to the method in previous studies [327,366]. Most food items reduced shifting from the average national diet to the EAT-Lancet diet across high-income countries (for specific food item changes, see Supplementary Table 9). However, some food items (especially fruits and plant-protein food) increased in some high-income countries (for specific food item changes, see Supplementary Table 9). Food quantities (in grams/capita/day) in each classification were split using proportions in the national average diets for reduced and increased food items. As a result of these changes we would witness an increase in soybean food supply for the plant-protein group in the EAT-Lancet diet due to increased availability of soybeans from land producing soybeans as feed for animal product consumption. The difference between the average national diet and the EAT-Lancet diet is the dietary change used in this study. There are no recommendations for alcohol, coffee, tea, cocoa, other meat (e.g. horse, ass, mule, camel, rabbit, snails) and edible offal intake in the EAT-Lancet diet, so we assumed these items to stay unchanged at the national average level [366].

It is important to note several critiques of the EAT-Lancet diet, most of which centre on the use of the universal diet for middle- and low-income nations [397,398]. Here we avoid much of this critique by focusing on high-income dietary changes. However, as noted above, there are some food groups and regions where the universal diet may need localisation even in high-income nations (for instance with respect to dairy intake in East Asia).

5.6.5 **Physical input-output model for agricultural products: FABIO**

The Food and Agriculture Biomass Input-Output model (FABIO) is a consistent, balanced, physical input-output database based on FAOSTAT data, covering 191 countries and 130 agriculture, food, and forestry products from 1986 to 2013 [36]. For further information on its construction see Bruckner et al.[36]. In this paper, we use the 2010 version of FABIO.

5.6.6 **Environmentally extended multi-regional input-output model**

Environmentally extended MRIO models have been widely used in studying environmental impacts driven by global consumption. In this work, we followed the standard Leontief model to compute the biomass carbon and GHG emissions driven by food consumption changes in high-income countries. The standard approach is:

$$\Delta \boldsymbol{F} = \boldsymbol{diag}(\boldsymbol{e})(\boldsymbol{I} - \boldsymbol{A})^{-\boldsymbol{1}}(\Delta \boldsymbol{Y})$$

If the number of countries is R, of agricultural sectors is N and of high-income countries is H, then: $\boldsymbol{\Delta F}$ is a ($RN \times H$) matrix of environmental impact change driven by final demand change in every country.

$\boldsymbol{e}$ is an environmental impact intensity row vector with dimension $1 \times RN$. ***diag(e)*** is a matrix of vector e when diagonalized. In this paper, the e stands for the production of crops, fodder, and pasture, or GHG emissions of crops, fodder, and livestock (including those emissions from enteric fermentation and manure management).

$\boldsymbol{A}$ is a matrix of technical coefficients with dimension $RN \times RN$, which gives the number of inputs that are required to produce a unit of output.

$\boldsymbol{\Delta Y}$ is a matrix of food demand change (measured in physical units) in high-income countries with dimensions $RN \times H$. The vector is derived from the last part (“Dietary change in high-income countries”) based on the difference between FBS and EAT-Lancet diet.

I is an identity matrix with dimension $RN \times RN$.

5.6.7 Carbon change due to dietary shift

We calculated GHG emissions at the national level, so the GHG change due to a dietary shift from average national diets to the EAT-Lancet diet can directly derive from the environmentally extended multi-regional input-output model.

For decreased crops and forage (fodder and pasture) production, firstly, we calculated the production change of crops or forage at the national level, and then allocated them to grid cells proportionally, as done in previous SMRIO studies [361]. We used AGBC as a proxy of production for pasture because aboveground biomass is used to feed livestock. Secondly, we used gridded production change divided by yield to get the spatial distribution of harvested area. The change in physical area was calculated by dividing harvested area by harvest frequency. The spared physical area of cropland and pastureland is where the potential natural vegetation can be restored.

For increased crop or forage production, firstly, we multiply the spared physical area map with the harvest frequency map to get the spatial distribution of harvested area, and then multiply with the yield maps of existing crops and pasture to get the spatial distribution of potential additional production. This means the potential production maps consist of grid cells where the products are already produced, and the land is spared. Secondly, we allocate national increased production derived from the MRIO model into the aforementioned potential production maps. We redirect some production to other countries if the spared land is not enough to produce more of specific crops. In our research, the redirection occurs in just a few small countries or countries with little production for some specific crops. Thirdly, we used the increased production of crops and forage divided by their yield maps to get the spatial distribution of the harvested area, and then we can get physical area change through the harvested area divided by the harvest frequency. The physical area offset the spared cropland or pastureland to restore potential natural vegetation.

We used the physical area maps to calculate the change of AGBC, BGBC and SOC between actual vegetation and potential natural vegetation as in the aforementioned method. In this paper, we focus on net carbon sequestration change, which is the sum of carbon sequestration of potential natural vegetation and increased agricultural vegetation minus the carbon stock in current agricultural vegetation.

5.6.8 Reporting of Results

The analysis was performed for the 54 high-income countries available in FABIO (there is no food supply data in FAOSTAT for 4 small high-income countries in FABIO: Bahrain, Puerto Rico, Qatar, and Singapore). Carbon change analysis was reported in 10 categories for ease of inspection, as done in previous studies [327]: Whole grains, tubers or starchy vegetables, vegetables, fruits, dairy food, animal proteins, plant proteins (nuts and legumes), added fats, added sugars, and others (namely, missing items in the EAT-Lancet diet) (details see Supplementary Tables 2 and 3).

6.

Chapter 6.
General discussion

6 General Discussion

Modern food systems have created large-scale environmental pressures yet do not result in food security for all. Due to the significant spatial heterogeneity of food production pressures, and complex supply chains, the assessment of such problems in the global agri-food system cannot be sufficiently addressed by classical GMRIO analyses. Such approaches are capable of analyzing how (in this case: food) consumption drives via international supply chains the pressures of production, but only as an average of a production sector in a country. Since food production and the related pressures depend highly on the location where this production takes place, this thesis has experimented with an alternative approach: Spatially explicit multi-regional input-output analysis (SMRIO). As indicated in the introduction, in principle SMRIO could make three elements of a traditional GMRIO matrix spatially explicit, i.e. pressures of production, expenditures related to consumption, and the intermediate inputs and outputs of production. Given the already high complexity of building traditional GMRIO databases, this thesis mainly focused on the first element by linking GMRIO databases like EXIOBASE, and the very detailed FABIO database covering agri-food products, with spatially explicit agricultural production maps. Using SMRIO, this thesis aims to answer the following overarching research question, next to drawing methodological conclusions on further improvement of the SMRIO method:

How can spatially explicit multi-regional input-output approaches be used to evaluate sustainability in the global agri-food system?

This chapter first reviews the progress made towards the specific research questions proposed in Chapter 1 and then answers the overall research question (section 6.1). It then discusses the experiences with the SMRIO method, and the prospects for developing improvements of SMRIO databases in relation to limitations experienced in the research for this thesis (section 6.2). Finally, the chapter discusses the policy implications for agri-food sustainability derived by this SMRIO perspective (section 6.3).

6.1 Answers to the research questions

Question 1: What is the current status of spatially explicit input-output analysis? (Chapter 2)

Environmentally Extended Input-Output (EEIO) analysis has been widely applied to many different environmental issues. However, EEIO analyses have been historically based on country-level analysis and hides spatial information of these impacts at a finer scale. Spatially explicit input-output analysis may offer improved visibility of heterogeneous environmental impacts along the supply chain. Chapter 2 reviewed studies of spatially explicit input-output analysis and summarized current developments. Spatially explicit input-output analyses can reveal finer spatial information of environmental impacts depending on which part of the table is disaggregated: spatially explicit environmental extensions (category 1), spatially explicit final demand (category 2), or a spatially explicit transaction matrix (category 3). Although a spatially explicit transaction matrix, as described by category 3, is ideal, it is extremely challenging and potentially intractable until a significant increase in production, transportation and consumption data becomes available. Category 2 aims to provide a better insight into consumption impacts of different consumers in the same country – for example between high-income and low-income consumers and mainly relies on regional statistics (e.g. household or enterprise surveys). With the development of high-resolution environmental impact maps, Category 1 has already seen wide use and is likely to become more popular in the future but could benefit from improved approaches for allocating production for domestic consumption and production for export.

Question 2: What are the local production hotspots of crops and livestock driven by global consumption and how does this impact food security through trade?

International trade plays a crucial role in global food security, with localizing primary crops and livestock. Chapter 2 shows that primary crop and livestock footprints were highly unequal among countries. Footprints for high-income countries are distributed over larger areas when compared to lower-income countries, since high-income countries have more trade links. Compared with primary crops, livestock consumption is mainly sourced from domestic production instead of import. In addition, consumption of primary crops and livestock in almost all high-income countries was beyond the tentative target for a safe operating space for humanity in terms of agricultural resource use. This is because high-income nations consume large amounts of animal products. Excessive consumption in high-income nations may threaten local food security in regions where they consumed.

The work also presented a different method for allocation of local and international consumption. In contrast to previous studies that assumed proportionality between production volumes and locations, this study used data from the Global Roads Inventory Project (GRIP) to allocate the spatial distribution of primary crops and livestock between domestic consumption and exports. This assumes exports of primary crops and livestock occur in locations with good transportation conditions. The study compared the results for Brazil for a previous national analysis using subnational trade data and it showed agreement, however a statistical comparison was not made due to data limitations. As a first attempt at such an approach for improving this allocation it shows promise.

Question 3: How does land use driven by final consumption affect global biodiversity within key biodiversity areas?

As an urgent, global, complex issue, biodiversity represents a critical common action problem. Key Biodiversity Areas (KBAs) are critical regions in efforts to preserve global biodiversity. However, KBAs are yet to be broadly protected by national and international treaties and as such can still be under pressure from human activities. The issue is addressed as the second application of SMRIO (Chapter 4).

The study found that land use significantly and disproportionately impacts global biodiversity within key biodiversity areas. In fact, land use within KBAs caused 16% of global plant loss and 12% of global vertebrate loss, with only 7% of total land use. This land use driven loss is especially high in tropical regions. The land use is mostly driven by consumption of animal products and housing, accounting for ~51% and 8% of species lost respectively. On its own, the consumption of bovine meat contributed to around 40% of biodiversity loss within KBAs. The type of land use also impacts biodiversity, for example, pastureland with light use contributed to around half of all species loss within KBAs. Finally, since 25%-33% of land use within KBAs is driven by international trade, it is clear that biodiversity protection needs international cooperation between producers and consumers.

Question 4: What are the global interactions between carbon emissions and carbon sequestration driven by diets and diet changes in high-income nations?

Current food system emissions may already preclude the limiting of climate change to 1.5 or even 2 °C[42]. Dietary shifts in high-income nations may help mitigate climate change by both reducing greenhouse gas (GHG) emissions from direct agricultural production and via an indirect increase in carbon sequestration if spared land is restored to its potential natural vegetation. As such, dietary change offers an opportunity for a double carbon dividend from both (1) reduced direct agricultural production emissions and (2) carbon sequestration via the land sparing whereby agricultural lands can revert to other uses. Therefore, the third application based on SMRIO is used to measure this double carbon benefit from dietary change (Chapter 5). This study found that dietary changes in high-income nations could reduce the global carbon emission of 0.61 Pg CO_2e yr^{-1} from direct agricultural production. The dietary change could also result in an increased carbon sequestration potential of 115.57 Pg CO_2e over the long term (~2.3 years of global CO_2e yr^{-1} emissions in 2010). Carbon sequestration would predominately locate in large countries with large amounts of agricultural production, especially feed crops and pasture. Often overlooked food and beverage items outside the EAT-Lancet diet could offer further potential carbon benefits but may prove difficult to harness since they include alcohol and other stimulants (a maximum increase of 27.78 Pg CO_2e sequestration and reduction of 0.08 Pg CO_2e yr^{-1} GHG emission).

In addressing these research questions this thesis shows several answers to the overall research question "*How can spatially explicit multi-regional input-output approaches be used to evaluate sustainability in the global agri-food system?*".

The thesis answered this question by providing a literature review of previous approaches and three new analyses based on a critical global issue. The review showed that SMRIO can help assess sustainability in many ways unique to this model. It was shown across all chapters that monetary-physical hybrid GMRIO datasets, when combined with spatial analyses can provide significant insights into the global food system. For instance, the spatial distribution of primary crops and livestock driven by global consumption showed the improvement potential to ensure global food security; and the comparison of per-capita primary crop and livestock footprints with a tentative target suggested a dietary change direction for each nation (Chapter 3). As a major driver of biodiversity loss and climate change, this framework was used to assess biodiversity loss driven by land use within Key Biodiversity Areas (Chapter 4) and the possibility of carbon sequestration via dietary change (Chapter 5). The results connected global food consumption to spatially explicit hotspots driven by local agricultural production.

In summary, the SMRIO approach can fully utilize spatial information and trace spatial differences along the global supply chain. With the approach, it is possible to identify actual locations where environmental pressures are predominantly driven by specific consumers. In addition, the consumption of different products caused the diverse spatial distribution of environmental pressures. The highly sectorial monetary-physical hybrid GMRIO datasets means environmental pressures can be explored on a product-resolution basis. The identified regions and specific drivers could suggest targeted implications to achieve agri-food sustainability by connecting producers, consumers, and governments along the global supply chain. While this thesis describes findings that have potentially international importance to other scientists, policy makers, and the public, there are many ways these assessments can be improved and avenues for future research.

6.2 Limitations and future research – ways forward for SMRIO

Chapter 2 provided an overview of what data would ideally be available to perform a comprehensive spatially explicit input-output analysis:

- Spatially explicit insight in production locations and the environmental pressures they cause.
- Spatially explicit insight in patterns of final demand.
- Spatially explicit insight in transaction matrices that describe value chain linkages between production and consumption activities at any spatial unit.

These three points describe options for spatializing the matrices (i.e. environmental extensions, final demand, and transaction matrix in Figure 1.1) involved in environmentally extended multi-regional input-output tables. The first point has been widely applied, given the availability of spatial datasets of extended environmental accounts. Linkage of such spatially explicit data sets on environmental pressures to GMRIO is a relatively recent phenomenon, though. Three case studies in this thesis all followed this concept for linking the spatial datasets of agri-food systems with GMRIO tables. Below I discuss the limitation of this approach and future avenues for research. I discuss the development of natural science datasets which may provide more opportunities to improve environmental pressure maps for SMRIO analysis in section 6.2.1. Locating specific consumption locations is more challenging than specific production locations given the complexity of human consumption behaviors. A blueprint or standard for geocoding consumption information for specific products in the GMRIO table is still missing and I discuss this further in section 6.2.2. The ideal situation of a full SMRIO analysis related to the third point above is intractable in the short term, given limitations in data collection, data quality, and computing power. However, proxies may be able to to help provide insights in the short term, and these are discussed in section 6.2.3.

6.2.1 **Improving environmental pressure maps for SMRIO**

This thesis relied heavily on global land use datasets, especially crop-specific maps. For example, the crop maps used in Chapter 3 to Chapter 5 were from the Spatial Production Allocation Model (SPAM), recognized as the best crop-specific maps available and widely used in research [353,377,399,400]. Most crop maps generally use a cross-entropy approach to downscale statistical data at different administrative levels depending on data availability. This cross-entropy approach optimizes the crop distribution considering related information, such as land cover and crop suitability. However, the method is still a top-down allocation approach, which may not reflect the actual crop distribution at the level of the grid cell.

Some studies have employed a remote sensing approach to illustrate the spatial distribution of some specific crops in particular regions, such as maize, wheat, soybean, barley, potato, rice, sugarcane, and cotton in the US, Zambia, India, China, Germany [313,401–404]. However, it is challenging to incorporate these case studies into a harmonized global crop atlas because these studies have different accuracies, use different interpretations of remote sensing data, and have different temporal ranges [405]: Further, definitions of cropland are sometimes inconsistent due to different application purposes and classification methods (and differs from statistical surveys), since it is difficult to identify cropland in a highly fragmented landscape with mixed cropland and other land cover types. Furthermore, satellite sensors struggle to characterize the human activities within cropland, for example, abandoned cropland from official statistics can still be detected as cropland by satellite sensors [405]. Some studies have used approaches based on machine learning to create a harmonized global picture for crops (e.g. oil palm) using remote sensing data[406]. However, these studies generally focus on one crop only and a globally harmonized crop-specific atlas will need a lot of resources and attention from the research community.

A further issue is that spatial information from satellites can only map natural impacts and not human activities. Therefore, improving the quality and attribution of natural science data to economic activities or commodities is as important as increasing spatial resolution of natural science data to better link with the economic model being used (i.e. an MRIO) [2]. A 10 km by 10 km grid cell (resolution of SPAM) may contain several types of crops and a number of associated environmental stressors (e.g. water use, GHG emissions) or impacts (e.g. biodiversity loss). Some recent projects have combined natural science datasets from satellite and *in situ* sites to estimate local production and associated impacts using artificial intelligence and machine learning [2]. If more natural stressors or impacts can be linked to GMRIO tables, an assessment with SMRIO could evaluate multiple indicators at once, which would provide a more comprehensive view of sustainable development.

6.2.2 **Locating consumption of specific products for SMRIO**

Chapter 2 argued that consumption-based environmental footprints were generally performed at the local authority level. Although a very high-resolution carbon footprint was shown, the spatial information was derived from the global gridded population dataset (at a 250-m resolution) and purchasing power datasets (the world is divided into 20,159 regions) rather than high-resolution maps of final consumption for specific products. [107]. With the development of the Internet of Things (IoT), increasing amounts of customer transaction data are digitally recorded. An increasing coverage and availability of transaction data may provide an opportunity to locate the final consumption of specific products. However, it is very challenging to harmonize these datasets since they are recorded by different suppliers and each dataset implies commercial interests.

Some geocoded consumption datasets, such as takeaway orders from an online food delivery platform in China [407,408], transactions from bank card records for point-of-sales terminals in Spain [409] and China [410], express delivery in China [411], building stocks in the US [412], and electricity consumption from supplying companies in Switzerland [413], have been applied in estimating environmental pressures. However, these datasets are samples of consumption (i.e. they do not fully cover the consumption of specific products) within a nation and do not link with GMRIO tables. In addition, there are concerns over data privacy given the high level of granularity of such data. Ideally, samples should be anonymized and data collection/application should follow international standards such as those suggested by the American Association for Public Opinion Research.

6.2.3 **Improving the accuracy of the transaction matrix within GMRIO tables**

In the available monetary GMRIO tables, economic sectors and regions are highly aggregated, especially for agricultural products. Monetary-physical hybrid MRIO frameworks are able to extend the number of product categories by connecting detailed agricultural products (e.g. in physical units in FABIO) and larger economic sectors (e.g. in monetary units in EXIOBASE). As such, the framework can trace the downstream impacts associated with agricultural production along the supply chain. However, there is no feedback from non-agricultural products to agricultural commodities within this framework. That is, this framework is unable to connect non-agricultural products and agricultural commodities (e.g. the processing or transportation of products). In addition, the number of regions in FABIO (192 countries/regions) differs from that in EXIOBASE (49 countries and nations), so the integrated framework cannot fully reveal the spatial heterogeneity across all countries. However, there are efforts to produce a version of EXIOBASE with all countries disaggregated[414].

Although adding finer spatial units and more sectors in GMRIO tables can improve SMRIO analysis, it is challenging to develop a GMRIO covering all economic sectors for all individual nations. Lenzen et al.(2017) designed a GMRIO lab, which can compile a GMRIO with any combination of regions and economic sectors according to need of users or policy makers [415]. However, the lab still needs more data sources and related technical support to achieve its ultimate goal.

In general, SMRIO studies link spatially explicit datasets with GMRIO tables and ignore the subnational trade or spatial differences in input and output transactions of the same sector within a nation. That is, the input and output coefficients are the same for each sector, regardless of location (i.e. local production is allocated to domestic consumption and export proportionally). This proportional allocation approach will create uncertainties, especially for large countries (e.g. the US, China, Brazil, Australia, and India). A robust approach for increasing spatial resolution would be to embed sub-national MRIO datasets within GMRIO datasets. For instance, Yang et al. (2020) linked China's high-resolution carbon emission maps with an integrated province-level Chinese MRIO embedded in GMRIO tables (Eora) using a proportional allocation assumption as described above[22]. However, China's material footprints derived using a proportional allocation show deviations from actual customs statistics [416]. As such, the proportional allocation approach may be an issue for other environmental pressures also. With the wider availability of national MRIO tables (e.g. the US, Japan, China, and Indonesia) and subnational trade data (e.g. the US, Brazil, Canada, Germany, Spain, and Japan) [417], linking national MRIO and subnational trade data with GMRIO can contribute to the further development of the SMRIO approach.

However, national MRIO tables or subnational trade are not available for each country. Therefore, finding a proxy is another way to allocate local production for SMRIO analysis. Chapter 3 used road density (Global Roads Inventory Project, GRIP) as a proxy to distinguish production for domestic consumption or export. However, other biophysical variables (e.g. slope and precipitation) and socio-economic variables (e.g. GDP and population density) have been found to influence local production [23]. In addition, in the absence of actual data such as local surveys the approach is not validated globally. To avoid introducing uncertainties that could be propagated through the model, Chapter 4 and Chapter 5 reverted to the proportional allocation approach.

Some recent work may help further address this proportionality issue. For production output, Malek et al. (2020) employed a cascade of related biophysical variables and socio-economic variables to create a probability map that describes the likelihood that a grid cell links with the market [23]. The allocation approach could be calibrated by trade data at the highest spatial detail available [417].

6.3 Policy implications

Locating environmental pressure hotspots driven by the demand of consumers at a high spatial resolution can help to connect local producers, consumers, environmentalists, and government to better target sustainable development[33,361]. While conventional MRIO analysis can provide policy information at a national level for social and environmental footprints, it cannot pinpoint hotspots in a spatially explicit way. The results of this thesis may help uncover the opportunities available to actors in product supply networks to address their corresponding responsibility in reducing these impacts. In terms of upstream impacts, spatially explicit hotspot maps can guide local producers to reduce social and environmental impacts. From a downstream perspective, the results can suggest options for sustainable consumption.

In practice this means actors along supply chains as identified by SMRIO could share technology and optimize financial investment to maximize global biodiversity conservation and climate mitigation [418]. Given the fact that the current net direction of traded goods moves from low- to high-income nations while high-income nations often have the technological and financial resources available to mitigate impacts, there is a large opportunity for international cooperation. The basis of this cooperation can be related to the spatial distribution of local pressures driven by the final consumption of specific nations. For example, the identified spatially explicit hotspots of primary crops and livestock could guide governments, retailers or final consumers in importing countries to support investments in pressure-reducing mitigation measures in regions which produce the food they consume, for example in improving agricultural productivity (e.g. closing yield gap) (Chapter 3). The consumption-based species loss of Western Europe and North America is mainly embodied in the imported products from tropical KBAs in Latin America, Africa, and Asia (Chapter 4). However, these tropical regions are facing rapid population growth, serious hunger and undernutrition issues, and show a rapid economic development largely relying on agriculture [419,420]. Therefore, future cropland expansion is more likely to occur in these regions to meet increasing demand for agricultural products on the one hand and expansion of economic activity on the other hand. To avoid further biodiversity loss in these biodiverse regions, Western Europe and North America could help their providers develop sustainable intensification of agricultural production. Some initiatives have highlighted an interest in international cooperation to address impacts and aid global sustainable development. For example, the Amsterdam Declarations (https://ad-partnership.org/) aims to eliminate deforestation associated with agricultural production. Similarly, The New York Declaration on Forests (https://forestdeclaration.org/) aims to halt global deforestation and restore forests. However, policies related to reducing consumption-based environmental impacts still see limited deployment. For example, less than 1% of EU's deforestation policy options address imported deforestation [421]. In addition, the implementation of policy interventions needs international cooperation across national borders. For example, the fact that biodiversity rich land areas cross socio-political boundaries could lead to a fragmentation of land use on the one hand and fragmented policy response on the other hand, and therefore drive biodiversity loss [422].

Implementing such improvement options should take the implications into account that may arise from changing production systems via policy and consumption changes in high-income nations. For examples, this thesis shows a need for addressing animal product consumption across nations as the largest driver of biodiversity loss and increasing carbon sequestration. The estimated spatial distribution of carbon benefits due to diet change led to the suggestion to restore the land use for mitigating climate change (Chapter 5). However, such climate benefits will only materialize if land upstream in the supply chain, often in developing countries, indeed is not anymore used for agricultural activities. Without additional policies – especially support for local producers that provide most agricultural products for the international market – this could cause a massive social upheaval as livelihoods in animal agriculture face rapid and deep change. The same is also true for taxes to internalize costs related to carbon emissions or biodiversity loss, and border adjustments implemented for similar purposes. Not only is implementing such measures a challenge in view of e.g. World Trade Organisation rules, but also since such external costs will differ between agricultural products and as shown in this thesis, also between different regions for the same product [353]. But such measures may also impact competitiveness of local producers significantly. Policies aiming at realizing climate and biodiversity goals related to agriculture hence must go hand in hand with measures fostering (local) economic development and poverty eradication[423].

References

7 References

1. Wiedmann, T. & Lenzen, M. Environmental and social footprints of international trade. *Nature Geoscience* vol. 11 314–321 (2018).

2. Moran, D., Giljum, S., Kanemoto, K. & Godar, J. From Satellite to Supply Chain: New Approaches Connect Earth Observation to Economic Decisions. *One Earth* **3**, 5–8 (2020).

3. Wood, S. A., Smith, M. R., Fanzo, J., Remans, R. & Defries, R. S. Trade and the equitability of global food nutrient distribution. *Nat. Sustain.* **1**, 34–37 (2018).

4. Kummu, M. *et al.* Interplay of trade and food system resilience: Gains on supply diversity over time at the cost of trade independency. *Glob. Food Sec.* **24**, 100360 (2020).

5. D'Odorico, P. *et al.* The Global Food-Energy-Water Nexus. *Reviews of Geophysics* vol. 56 456–531 (2018).

6. D'Odorico, P., Carr, J. A., Laio, F., Ridolfi, L. & Vandoni, S. Feeding humanity through global food trade. *Earth's Futur.* **2**, 458–469 (2014).

7. Janssens, C. *et al.* Global hunger and climate change adaptation through international trade. *Nat. Clim. Chang.* **10**, 829–835 (2020).

8. Seekell, D. *et al.* Resilience in the global food system. *Environ. Res. Lett.* **12**, 025010 (2017).

9. Li, Y. L., Chen, B. & Chen, G. Q. Carbon network embodied in international trade: Global structural evolution and its policy implications. *Energy Policy* **139**, 111316 (2020).

10. Kastner, T., Erb, K. H. & Haberl, H. Rapid growth in agricultural trade: Effects on global area efficiency and the role of management. *Environ. Res. Lett.* **9**, 034015 (2014).

11. Qiang, W. *et al.* Trends in global virtual land trade in relation to agricultural products. *Land use policy* **92**, 104439 (2020).

12. Marques, A. *et al.* Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. *Nat. Ecol. Evol.* **3**, 628–637 (2019).

13. Wang, R., Hertwich, E. & Zimmerman, J. B. Virtual water flows uphill toward money. *Environ. Sci. Technol.* **50**, 12320–12330 (2016).

14. Wiedmann, T., Lenzen, M., Keyßer, L. T. & Steinberger, J. K. Scientists' warning on affluence. *Nat. Commun.* **11**, 1–10 (2020).

15. UNEP. Decoupling Natural Resource Use and Environmental Impacts from Economic Growth. (2011).

16. Kanemoto, K. & Moran, D. Carbon-Footprint Accounting for the Next Phase of Globalization: Status and Opportunities. *One Earth* **1**, 35–38 (2019).

17. Fuchs, R., Brown, C. & Rounsevell, M. Europe's Green Deal offshores environmental damage to other nations. *Nature* vol. 586 671–673 (2020).

18. Scheelbeek, P. F. D. *et al.* United Kingdom's fruit and vegetable supply is increasingly dependent on imports from climate-vulnerable producing countries. *Nat. Food* **1**, 705–712 (2020).

19. Pendrill, F. *et al.* Agricultural and forestry trade drives large share of tropical deforestation emissions. *Glob. Environ. Chang.* **56**, 1–10 (2019).

20. Tukker, A., Pollitt, H. & Henkemans, M. Consumption-based carbon accounting: sense and sensibility. *Clim. Policy* **20**, S1–S13 (2020).

21. Owen, A. E. Techniques for evaluating the differences in consumption-based accounts. (University of Leeds, 2015).

22. Yang, Y. *et al.* Mapping global carbon footprint in China. *Nat. Commun.* **11**, 1–8 (2020).

23. Malek, Ž. & Verburg, P. H. Mapping global patterns of land use decision-making. *Glob. Environ. Chang.* **65**, 102170 (2020).

24. Meijaard, E. *et al. Oil palm and biodiversity: a situation analysis*. *IUCN Oil Palm Task Force* (2018) doi:10.2305/iucn.ch.2018.11.en.

25. Grassini, P., Specht, J. E., Tollenaar, M., Ciampitti, I. & Cassman, K. G. High-yield maize-soybean cropping systems in the US Corn Belt. in *Crop Physiology: Applications for Genetic Improvement and Agronomy: Second Edition* 17–41 (Elsevier Inc., 2015). doi:10.1016/B978-0-12-417104-6.00002-9.

26. Yu, Q. *et al.* A cultivated planet in 2010 – Part 2: The global gridded agricultural-production maps. *Earth Syst. Sci. Data* **12**, 3545–3572 (2020).

27. Buchhorn, M. *et al.* Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. (2020) doi:10.5281/ZENODO.3939050.

28. Jun, C., Ban, Y. & Li, S. Open access to Earth land-cover map. *Nature* vol. 514 434 (2014).

29. Li, W. *et al.* Gross and net land cover changes in the main plant functional types derived from the annual ESA CCI land cover maps (1992–2015). *Earth Syst. Sci. Data* **10**, 219 (2018).

30. Channan, S., Collins, K. & Emanuel, W. R. Global mosaics of the standard MODIS land cover type data. *Univ. Maryl. Pacific Northwest Natl. Lab. Coll. Park. Maryland, USA* **30**, (2014).

31. Eros, U., Falls, S. & South, D. *NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-support Analysis Data (GFSAD) @ 30-m for Southeast and Northeast Asia Cropland Extent-Product (GFSAD30SEACE) User Guide*. (2018).

32. Pfister, S., Bayer, P., Koehler, A. & Hellweg, S. Environmental impacts of water use in global crop production: Hotspots and trade-offs with land use. *Environ. Sci. Technol.* **45**, 5761–5768 (2011).

33. Moran, D. & Kanemoto, K. Identifying species threat hotspots from global supply chains. *Nat. Ecol. Evol.* **1**, 23 (2017).

34. Sun, Z., Tukker, A. & Behrens, P. Going Global to Local: Connecting Top-Down Accounting and Local Impacts, A Methodological Review of Spatially Explicit Input-Output Approaches. *Environmental Science and Technology* vol. 53 1048–1062 (2019).

35. Ramankutty, N., Evan, A. T., Monfreda, C. & Foley, J. A. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochem. Cycles* **22**, n/a-n/a (2008).

36. Bruckner, M. *et al.* FABIO - The Construction of the Food and Agriculture Biomass Input-Output Model. *Environ. Sci. Technol.* **53**, 11302–11312 (2019).

37. Poore, J. & Nemecek, T. Reducing food's environmental impacts through producers and consumers. *Science (80-.).* **360**, 987–992 (2018).

38. Ceballos, G. *et al.* Accelerated modern human-induced species losses: Entering the sixth mass extinction. *Sci. Adv.* **1**, e1400253 (2015).

39. Pimm, S. L. *et al.* The biodiversity of species and their rates of extinction, distribution, and protection. *Science (80-.).* **344**, 1246752–1246752 (2014).

40. IPBES. *Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. (2019).

41. Díaz, S. *et al.* Pervasive human-driven decline of life on Earth points to the need for transformative change. *Science* vol. 366 (2019).

42. Clark, M. A. *et al.* Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets. *Science (80-.).* **370**, 705–708 (2020).

43. Mottet, A. *et al.* Livestock: On our plates or eating at our table? A new analysis of the feed/food debate. *Global Food Security* vol. 14 1–8 (2017).

44. Shepon, A., Eshel, G., Noor, E. & Milo, R. Energy and protein feed-to-food conversion efficiencies in the US and potential food security gains from dietary changes. *Environ. Res. Lett.* **11**, 105002 (2016).

45. Godfray, H. C. J. *et al.* Meat consumption, health, and the environment. *Science* vol. 361 (2018).

46. Clark, M. A., Springmann, M., Hill, J. & Tilman, D. Multiple health and environmental impacts of foods. *Proc. Natl. Acad. Sci. U. S. A.* **116**, 23357–23362 (2019).

47. Foley, J. A. *et al.* Solutions for a cultivated planet. *Nature* **478**, 337–342 (2011).

48. Pingali, P. L. Green revolution: Impacts, limits, andthe path ahead. *Proceedings of the National Academy of Sciences of the United States of America* vol. 109 12302–12308 (2012).

49. Fears, R., Canales Holzeis, C. & ter Meulen, V. Designing inter-regional engagement to inform cohesive policy making. *Palgrave Communications* vol. 6 1–5 (2020).

50. Lutter, S., Pfister, S., Giljum, S., Wieland, H. & Mutel, C. Spatially explicit assessment of water embodied in European trade: A product-level multi-regional input-output analysis. *Glob. Environ. Chang.* **38**, 171–182 (2016).

51. Behrens, P. *et al.* Evaluating the environmental impacts of dietary recommendations. *Proc. Natl. Acad. Sci. U. S. A.* **114**, 13412–13417 (2017).

52. Wiedmann, T., Lenzen, M., Turner, K. & Barrett, J. Examining the global environmental impact of regional consumption activities—Part 2: Review of input–output models for the assessment of environmental impacts embodied in trade. *Ecol. Econ.* **61**, 15–26 (2007).

53. Hertwich, E. G. & Peters, G. P. Carbon footprint of nations: A global, trade-linked analysis. *Environ. Sci. Technol.* **43**, 6414–6420 (2009).

54. Weber, C. L. & Matthews, H. S. Embodied environmental emissions in US international trade, 1997− 2004. (2007).

55. Guan, D. *et al.* The socioeconomic drivers of China's primary PM2. 5 emissions. *Environ. Res. Lett.* **9**, 24010 (2014).

56. Takase, K., Kondo, Y. & Washizu, A. An analysis of sustainable consumption by the waste Input-Output model. *J. Ind. Ecol.* **9**, 201–219 (2005).

57. Zhao, X. *et al.* Physical and virtual water transfers for regional water stress alleviation in China. *Proc. Natl. Acad. Sci.* **112**, 1031–1035 (2015).

58. Yu, Y., Feng, K. & Hubacek, K. Tele-connecting local consumption to global land use. *Glob. Environ. Chang.* **23**, 1178–1186 (2013).

59. Lenzen, M. *et al.* International trade drives biodiversity threats in developing nations. *Nature* **486**, 109–112 (2012).

60. Tukker, A. *et al.* Environmental and resource footprints in a global context: Europe's

structural deficit in resource endowments. *Glob. Environ. Chang.* **40**, 171–181 (2016).

61. Yuan, R., Behrens, P. & Rodrigues, J. F. D. The evolution of inter-sectoral linkages in China's energy-related CO2 emissions from 1997 to 2012. *Energy Econ.* **69**, 404–417 (2018).

62. Moran, D., Petersone, M. & Verones, F. On the suitability of input–output analysis for calculating product-specific biodiversity footprints. *Ecol. Indic.* **60**, 192–201 (2016).

63. Peters, G. P. From production-based to consumption-based national emission inventories. *Ecol. Econ.* **65**, 13–23 (2008).

64. Yuan, R., Behrens, P., Tukker, A. & Rodrigues, J. F. D. Carbon overhead: The impact of the expansion in low-carbon electricity in China 2015–2040. *Energy Policy* **119**, 97–104 (2018).

65. Wiedmann, T. A review of recent multi-region input–output models used for consumption-based emission and resource accounting. *Ecol. Econ.* **69**, 211–222 (2009).

66. Marques, A., Rodrigues, J., Lenzen, M. & Domingos, T. Income-based environmental responsibility. *Ecol. Econ.* **84**, 57–65 (2012).

67. Behrens, P., Rodrigues, J. F. D., Brás, T. & Silva, C. Environmental, economic, and social impacts of feed-in tariffs: A Portuguese perspective 2000–2010. *Appl. Energy* **173**, 309–319 (2016).

68. Liang, S., Qu, S. & Xu, M. Betweenness-Based Method to Identify Critical Transmission Sectors for Supply Chain Environmental Pressure Mitigation. *Environ. Sci. Technol.* **50**, 1330–1337 (2016).

69. Janssens-Maenhout, G. *et al.* EDGAR v4. 3.2 Global Atlas of the three major Greenhouse Gas Emissions for the period 1970–2012. *Earth Syst. Sci. Data Discuss* (2017).

70. Flörke, M. *et al.* Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: A global simulation study. *Glob. Environ. Chang.* **23**, 144–156 (2013).

71. van Vliet, M. T. H., Flörke, M. & Wada, Y. Quality matters for water scarcity. *Nat. Geosci.* **10**, 800 (2017).

72. IUCN. The IUCN red list of threatened species: 2015-14. (2015).

73. International, B. IUCN Red List for birds. (2013).

74. Beer, C. *et al.* Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. *Science (80-.).* **329**, 834–838 (2010).

75. Van Donkelaar, A., Martin, R. V, Brauer, M. & Boys, B. L. Use of satellite observations

for long-term exposure assessment of global concentrations of fine particulate matter. *Environ. Health Perspect.* **123**, 135 (2015).

76. Friedl, M. A. *et al.* MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sens. Environ.* **114**, 168–182 (2010).

77. Teng, Y. *et al.* Soil and soil environmental quality monitoring in China: a review. *Environ. Int.* **69**, 177–199 (2014).

78. Lloyd, C. E. M., Freer, J. E., Johnes, P. J. & Collins, A. L. Using hysteresis analysis of high-resolution water quality monitoring data, including uncertainty, to infer controls on nutrient and sediment transfer in catchments. *Sci. Total Environ.* **543**, 388–404 (2016).

79. Lamarche, C. *et al.* Compilation and validation of SAR and optical data products for a complete and global map of inland/ocean water tailored to the climate modeling community. *Remote Sens.* **9**, 36 (2017).

80. Meyer, C., Kreft, H., Guralnick, R. & Jetz, W. Global priorities for an effective information basis of biodiversity distributions. *Nat. Commun.* **6**, (2015).

81. Rost, S. *et al.* Agricultural green and blue water consumption and its influence on the global water system. *Water Resour. Res.* **44**, (2008).

82. Alcamo, J. *et al.* Development and testing of the WaterGAP 2 global model of water use and availability. *Hydrol. Sci. J.* **48**, 317–337 (2003).

83. Hansen, K. M., Christensen, J. H., Brandt, J., Frohn, L. M. & Geels, C. Modelling atmospheric transport of α-hexachlorocyclohexane in the Northern Hemispherewith a 3-D dynamical model: DEHM-POP. *Atmos. Chem. Phys.* **4**, 1125–1137 (2004).

84. Klein Goldewijk, K., Beusen, A., Van Drecht, G. & De Vos, M. The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years. *Glob. Ecol. Biogeogr.* **20**, 73–86 (2011).

85. Hoekstra, A. Y. & Wiedmann, T. O. Humanity's unsustainable environmental footprint. *Science (80-.).* **344**, 1114–1117 (2014).

86. Hoekstra, A. Y. & Mekonnen, M. M. The water footprint of humanity. *Proc. Natl. Acad. Sci.* **109**, 3232–3237 (2012).

87. Mekonnen, M. & Hoekstra, A. Y. The green, blue and grey water footprint of crops and derived crops products. *Hydrol. earth Syst. Sci. Discuss.* **8**, 763–809 (2011).

88. Wang, Y. *et al.* Spatial production fragmentation and PM2.5 related emissions transfer through three different trade patterns within China. *J. Clean. Prod.* **195**, 703–720 (2018).

89. Ridoutt, B. G., Hadjikakou, M., Nolan, M. & Bryan, B. A. From Water-Use to Water-Scarcity Footprinting in Environmentally Extended Input–Output Analysis. *Environ. Sci. Technol.* **52**, 6761–6770 (2018).

90. Wilting, H. C., Schipper, A. M., Bakkenes, M., Meijer, J. R. & Huijbregts, M. A. J. Quantifying Biodiversity Losses Due to Human Consumption: A Global-Scale Footprint Analysis. *Environ. Sci. Technol.* **51**, 3298–3306 (2017).

91. Verones, F., Moran, D., Stadler, K., Kanemoto, K. & Wood, R. Resource footprints and their ecosystem consequences. *Sci. Rep.* **7**, 40743 (2017).

92. Ploszaj, A., Celinska-Janowicz, D., Rok, J. & Zawalinska, K. *Regional Input-Output Studies: A Systematic Literature Review*. (2015).

93. James, D. E., Chambers, J. A., Kalma, J. D. & Bridgman, H. A. Air quality prediction in urban and semi-urban regions with generalised input–output analysis: the Hunter Region, Australia. *Urban Ecol.* **9**, 25–44 (1985).

94. Gassert, F., Landis, M., Luck, M., Reig, P. & Shiao, T. Aqueduct global maps 2.0. *Water Resour. Inst. Washington, DC* 202011–202012 (2013).

95. Kanemoto, K., Moran, D. & Hertwich, E. G. Mapping the carbon footprint of nations. *Environ. Sci. Technol.* **50**, 10512–10517 (2016).

96. Moran, D. & Kanemoto, K. Tracing global supply chains to air pollution hotspots. *Environ. Res. Lett.* **11**, 94017 (2016).

97. Wang, R., Zimmerman, J., Wangt, R. & Zimmerman, J. Hybrid Analysis of Blue Water Consumption and Water Scarcity Implications at the Global, National, and Basin Levels in an Increasingly Globalized World. *Environ. Sci. Technol.* **50**, 5143–5153 (2016).

98. Lin, J. *et al.* China's international trade and air pollution in the United States. *Proc. Natl. Acad. Sci.* **111**, 1736–1741 (2014).

99. Wang, H. *et al.* Trade-driven relocation of air pollution and health impacts in China. *Nat. Commun.* **8**, 738 (2017).

100. Chen, L. *et al.* Trade-induced atmospheric mercury deposition over China and implications for demand-side controls. *Environ. Sci. Technol.* **52**, 2036–2045 (2018).

101. Zhao, H. *et al.* Effects of atmospheric transport and trade on air pollution mortality in China. *Atmos. Chem. Phys.* **17**, 10367–10381 (2017).

102. Lin, J. *et al.* Global climate forcing of aerosols embodied in international trade. *Nat. Geosci.* **9**, 790 (2016).

103. Jiang, X. *et al.* Revealing the hidden health costs embodied in Chinese exports. *Environ. Sci. Technol.* **49**, 4381–4388 (2015).

104. Zhang, Q. *et al.* Transboundary health impacts of transported global air pollution and international trade. *Nature* **543**, 705–709 (2017).

105. Ivanova, D. *et al.* Mapping the carbon footprint of EU regions. *Environ. Res. Lett.* **12**,

54013 (2017).

106. Marin, G. & Modica, M. Socio-economic exposure to natural disasters. *Environ. Impact Assess. Rev.* **64**, 57–66 (2017).

107. Moran, D. *et al.* Carbon footprints of 13 000 cities. *Environ. Res. Lett.* **13**, 064041 (2018).

108. Feng, K. *et al.* Spatially Explicit Analysis of Water Footprints in the UK. *Water* **3**, 47–63 (2011).

109. Godar, J., Persson, U. M., Tizado, E. J. & Meyfroidt, P. Towards more accurate and policy relevant footprint analyses: tracing fine-scale socio-environmental impacts of production to consumption. *Ecol. Econ.* **112**, 25–35 (2015).

110. Steen-Olsen, K., Wood, R. & Hertwich, E. G. The Carbon Footprint of Norwegian Household Consumption 1999-2012. *J. Ind. Ecol.* **20**, 582–592 (2016).

111. Malik, A., McBain, D., Wiedmann, T. O., Lenzen, M. & Murray, J. Advancements in Input-Output Models and Indicators for Consumption-Based Accounting. *J. Ind. Ecol.* (2018) doi:10.1111/jiec.12771.

112. Mi, Z. *et al.* A multi-regional input-output table mapping China's economic outputs and interdependencies in 2012. *Sci. Data* **5**, 180155 (2018).

113. Holland, R. A. *et al.* Global impacts of energy demand on the freshwater resources of nations. *Proc. Natl. Acad. Sci. U. S. A.* **112**, E6707–E6716 (2015).

114. Moran, D. & Kanemoto, K. Identifying species threat hotspots from global supply chains. *Nat. Ecol. Evol.* **1**, 23 (2017).

115. Mekonnen, M. M., Lutter, S. & Martinez, A. Anthropogenic Nitrogen and Phosphorus Emissions and Related Grey Water Footprints Caused by EU-27's Crop Production and Consumption. *Water* **8**, 30 (2016).

116. Cazcarro, I., Duarte, R., Sanchez-Choliz, J. & Sánchez Chóliz, J. Downscaling the grey water footprints of production and consumption. *J. Clean. Prod.* **132**, 171–183 (2016).

117. McDonald, G. W., Smith, N. J., Kim, J., Cronin, S. J. & Proctor, J. N. The spatial and temporal 'cost'of volcanic eruptions: assessing economic impact, business inoperability, and spatial distribution of risk in the Auckland region, New Zealand. *Bull. Volcanol.* **79**, 48 (2017).

118. Kim, J. H. & Hewings, G. J. D. Integrating the fragmented regional and subregional socioeconomic forecasting and analysis: a spatial regional econometric input-output framework. *Ann. Reg. Sci.* **49**, 485–513 (2012).

119. Zhou, X., Lei, K., Khu, S.-T. T. & Meng, W. Spatial flow analysis of water pollution in eco-natural systems. *Ecol. Indic.* **69**, 310–317 (2016).

120. Zhou, X., Lei, K., Meng, W. & Khu, S.-T. T. Industrial structural upgrading and spatial optimization based on water environment carrying capacity. *J. Clean. Prod.* **165**, 1462–1472 (2017).

121. Van Der Veen, A. & Logtmeijer, C. Economic hotspots: visualizing vulnerability to flooding. *Nat. hazards* **36**, 65–80 (2005).

122. Long, Y., Yoshida, Y. & Dong, L. Exploring the indirect household carbon emissions by source: Analysis on 49 Japanese cities. *J. Clean. Prod.* **167**, 571–581 (2017).

123. Zhang, Z. *et al.* Assessment of the ripple effects and spatial heterogeneity of total losses in the capital of China after a great catastrophic shock. *Nat. Hazards Earth Syst. Sci.* **17**, 367 (2017).

124. Larsen, H. N. & Hertwich, E. G. Identifying important characteristics of municipal carbon footprints. *Ecol. Econ.* **70**, 60–66 (2010).

125. Larsen, H. N. & Hertwich, E. G. Analyzing the carbon footprint from public services provided by counties. *J. Clean. Prod.* **19**, 1975–1981 (2011).

126. Minx, J. *et al.* Carbon footprints of cities and other human settlements in the UK. *Environ. Res. Lett.* **8**, 35039 (2013).

127. Baiocchi, G., Minx, J. & Hubacek, K. The impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom. *J. Ind. Ecol.* **14**, 50–72 (2010).

128. Poom, A. & Ahas, R. How Does the Environmental Load of Household Consumption Depend on Residential Location? *Sustainability* **8**, 799 (2016).

129. Lenzen, M., Dey, C. & Foran, B. Energy requirements of Sydney households. *Ecol. Econ.* **49**, 375–399 (2004).

130. Chen, G., Hadjikakou, M., Wiedmann, T. & Shi, L. Global warming impact of suburbanization: The case of Sydney. *J. Clean. Prod.* **172**, 287–301 (2018).

131. Lenzen, M. & Peters, G. M. How city dwellers affect their resource hinterland. *J. Ind. Ecol.* **14**, 73–90 (2010).

132. Baynes, T., Lenzen, M., Steinberger, J. K. & Bai, X. Comparison of household consumption and regional production approaches to assess urban energy use and implications for policy. *Energy Policy* **39**, 7298–7309 (2011).

133. Isman, M. *et al.* Ecological Footprint assessment for targeting climate change mitigation in cities: A case study of 15 Canadian cities according to census metropolitan areas. *J. Clean. Prod.* **174**, 1032–1043 (2018).

134. Jones, C. M. & Kammen, D. M. Quantifying Carbon Footprint Reduction Opportunities for U.S. Households and Communities. *Environ. Sci. Technol.* **45**, 4088–4095 (2011).

135. Baabou, W., Grunewald, N., Ouellet-Plamondon, C., Gressot, M. & Galli, A. The Ecological Footprint of Mediterranean cities: Awareness creation and policy implications. *Environ. Sci. Policy* **69**, 94–104 (2017).

136. Ottelin, J., Heinonen, J. & Junnila, S. Carbon footprint trends of metropolitan residents in Finland: How strong mitigation policies affect different urban zones. *J. Clean. Prod.* **170**, 1523–1535 (2018).

137. Thomas, B. A., Hausfather, Z. & Azevedo, I. L. Comparing the magnitude of simulated residential rebound effects from electric end-use efficiency across the US. *Environ. Res. Lett.* **9**, 074010 (2014).

138. Liu, L. *et al.* Assessment and determinants of per capita household CO2 emissions (PHCEs) based on capital city level in China. *J. Geogr. Sci.* **28**, 1467–1484 (2018).

139. Gill, B. & Moeller, S. GHG Emissions and the Rural-Urban Divide. A Carbon Footprint Analysis Based on the German Official Income and Expenditure Survey. *Ecol. Econ.* **145**, 160–169 (2018).

140. Laine, J. *et al.* Consequential Implications of Municipal Energy System on City Carbon Footprints. *Sustainability* **9**, 1801 (2017).

141. Goldstein, B. P., Hauschild, M. Z., Fernández, J. E. & Birkved, M. Contributions of Local Farming to Urban Sustainability in the Northeast United States. *Environ. Sci. Technol.* **51**, 7340–7349 (2017).

142. Han, L., Xu, X. & Han, L. Applying quantile regression and Shapley decomposition to analyzing the determinants of household embedded carbon emissions: evidence from urban China. *J. Clean. Prod.* **103**, 219–230 (2015).

143. Jones, C. & Kammen, D. M. Spatial distribution of US household carbon footprints reveals suburbanization undermines greenhouse gas benefits of urban population density. *Environ. Sci. Technol.* **48**, 895–902 (2014).

144. Jones, C. M., Wheeler, S. M. & Kammen, D. M. Carbon Footprint Planning: Quantifying Local and State Mitigation Opportunities for 700 California Cities. *Urban Plan.* **3**, 35 (2018).

145. Boero, R., Edwards, B. K. & Rivera, M. K. Regional input–output tables and trade flows: an integrated and interregional non-survey approach. *Reg. Stud.* **52**, 225–238 (2018).

146. Faturay, F., Lenzen, M. & Nugraha, K. A new sub-national multi-region input–output database for Indonesia. *Econ. Syst. Res.* **29**, 234–251 (2017).

147. Jahn, M. Extending the FLQ formula: a location quotient-based interregional input–output framework. *Reg. Stud.* **51**, 1518–1529 (2017).

148. Sargento, A. L. M., Ramos, P. N. & Hewings, G. J. D. Inter-regional Trade Flow Estimation Through Non-Survey Models: An Empirical Assessment. *Econ. Syst. Res.* **24**,

173–193 (2012).

149. Többen, J. & Kronenberg, T. H. Construction of Multiregional Input–Ouptput Tables Using The CHARM Method. *Econ. Syst. Res.* **27**, 487–507 (2015).

150. Lenzen, M. *et al.* Compiling and using input–output frameworks through collaborative virtual laboratories. *Sci. Total Environ.* **485–486**, 241–251 (2014).

151. Hasegawa, R., Kagawa, S. & Tsukui, M. Carbon footprint analysis through constructing a multi-region input–output table: a case study of Japan. *J. Econ. Struct.* **4**, 5 (2015).

152. Cazcarro, I., Duarte, R. & Sánchez Chóliz, J. Multiregional Input–Output Model for the Evaluation of Spanish Water Flows. *Environ. Sci. Technol.* **47**, 12275–12283 (2013).

153. Flach, R., Ran, Y., Godar, J., Karlberg, L. & Suavet, C. Towards more spatially explicit assessments of virtual water flows: linking local water use and scarcity to global demand of Brazilian farming commodities. *Environ. Res. Lett.* **11**, 75003 (2016).

154. Godar, J., Suavet, C., Gardner, T. A., Dawkins, E. & Meyfroidt, P. Balancing detail and scale in assessing transparency to improve the governance of agricultural commodity supply chains. *Environ. Res. Lett.* **11**, 35015 (2016).

155. Lenzen, M. *et al.* New multi-regional input–output databases for Australia – enabling timely and flexible regional analysis. *Econ. Syst. Res.* **29**, 275–295 (2017).

156. Davis, S. J., Peters, G. P. & Caldeira, K. The supply chain of CO_2 emissions. *Proc. Natl. Acad. Sci.* **108**, 18554–18559 (2011).

157. You, L., Wood, S., Wood-Sichra, U. & Wu, W. Generating global crop distribution maps: From census to grid. *Agric. Syst.* **127**, 53–60 (2014).

158. Robinson, T. P. *et al.* Mapping the Global Distribution of Livestock. *PLoS One* **9**, e96084 (2014).

159. Tong, D. *et al.* Targeted emission reductions from global super-polluting power plant units. *Nat. Sustain.* **1**, 59 (2018).

160. Platnick, S. *the earth observer National Aeronautics and Space Administration The Earth Observer*. vol. 30.

161. Meijer, J. R., Huijbregts, M. A. J., Schotten, K. C. G. J. & Schipper, A. M. Global patterns of current and future road infrastructure. *Environ. Res. Lett.* **13**, 064006 (2018).

162. Verburg, P. H., Ellis, E. C. & Letourneau, A. A global assessment of market accessibility and market influence for global environmental change studies. *Environ. Res. Lett.* **6**, 034019 (2011).

163. SECEX. SISCOMEX system. *Secretariat of Foreign Trade of the Brazilian Ministry of Development, Industry and Foreign Trade* (2018).

164. Kirches, G. *et al.* Land Cover CCI-Product User Guide-Version 2. *ESA Public Doc. CCI-LC-PUG* 4 (2014).

165. Teluguntla, P. *et al.* Global Food Security Support Analysis Data (GFSAD) at Nominal 1 km (GCAD) Derived from Remote Sensing in Support of Food Security in the Twenty-First Century: Current Achievements and Future Possibilities. (2015).

166. Gassert, F., Luck, M., Landis, M., Reig, P. & Shiao, T. Aqueduct global maps 2.1: Constructing decision-relevant global water risk indicators. *World Resour. Inst.* (2014).

167. Sood, A. & Smakhtin, V. Global hydrological models: a review. *Hydrol. Sci. J.* **60**, 549–565 (2015).

168. Nakagaki, N. *Grids of agricultural pesticide use in the conterminous United States, 1997*. (2007).

169. Rondinini, C. *et al.* Global habitat suitability models of terrestrial mammals. *Philos. Trans. R. Soc. B Biol. Sci.* **366**, 2633–2641 (2011).

170. Rosenzweig, C. *et al.* Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proc. Natl. Acad. Sci.* **111**, 3268–3273 (2014).

171. You, L. *et al.* Spatial production allocation model (SPAM) 2005 v2. 0. *Available mapspam. info. Accessed June* **29**, 2015 (2014).

172. Arrouays, D. *et al.* GlobalSoilMap for Soil Organic Carbon Mapping and as a Basis for Global Modeling. in *Proceedings of the global symposium on soil organic carbon 2017* 27–30 (2017).

173. Kshetri, N. 1 Blockchain's roles in meeting key supply chain management objectives. *Int. J. Inf. Manage.* **39**, 80–89 (2018).

174. Hubacek, K., Feng, K., Minx, J., Pfister, S. & Zhou, N. Teleconnecting consumption to environmental impacts at multiple spatial scales–research frontiers in environmental footprinting. *J. Ind. Ecol.* **18**, 7–9 (2014).

175. Tukker, A. *et al.* Towards Robust, Authoritative Assessments of Environmental Impacts Embodied in Trade: Current State and Recommendations. *J. Ind. Ecol.* **22**, 585–598 (2018).

176. Riddington, G., Gibson, H. & Anderson, J. Comparison of Gravity Model, Survey and Location Quotient-based Local Area Tables and Multipliers. *Reg. Stud.* **40**, 1069–1081 (2006).

177. Hirbli, T. *Palm Oil traceability: Blockchain meets supply chain*. (2018).

178. Behrens, P., van Vliet, M. T. H., Nanninga, T., Walsh, B. & Rodrigues, J. F. D. Climate change and the vulnerability of electricity generation to water stress in the European

Union. *Nat. Energy* **2**, 17114 (2017).

179. Su, B., Huang, H. C., Ang, B. W. & Zhou, P. Input–output analysis of CO 2 emissions embodied in trade: the effects of sector aggregation. *Energy Econ.* **32**, 166–175 (2010).

180. Wiedmann, T. O. *et al.* The material footprint of nations. *Proc. Natl. Acad. Sci.* **112**, 6271–6276 (2015).

181. Su, B. & Ang, B. W. Input–output analysis of CO 2 emissions embodied in trade: the effects of spatial aggregation. *Ecol. Econ.* **70**, 10–18 (2010).

182. Dietzenbacher, E. *et al.* Input–output analysis: the next 25 years. *Econ. Syst. Res.* **25**, 369–389 (2013).

183. Mattila, T., Koskela, S., Seppälä, J. & Mäenpää, I. Sensitivity analysis of environmentally extended input–output models as a tool for building scenarios of sustainable development. *Ecol. Econ.* **86**, 148–155 (2013).

184. Wu, X. & Chen, G. Energy use by Chinese economy: A systems cross-scale input-output analysis. *Energy Policy* **108**, 81–90 (2017).

185. Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I. & Heynen, M. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS J. Photogramm. Remote Sens.* **58**, 239–258 (2004).

186. Sandefur, J. & Glassman, A. The political economy of bad data: evidence from African survey and administrative statistics. *J. Dev. Stud.* **51**, 116–132 (2015).

187. Lenzen, M., Wood, R. & Wiedmann, T. Uncertainty analysis for multi-region input–output models–a case study of the UK's carbon footprint. *Econ. Syst. Res.* **22**, 43–63 (2010).

188. Karstensen, J., Peters, G. P. & Andrew, R. M. Uncertainty in temperature response of current consumption-based emissions estimates. *Earth Syst. Dyn.* **6**, 287 (2015).

189. Wiedmann, T., Wood, R., Minx, J., Lenzen, M. & Harris, R. Emissions embedded in UK trade–UK-MRIO model results and error estimates. in *International input–output meeting on managing the environment* 9–11 (2008).

190. Bullard, C. W. & Sebald, A. V. Monte Carlo sensitivity analysis of input-output models. *Rev. Econ. Stat.* 708–712 (1988).

191. Oita, A. *et al.* Substantial nitrogen pollution embedded in international trade. *Nat. Geosci.* **9**, 111–115 (2016).

192. Wilting, H. C. Sensitivity and uncertainty analysis in mrio modelling; some empirical results with regard to the dutch carbon footprint. *Econ. Syst. Res.* **24**, 141–171 (2012).

193. Yan, J., Zhao, T. & Kang, J. Sensitivity analysis of technology and supply change for

CO 2 emission intensity of energy-intensive industries based on input–output model. *Appl. Energy* **171**, 456–467 (2016).

194. Lenzen, M. Errors in conventional and Input-Output—based Life—Cycle inventories. *J. Ind. Ecol.* **4**, 127–148 (2000).

195. Rodrigues, J. F. D., Moran, D., Wood, R. & Behrens, P. Uncertainty of Consumption-Based Carbon Accounts. *Environ. Sci. Technol.* **52**, 7577–7586 (2018).

196. Stehfest, E., van Vuuren, D., Bouwman, L. & Kram, T. *Integrated assessment of global environmental change with IMAGE 3.0: Model description and policy applications*. (Netherlands Environmental Assessment Agency (PBL), 2014).

197. West, T. O., Le Page, Y., Huang, M., Wolf, J. & Thomson, A. M. Downscaling global land cover projections from an integrated assessment model for use in regional analyses: results and evaluation for the US from 2005 to 2095. *Environ. Res. Lett.* **9**, 64004 (2014).

198. Hasegawa, T., Fujimori, S., Ito, A., Takahashi, K. & Masui, T. Global land-use allocation model linked to an integrated assessment model. *Sci. Total Environ.* **580**, 787–796 (2017).

199. Hurtt, G. C. *et al.* Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands. *Clim. Change* **109**, 117 (2011).

200. Humpenöder, F. *et al.* Land-use and carbon cycle responses to moderate climate change: implications for land-based mitigation? *Environ. Sci. Technol.* **49**, 6731–6739 (2015).

201. Fujimori, S. *et al.* Downscaling Global Emissions and Its Implications Derived from Climate Model Experiments. *PLoS One* **12**, e0169733 (2017).

202. Hellmann, F. & Verburg, P. H. Spatially explicit modelling of biofuel crops in Europe. *Biomass and Bioenergy* **35**, 2411–2424 (2011).

203. Verburg, P. H., Eickhout, B. & van Meijl, H. A multi-scale, multi-model approach for analyzing the future dynamics of European land use. *Ann. Reg. Sci.* **42**, 57–77 (2008).

204. Hurtt, G. C. *et al.* The underpinnings of land-use history: Three centuries of global gridded land-use transitions, wood-harvest activity, and resulting secondary lands. *Glob. Chang. Biol.* **12**, 1208–1229 (2006).

205. Thomson, A. M. *et al.* Climate mitigation and the future of tropical landscapes. *Proc. Natl. Acad. Sci.* **107**, 19633–19638 (2010).

206. Kraucunas, I. *et al.* Investigating the nexus of climate, energy, water, and land at decision-relevant scales: the Platform for Regional Integrated Modeling and Analysis (PRIMA). *Clim. Change* **129**, 573–588 (2015).

207. Hejazi, M. I. *et al.* Integrated assessment of global water scarcity over the 21st century under multiple climate change mitigation policies. *Hydrol. Earth Syst. Sci.* **18**, 2859–

2883 (2014).

208. Voisin, N. *et al.* Effects of spatially distributed sectoral water management on the redistribution of water resources in an integrated water model. *Water Resour. Res.* **53**, 4253–4270 (2017).

209. Müller, C. *et al.* Drivers and patterns of land biosphere carbon balance reversal. *Environ. Res. Lett.* **11**, 44002 (2016).

210. Pauliuk, S., Arvesen, A., Stadler, K. & Hertwich, E. G. Industrial ecology in integrated assessment models. *Nat. Clim. Chang.* **7**, 13–20 (2017).

211. Wiebe, K. S. The impact of renewable energy diffusion on European consumption-based emissions. *Econ. Syst. Res.* **28**, 133–150 (2016).

212. De Koning, A., Huppes, G., Deetman, S. & Tukker, A. Scenarios for a 2 °C world: a trade-linked input–output model with high sector detail. *Clim. Policy* **16**, 301–317 (2016).

213. Meyfroidt, P. Trade-offs between environment and livelihoods: Bridging the global land use and food security discussions. *Glob. Food Sec.* **16**, 9–16 (2018).

214. Godfray, H. C. J. *et al.* Food Security: The Challenge of Feeding 9 Billion People. *Science (80-.).* **327**, 812–818 (2010).

215. UN. *World Population Prospects 2019:Highlights*. (2019).

216. FAO. *The future of food and agriculture – Alternative pathways to 2050*. (2018) doi:CC BY-NC-SA 3.0 IGO.

217. Pellegrini, P. & Fernández, R. J. Crop intensification, land use, and on-farm energy-use efficiency during the worldwide spread of the green revolution. **6**, 2335–2340 (2018).

218. Wood, S. A., Smith, M. R., Fanzo, J., Remans, R. & DeFries, R. S. Trade and the equitability of global food nutrient distribution. *Nat. Sustain.* **1**, 34–37 (2018).

219. Alston, J. M., Beddow, J. M. & Pardey, P. G. Agricultural research, productivity, and food prices in the long run. *Science (80-.).* **325**, 1209–1210 (2009).

220. Ray, D. K., Mueller, N. D., West, P. C. & Foley, J. A. Yield trends are insufficient to double global crop production by 2050. *PLoS One* **8**, e66428 (2013).

221. Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C. & Foley, J. A. Recent patterns of crop yield growth and stagnation. *Nat. Commun.* **3**, 1293 (2012).

222. Springmann, M. *et al.* Options for keeping the food system within environmental limits. *Nature* **562**, 519–525 (2018).

223. Bruckner, M. *et al.* Quantifying the global cropland footprint of the European Union's non-food bioeconomy. *Environ. Res. Lett.* (2019) doi:10.1088/1748-9326/ab07f5.

224. Wang, R. & Zimmerman, J. Hybrid Analysis of Blue Water Consumption and Water Scarcity Implications at the Global, National, and Basin Levels in an Increasingly Globalized World. *Environ. Sci. Technol.* **50**, 5143–5153 (2016).

225. Henning, S. *et al.* Livestock's long shadow–environmental issues and options. *Roma, IT, FAO* (2006).

226. Van Boeckel, T. P. *et al.* Global trends in antimicrobial use in food animals. *Proc. Natl. Acad. Sci. U. S. A.* **112**, 5649–54 (2015).

227. Xue, L. *et al.* Missing Food, Missing Data? A Critical Review of Global Food Losses and Food Waste Data. *Environ. Sci. Technol.* **51**, 6618–6633 (2017).

228. Lesk, C., Rowhani, P. & Ramankutty, N. Influence of extreme weather disasters on global crop production. *Nature* **529**, 84–87 (2016).

229. Green, R. E., Cornell, S. J., Scharlemann, J. P. W. & Balmford, A. Farming and the fate of wild nature. *Science (80-.).* **307**, 550–555 (2005).

230. Balmford, A., Green, R. & Scharlemann, J. P. W. Sparing land for nature: exploring the potential impact of changes in agricultural yield on the area needed for crop production. *Glob. Chang. Biol.* **11**, 1594–1605 (2005).

231. Scherer, L. *et al.* Trade-offs between social and environmental Sustainable Development Goals. *Environ. Sci. Policy* **90**, 65–72 (2018).

232. Lambin, E. F. & Meyfroidt, P. Global land use change, economic globalization, and the looming land scarcity. *Proc. Natl. Acad. Sci. U. S. A.* **108**, 3465–72 (2011).

233. Kissinger, M. International trade related food miles–The case of Canada. *Food Policy* **37**, 171–178 (2012).

234. Fader, M., Gerten, D., Krause, M., Lucht, W. & Cramer, W. Spatial decoupling of agricultural production and consumption: quantifying dependences of countries on food imports due to domestic land and water constraints. *Environ. Res. Lett.* **8**, 14046 (2013).

235. D'Odorico, P., Carr, J. A., Laio, F., Ridolfi, L. & Vandoni, S. Feeding humanity through global food trade. *Earth's Futur.* **2**, 458–469 (2014).

236. Barona, E., Ramankutty, N., Hyman, G. & Coomes, O. T. The role of pasture and soybean in deforestation of the Brazilian Amazon. *Environ. Res. Lett.* **5**, 024002 (2010).

237. Lapola, D. M. *et al.* Pervasive transition of the Brazilian land-use system. *Nat. Clim. Chang.* **4**, 27–35 (2014).

238. Naylor, R. L. Oil crops, aquaculture, and the rising role of demand: A fresh perspective on food security. *Glob. Food Sec.* **11**, 17–25 (2016).

239. Austin, K. G. *et al.* Shifting patterns of oil palm driven deforestation in Indonesia and

implications for zero-deforestation commitments. *Land use policy* **69**, 41–48 (2017).

240. Suweis, S., Carr, J. A., Maritan, A., Rinaldo, A. & D'Odorico, P. Resilience and reactivity of global food security. *Proc. Natl. Acad. Sci. U. S. A.* **112**, 6902–7 (2015).

241. Stadler, K. *et al.* EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *J. Ind. Ecol.* (2017).

242. Schulte-Mecklenbeck, M., Sohn, M., de Bellis, E., Martin, N. & Hertwig, R. A lack of appetite for information and computation. Simple heuristics in food choice. *Appetite* **71**, 242–251 (2013).

243. Tukker, A. & Dietzenbacher, E. Global multiregional input–output frameworks: an introduction and outlook. *Econ. Syst. Res.* **25**, 1–19 (2013).

244. Robinson, T. P. *et al.* Mapping the global distribution of livestock. *PLoS One* **9**, e96084 (2014).

245. Steffen, W. *et al.* Planetary boundaries: guiding human development on a changing planet. *Science* **347**, 1259855 (2015).

246. Campbell, B. M. *et al.* Agriculture production as a major driver of the Earth system exceeding planetary boundaries. *Ecol. Soc.* **22**, art8 (2017).

247. UNEP. *The Emissions Gap Report*. (2014).

248. IPCC. *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,*. (2018).

249. Hoekstra, A. Y. & Wiedmann, T. O. Humanity's unsustainable environmental footprint. *Science* **344**, 1114–7 (2014).

250. Bringezu, S. Possible Target Corridor for Sustainable Use of Global Material Resources. *Resources* **4**, 25–54 (2015).

251. FAOSTAT. FAOSTAT. (2019).

252. Willett, W. *et al.* Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. *Lancet* **393**, 447–492 (2019).

253. Suweis, S., Carr, J. A., Maritana, A., Rinaldo, A. & D'Odorico, P. Resilience and reactivity of global food security. *Proc. Natl. Acad. Sci. U. S. A.* **112**, 6902–6907 (2015).

254. Behrens, P. *et al.* Evaluating the environmental impacts of dietary recommendations. *Proc. Natl. Acad. Sci.* **114**, 13412–13417 (2017).

255. Godar, J., Persson, U. M., Tizado, E. J. & Meyfroidt, P. Towards more accurate and

policy relevant footprint analyses: Tracing fine-scale socio-environmental impacts of production to consumption. *Ecol. Econ.* **112**, 25–35 (2015).

256. Google Map. World Ports.

257. Gardner, T. A. *et al.* Transparency and sustainability in global commodity supply chains. *World Dev.* **121**, 163–177 (2019).

258. Coates, J. Build it back better: Deconstructing food security for improved measurement and action. *Glob. Food Sec.* **2**, 188–194 (2013).

259. Chen, B. *et al.* Global land-water nexus: Agricultural land and freshwater use embodied in worldwide supply chains. *Sci. Total Environ.* **613–614**, 931–943 (2018).

260. Chen, G. & Han, M. Global supply chain of arable land use: Production-based and consumption-based trade imbalance. *Land use policy* **49**, 118–130 (2015).

261. Fuglie, K. O. Is agricultural productivity slowing? *Glob. Food Sec.* **17**, 73–83 (2018).

262. Rulli, M. C., Saviori, A., D'Odorico, P. & D'Odorico, P. Global land and water grabbing. *Proc. Natl. Acad. Sci.* **110**, 892–897 (2013).

263. Fukase, E. & Martin, W. Who will feed China in the 21st century? Income growth and food demand and supply in China. *J. Agric. Econ.* **67**, 3–23 (2016).

264. Yao, G., Hertel, T. W. & Taheripour, F. Economic drivers of telecoupling and terrestrial carbon fluxes in the global soybean complex. *Glob. Environ. Chang.* **50**, 190–200 (2018).

265. FAO, IFAD, UNICEF, WFP & WHO. *The State of Food Security and Nutrition in the World 2019. Safeguarding against economic slowdowns and downturns*. (FAO, 2019).

266. Scherer, L. & Pfister, S. Global Biodiversity Loss by Freshwater Consumption and Eutrophication from Swiss Food Consumption. *Environ. Sci. Technol.* **50**, 7019–7028 (2016).

267. Moran, D. & Kanemoto, K. Identifying species threat hotspots from global supply chains. *Nat. Ecol. Evol.* **1**, 0023 (2017).

268. Gilbert, M. *et al.* Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010. *Sci. Data* **5**, 180227 (2018).

269. Smith, T. M. *et al.* Subnational mobility and consumption-based environmental accounting of US corn in animal protein and ethanol supply chains. *Proc. Natl. Acad. Sci. U. S. A.* **114**, E7891–E7899 (2017).

270. Sandström, V. *et al.* The role of trade in the greenhouse gas footprints of EU diets. *Glob. Food Sec.* **19**, 48–55 (2018).

271. Zuo, L. *et al.* Progress towards sustainable intensification in China challenged by land-

use change. *Nat. Sustain.* **1**, 304–313 (2018).

272. Carlson, K. M. *et al.* Greenhouse gas emissions intensity of global croplands. *Nat. Clim. Chang.* **7**, 63–68 (2017).

273. He, P., Baiocchi, G., Hubacek, K., Feng, K. & Yu, Y. The environmental impacts of rapidly changing diets and their nutritional quality in China. *Nat. Sustain.* **1**, 122–127 (2018).

274. Liu, J. *et al.* A high-resolution assessment on global nitrogen flows in cropland. *Proc. Natl. Acad. Sci. U. S. A.* **107**, 8035–40 (2010).

275. Weinzettel, J., Vačkář, D. & Medková, H. Human footprint in biodiversity hotspots. *Front. Ecol. Environ.* **16**, 447–452 (2018).

276. Pfister, S., Bayer, P., Koehler, A. & Hellweg, S. Environmental Impacts of Water Use in Global Crop Production: Hotspots and Trade-Offs with Land Use. *Environ. Sci. Technol.* **45**, 5761–5768 (2011).

277. Obersteiner, M. *et al.* Assessing the land resource–food price nexus of the Sustainable Development Goals. *Sci. Adv.* **2**, e1501499 (2016).

278. Isbell, F. *et al.* Linking the influence and dependence of people on biodiversity across scales. *Nature* **546**, 65–72 (2017).

279. Díaz, S. *et al.* Assessing nature's contributions to people. *Science (80-.).* **359**, 270 LP-272 (2018).

280. Rockström, J. *et al.* A safe operating space for humanity. *Nature* **461**, 472–475 (2009).

281. Steffen, W. *et al.* Planetary boundaries: Guiding human development on a changing planet. *Science (80-.).* **347**, 1259855 (2015).

282. Samper, C. Planetary boundaries: Rethinking biodiversity. *Nat. Clim. Chang.* **1**, 118–119 (2009).

283. UN. Transforming our world: The 2030 agenda for sustainable development. *Resolut. Adopt. by Gen. Assem.* (2015).

284. CBD High-Level Panel. *Resourcing the Aichi Biodiversity Targets: An Assessment of Benefits, Investments and Resource needs for Implementing the Strategic Plan for Biodiversity 2011-2020.* (2014).

285. KBA Standards and Appeals Committee. *Guidelines for using a global standard for the identification of Key Biodiversity Areas : version 1.0.* (2019) doi:10.2305/IUCN.CH.2019.KBA.1.0.en.

286. BirdLife International. *Digital boundaries of Key Biodiversity Areas from the World Database of Key Biodiversity Areas.*

http://www.keybiodiversityareas.org/site/requestgis (2020).

287. Langhammer, P. F. *et al*. *Identification and Gap Analysis of Key Biodiversity Areas: Targets for Comprehensive Protected Area Systems*. (2007).

288. Convention on Biological Diversity. *Updated synthesis of the proposals of Parties and observers on the structure of the post-2020 global biodiversity framework and its targets*. (2020) doi:https://www.cbd.int/conferences/post2020/post2020-prep-01/documents.

289. Visconti, P. *et al.* Protected area targets post-2020. *Science (80-.).* **364**, 239 LP-241 (2019).

290. Dudley, N., Boucher, J. L., Cuttelod, A., Brooks, T. M. & Langhammer, P. F. *Applications of Key Biodiversity Areas: End-user consultations*. (2014).

291. Marques, A. *et al.* Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. *Nat. Ecol. Evol.* **3**, 628–637 (2019).

292. Chaudhary, A. & Brooks, T. M. Land Use Intensity-Specific Global Characterization Factors to Assess Product Biodiversity Footprints. *Environ. Sci. Technol.* **52**, 5094–5104 (2018).

293. Sun, Z., Scherer, L., Tukker, A. & Behrens, P. Linking global crop and livestock consumption to local production hotspots. *Glob. Food Sec.* **25**, 100323 (2020).

294. Lenzen, M. *et al.* International trade drives biodiversity threats in developing nations. *Nature* **486**, 109–112 (2012).

295. Peters, G. P., Minx, J. C., Weber, C. L. & Edenhofer, O. Growth in emission transfers via international trade from 1990 to 2008. *Proc. Natl. Acad. Sci. U. S. A.* **108**, 8903–8908 (2011).

296. Moran, D. & Kanemoto, K. Identifying species threat hotspots from global supply chains. *Nat. Ecol. Evol.* **1**, 0023 (2017).

297. Vijay, V. & Armsworth, P. R. Pervasive cropland in protected areas highlight trade-offs between conservation and food security. *Proc. Natl. Acad. Sci. U. S. A.* **118**, (2021).

298. Green, J. M. H. *et al.* Linking global drivers of agricultural trade to on-the-ground impacts on biodiversity. *Proc. Natl. Acad. Sci. U. S. A.* **116**, 23202–23208 (2019).

299. Alkemade, R., Reid, R. S., Van Den Berg, M., De Leeuw, J. & Jeuken, M. Assessing the impacts of livestock production on biodiversity in rangeland ecosystems. *Proc. Natl. Acad. Sci. U. S. A.* **110**, 20900–20905 (2013).

300. Reid, R. *et al.* Global Livestock Impacts on Biodiversity. in *Livestock in a Changing Landscape. Drivers, Consequences, and Responses* (eds. Steinfeld, H., Mooney, H. A., Schneider, F. & Neville, L. E.) 111–138 (Island Press, 2010).

301. Jones, P. J. Biodiversity in the Gulf of Guinea: an overview. *Biodivers. Conserv.* **3**, 772–784 (1994).

302. Chaudhary, A., Verones, F., de Baan, L. & Hellweg, S. Quantifying Land Use Impacts on Biodiversity: Combining Species–Area Models and Vulnerability Indicators. *Environ. Sci. Technol.* **49**, 9987–9995 (2015).

303. Newbold, T. *et al.* Global effects of land use on local terrestrial biodiversity. *Nature* **520**, 45–50 (2015).

304. Chaudhary, A., Pfister, S. & Hellweg, S. Spatially Explicit Analysis of Biodiversity Loss Due to Global Agriculture, Pasture and Forest Land Use from a Producer and Consumer Perspective. *Environ. Sci. Technol.* **50**, 3928–3936 (2016).

305. Henry, R. C. *et al.* The role of global dietary transitions for safeguarding biodiversity. *Glob. Environ. Chang.* **58**, 101956 (2019).

306. Leclère, D. *et al.* Bending the curve of terrestrial biodiversity needs an integrated strategy. *Nature* 1–6 (2020).

307. Weinzettel, J., Vačkář, D. & Medková, H. Human footprint in biodiversity hotspots. *Front. Ecol. Environ.* **16**, 447–452 (2018).

308. Chaudhary, A. & Brooks, T. M. National Consumption and Global Trade Impacts on Biodiversity. *World Dev.* **121**, 178–187 (2019).

309. Balmford, A. *et al.* Conservation conflicts across africa. *Science (80-.).* **291**, 2616–2619 (2001).

310. Rands, M. R. W. *et al.* Biodiversity conservation: Challenges beyond 2010. *Science* vol. 329 1298–1303 (2010).

311. Kullberg, P., Di Minin, E. & Moilanen, A. Using key biodiversity areas to guide effective expansion of the global protected area network. *Glob. Ecol. Conserv.* **20**, e00768 (2019).

312. Bingham, H. C. *et al.* Sixty years of tracking conservation progress using the World Database on Protected Areas. *Nat. Ecol. Evol.* **3**, 737–743 (2019).

313. Johnson, D. M. Using the Landsat archive to map crop cover history across the United States. *Remote Sens. Environ.* **232**, 111286 (2019).

314. Descals, A. *et al.* High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth Syst. Sci. Data Discuss.* (2020) doi:10.5194/essd-2020-159.

315. Fritz, S. *et al.* Mapping global cropland and field size. *Glob. Chang. Biol.* **21**, 1980–1992 (2015).

316. Marques, A., Verones, F., Kok, M. T. J., Huijbregts, M. A. J. & Pereira, H. M. How to

quantify biodiversity footprints of consumption? A review of multi-regional input–output analysis and life cycle assessment. *Curr. Opin. Environ. Sustain.* **29**, 75–81 (2017).

317. Duelli, P. & Obrist, M. K. Biodiversity indicators: the choice of values and measures. *Agric. Ecosyst. Environ.* **98**, 87–98 (2003).

318. Scherer, L., van Baren, S. A. & van Bodegom, P. M. Characterizing land use impacts on functional plant diversity for life cycle assessments. *Environ. Sci. Technol.* acs.est.9b07228 (2020) doi:10.1021/acs.est.9b07228.

319. Chiarucci, A., Bacaro, G. & Scheiner, S. M. Old and new challenges in using species diversity for assessing biodiversity. *Philos. Trans. R. Soc. B Biol. Sci.* **366**, 2426–2437 (2011).

320. Marquardt, S. G. *et al.* Consumption-based biodiversity footprints – Do different indicators yield different results? *Ecol. Indic.* **103**, 461–470 (2019).

321. Mazor, T. *et al.* Global mismatch of policy and research on drivers of biodiversity loss. *Nat. Ecol. Evol.* **2**, 1071–1074 (2018).

322. IPBES. *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. (2019) doi:https://doi.org/10.5281/zenodo.3553579.

323. Bruckner, M. *et al.* FABIO—The Construction of the Food and Agriculture Biomass Input–Output Model. *Environ. Sci. Technol.* **53**, 11302–11312 (2019).

324. Stadler, K. *et al.* EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *J. Ind. Ecol.* **22**, 502–515 (2018).

325. Kanemoto, K., Moran, D. & Hertwich, E. G. Mapping the Carbon Footprint of Nations. *Environ. Sci. Technol.* **50**, 10512–10517 (2016).

326. Scherer, L. *et al.* Trade-offs between social and environmental Sustainable Development Goals. *Environ. Sci. Policy* **90**, 65–72 (2018).

327. Semba, R. D. *et al.* Adoption of the 'planetary health diet' has different impacts on countries' greenhouse gas emissions. *Nat. Food* **1**, 481–484 (2020).

328. Behrens, P. *et al.* Evaluating the environmental impacts of dietary recommendations. *Proc. Natl. Acad. Sci. U. S. A.* **114**, 13412–13417 (2017).

329. FAOSTAT. FAOSTAT. *FAOSTAT* (2019).

330. You, L., Wood-Sichra, U., Bacou, M. & Koo, J. Spatial Production Allocation Model (SPAM) 2005 v3.2. (2017).

331. Monfreda, C., Ramankutty, N. & Foley, J. A. Farming the planet: 2. Geographic

distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochem. Cycles* **22**, n/a-n/a (2008).

332. Bruckner, M., Fischer, G., Tramberend, S. & Giljum, S. Measuring telecouplings in the global land system: A review and comparative evaluation of land footprint accounting methods. *Ecol. Econ.* **114**, 11–21 (2015).

333. Schulze, K., Malek, Ž. & Verburg, P. H. Towards better mapping of forest management patterns: A global allocation approach. *For. Ecol. Manage.* **432**, 776–785 (2019).

334. Hansen, M. C. *et al.* High-resolution global maps of 21st-century forest cover change. *Science (80-.).* **342**, 850–853 (2013).

335. Hoskins, A. J. *et al.* Downscaling land-use data to provide global 30″ estimates of five land-use classes. *Ecol. Evol.* **6**, 3040–3055 (2016).

336. Erb, K.-H. *et al.* A comprehensive global 5 min resolution land-use data set for the year 2000 consistent with national census data. *J. Land Use Sci.* **2**, 191–224 (2007).

337. Sun, Z., Tukker, A. & Behrens, P. Going Global to Local: Connecting Top-Down Accounting and Local Impacts, A Methodological Review of Spatially Explicit Input–Output Approaches. *Environ. Sci. Technol.* **53**, 1048–1062 (2019).

338. Martins, I. S. & Pereira, H. M. Improving extinction projections across scales and habitats using the countryside species-area relationship. *Sci. Rep.* **7**, 1–7 (2017).

339. Chaudhary, A., Verones, F., De Baan, L., Pfister, S. & Hellweg, S. *Land stress: Potential species loss from land use (global; PSSRg)*. (2016).

340. Clark, M. A. *et al.* Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets. *Science (80-.).* **370**, 705–708 (2020).

341. Griscom, B. W. *et al.* Natural climate solutions. *Proc. Natl. Acad. Sci. U. S. A.* **114**, 11645–11650 (2017).

342. Willett, W. *et al.* Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. *The Lancet* vol. 393 447–492 (2019).

343. Searchinger, T., Waite, R., Hanson, C. & Ranganathan, J. *Creating a sustainable food future: a menu of solutions to feed nearly 10 billion people by 2050. World Resources Institute* vol. 1 (2019).

344. Canadell, J. G. & Schulze, E. D. Global potential of biospheric carbon management for climate mitigation. *Nat. Commun.* **5**, 1–12 (2014).

345. Herrero, M. *et al.* Greenhouse gas mitigation potentials in the livestock sector. *Nature Climate Change* vol. 6 452–461 (2016).

346. Meier, T. & Christen, O. Environmental impacts of dietary recommendations and dietary

styles: Germany as an example. *Environ. Sci. Technol.* **47**, 877–888 (2013).

347. Westhoek, H. *et al.* Food choices, health and environment: Effects of cutting Europe's meat and dairy intake. *Glob. Environ. Chang.* **26**, 196–205 (2014).

348. Sahlin, K. R., Röös, E. & Gordon, L. J. 'Less but better'meat is a sustainability message in need of clarity. *Nat. Food* **1**, 520–522 (2020).

349. Behrens, P. *et al.* Evaluating the environmental impacts of dietary recommendations. *Proc. Natl. Acad. Sci. U. S. A.* **114**, 13412–13417 (2017).

350. Fargione, J. E. *et al.* Natural climate solutions for the United States. *Sci. Adv.* **4**, eaat1869 (2018).

351. Lamb, A. *et al.* The potential for land sparing to offset greenhouse gas emissions from agriculture. *Nat. Clim. Chang.* **6**, 488–492 (2016).

352. Erb, K. H. *et al.* Unexpectedly large impact of forest management and grazing on global vegetation biomass. *Nature* **553**, 73–76 (2018).

353. Searchinger, T. D., Wirsenius, S., Beringer, T. & Dumas, P. Assessing the efficiency of changes in land use for mitigating climate change. *Nature* vol. 564 249–253 (2018).

354. Cook-Patton, S. C. *et al.* Mapping carbon accumulation potential from global natural forest regrowth. *Nature* **585**, 545–550 (2020).

355. Soto-Navarro, C. *et al.* Mapping co-benefits for carbon storage and biodiversity to inform conservation policy and action. *Philos. Trans. R. Soc. B Biol. Sci.* **375**, 20190128 (2020).

356. Sanderman, J., Hengl, T. & Fiske, G. J. Soil carbon debt of 12,000 years of human land use. *Proc. Natl. Acad. Sci. U. S. A.* **114**, 9575–9580 (2017).

357. FAO. FAOSTAT. (2020).

358. Spawn, S. A., Sullivan, C. C., Lark, T. J. & Gibbs, H. K. Harmonized global maps of above and belowground biomass carbon density in the year 2010. *Sci. Data* **7**, (2020).

359. Hengl, T. & Wheeler, I. Soil organic carbon stock in kg/m2 for 5 standard depth intervals (0–10, 10–30, 30–60, 60–100 and 100–200 cm) at 250 m resolution. (2018) doi:10.5281/ZENODO.2536040.

360. Sun, Z., Scherer, L., Tukker, A. & Behrens, P. Linking global crop and livestock consumption to local production hotspots. *Glob. Food Sec.* **25**, 100323 (2019).

361. Kanemoto, K., Moran, D. & Hertwich, E. G. Mapping the Carbon Footprint of Nations. *Environ. Sci. Technol.* **50**, 10512–10517 (2016).

362. Hayek, M. N., Harwatt, H., Ripple, W. J. & Mueller, N. D. The carbon opportunity cost

of animal-sourced food production on land. *Nat. Sustain.* 1–4 (2020) doi:10.1038/s41893-020-00603-4.

363. De Vrese, M. *et al.* Probiotics - Compensation for lactase insufficiency. in *American Journal of Clinical Nutrition* vol. 73 421s–429s (American Society for Nutrition, 2001).

364. Scherer, L., Behrens, P. & Tukker, A. Opportunity for a Dietary Win-Win-Win in Nutrition, Environment, and Animal Welfare. *One Earth* **1**, 349–360 (2019).

365. Shepon, A., Eshel, G., Noor, E. & Milo, R. The opportunity cost of animal based diets exceeds all food losses. *Proc. Natl. Acad. Sci. U. S. A.* **115**, 3804–3809 (2018).

366. Laroche, P. C. S. J., Schulp, C. J. E., Kastner, T. & Verburg, P. H. Telecoupled environmental impacts of current and alternative Western diets. *Glob. Environ. Chang.* **62**, 102066 (2020).

367. Scherer, L. A., Verburg, P. H. & Schulp, C. J. E. Opportunities for sustainable intensification in European agriculture. *Glob. Environ. Chang.* **48**, 43–55 (2018).

368. Lire Wachamo, H. Review on Health Benefit and Risk of Coffee Consumption. *Med. Aromat. Plants* **6**, (2017).

369. Zaitsu, M., Takeuchi, T., Kobayashi, Y. & Kawachi, I. Light to moderate amount of lifetime alcohol consumption and risk of cancer in Japan. *Cancer* **126**, 1031–1040 (2020).

370. Osorio-Paz, I., Brunauer, R. & Alavez, S. Beer and its non-alcoholic compounds in health and disease. *Critical Reviews in Food Science and Nutrition* (2019) doi:10.1080/10408398.2019.1696278.

371. de Coninck, P. & Gilmore, I. Long overdue: a fresh start for EU policy on alcohol and health. *The Lancet* vol. 395 10–13 (2020).

372. Manthey, J. *et al.* Global alcohol exposure between 1990 and 2017 and forecasts until 2030: a modelling study. *Lancet* **393**, 2493–2502 (2019).

373. Bansback, B. Future Directions for the Global Meat Industry? *EuroChoices* **13**, 4–11 (2014).

374. Xue, L. *et al.* Efficiency and Carbon Footprint of the German Meat Supply Chain. *Environ. Sci. Technol.* **53**, 5133–5142 (2019).

375. IPCC. *Global warming of 1.5°C*. (2018) doi:https://www.ipcc.ch/sr15/.

376. Pozo, C., Galán-Martín, Á., Reiner, D. M., Mac Dowell, N. & Guillén-Gosálbez, G. Equity in allocating carbon dioxide removal quotas. *Nat. Clim. Chang.* **10**, 640–646 (2020).

377. Folberth, C. *et al.* The global cropland-sparing potential of high-yield farming. *Nat. Sustain.* **3**, 281–289 (2020).

378. Goldstein, A. *et al.* Protecting irrecoverable carbon in Earth's ecosystems. *Nat. Clim. Chang.* 1–9 (2020).

379. Yang, Y. *et al.* Restoring Abandoned Farmland to Mitigate Climate Change on a Full Earth. *One Earth* **3**, 176–186 (2020).

380. Yang, Y., Tilman, D., Furey, G. & Lehman, C. Soil carbon sequestration accelerated by restoration of grassland biodiversity. *Nat. Commun.* **10**, 1–7 (2019).

381. Lewis, S. L., Wheeler, C. E., Mitchard, E. T. A. & Koch, A. Restoring natural forests is the best way to remove atmospheric carbon. *Nature* **568**, 25–28 (2019).

382. van Zalk, J. & Behrens, P. The spatial extent of renewable and non-renewable power generation: A review and meta-analysis of power densities and their application in the U.S. *Energy Policy* **123**, 83–91 (2018).

383. Field, J. L. *et al.* Robust paths to net greenhouse gas mitigation and negative emissions via advanced biofuels. *Proc. Natl. Acad. Sci. U. S. A.* **117**, 21968–21977 (2020).

384. Tilman, D., Hill, J. & Lehman, C. Carbon-negative biofuels from low-input high-diversity grassland biomass. *Science (80-.).* **314**, 1598–1600 (2006).

385. Robertson, G. P. *et al.* Cellulosic biofuel contributions to a sustainable energy future: Choices and outcomes. *Science* vol. 356 (2017).

386. Philipso, C. D. *et al.* Active restoration accelerates the carbon recovery of human-modified tropical forests. *Science (80-.).* **369**, 838–841 (2020).

387. Zahawi, R. A., Reid, J. L. & Holl, K. D. Hidden Costs of Passive Restoration. *Restor. Ecol.* **22**, 284–287 (2014).

388. Scown, M. W., Brady, M. V. & Nicholas, K. A. Billions in Misspent EU Agricultural Subsidies Could Support the Sustainable Development Goals. *One Earth* **3**, 237–250 (2020).

389. The Food and Land Use Coalition. *Growing Better: Ten Critical Transitions to Transform Food and Land Use*. (2019).

390. International Food Policy Research Institute (IFPRI). Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 1.1. *Harvard Dataverse, V3* (2019) doi:https://doi.org/10.7910/DVN/PRFF8V.

391. Wolf, J. *et al.* Biogenic carbon fluxes from global agricultural production and consumption. *Global Biogeochem. Cycles* **29**, 1617–1639 (2015).

392. Lal, R. Digging deeper: A holistic perspective of factors affecting soil organic carbon sequestration in agroecosystems. *Global Change Biology* vol. 24 3285–3301 (2018).

393. Sloat, L. L. *et al.* Increasing importance of precipitation variability on global livestock

grazing lands. *Nat. Clim. Chang.* **8**, 214–218 (2018).

394. West, P. C. *et al.* Trading carbon for food: Global comparison of carbon stocks vs. crop yields on agricultural land. *Proc. Natl. Acad. Sci. U. S. A.* **107**, 19645–19648 (2010).

395. Johnson, J. A., Runge, C. F., Senauer, B., Foley, J. & Polasky, S. Global agriculture and carbon trade-offs. *Proc. Natl. Acad. Sci. U. S. A.* **111**, 12342–12347 (2014).

396. Beck, H. E. *et al.* Present and future köppen-geiger climate classification maps at 1-km resolution. *Sci. Data* **5**, 1–12 (2018).

397. Hirvonen, K., Bai, Y., Headey, D. & Masters, W. A. Affordability of the EAT–Lancet reference diet: a global analysis. *Lancet Glob. Heal.* **8**, e59–e66 (2020).

398. Hanley-Cook, G. T. *et al.* EAT- Lancet Diet Score Requires Minimum Intake Values to Predict Higher Micronutrient Adequacy of Diets in Rural Women of Reproductive Age from Five Low- And Middle-Income Countries. *Br. J. Nutr.* 1–9 (2020) doi:10.1017/S0007114520003864.

399. Xie, W. *et al.* Decreases in global beer supply due to extreme drought and heat. *Nat. Plants* **4**, 964–973 (2018).

400. Hasegawa, T. *et al.* Risk of increased food insecurity under stringent global climate change mitigation policy. *Nat. Clim. Chang.* **8**, 699–703 (2018).

401. Griffiths, P., Nendel, C. & Hostert, P. Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping. *Remote Sens. Environ.* **220**, 135–151 (2019).

402. Wang, J. *et al.* Mapping sugarcane plantation dynamics in Guangxi, China, by time series Sentinel-1, Sentinel-2 and Landsat images. *Remote Sens. Environ.* **247**, 111951 (2020).

403. Massey, R. *et al.* MODIS phenology-derived, multi-year distribution of conterminous U.S. crop types. *Remote Sens. Environ.* **198**, 490–503 (2017).

404. Azzari, G., Jain, M. & Lobell, D. B. Towards fine resolution global maps of crop yields: Testing multiple methods and satellites in three countries. *Remote Sens. Environ.* **202**, 129–141 (2017).

405. Lu, M. *et al.* A cultivated planet in 2010 – Part 1: The global synergy cropland map. *Earth Syst. Sci. Data* **12**, 1913–1928 (2020).

406. Descals, A. *et al.* High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth Syst. Sci. Data Discuss.* 1–22 (2020) doi:10.5194/essd-2020-159.

407. Zhou, Y. *et al.* Sharing tableware reduces waste generation, emissions and water consumption in China’s takeaway packaging waste dilemma. *Nat. Food* **1**, 552–561 (2020).

408. Chu, J., Liu, H. & Salvo, A. Air pollution as a determinant of food delivery and related plastic waste. *Nat. Hum. Behav.* **5**, 212–220 (2020).

409. Carvalho, V. M. *et al.* Tracking the COVID-19 crisis with high-resolution transaction data. (2020).

410. Dong, L., Ratti, C. & Zheng, S. Predicting neighborhoods' socioeconomic attributes using restaurant data. *Proc. Natl. Acad. Sci. U. S. A.* **116**, 15447–15452 (2019).

411. Kang, P. *et al.* Low-carbon pathways for the booming express delivery sector in China. *Nat. Commun.* **12**, 1–8 (2021).

412. Goldstein, B., Gounaridis, D. & Newell, J. P. The carbon footprint of household energy use in the United States. *Proc. Natl. Acad. Sci. U. S. A.* **117**, 19122–19130 (2020).

413. Liebe, U., Gewinner, J. & Diekmann, A. Large and persistent effects of green energy defaults in the household and business sectors. *Nat. Hum. Behav.* 1–10 (2021) doi:10.1038/s41562-021-01070-3.

414. Bjelle, E. L. *et al.* Adding country resolution to EXIOBASE: impacts on land use embodied in trade. *J. Econ. Struct.* **9**, 14 (2020).

415. Lenzen, M. *et al.* The Global MRIO Lab–charting the world economy. *Econ. Syst. Res.* **29**, 158–186 (2017).

416. Jiang, M. *et al.* Improving Subnational Input-Output Analyses Using Regional Trade Data: A Case-Study and Comparison. *Environ. Sci. Technol.* **54**, 12732–12741 (2020).

417. OEC. The Observatory of Economic Complexity. *OEC* https://oec.world/ (2021).

418. Barbier, E. B., Burgess, J. C. & Dean, T. J. How to pay for saving biodiversity. *Science (80-.).* **360**, 486 LP-488 (2018).

419. Vijay, V. & Armsworth, P. R. Pervasive cropland in protected areas highlight trade-offs between conservation and food security. *Proc. Natl. Acad. Sci. U. S. A.* **118**, 2021 (2021).

420. Vollset, S. E. *et al.* Fertility, mortality, migration, and population scenarios for 195 countries and territories from 2017 to 2100: a forecasting analysis for the Global Burden of Disease Study. *Lancet* (2020) doi:10.1016/S0140-6736(20)30677-2.

421. Bager, S. L., Persson, U. M. & dos Reis, T. N. P. Eighty-six EU policy options for reducing imported deforestation. *One Earth* **4**, 289–306 (2021).

422. Dallimer, M. & Strange, N. Why socio-political borders and boundaries matter in conservation. *Trends in Ecology and Evolution* vol. 30 132–139 (2015).

423. Wilman, E. A. Market Redirection Leakage in the Palm Oil Market. *Ecol. Econ.* **159**, 226–234 (2019).

424. Moher, D. *et al.* Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Syst. Rev.* **4**, 1 (2015).

425. Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G. & Group, P. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Med.* **6**, e1000097 (2009).

426. Didan, K. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. NASA EOSDIS Land Processes DAAC. *USGS* vol. 5 2002–2015 (2015).

427. European Space Agency. 300 m Annual global land cover time series from 1992 to 2015. *Eur. Sp. Agency - Clim. Chang. Initiat.* (2017).

428. Heffer, P. *Assessment of Fertilizer Use by Crop at the Global Level*. (2013).

429. Scherer, L. & Verburg, P. H. Mapping and linking supply- and demand-side measures in climate-smart agriculture. A review. *Agronomy for Sustainable Development* vol. 37 1–17 (2017).

430. Sakiroglu, M., Dong, C., Hall, M. B., Jungers, J. & Picasso, V. How does nitrogen and forage harvest affect belowground biomass and nonstructural carbohydrates in dual-use Kernza intermediate wheatgrass? *Crop Sci.* **60**, 2562–2573 (2020).

431. Lanker, M., Bell, M. & Picasso, V. D. Farmer perspectives and experiences introducing the novel perennial grain Kernza intermediate wheatgrass in the US Midwest. *Renew. Agric. Food Syst.* 1–10 (2019) doi:10.1017/S1742170519000310.

432. Hristov, A. N. *et al.* An inhibitor persistently decreased enteric methane emission from dairy cows with no negative effect on milk production. *Proc. Natl. Acad. Sci. U. S. A.* **112**, 10663–10668 (2015).

433. EURL. *Evaluation Report on the Analytical Methods submitted in connection with the Application for Authorisation of a Feed Additive according to Regulation (EC) No 1831/2003 3-Nitrooxypropanol (preparation of minimum of 10 % of 3-nitrooxypropanol)*. (2020).

434. Popkin, B. M., Corvalan, C. & Grummer-Strawn, L. M. Dynamics of the double burden of malnutrition and the changing nutrition reality. *The Lancet* vol. 395 65–74 (2020).

435. Xue, L. *et al.* Missing Food, Missing Data? A Critical Review of Global Food Losses and Food Waste Data. *Environ. Sci. Technol.* **51**, 6618–6633 (2017).

436. Yu, Y. & Jaenicke, E. C. Estimating Food Waste as Household Production Inefficiency. *Am. J. Agric. Econ.* **102**, 525–547 (2020).

437. Roe, S. *et al.* Contribution of the land sector to a 1.5 °C world. *Nature Climate Change* vol. 9 817–828 (2019).

438. Reganold, J. P. & Wachter, J. M. Organic agriculture in the twenty-first century. *Nature*

plants vol. 2 15221 (2016).

439. Knapp, S. & van der Heijden, M. G. A. A global meta-analysis of yield stability in organic and conservation agriculture. *Nat. Commun.* **9**, 1–9 (2018).

Appendix

8 Appendix

8.1 Supporting information to chapter 2

8.1.1 Critical review methodology – selection of the literature

We searched all papers using spatially-explicit input-output (SIO) approaches published before March, 2018 and analyzed their spatial scale, method, and environmental impacts.

We use Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to search for articles using SIO approaches, on March, 2018 (Figure S 8.1) [424]. PRISMA aims to be a standard operating procedure for systematic reviews, in order give a more reliable and less biased result [425]. The systematic and explicit methods for this systematic review reduces issues with identifying, selecting, synthesizing, summarizing, collecting and analyzing data [425]. It also allows for reproducibility by providing all the information required to perform the review. We searched three scientific catalogues: Web of Science, ScienceDirect and the Leiden University Catalogue. There is a large diversity of terms in the literature describing the same, spatially-explicit concept, including “map”, “mapping”, and “hotspots”. Of course, not all of these are synonyms, and not all of these studies are in fact spatially-explicit. In order to restrict the search further we included terms including “input-output” and “MRIO (Multi-Regional Input Output)”, For example, we use the combination of (“spatial*” or “map*” or “hotspot*”) and ("input output analysis" or "input output model" or "input output table" or "MRIO") in for the research topic in Web of Science. For the detailed protocol please see the Supporting Information.

The search criteria are: (1) that all papers are in English; (2) that all papers are in peer-reviewed; (3) that all papers use input-output method; (4) that all papers have spatially distributed results at a resolution higher than regional. A flow diagram of the search methodology is shown in Table S 8.1. After using search protocols, we find another 15 papers using Google Scholar, and then perform a snowball sampling of these papers, finding a further 14 eligible papers.

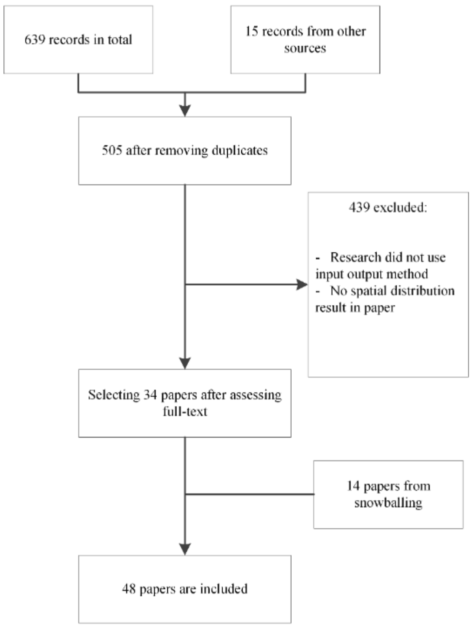

Figure S 8.1 Flow diagram of the search methodology used. After a large number of initial studies were found, these were filtered on the criteria described above to 48 analyses.

All these search terms are based on snowball sampling for each search library. Details are in Table S 8.1

Table S 8.1 Search terms used in meta-analysis for each database.

Database	Code	Search Results	After Duplicates Removed	Titles and Abstracts Screened				
Web of Science	(TS=("spatial*" OR "map*" OR "hotspot*") AND TS=("input output analysis" OR "input output model" OR "input output table" OR "MRIO")) *AND* LANGUAGE:(English)*AND* DOCUMENT TYPES:(Article OR Book OR Book Chapter OR Data Paper OR Database Review)	243	168	28				
ScienceDirect	(tak("input output analysis" OR "input output model" OR "input output table" or "MRIO")) AND (tak("spatial*" OR "map*" OR "hotspot*"))	155	110	16				
Leiden University Catalogue	(Any("input output analysis" OR "input output model" OR "input output table" OR "MRIO")) AND (Title("spatial*" OR "hotspot" OR "map*" OR "spatially-explicit")) AND Language(Englsih)	241	227	22	Full-text Assessed for Eligibility	Derived from other References	Derived from snowballing	Total
Total		639	505	66	19	15	14	48

8.1.2 **Methodological approaches in the literature**

Method 1: mapping between MRIO model and hydrological model—WaterGAP

Lutter et al. and Holland et al. combined an MRIO model (EXIOBASE in the case of Lutter et al. and GTAP8 in the case of Holland et al.), with WaterGAP model to research fresh water consumption embodied in trade almost at the same time [50,113]. Their core work is to build up mapping relationship between MRIO table and water consumption data from WaterGAP model by production sector, particularly different agricultural sectors (Table S 8.2).The difference was that Lutter et al mapped MRIO data into watershed scale, but Holland et al. mapped MRIO data into original resolution—0.5°×0.5° grid cell—of WaterGAP [113].

Table S 8.2 Example of disaggregation matrix, indicating which share of water consumption in a specific industry-region combination is originating form which watershed.

	Region 1			…	Region n		
	Ind 1	…	Ind n	…	Ind 1	…	Ind n
Watershed 1	0	…	0.95	…	0.57		0.3
…	…	…	…	…	…	…	…
Watershed m	1	…	0.05	…	0.43	…	0.7

Source: from Lutter et al.[50]

Method 2: identifying hotspots from supply chains

Kanemoto et al. developed a spatially-explicit MRIO method to identify spatially-explicit environmental impacts hotspots embodied in supply chain [95]. The core of this method is to nest spatial distribution map (R) into traditional multi-regional input-output model.

$$H_{(m)s} = \sum_r R^r \frac{\sum_i f_i^r \sum_{jt \neq s} L_{ij}^{rt} y_j^{ts}}{\sum_i d_i^r} \tag{S1}$$

$$H^{(c)s} = \sum_r R^r \frac{\sum_i f_i^r \sum_{jt} L_{ij}^{rt} y_j^{ts}}{\sum_i d_i^r} \tag{S2}$$

Table S 8.3 Variables and description of hotspots method.

Variables	Description
$H_{(m)s}$	the $PM_{2.5}$ emission hotspots H driven by imports (m) into country s
$H^{(c)s}$	the $PM_{2.5}$ emission hotspots H driven by total consumption (c) into country s
R	$PM_{2.5}$ emission maps term (R) are in absolute values
d	total emissions
f	intensity of $PM_{2.5}$

L	Leontief inverse
y	final demand
i	sector of origin and destination
j	sector of destination
r	exporting country
s	importing country
t	country of last sale in the consumption and imports terms

Method 3: integrating process-based model with input-output model

Wang et al. developed hybrid method that integrated process-based model with input-output model to analyze global water scarcity at basin level [97]. The most pivotal part of this method is

$$WSI_i^{BAU} = \frac{WW_i^{BAU}}{BA_i} \tag{S3}$$

$$WSI_i^{NT} = \frac{WW_i^{NT}}{BA_i} \tag{S4}$$

Table S 8.4 Variables and description of integrating process-based model with input-output model.

Variables	Description
WSI_i^{BAU}	Water stress index with international trade at basin ***i***
WSI_i^{NT}	Water stress index without international trade at basin ***i***
WW_i^{BAU}	Water withdraw at basin ***i*** with international trade
WW_i^{NT}	Water withdraw at basin ***i*** without international trade
BA_i	Blue water availability annually at basin ***i***

WW_i^{BAU} was calculated by downscaling production-based national water withdraws into basins based on water withdraw estimated Aqueduct Global Maps in 2010.

WW_i^{NT} was calculated by downscaling consumption-based national water withdraws, which got from MRIO model, into basins based on the same proportion of WW_i^{BAU}

Method 4: Integrating MRIO model with production-side location information.

Cazcarro et al. integrated input-output model with spatial location information to downscale grey water footprints into business level [116]. There were three steps to downscaling grey water footprints as following figure (Figure S 8.2): (1) estimating direct intensities of grey water footprints; (2) calculating grey water footprints with multi-regional input-output model; (3) downscaling grey water footprints into business level.

Mekonnen et al. estimated global agricultural grey water footprints driven by EU27 consumption with similar method of agricultural part in Cazcarro et al [115].

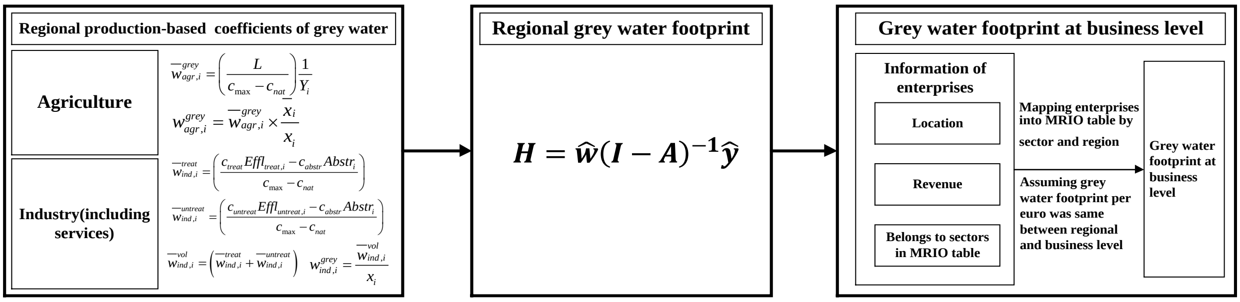

Figure S 8.2 Process of downscaling grey water footprints into business level.

Table S 8.5 Variables and description of method that downscales grey water footprints.

Variables	Description
$\overline{w}_{agr,i}^{grey}$	Agricultural physical grey water coefficient (m^3/ton) for i^{th} crop
L	Excess of nitrogen (kg/ha per year)
c_{max}	Maximum acceptable concentration
c_{nat}	Natural concentration
Y_i	Crop yield for i^{th} crop
$w_{agr,i}^{grey}$	Agricultural direct grey water coefficient (m^3/euro) for i^{th} crop
x_i	Agricultural output (euro) for i^{th} crop
$\bar{x}_i$	Agricultural production (ton) for i^{th} crop
$\overline{w}_{ind,i}^{treat}$	Amount of grey water from treated water(m^3) for sector i
$\overline{w}_{ind,i}^{untreat}$	Amount of grey water from untreated water(m^3) for sector i
c_{treat}	Concentration of treated effluent(mg/l)
c_{abstr}	Actual concentration(mg/l)
$Effl_{treat,i}$	Volume of treated effluent for sector i
$Abstr_i$	Water volume(m^3) for sector i
$c_{untreat}$	Concentration of untreated effluent(mg/l)
$Effl_{untreat,i}$	Volume of untreated effluent for sector i
$\overline{w}_{ind,i}^{vol}$	Total amount of grey water(m^3) for sector i

$w_{ind,i}^{grey}$	Direct grey water coefficient for sector *i*
$\boldsymbol{H}$	Grey water footprint matrix
$\hat{\boldsymbol{w}}$	Grey water coefficient matrix
$\boldsymbol{I}$	Identify matrix
$\boldsymbol{A}$	Technical coefficient matrix for input-output table
$\hat{\boldsymbol{y}}$	Final demand vector

Method 5: dynamic inoperability input-output model (DIIM)

Inoperability input-output model is a good tool to assess risk, and McDonald et al. integrated dynamic inoperability input-output model with volcanic locations to estimate economic loss [117].

Four steps to construct spatial map of risk by DIIM:

- splitting regional output into the finest spatial scale;
- evaluating production inoperability in each finest spatial location;
- estimating total economic impact by DIIM;
- adjusting total economic impacts based on hazard probability.

Method 6: combining data from MRIO table and demand-side subnational information.

Several researchers linked subnational information with input-output model to estimate subnational environmental impacts, the details referenced to their papers [105,108,123,126–128]. Maybe some small difference existed in their method, but the core of their method is to combine supply chain information in national input-output database or multi-regional input output database to track upstream environmental impacts with subnational consumption information to calculate subnational environmental impacts, for example consumer expenditure surveys (CESs), to calculate subnational environmental impacts.

For example, Feng et al. combined with geo-demographic data to calculate water footprints at subnational area. The core equations are as follows.

$$w_{Int} = e^{d^*}(I - A)^{-1}y + w_{hh} \tag{S10}$$

$$w_{Ext} = e^{i^*}(I - A)^{-1}y \tag{S11}$$

$$e^{d^*} = [e^d, 0] \tag{S12}$$

$$e^{i^*} = [0, e^i] \tag{S13}$$

$$y = \begin{bmatrix} y^d \\ y^i \end{bmatrix} \tag{S14}$$

Table S 8.6 Variables and description of method that combines with subnational information.

Variables	Description

w_{Int}	Water footprint from domestic consumption
w_{Ext}	Water footprint from other countries
w_{hh}	Water consumption from direct household consumption
e^d	Water consumption coefficients of domestic commodities
e^i	Water consumption coefficients of commodities from other countries
y^d	Final demand from domestic and export commodities
y^i	Final demand from other countries
$\boldsymbol{I}$	Identify matrix
$\boldsymbol{A}$	Technological coefficients matrix

A is from MRIO table at country level, and replace final demand ***y*** at regional level, it would calculate water footprint at local regional scale.

Method 7: integrating MRIO with GEOS-Chem model

Lin et al. and Zhang et al. combined multi-regional input-output model with GEOS-Chem to simulate transport of emissions [98,104]. Firstly, calculating environmental impacts (or emissions) embodied in trade at country level, and then using GEOS-Chem model to simulate the spatial distribution of environmental impacts on worldwide (Figure S 8.3). Zhang et al., also link health impacts model, Integrated Exposure-Response (IER), to simulate spatial distribution of premature death driven by consumption

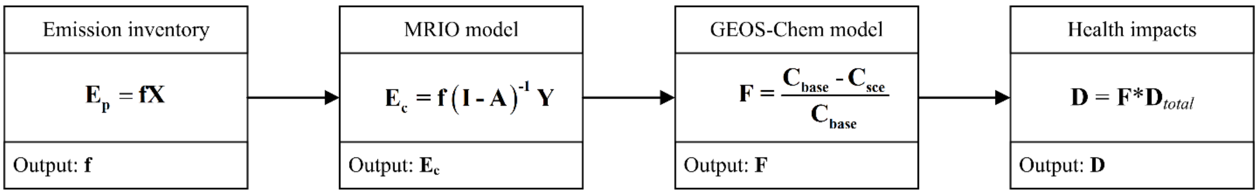

Figure S 8.3 Process of method that integrated with GEOS-Chem model.

Table S 8.7 Variables and description of method that integrated with GEOS-Chem model.

Variables	**Description**
$\boldsymbol{E_p}$	Emission matrix from production
$\boldsymbol{F}$	Emission intensity vector
$\boldsymbol{X}$	Total output
$\boldsymbol{E_c}$	Consumption-based emission matrix
$\boldsymbol{I}$	Identify matrix

A	Technological matrix
Y	Final demand vector
F	Spatial distribution of fractional contribution of emission derived from different scenarios
$\boldsymbol{C_{base}}$	Emission concentration on base scenarios
$\boldsymbol{C_{sce}}$	Emission concentration on different scenarios
D	Premature death population at grid cell driven by consumption
$\boldsymbol{D_{total}}$	Global total premature death population using IER model at grid cell

Method 8: combing input-output model with air pollution dispersion model.

Firstly, applying regional input-output table and emission inventory data to calculate emission coefficients of different sectors, and then using these coefficients to calculate amount of emission discharging sites [93]. Finally, applying smeared concentration approximation method (SCA) to simulate spatial diffusion of these emissions (Figure S 8.4).

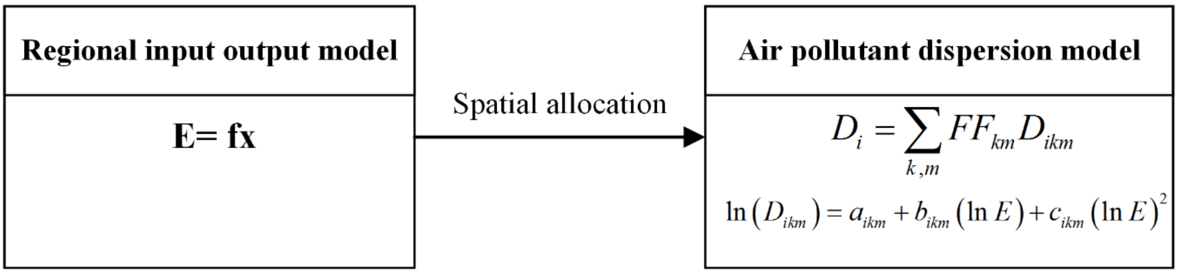

Figure S 8.4 Process of combing with air pollution dispersion model

Table S 8.8 Parameters and description of method that combines with air pollution dispersion model

Variables	Description
E	Production-based emission
F	Emission intensity
X	total output
D_i	Average concentration of emission between source and receiver
FF_{km}	Frequency of emission occur
D_{ikm}	Average contribution of concentration of emission at different situation
I	Emission classes
K	Atmospheric stability condition
M	Windspeed classes

Method 9: spatial regional econometric input–output model

Kim et al. developed spatial regional econometric input-output model through integrating regional econometric input–output model(REIM) with disequilibrium adjustment model, and they used the model to predict population and employment change of 296 municipalities in Chicago, USA [118]. The core of this method included 5 steps:

- Quantifying potential employment growth for year *t* based on exogenous national economic growth.
- Estimating information for grid cell in year *t*-1.
- Calculating employment and population at local level for year *t* based on information: (a) potential employment growth for year *t*-1 (b) information of grid cell for year *t* -1(c) their own information for year *t*-1 (d) interaction relationship between local-level employment and population.
- Updating macroeconomic variables for year *t* based on information of employment and population change with modified REIM formulation.
- Predicting information at grid cell level for year *t* via simple logic econometrics model or other more complicated simulation approach.

Method 10: Integrating MRIO model with GIS technology.

Van Der Veen et al. constructed contour map of value added based on employment data from enterprises and spatial interpolation methods with GIS platform, regarding multipliers from input-output model as the weight [121]. Similarly, Zhou et al. estimated spatial flow of chemical oxygen demand (COD) in Changzhou city, China at GIS platform [119,120,122].

Method 11 (in Trase.earth): spatially-explicit information on production to consumption systems(SEI-PCS) model

In order to trace spatial heterogeneity of environmental impacts related to production consumed by other regions within a country, especially large country, which contributes to global consumption. Godar et al. developed SEI-PCS model [109], and they used the model to analyse crops and virtual water embedded in farming commodities in Brazil at subnational scale [153,154]. The model downscales production consumed by domestic and other countries into finest scale, the municipality level, in a country. The following graph (Figure S 8.5) describes the core theory of this model, and the detail can reference to Godar et al. 2015 [109].

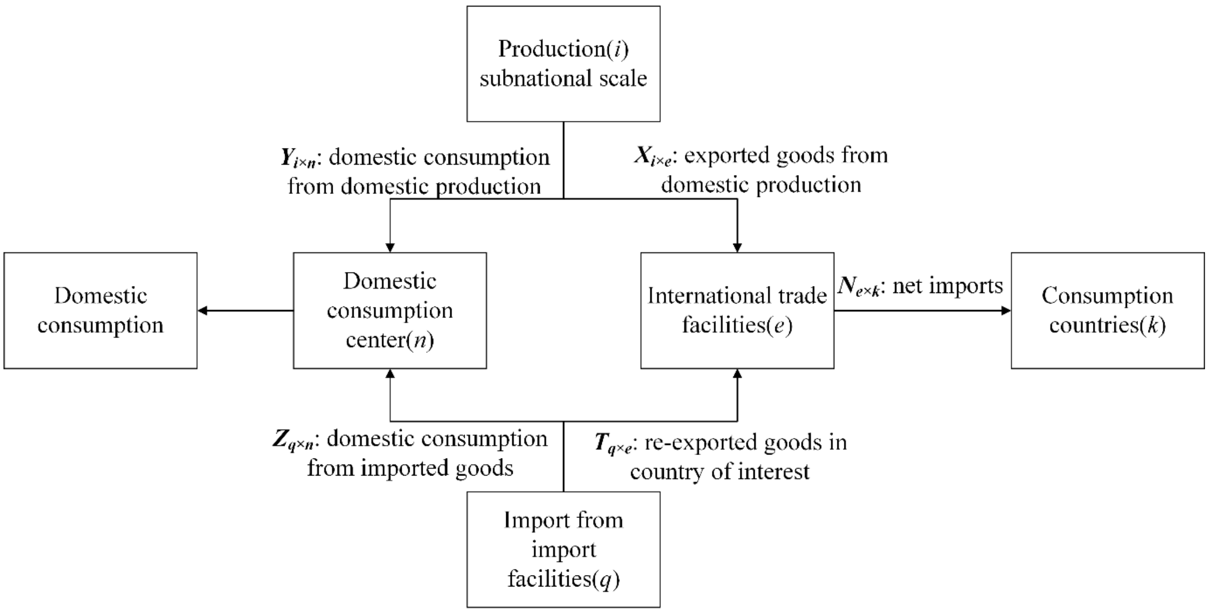

Figure S 8.5 The framework of SEI-PEC.

$$R_{i\times k} = D_{i\times e} \times L_{e\times k} \times B_{k\times k} \tag{S5}$$

$$\bar{r}_{i,k} \begin{cases} r_{i,k} & if\ k \neq country\ of\ interest \\ P_i - \sum_j r_{i,j} & if\ country = country\ of\ interst \end{cases} \tag{S6}$$

$$EI_k = EII_i \times \bar{R}_{i\times k} \tag{S7}$$

$$d_{i,e} = \frac{x_{i,e}}{\sum_i x_{i,e}} \tag{S8}$$

$$l_{e,k} = \frac{n_{e,k}}{P^k} \tag{S9}$$

Table S 8.9 Variables and description of equation in model SEI-PCS.

Variables	**description**
$R_{i\times k}$	consumption of ***k*** countries produced by ***i*** domestic producers in country of interest
$\bar{R}_{i,k}$	The revised value of $R_{i\times k}$
$D_{i\times e}$	Share of commodities from ***i*** sub-regional producers to ***e*** trade facilities
$L_{e\times k}$	Ratio between imports from countries ***k*** and production of that country
$B_{k\times k}$	Bilateral trade flow between ***k*** countries
EI_k	Environmental impacts in ***k*** countries
EII_i	Environmental impacts intensity in subnational regions ***i***
$X_{i\times e}$	Exported commodities produced in subnational regions

$\boldsymbol{Y_{i \times n}}$	Domestic production produced in subnational regions
$\boldsymbol{T_{q \times e}}$	Re-exported commodities in country of interest
$\boldsymbol{Z_{q \times n}}$	Imported commodities were consumed in country of interest
$\boldsymbol{P^k}$	Production of consumption countries $\boldsymbol{k}$
$\boldsymbol{x_{i,e}}$	The elements of $\boldsymbol{X_{i \times e}}$
$\boldsymbol{d_{i,e}}$	The elements of $\boldsymbol{D_{i \times e}}$
$\boldsymbol{l_{e,k}}$	The elements of $\boldsymbol{L_{e \times k}}$
$\boldsymbol{n_{e,k}}$	The elements of $\boldsymbol{N_{e \times k}}$
$\boldsymbol{r_{i,k}}$	The elements of $\boldsymbol{R_{i \times k}}$
$\boldsymbol{\bar{r}_{i,k}}$	The elements of $\boldsymbol{\bar{R}_{i,k}}$

8.2 Supporting information to chapter 3

8.2.1 Explanatory note 1

8.2.1.1 Methods for aggregating Millet and Coffee

In the SPAM databases, there are *Millet Pearl* and *Millet Small*, and *Coffee Arabica* and *Coffee Robusta*. But there are only *Millet* and *Coffee* in FAOSTAT and so EXIOBASE as well. In order to match SPAM databases with EXIOBASE, we aggregate *Millet Pearl* and *Millet Small* into *Millet*, and aggregate *Coffee Arabica* and *Coffee Robusta* into *Coffee*. Because we use total production of primary crops in SPAM, namely a value in grid cell stands for its production quantity in metric tons, we use Raster Calculator tools in ArcGIS 10.2.2 to add two raster databases of production of *Millet Pearl* and *Millet Small* as the spatial distribution of total production of *Millet*. And the similar way for calculation for *Coffee*.

8.2.1.2 Special solution for Canada

Canada is a special case for the spatial distribution of some livestock. There is no major road further north than a latitude of 70° N; yet ducks and sheep are in relative abundance north of that. Therefore, we regard the region below 70° N within a concave hull based on a 1-degree buffer around all roads as the first-priority region for export and the second-priority region for domestic consumption, and the rest as the first-priority region for second-priority region for export and the first-priority region for domestic consumption.

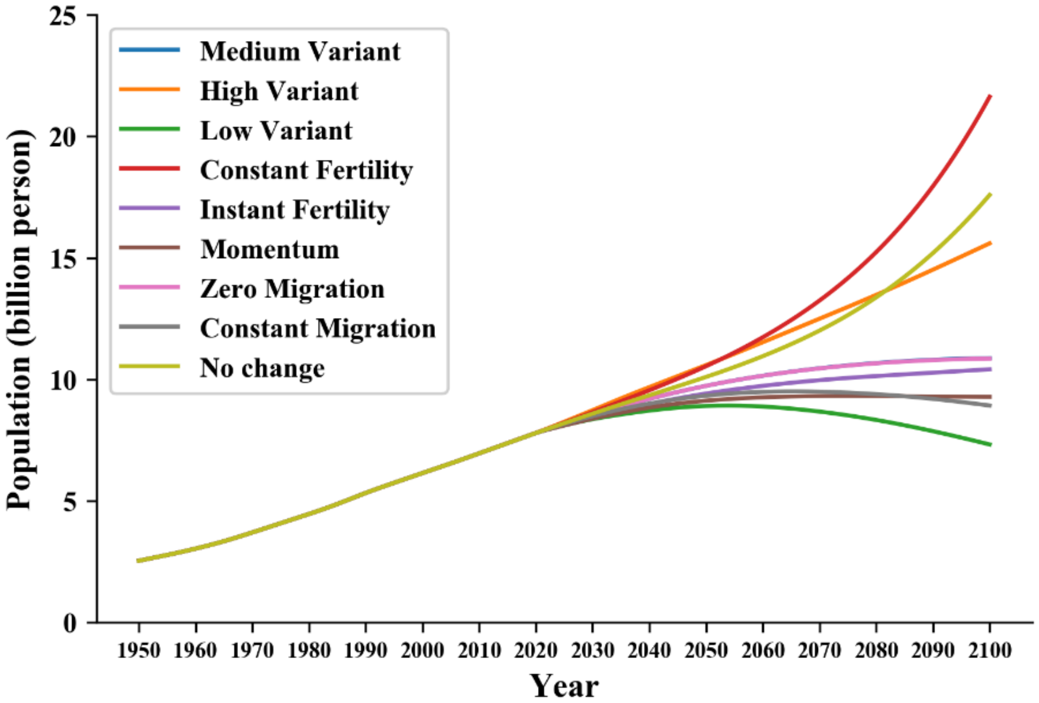

Figure S 8.6. World Population from 1950 to 2100. Source: World Population Prospects: The 2019 Revision.

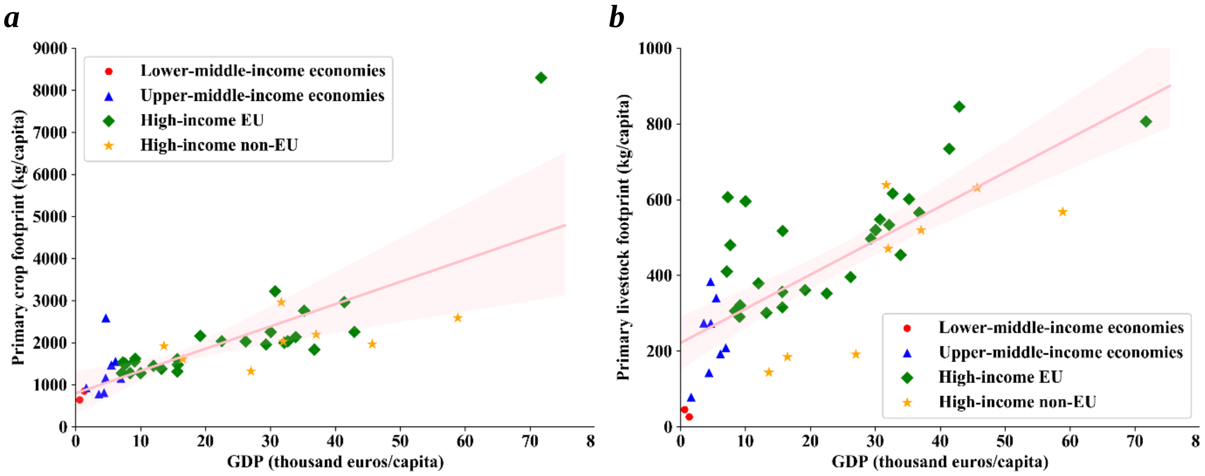

Figure S 8.7. Per-capita embodied primary crop (a) and livestock (b) consumption and per-capita GDP for 44 countries in EXIOBASE.

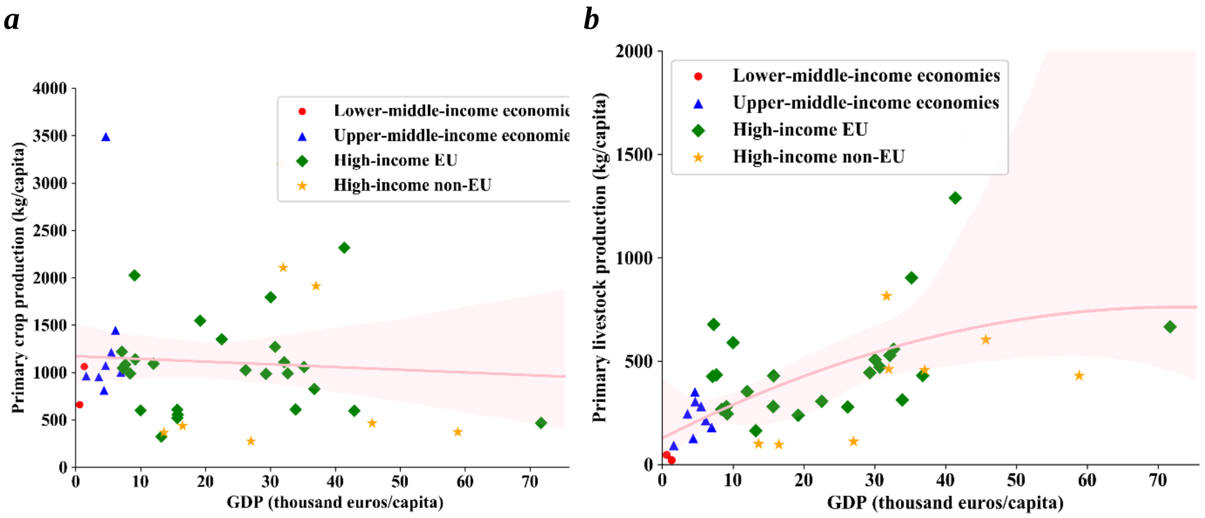

Figure S 8.8. Per-capita primary crop (a) and livestock (b) production and per-capita GDP for 44 countries in EXIOBASE.

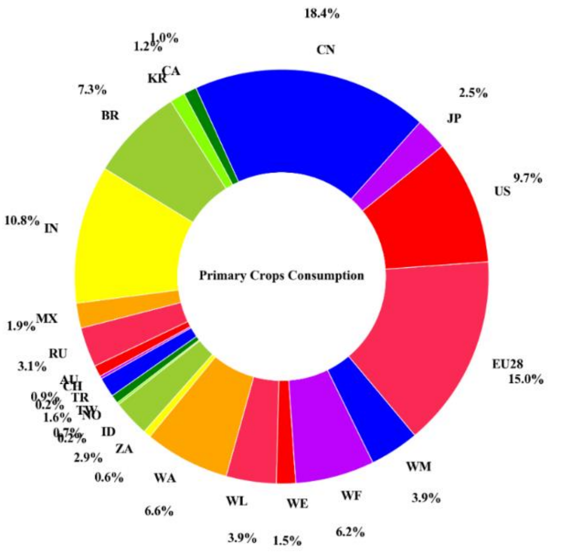

Figure S 8.9. Embodied primary crop consumption for each region in EXIOBASE

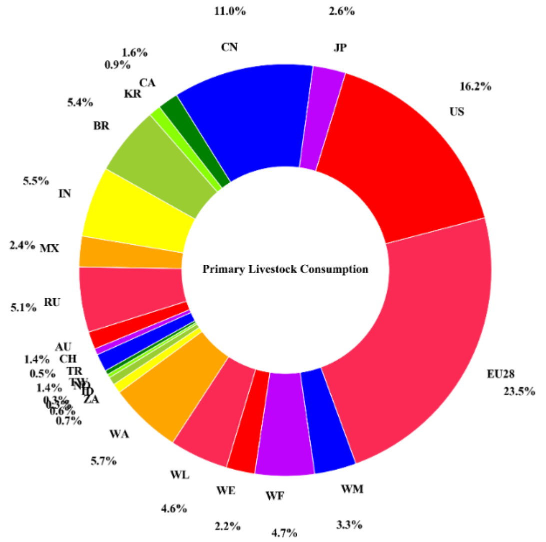

Figure S 8.10. Embodied livestock for each region in EXIOBASE

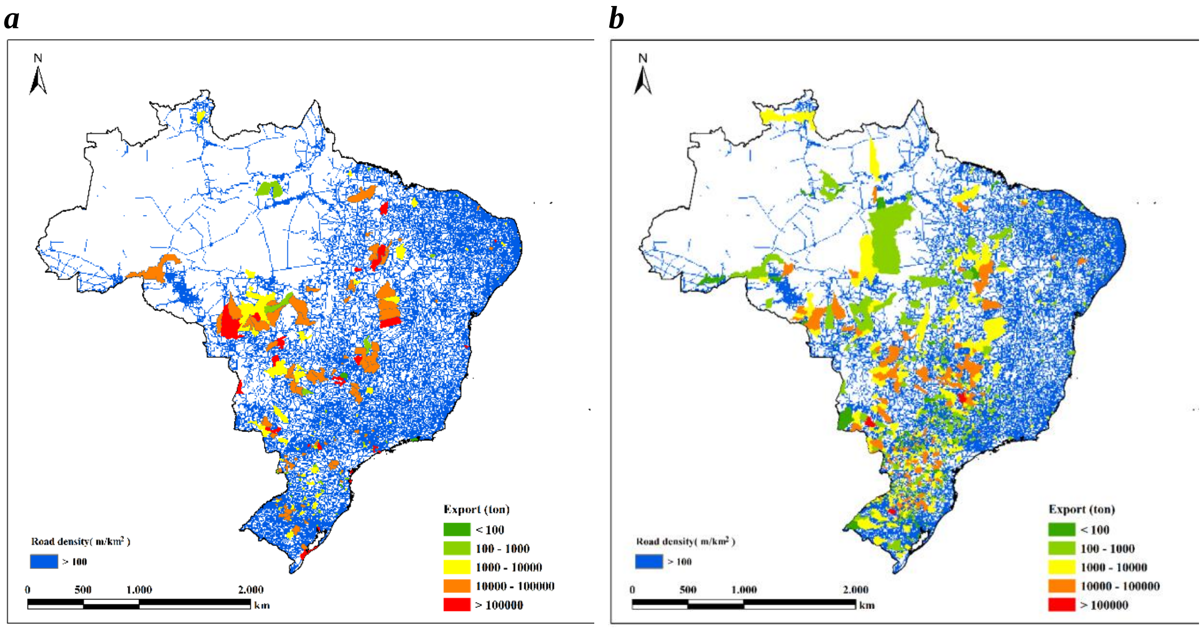

Figure S 8.11. Soybean export from official statistics data (a) and Trase.earth calculation (b) in 2006 at municipality level.

Table S 8.10. Mapping relationship between resource extensions about crop accounts in EXIOBASE with SPAM

Extensions in EXIOBASE	unit	SPAM code	name in SPAM	Sector in EXIOBASE
Domestic Extraction Used - Primary Crops – Abaca	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops - Agave Fibres nes	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops – Almonds	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Anise, Badian, Fennel	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops – Apples	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Apricots	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Arecanuts	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Artichokes	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Asparagus	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Avocados	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Bambara beans	kt	19	other pulses	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Bananas	kt	37	banana	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Barley	kt	4	Barley	Cereal grains nec
Domestic Extraction Used - Primary Crops - Beans, dry	kt	14	Bean	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Beans, green	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Berries nec	kt	40	temperate fruit	Vegetables, fruit, nuts

Domestic Extraction Used - Primary Crops – Blueberries	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Brazil nuts, with shell	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Broad beans, horse beans, dry	kt	19	other pulses	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Buckwheat	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops – Cabbages	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Canary Seed	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops – Carobs	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Carrots	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Cashew nuts, with shell	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Cashewapple	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Cassava	kt	12	cassava	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Cassava leaves	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Castor oil seed	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Cauliflower	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Cereals nec	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops – Cherries	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Chestnuts	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Chick peas	kt	15	chickpea	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Chicory Roots	kt	41	vegetables	Vegetables, fruit, nuts

Domestic Extraction Used - Primary Crops - Chillies and peppers, dry	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops - Chillies and peppers, green	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Cinnamon	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops - Citrus Fruit nec	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Cloves	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops - Cocoa Beans	kt	34	Cocoa	Crops nec
Domestic Extraction Used - Primary Crops – Coconuts	kt	22	coconut	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Coffee, Green	kt	32	arabica coffee	Crops nec
Domestic Extraction Used - Primary Crops – Coir	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops - Cotton Lint	kt	30	Cotton	Plant-based fibers
Domestic Extraction Used - Primary Crops – Cottonseed	kt	30	Cotton	Oil seeds
Domestic Extraction Used - Primary Crops - Cow peas, dry	kt	16	cowpea	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Cranberries	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Cucumbers and Gherkins	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Currants	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Dates	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Eggplants	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Fibre Crops nes	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops – Figs	kt	39	tropical fruit	Vegetables, fruit, nuts

Domestic Extraction Used - Primary Crops - Flax Fibre and Tow	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops – Fonio	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops - Fruit Fresh Nes	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Fruit, tropical fresh nes	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Garlic	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Ginger	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops – Gooseberries	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Grapefruit and Pomelos	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Grapes	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Groundnuts in Shell	kt	21	groundnut	Oil seeds
Domestic Extraction Used - Primary Crops – Hazelnuts	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Hemp Fibre and Tow	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops – Hempseed	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Hops	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops - Jojoba Seeds	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops - Jute and Jute-like Fibres	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops - Kapok Fibre	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops - Karite Nuts	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops - Kiwi Fruit	kt	40	temperate fruit	Vegetables, fruit, nuts

Domestic Extraction Used - Primary Crops – Kolanuts	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Leeks and other Alliac. Veg.	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Leguminous vegetables, nes	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Lemons and Limes	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Lentils	kt	18	Lentil	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Lettuce	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Linseed	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Lupins	kt	19	other pulses	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Maize	kt	3	Maize	Cereal grains nec
Domestic Extraction Used - Primary Crops - Maize, green	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Mangoes, mangosteens, guavas	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Mate	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops – Melonseed	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Millet	kt	5	pearl millet	Cereal grains nec
Domestic Extraction Used - Primary Crops - Mixed Grain	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops – Mushrooms	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Mustard Seed	kt	25	rapeseed	Oil seeds
Domestic Extraction Used - Primary Crops - Natural Rubber	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops - Nutmeg, mace and cardamoms	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops - Nuts, nes	kt	42	rest of crops	Vegetables, fruit, nuts

Domestic Extraction Used - Primary Crops – Oats	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops - Oil Palm Fruit	kt	23	oilpalm	Oil seeds
Domestic Extraction Used - Primary Crops - Oilseeds nec	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Okra	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Olives	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Onions	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Onions, dry	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Oranges	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Other Bastfibres	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops - Other melons	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Papayas	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Peaches and Nectarines	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Pears	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Peas, dry	kt	19	other pulses	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Peas, Green	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Pepper	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops – Peppermint	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops – Persimmons	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Pigeon peas	kt	17	pigeonpea	Vegetables, fruit, nuts

Domestic Extraction Used - Primary Crops – Pineapples	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Pistachios	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Plantains	kt	38	plantain	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Plums	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Pome fruit, nes	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Poppy Seed	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Potatoes	kt	9	Potato	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Pulses nec	kt	19	other pulses	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Pumpkins, Squash, Gourds	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Pyrethrum, Dried Flowers	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops – Quinces	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Quinoa	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops – Ramie	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops – Rapeseed	kt	25	rapeseed	Oil seeds
Domestic Extraction Used - Primary Crops – Raspberries	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Rice	kt	2	Rice	Paddy rice
Domestic Extraction Used - Primary Crops - Roots and Tubers, nes	kt	13	other roots	Cereal grains nec
Domestic Extraction Used - Primary Crops – Rye	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops - Safflower Seed	kt	27	other oil crops	Oil seeds

Domestic Extraction Used - Primary Crops - Sesame Seed	kt	26	sesameseed	Oil seeds
Domestic Extraction Used - Primary Crops – Sisal	kt	31	other fibre crops	Plant-based fibers
Domestic Extraction Used - Primary Crops – Sorghum	kt	7	sorghum	Cereal grains nec
Domestic Extraction Used - Primary Crops - Sour Cherries	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Soybeans	kt	20	soybean	Oil seeds
Domestic Extraction Used - Primary Crops - Spices nec	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops – Spinach	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Stone Fruit nec,	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Strawberries	kt	40	temperate fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - String beans	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Sugar Beets	kt	29	sugarbeet	Sugar cane, sugar beet
Domestic Extraction Used - Primary Crops - Sugar Cane	kt	28	sugarcane	Sugar cane, sugar beet
Domestic Extraction Used - Primary Crops - Sugar Crops nes	kt	42	rest of crops	Sugar cane, sugar beet
Domestic Extraction Used - Primary Crops - Sunflower Seed	kt	24	sunflower	Oil seeds
Domestic Extraction Used - Primary Crops - Sweet Potatoes	kt	10	sweet potato	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops - Tallowtree Seeds	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops - Tang. Mand Clement. Satsma	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Taro	kt	13	other roots	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Tea	kt	35	Tea	Crops nec
Domestic Extraction Used - Primary Crops - Tea nes	kt	35	Tea	Crops nec

Domestic Extraction Used - Primary Crops - Tobacco Leaves	kt	36	tobacco	Crops nec
Domestic Extraction Used - Primary Crops – Tomatoes	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Triticale	kt	8	other cereals	Cereal grains nec
Domestic Extraction Used - Primary Crops - Tung Nuts	kt	27	other oil crops	Oil seeds
Domestic Extraction Used - Primary Crops – Vanilla	kt	42	rest of crops	Crops nec
Domestic Extraction Used - Primary Crops - Vegetables Fresh nec	kt	41	vegetables	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Vetches	kt	19	other pulses	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Walnuts	kt	42	rest of crops	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Watermelons	kt	39	tropical fruit	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Wheat	kt	1	Wheat	Wheat
Domestic Extraction Used - Primary Crops – Yams	kt	11	Yams	Vegetables, fruit, nuts
Domestic Extraction Used - Primary Crops – Yautia	kt	13	other roots	Vegetables, fruit, nuts

Table S 8.11. Mapping relationship between EXIOABSE account with FAOSTAT product of livestock

EXIOBASE sector number	EXIOBASE name	FAOSTAT product names
11	Poultry	Eggs, hen, in shell
14	Raw milk	Milk, whole fresh cow; Milk, whole fresh goat; Milk, whole fresh sheep
43	Products of meat cattle	Hides, cattle, fresh; Meat indigenous, cattle
44	Products of meat pigs	Meat indigenous, pig.
45	Products of meat poultry	Meat indigenous, chicken; Meat indigenous, duck
46	Meat products nec	Meat indigenous, goat; Skins, goat, fresh; Meat indigenous, sheep; Skins, sheep, fresh.

Table S 8.12. Mapping relationship between countries in FAOSTAT with regions in EXIOABSE for livestock

FAOSTAT countries	EXIOBASE regions	Region abbreviation in EXIOBASE
Austria	Austria	AT
Belgium	Belgium	BE
Bulgaria	Bulgaria	BG
Cyprus	Cyprus	CY
Czechia	Czech Republic	CZ
Germany	Germany	DE
Denmark	Denmark	DK
Estonia	Estonia	EE
Spain	Spain	ES
Finland	Finland	FI
France	France	FR
Greece	Greece	GR
Croatia	Croatia	HR
Hungary	Hungary	HU
Ireland	Ireland	IE
Italy	Italy	IT
Lithuania	Lithuania	LT
Luxembourg	Luxembourg	LU
Latvia	Latvia	LV
Malta	Malta	MT
Netherlands	Netherlands	NL
Netherlands Antilles (former)	Netherlands	NL
Poland	Poland	PL
Portugal	Portugal	PT

Romania	Romania	RO
Sweden	Sweden	SE
Slovenia	Slovenia	SI
Slovakia	Slovakia	SK
United Kingdom	United Kingdom	GB
United States of America	United States	US
Japan	Japan	JP
China, Hong Kong SAR	China	CN
China, mainland	China	CN
Canada	Canada	CA
Republic of Korea	South Korea	KR
Brazil	Brazil	BR
India	India	IN
Mexico	Mexico	MX
Russian Federation	Russia	RU
Australia	Australia	AU
Switzerland	Switzerland	CH
Turkey	Turkey	TR
China, Taiwan Province of	Taiwan	TW
Norway	Norway	NO
Indonesia	Indonesia	ID
South Africa	South Africa	ZA
New Caledonia	RoW Asia and Pacific	WA
Afghanistan	RoW Asia and Pacific	WA
American Samoa	RoW Asia and Pacific	WA
Armenia	RoW Asia and Pacific	WA

Azerbaijan	RoW Asia and Pacific	WA
Bangladesh	RoW Asia and Pacific	WA
Bhutan	RoW Asia and Pacific	WA
Brunei	RoW Asia and Pacific	WA
Cambodia	RoW Asia and Pacific	WA
Cook Islands	RoW Asia and Pacific	WA
Democratic People's Republic of Korea	RoW Asia and Pacific	WA
Fiji	RoW Asia and Pacific	WA
French Polynesia	RoW Asia and Pacific	WA
Georgia	RoW Asia and Pacific	WA
Guam	RoW Asia and Pacific	WA
Kazakhstan	RoW Asia and Pacific	WA
Kyrgyzstan	RoW Asia and Pacific	WA
Lao People's Democratic Republic	RoW Asia and Pacific	WA
Malaysia	RoW Asia and Pacific	WA
Micronesia (Federated States of)	RoW Asia and Pacific	WA
Mongolia	RoW Asia and Pacific	WA
Myanmar	RoW Asia and Pacific	WA
Nepal	RoW Asia and Pacific	WA
New Zealand	RoW Asia and Pacific	WA
Niue	RoW Asia and Pacific	WA
Norfolk Island	RoW Asia and Pacific	WA
Pakistan	RoW Asia and Pacific	WA
Papua New Guinea	RoW Asia and Pacific	WA
Philippines	RoW Asia and Pacific	WA
Samoa	RoW Asia and Pacific	WA

Singapore	RoW Asia and Pacific	WA
Solomon Islands	RoW Asia and Pacific	WA
Sri Lanka	RoW Asia and Pacific	WA
Tajikistan	RoW Asia and Pacific	WA
Thailand	RoW Asia and Pacific	WA
Timor-Leste	RoW Asia and Pacific	WA
Tonga	RoW Asia and Pacific	WA
Turkmenistan	RoW Asia and Pacific	WA
Uzbekistan	RoW Asia and Pacific	WA
Vanuatu	RoW Asia and Pacific	WA
Viet Nam	RoW Asia and Pacific	WA
Wallis and Futuna Islands	RoW Asia and Pacific	WA
Antigua and Barbuda	RoW America	WL
Argentina	RoW America	WL
Bahamas	RoW America	WL
Barbados	RoW America	WL
Belize	RoW America	WL
Bermuda	RoW America	WL
Bolivia	RoW America	WL
British Virgin Islands	RoW America	WL
Cayman Islands	RoW America	WL
Chile	RoW America	WL
Colombia	RoW America	WL
Costa Rica	RoW America	WL
Cuba	RoW America	WL
Dominica	RoW America	WL

Dominican Republic	RoW America	WL
Ecuador	RoW America	WL
El Salvador	RoW America	WL
Falkland Islands (Malvinas)	RoW America	WL
French Guiana	RoW America	WL
Greenland	RoW America	WL
Grenada	RoW America	WL
Guadeloupe	RoW America	WL
Guatemala	RoW America	WL
Guyana	RoW America	WL
Haiti	RoW America	WL
Honduras	RoW America	WL
Jamaica	RoW America	WL
Martinique	RoW America	WL
Montserrat	RoW America	WL
Nicaragua	RoW America	WL
Panama	RoW America	WL
Paraguay	RoW America	WL
Peru	RoW America	WL
Puerto Rico	RoW America	WL
Saint Kitts and Nevis	RoW America	WL
Saint Lucia	RoW America	WL
Saint Pierre and Miquelon	RoW America	WL
Saint Vincent and the Grenadines	RoW America	WL
Suriname	RoW America	WL
Trinidad and Tobago	RoW America	WL

United States Virgin Islands	RoW America	WL
Uruguay	RoW America	WL
Venezuela (Bolivarian Republic of)	RoW America	WL
Albania	RoW Europe	WE
Belarus	RoW Europe	WE
Bosnia and Herzegovina	RoW Europe	WE
Faroe Islands	RoW Europe	WE
Iceland	RoW Europe	WE
Liechtenstein	RoW Europe	WE
Montenegro	RoW Europe	WE
Republic of Moldova	RoW Europe	WE
Serbia	RoW Europe	WE
The former Yugoslav Republic of Macedonia	RoW Europe	WE
Ukraine	RoW Europe	WE
Algeria	RoW Africa	WF
Angola	RoW Africa	WF
Benin	RoW Africa	WF
Botswana	RoW Africa	WF
Burkina Faso	RoW Africa	WF
Burundi	RoW Africa	WF
C+¦te d'Ivoire	RoW Africa	WF
Cabo Verde	RoW Africa	WF
Cameroon	RoW Africa	WF
Central African Republic	RoW Africa	WF
Chad	RoW Africa	WF
Comoros	RoW Africa	WF

Congo	RoW Africa	WF
Democratic Republic of the Congo	RoW Africa	WF
Djibouti	RoW Africa	WF
Equatorial Guinea	RoW Africa	WF
Eritrea	RoW Africa	WF
Ethiopia	RoW Africa	WF
Gabon	RoW Africa	WF
Gambia	RoW Africa	WF
Ghana	RoW Africa	WF
Guinea	RoW Africa	WF
Guinea-Bissau	RoW Africa	WF
Kenya	RoW Africa	WF
Lesotho	RoW Africa	WF
Liberia	RoW Africa	WF
Libya	RoW Africa	WF
Madagascar	RoW Africa	WF
Malawi	RoW Africa	WF
Mali	RoW Africa	WF
Mauritania	RoW Africa	WF
Mauritius	RoW Africa	WF
Morocco	RoW Africa	WF
Mozambique	RoW Africa	WF
Namibia	RoW Africa	WF
Niger	RoW Africa	WF
Nigeria	RoW Africa	WF
Reunion	RoW Africa	WF

Rwanda	RoW Africa	WF
Saint Helena, Ascension and Tristan da Cunha	RoW Africa	WF
Sao Tome and Principe	RoW Africa	WF
Senegal	RoW Africa	WF
Seychelles	RoW Africa	WF
Sierra Leone	RoW Africa	WF
Somalia	RoW Africa	WF
Sudan (former)	RoW Africa	WF
Swaziland	RoW Africa	WF
Togo	RoW Africa	WF
Tunisia	RoW Africa	WF
Uganda	RoW Africa	WF
United Republic of Tanzania	RoW Africa	WF
Western Sahara	RoW Africa	WF
Zambia	RoW Africa	WF
Zimbabwe	RoW Africa	WF
Bahrain	RoW Middle East	WM
Egypt	RoW Middle East	WM
Iran (Islamic Republic of)	RoW Middle East	WM
Iraq	RoW Middle East	WM
Israel	RoW Middle East	WM
Jordan	RoW Middle East	WM
Kuwait	RoW Middle East	WM
Lebanon	RoW Middle East	WM
Occupied Palestinian Territory	RoW Middle East	WM
Oman	RoW Middle East	WM

Qatar	RoW Middle East	WM
Saudi Arabia	RoW Middle East	WM
Syrian Arab Republic	RoW Middle East	WM
United Arab Emirates	RoW Middle East	WM
Yemen	RoW Middle East	WM

8.3 Supporting information to chapter 4

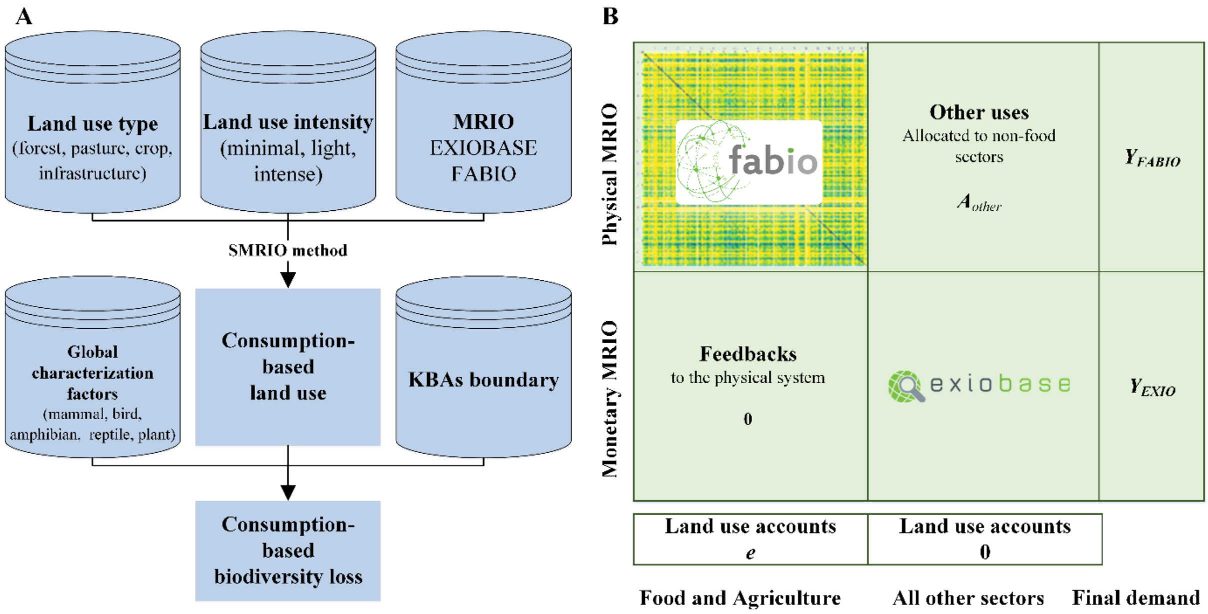

Figure S 8.12. Schematic of the methodology in general (a), and of linking FABIO and EXIOBASE (b).

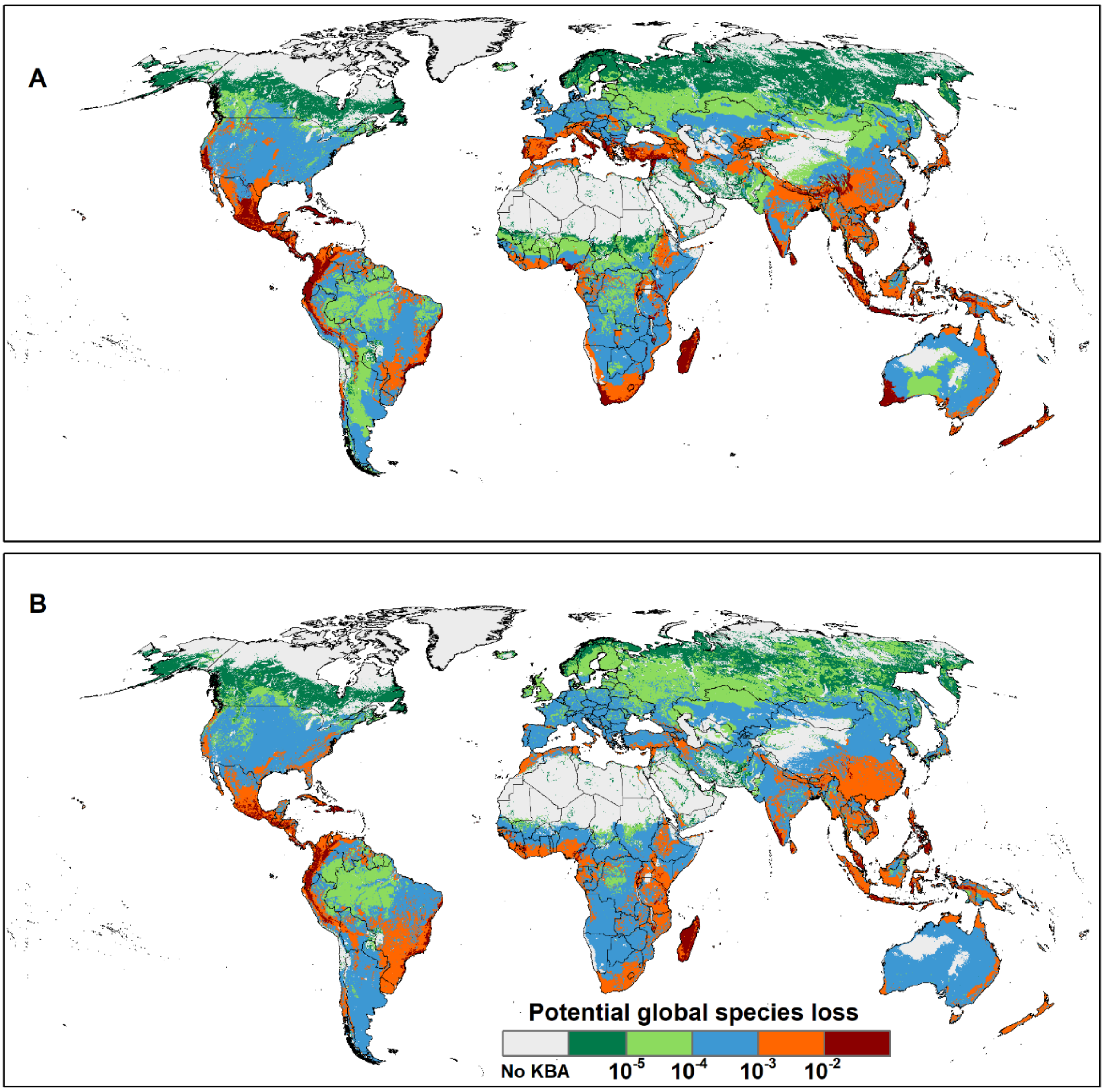

Figure S 8.13. Spatial distribution of potential global species loss driven by land use inside and outside KBAs for a) plants, and b) vertebrates (mammals + birds + amphibians + reptiles). The spatial resolution is 5 arc min.

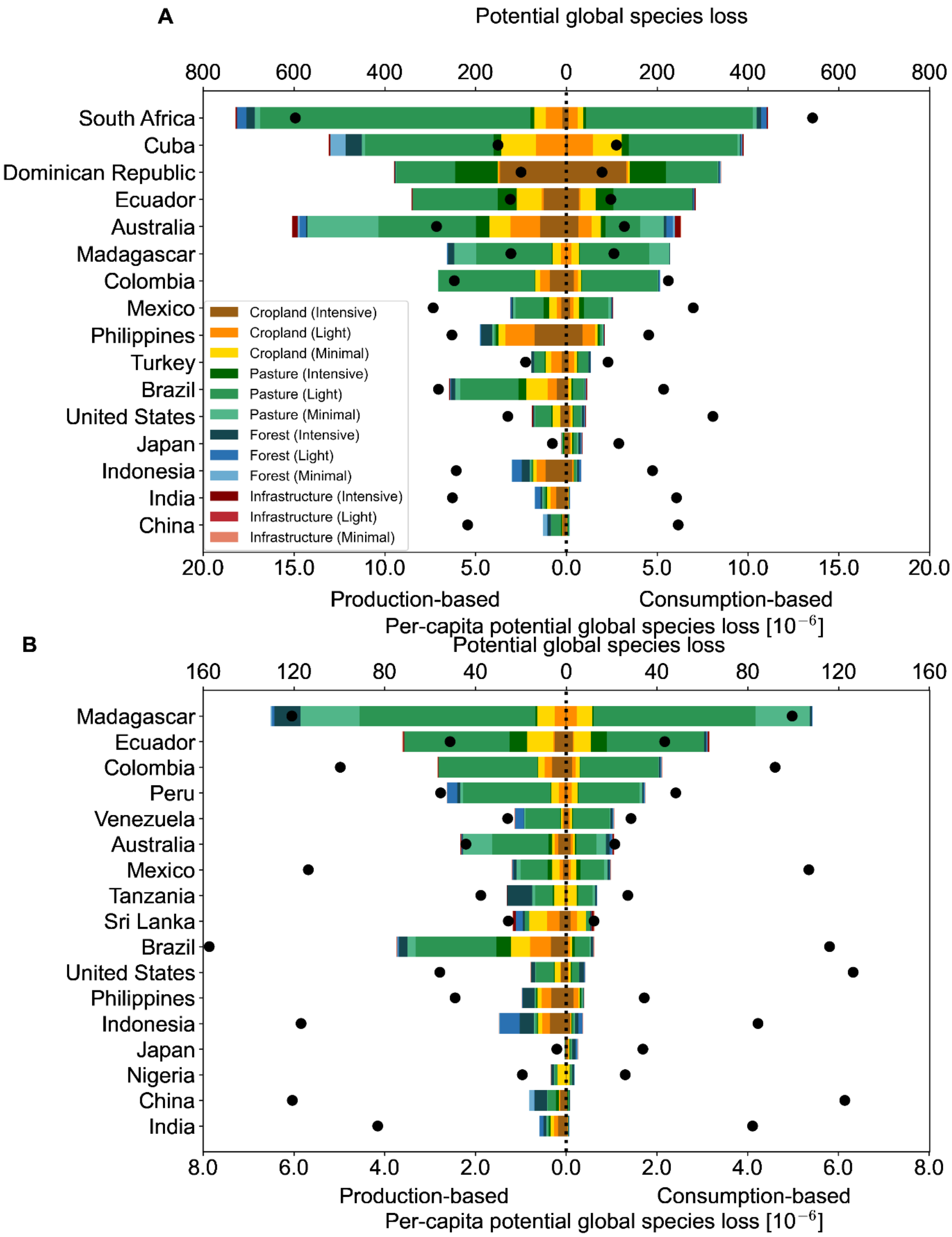

Figure S 8.14. The potential global species loss from land use inside and outside KBAs for plants (a) and vertebrates (b) (mammals, birds, amphibians, and reptiles). On each *x*-axis (bottom and top of figures), the production-based perspective is shown to the left of zero and the consumption-based perspective to the right. The *y*-axis lists the top 15 countries/regions with the largest consumption-based or production-based biodiversity loss from land use within and outside KBAs at the national level. The bar shows the per-capita value of biodiversity loss per land type and land use intensity. The circles show the total national biodiversity loss with a value shown by the upper *x*-axes on the top of each plot.

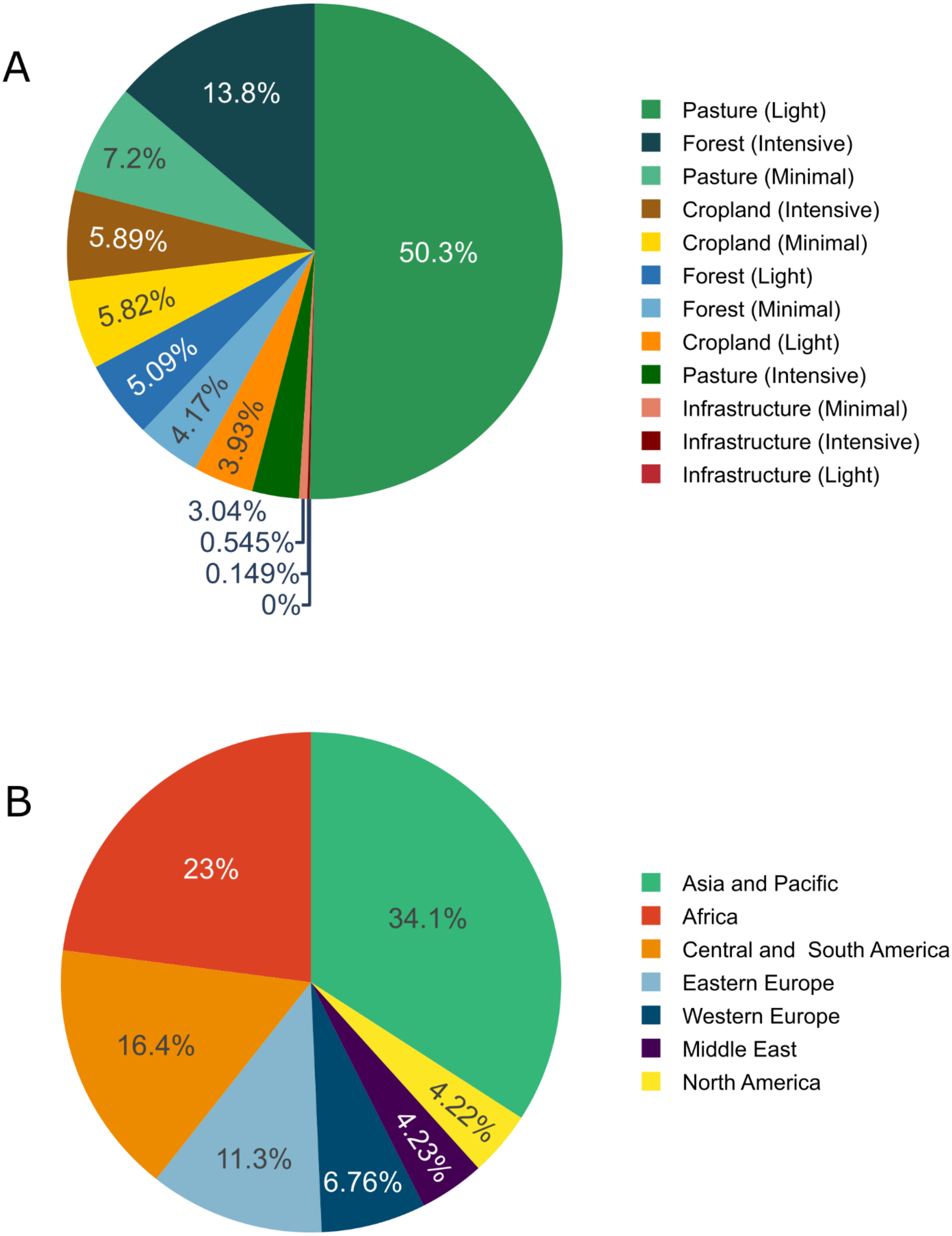

Figure S 8.15. Land use within KBAs with different land use types and land use intensities (a) and in different regions (b).

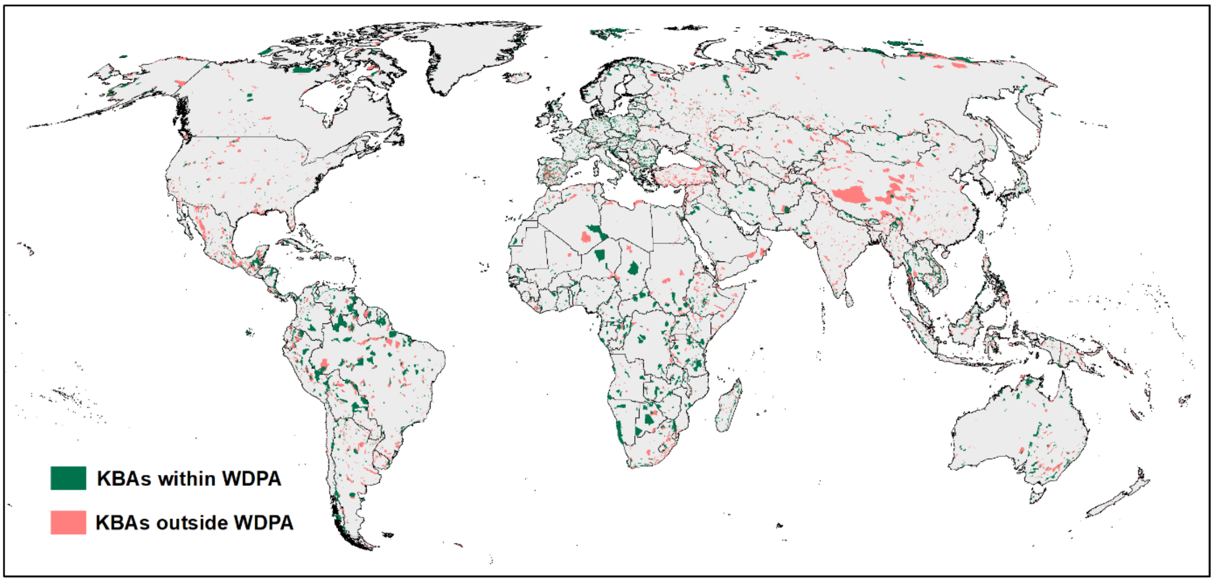

Figure S 8.16. Intersections between KBAs and the World Database on Protected Areas (WDPA).

8.4 Supporting information to chapter 5

8.4.1 Supplementary Methods

Biomass carbon and soil organic carbon in current vegetation

The calculation of aboveground biomass carbon (AGBC) and belowground biomass carbon (BGBC) is based on the latest harmonized carbon density map in the year 2010 developed by Spawn et al[358]. For herbaceous crops, Spawn et al. employed gridded crop maps from EarthStat [35], and we used the latest crop maps from Spatial Production Allocation Model (SPAM) [390] in 2010 and method from Spawn et al. [358]to get the latest AGBC and BGBC maps of herbaceous crops. For woody crops and pasture, we extract AGBC and BGBC from the latest harmonized carbon density maps directly.

Primary crops and fodder:

The production and harvested area of 163 types of primary crops and 16 types of fodder crops in 2010 come from FAOSTAT [357]. The fodder crops are not available in FAOSTAT now, and are provided by one of developers of The Food and Agriculture Biomass Input-Output model (FABIO) [36]. We then use the SPAM [390] to build a spatially-explicit picture of crop production. SPAM employs a cross-entropy approach to make estimates of 42 crop maps in 2010 at 5 arc min resolution. Since “Pearl Millet” and “Small Millet” are not split in FAOSTAT, we aggregate them into millet; similarly “Arabica Coffee” and “Robusta Coffee” are not split and we aggregate them into “Coffee”. These 40 crops are aggregated from an average of 163 types of primary crops contained in the FAOSTAT database between 2009 and 2011. Therefore, we used national data from FAOSTAT in 2010 to calibrate the SPAM for each country. However, since SPAM does not include fodder crop maps, we use EarthStat fodder maps [35] at 5 arc min resolution in 2000. We aggregate the 16 fodder maps into one fodder map for ease of analysis.

Pasture

There are many ways to estimate pasture for grazing. Ramankutty et al. created a map in which they estimate the percentage of pasture per grid cell at 5 min resolution [35] in 2000. Sloat et al., updated this map to the year 2010 at 500 meters resolution [393]. They considered a grid cell to be pasture if it fell into a livestock category on the global livestock production systems (GLPS) map and also contained at least 30% pasture by area [393]. Marques et al.,[12] used pasture map from Ramankutty et al.,[35] as permanent pasture, and excluded non-productive area (below NPP over 20 $g\,C\,m^{-2}\,yr^{-1}$) is used to feed livestock in the year 2000. In the end, we employed the pasture map developed by Sloat et al. [393] because their dataset is the latest and the time is in line with our research. We assume pasture layer was capped if all land-use types (cropland, infrastructure, and forest) fill 100% of the grid cell. For forest, we employed fractional tree cover from MODIS in 2010 [426]. We linearly stretched values such that 80% was treated as complete tree cover (100%), since MODIS tree cover estimates saturate at around 80%, following Spawn et al.[358]. For infrastructure, we used ESA CCI Land cover Maps at 300 meters resolution in 2010 [427].

GHG emissions

For animal-specific sectors, this includes: “Enteric Fermentation”, “Manure Management”, “Manure applied to Soils”, and “Manure left on Pasture”. For crop-specific sectors, this includes: “Rice Cultivation”, “Crop Residues”, and “Burning - Crop Residues”. There are two outstanding, high-emission sectors: “Synthetic Fertilizers”, and “Energy Use” which are not allocated to specific agricultural sectors. In FAOSTAT, GHG emission of “Synthetic Fertilizers” is only derived from nitrogen fertilizers, so we first classify their GHG emissions into 28 countries/regions, and 13 crop groups based on the amount of nitrogen fertilizer use from the International Fertilizer Association (IFA) in 2010 [428]. Mapping relationship of countries and crops between FABIO and IFA see Tables S5 and S6. We then allocate GHG emission of “Synthetic Fertilizers” of 28 countries/regions, and 13 crop groups into separated countries and agricultural sectors in FABIO based on the monetary value of crops in each group from FAOSTAT [357]. Similarly, we allocate CO_2, CH_4, and N_2O from the “Energy Use” sector into 49 countries/regions and 14 agricultural sectors based on the combustion emissions of CO_2, CH_4, N_2O in EXIOBASE v3.6. Mapping relationship of countries and sectors between FABIO and EXIOBASE see Supplementary Tables S7 and S8. We then allocate these cases from “Energy Use” into agricultural sectors and countries using FABIO and based on the monetary value of crops from FAOSTAT in every group.

8.4.2 **Supplementary Discussion**

Potential opportunities for carbon sequestration.

Climate-smart agriculture may provide another opportunity to increase carbon benefits [429]. For example, novel plants like intermediate wheatgrass (*Thinopyrum intermedium* (Host) Barkworth & D.R.Dewey) is an emerging cool-season perennial grain (the name for commercialized grain is “Kernza”) and forage dual-use grass, and its extensive root system can improve belowground carbon fixing and reduce soil erosion [430]. Intermediate wheatgrass is becoming commercially available to farmers for some areas in the US [431]. A further opportunity is biochar. While carbon stocks will saturate when the land restores to mature and stable vegetation, biochar can break the biophysical limits of carbon sequestration[379]. Feedstocks for biochar come from residues of forest/crop/pasture, animal manure, and food waste[379]. Removing forest residue can reduce risks of wildfire, but may disturb habitats of some fungi and wildlife, along with other ecosystem services [379]. This represents a tradeoff among carbon sequestration and other ecosystem services [379]. New technologies in agricultural production can also help to mitigate climate change. For example, 3-nitrooxypropanol (3NOP), a methane inhibitor, can persistently decrease enteric methane emissions by 30% under industry-relevant conditions without affecting animal productivity negatively [432], and has been approved as a feed additive in the European Union [433].

Potential carbon offset.

Here, we focus on dietary change in high-income countries where most food supply is higher than the recommendation in the EAT diet, and the dietary change could increase carbon sequestration and reduce CO2 emission. However, the carbon benefit may be offset by population growth and malnutrition in some low- and middle-income countries in the long term [327]. For example, most low- and middle-income countries face a severe double burden of malnutrition which means simultaneous manifestation of both undernutrition and overweight and obesity [434]. The obesity in low- and middle-income countries is due to overconsumption of cheap ultra-processed food and beverages which is an unhealthy diet [434]. The EAT diet is not suitable in low-income countries because they cannot afford it, and it estimated at least 1.58 billion people are not able to pay for the cost of the EAT diet in the world [397]. People will consume more food with income growth, especially animal products in low- and middle-income countries [45]. In addition population growth low- and middle-income countries will increase food needs further. For example, population is projected to increase by 199% (1026·04 million in 2017 to 3071·21 million in 2100) in Sub-Saharan Africa [420]. The increasing food demand in low- and middle-income countries will offset carbon benefit from dietary change in high-income countries.

Another carbon offset is food waste in high-income countries. EAT diet recommends per-capita food intake instead of food purchase. Pre-capita food waste is positively related to per-capita income, and most food waste occurs in consumption stage in high-income countries because of overstocking, and too much cooking or serving [435]. In addition, healthier diets would cause more food waste because healthier diets need more consumption of perishable produce such as fruit and vegetables, which has substantial hidden costs from food waste [436]. Therefore, it is very necessary to halt food waste and loss. It is estimated about one third of global food is lost or wasted [222]. If reducing 50% of global food waste and loss, another 0.9 Pg CO_2e yr^{-1} would be mitigated [437].

Recently, organic food consumption and organic agriculture production are surging in high-income countries because they are more environmentally friendly (e.g. less fertilizer or pesticide input, and fewer biodiversity losses) also higher price compared to conventional farming [438,439]. However, organic production has lower yield which means it needs more land use to satisfy the same food demand [438,439]. The high quality and environmentally friendly food consumption is at the expense of carbon benefit.

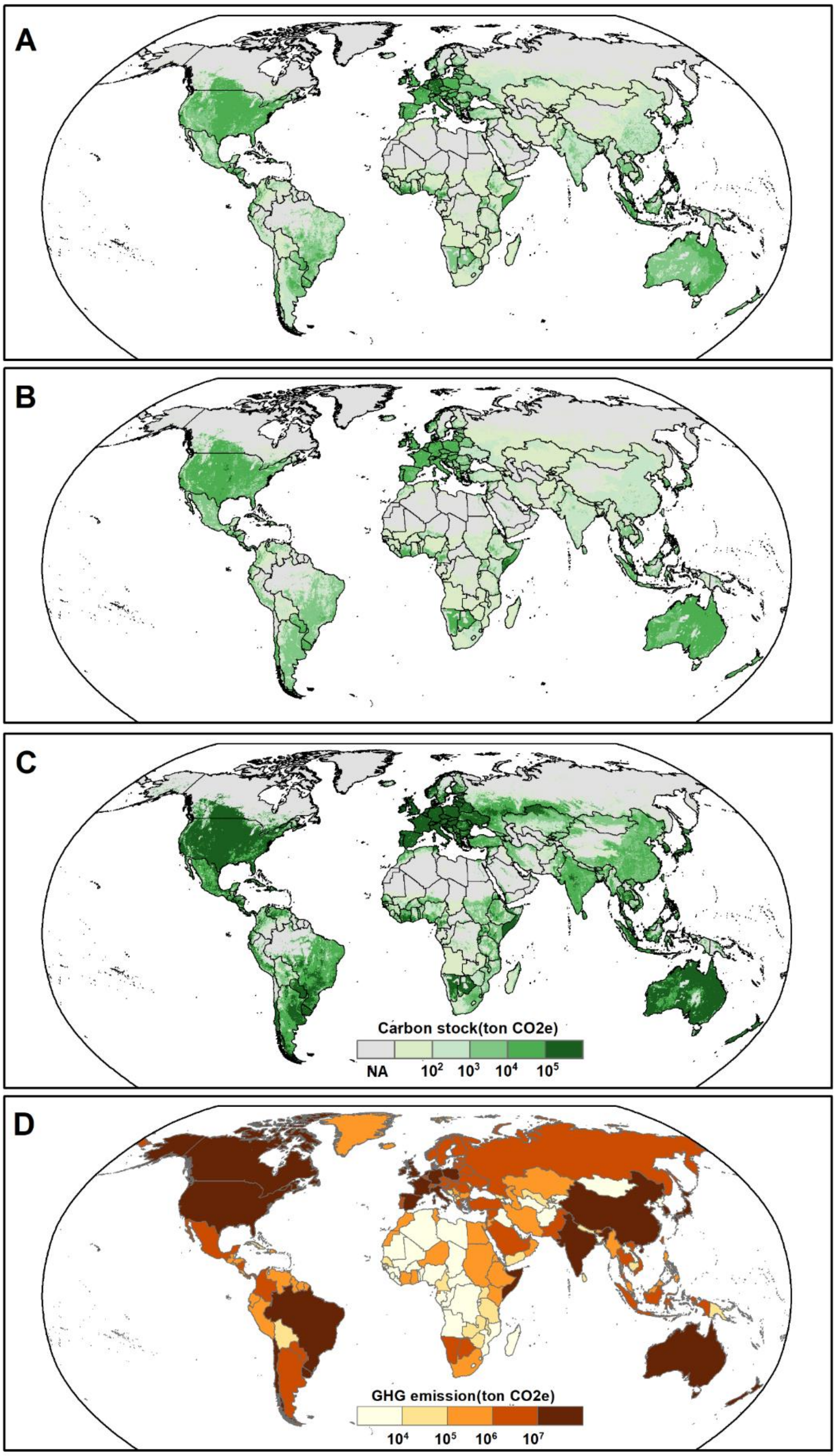

Figure S 8.17. Aboveground biomass carbon (AGBC, A), belowground biomass carbon (BGBC, B), soil organic carbon (SOC, C) and GHG emission (D) embodied in current national average diets of high-income countries.

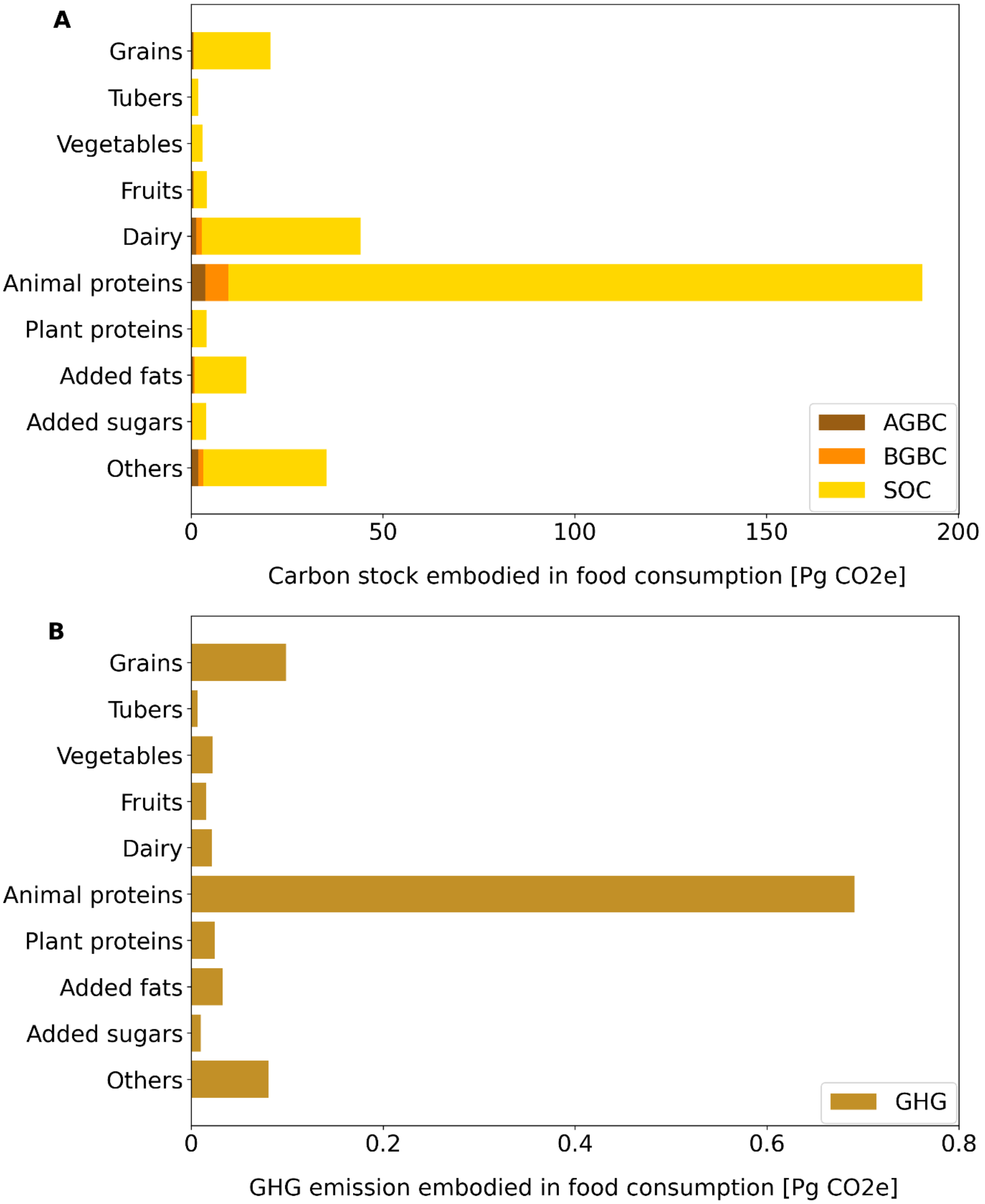

Figure S 8.18. Embodied carbon stocks (A) and GHG emission flows (B) in national average diets for high-income countries by food category. Carbon stock means aboveground biomass carbon (AGBC), belowground biomass carbon (BGBC), and soil organic carbon (SOC) in present agricultural production related vegetation (primary crops, fodder, and pasture) used for human food consumption.

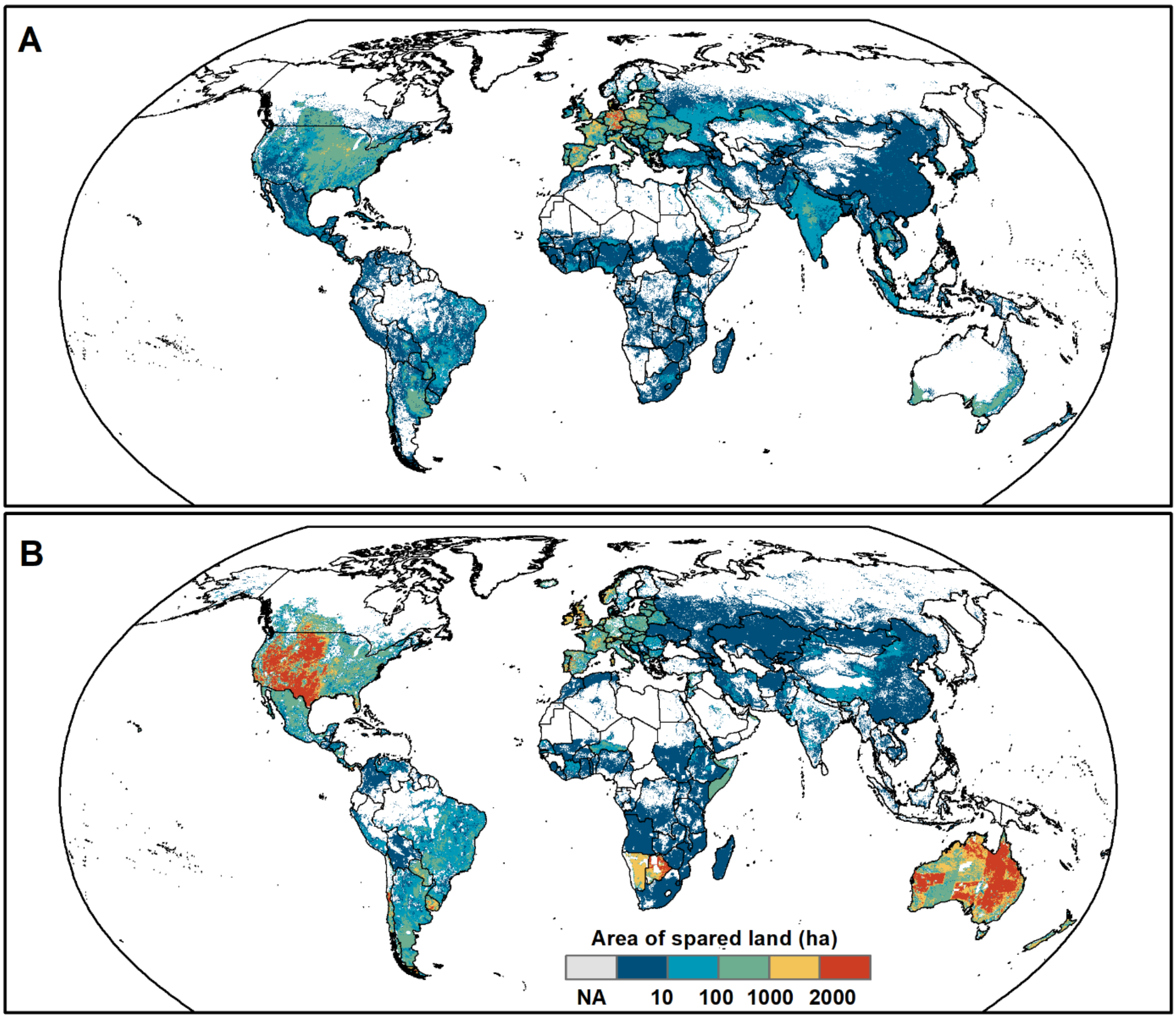

Figure S 8.19. Area of spared land due to dietary shift from national average diets to EAT diet in high-income countries for cropland (A) and pastureland (B).

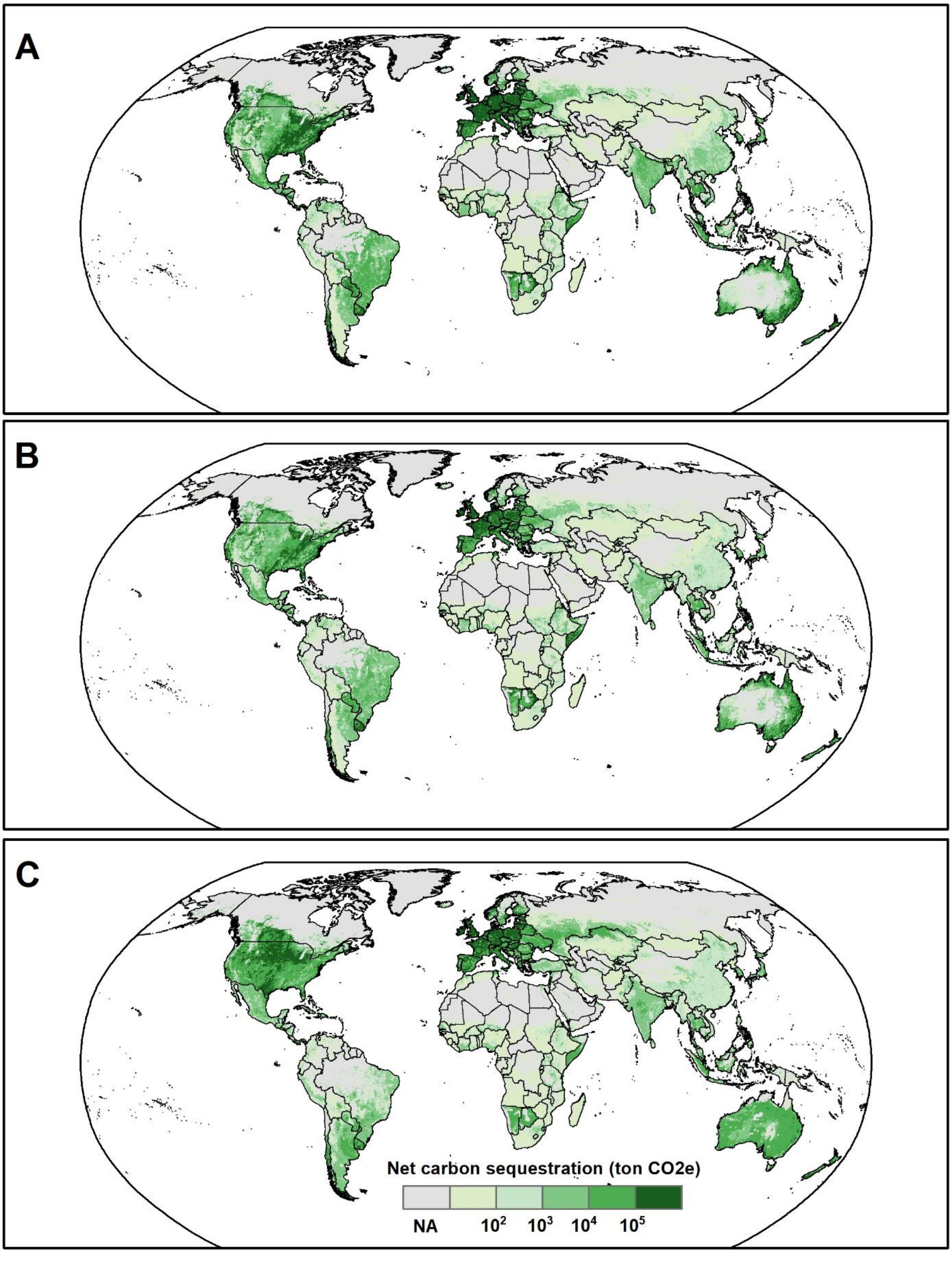

Figure S 8.20. Net carbon sequestration due to dietary shift from national average diets to EAT diet in high-income countries. Increasing amount of carbon sequestration in spared land due to dietary change for AGBC (A), BGBC (B), SOC (C).

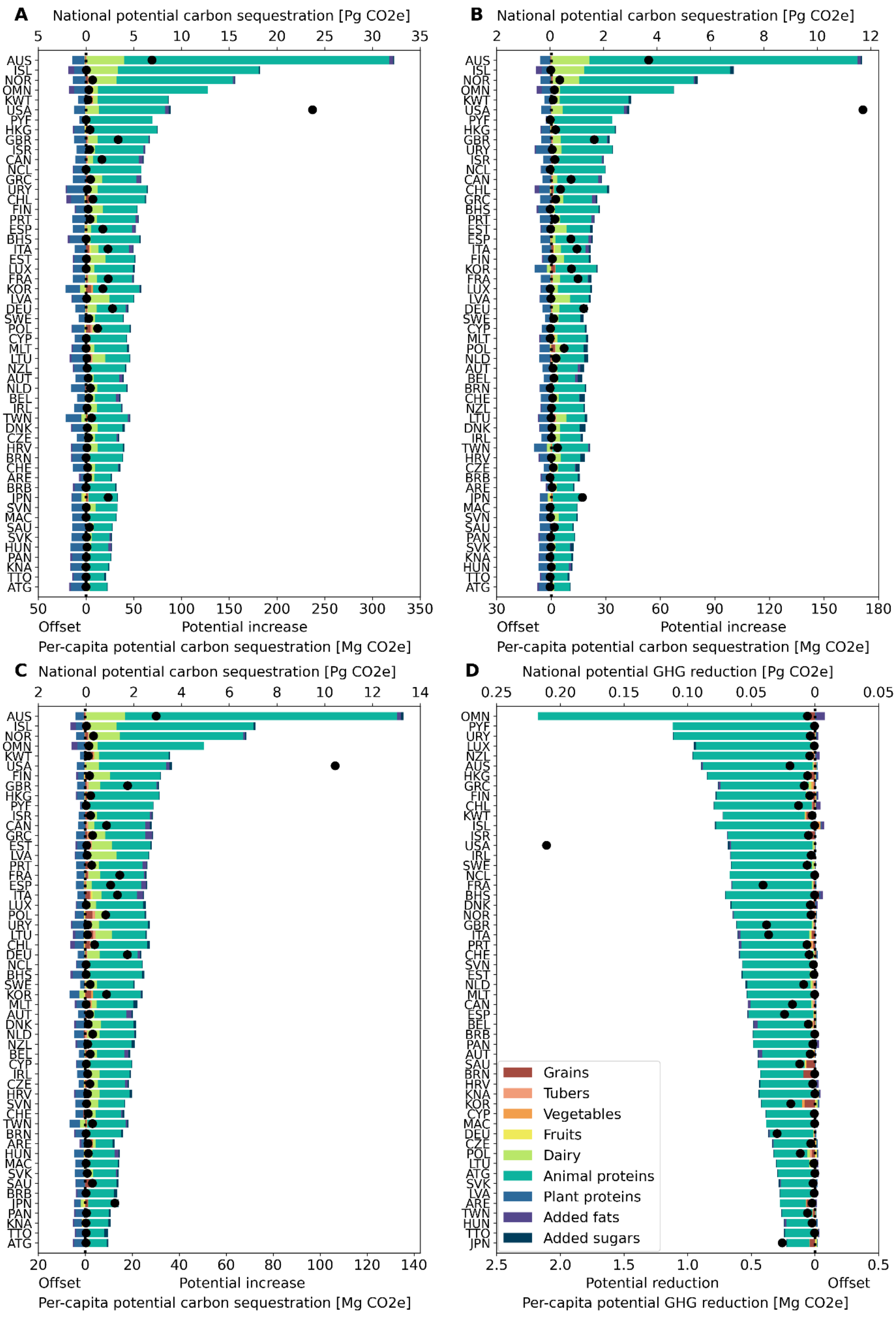

Figure S 8.21. National and Per-capita net carbon benefit due to dietary shift from national average diets to EAT diet in individual high-income country by food category. Increasing amount of carbon sequestration due to dietary change for AGBC (A), BGBC (B), SOC (C), and reducing amount of GHG emission (D) by food category. The bar means per-capita carbon sequestration and GHG emission change by food categories, and the dot means national net carbon sequestration and GHG emission change. The potential increase of carbon sequestration means carbon sequestration in potential natural vegetation minus that of current agricultural vegetation. The offset of carbon sequestration means carbon sequestration in potential natural vegetation minus that of increased agricultural vegetation. The carbon reduction of GHG emission means the GHG reduction due to reduction of food categories, and the offset means the GHG increase due to increase of food categories.

Summary

The global agri-food system plays a critical role in food security and environmental issues including land use, biodiversity loss and climate change. Increasing globalization has resulted in a complex international food system where production and consumption along the international supply chain can incorporate many geographically distinct regions. This interconnection means that it is difficult for any single producer or consumer to address these impacts. This thesis represents a step towards mapping the global food system from producers to consumers and offers several policy-relevant insights, especially in the national accounting of environmental footprints. Given that many drivers occur locally, but are traded globally, and that inter-regional differences in consumption are increasingly important, it is a natural next step to find approaches that can connect local impacts (production side) with global consumption (consumption side) through trade. Global spatially explicit multi-regional input-output (SMRIO) analyses can help to identify hotspots of local production and associated social and environmental impacts driven by global consumption. Therefore, this thesis puts forward the following overarching research question:

"*How can spatially explicit multi-regional input-output approaches be used to evaluate sustainability in the global agri-food system?*".

In this thesis, I first assessed the past use of SMRIO to evaluate *what is the current status of spatially explicit input-output analysis (sub-question 1)?*.

To further assess the potential of the technique, I built a variety of SMRIO models for three different case studies. I used SMRIO models to investigate three critical issues (i.e. food security, biodiversity loss, and climate change) in the agri-food system. They address the following questions:

What are the local production hotspots of crops and livestock driven by global consumption and how does this impact food security through trade (sub-question 2)?

How does land use driven by final consumption affect global biodiversity within key biodiversity areas (sub-question 3)?

What are the global interactions between carbon emissions and carbon sequestration driven by diets and diet changes in high-income nations (sub-question 4)?

To answer the first sub-question, Chapter 2 reviews the literature on spatially explicit input-output analysis and assesses the mechanisms proposed for connecting global consumption with local environmental pressures. I define spatially explicit input-output analysis as cases where the spatial resolution of results are greater than the underlying input-output transaction matrix. I assess past attempts at combining these perspectives at varying temporal and spatial scales, and with different environmental stressors. Past studies covered various environmental pressures and impacts, such as GHG emissions, water use, air pollution, and biodiversity loss. Three ways are identified to make input-output analysis spatially explicit based on the structure of environmentally extended input-output databases (i.e. environmental extensions, final demand, and transaction matrix). On the global scale, most studies linked spatial environmental extensions with global multi-regional input-output (GMRIO) tables to estimate local environmental impacts driven by global consumption. In general, it is more challenging to disaggregate the final demand and transaction matrix than the extensions matrix given the limitation of present datasets and computational power. The review proposed a theoretical framework of global SMRIO analysis and provided methodological support to answer the remaining sub-questions.

In the first case study, Chapter 3 identifies hotspots (i.e. the most significant production regions) for primary crops and livestock driven by international consumption, by linking high-resolution production maps of crop and livestock with a GMRIO table (EXIOBASE in Chapter 3). The embodied primary crops and livestock for high-income countries are distributed over larger areas is the case for middle- and low-income countries. This is driven by the higher number and complexity of trade links for high-income countries and higher per-capita consumption volumes, particular of animal products. This means low- and middle-income countries rely for feeding their own population more on their own production and export large amounts of fodder and food for use in high-income countries, that often see overconsumption of food and/or have systems of intensive husbandry. This has clear ramifications on food security for low- and middle-income nations. Therefore, identified hotspots driven by global consumption can facilitate targeted cooperation between consumers and producers to safeguard global food security. In terms of methodology, this chapter moves SMRIO forward by using road density from the Global Roads Inventory Project (GRIP) to distinguish the spatial distribution of production for local consumption and export (i.e. whether local production within a grid cell is used for export or domestic consumption). The comparison between these results and subnational trade data in Brazil shows some agreement. However, global calibration using such a proxy approach is still not possible due to data limitations.

In the second case study, Chapter 4 presents a comprehensive assessment of the potential global loss of terrestrial species driven by domestic and teleconnected land use within key biodiversity areas (KBAs). For this, I build an SMRIO model from physical and monetary input-output databases, spatially-explicit land use maps, and characterization factors of biodiversity loss. Human land use is dominated by agriculture sectors. Traditional GMRIO databases have highly aggregated agricultural sectors or regions. This limitation is addressed by using the Food and Agriculture Biomass Input-Output (FABIO) table, a consistent, balanced, physical input-output database based on FAOSTAT data, covering 191 countries and 130 agriculture, food, and forestry products. However, FABIO only has a partial coverage of the global economy does not include production and trade of non-agricultural products. In order to cover non-agricultural sectors, this chapter uses an integrated model framework linking FABIO and EXIOBASE. EXIOBASE is a highly detailed GMRIO database, including 200 products and 49 countries or regions. The chapter finds that land use within KBAs only accounts for 7% of total land use, while it causes 16% of global plant loss and 12% of global vertebrate loss compared to total land use. Animal product consumption accounted for more than half of biodiversity loss within KBAs. Bovine meat consumption alone contributed to about 40% of biodiversity loss within KBAs. In terms of land use, lightly grazed pastureland contributes to around half of all species loss. International trade is an important driver of loss, accounting for 25-33% of plant and vertebrate loss. The comprehensive assessment can provide guidance for maintaining the integrity of KBAs and global biodiversity.

In the third case study, Chapter 5 assesses the potential for a ‘double dividend’ for climate change mitigation via the dietary change in high-income countries from both (1) reduced direct agricultural production emissions and (2) carbon sequestration via land sparing whereby agricultural lands can revert to other uses. I employ the SMRIO approach by linking FABIO with spatially explicit maps agricultural GHG emissions and of storage of harmonized aboveground biomass carbon (AGBC), belowground biomass carbon (BGBC) and soil organic carbon (SOC), in the case of use of land for agriculture and agricultural land reverted to other uses (most notably rewilding). The dividend is estimated for a scenario in which national average diets in 54 high-income nations representing 68% of global GDP and 17% of population shift to a planetary health diet as proposed by the EAT-Lancet Commission, which is committed to co-development of healthy diets and sustainable food production. I find that dietary changes in high-income nations could result in an increased carbon sequestration potential of 115.57 Pg CO_2e over the long term (~2.3 years of global CO_2e yr^{-1} emissions in 2010), and a decrease in food system emissions of 0.61 Pg CO_2e yr^{-1}. Animal protein consumption reduction contributes the largest benefit. Including often-overlooked food and beverage items outside the EAT-Lancet diet could offer another potential carbon benefit. For example, about 1.8 Pg CO_2e carbon sequestration would benefit from cutting out beer consumption in high-income nations. The carbon sequestration from land sparing due to dietary change represents potentially a significant contribution to limiting GHG atmospheric concentrations. Linking land, food, climate, and public health policy will be vital to harnessing the opportunities of this double dividend.

Finally, Chapter 6 concludes that SMRIO analysis is capable of contributing novel insights into the sustainability of the agri-food system. The results based on SMRIO analysis can help to identify local impact hotspots, set effective impact reduction priorities, and facilitate targeted cooperation between producers and consumers. Chapter 6 also gives a general discussion on SMRIO analysis and presents three potential lines for their improvement, including the improvement of spatial data and the potential for further applications not explored in this thesis. The latest high-resolution satellite data in combination with machine learning approaches may include greater amounts of natural science data in SMRIO analysis. Improving the accuracy of the transaction matrix is very challenging, and a key opportunity for future research is the use of greater amounts of subnational trade information to map a more precise relationship between producers and consumers. This can lead particularly to better estimate in which sub-national regions food produced is mainly used for regional consumption (including e.g. subsistence farming), and in which regions mainly for exports. If data on subnational trade is not available then the use of a proxy may be considered, like e.g. road density as used in Chapter 3. However, better validation of proxy approaches would be beneficial.

Overall, each study found results with scientific and policy relevance. The consumption of animal products played a prominent role in every case study of this thesis. As these studies and others highlight, there is an urgent need for different forms of protein production and dietary change. These sorts of assessments can help provide insights into how we might avoid catastrophic environmental problems in a globalized world. However, any of the benefits highlighted in these studies will require significant international action and collaboration. They will also have to be sensitive to local conditions and the economic ramifications at both global and local level of rapid food transitions.

Samenvatting

Het wereldwijde landbouw en voedingssysteem speelt een cruciale rol in het realiseren van voedselzekerheid en milieukwesties, waaronder landgebruik, verlies van biodiversiteit en klimaatverandering. De toenemende globalisering heeft geresulteerd in een complex internationaal voedselsysteem waarin productie en consumptie in de internationale toeleveringsketens veel verschillende geografische regio's kunnen omvatten. Deze onderlinge afhankelijkheid betekent dat het moeilijk is voor een enkele producent of consument om problemen in dit systeem aan te pakken. Dit proefschrift maakt een stap in het in kaart brengen van het wereldwijde systeem van productie en consumptie van voeding en biedt verschillende beleidsrelevante inzichten, bijvoorbeeld ten aanzien van de milieuvoetafdruk. Gezien het feit dat veel milieudruk van voeding locatiespecifiek is, maar voeding wereldwijd wordt verhandeld, en dat interregionale verschillen in consumptie steeds belangrijker worden, is het een logische volgende stap om benaderingen te vinden die lokale effecten (productiekant) kunnen verbinden met wereldwijde consumptie (consumptiekant). Globale ruimtelijk (‘spatial’) expliciete multiregionale input-output (SMRIO) -analyses kunnen helpen bij het identificeren van hotspots van lokale productie en de daarmee samenhangende sociale en milieueffecten die het gevolg zijn van consumptie elders. Daarom stelt dit proefschrift de volgende overkoepelende onderzoeksvraag:

‘Hoe kunnen ruimtelijk expliciete multiregionale input output benaderingen gebruikt worden om de duurzaamheid van het wereldwijde landbouw- en voedselsysteem te beoordelen?’

In dit proefschrift heb ik eerst het eerdere gebruik van SMRIO geanalyseerd, om het volgende na te gaan: *wat is de huidige status van ruimtelijk expliciete input-outputanalyse (deelvraag 1) ?*

Om het potentieel van de techniek verder te beoordelen, heb ik een aantal verschillende SMRIO modellen gebouwd voor gebruik in drie verschillende case studies. Ik gebruik de SMRIO modellen om drie kritieke problemen in het landbouw- en voedselsysteem te onderzoeken: voedselzekerheid, het verlies aan biodiversiteit, en klimaatverandering. De case studies behandelen de volgende vragen:

Wat zijn de hotspots voor lokale productie van gewassen en vee die zijn gerelateerd aan wereldwijde consumptie van voeding en hoe beïnvloedt deze wereldwijde handel de voedselzekerheid (deelvraag 2)?

Hoe beïnvloedt landgebruik gerelateerd aan eindconsumptie van voeding de biodiversiteit binnen de zogenaamde ‘Key Biodiversity Areas’ (deelvraag 3)?

Hoe beïnvloeden diëten en veranderingen daarin in landen met een hoog inkomen koolstofemissies en koolstofvastlegging in vegetatie en bodem (subvraag 4)?

Om de eerste deelvraag te beantwoorden , bespreekt Hoofdstuk 2 de literatuur over ruimtelijk expliciete input-outputanalyse en beoordeelt het de mechanismen die worden voorgesteld om wereldwijde consumptie in verband te brengen met lokale milieudruk. Ik definieer ruimtelijk expliciete input-outputanalyse als een aanpak waarin de ruimtelijke resolutie van resultaten groter is dan de onderliggende input-output transactiematrix. Ik beoordeel eerdere pogingen om deze perspectieven te combineren op verschillende temporele en ruimtelijke schalen, voor verschillende vormen van milieudruk. Eerdere studies hadden betrekking op verschillende soorten van milieudruk, zoals de uitstoot van broeikasgassen, watergebruik, luchtvervuiling en verlies van biodiversiteit. Ik identificeer drie manieren om traditionele input-outputanalyse ruimtelijk expliciet te maken: te weten het ruimtelijk expliciet maken van milieu-extensies, de finale vraag en de transactiematrix. De meeste studies op wereldschaal koppelden globale multiregionale input-output (GMRIO) tabellen aan ruimtelijk expliciete informatie over

milieudruk van productie. Zo kunnen locatie specifieke milieueffecten worden ingeschat veroorzaakt door wereldwijde consumptie. Het blijkt echter veel lastiger om de finale vraag of transactiematrix ruimtelijk expliciet et maken. Beperkingen in beschikbaarheid van data, maar ook rekenkracht, zijn nog groot. Hoofdstuk 2 ontwikkelde kort gezegd een theoretisch kader voor het uitvoeren van wereldwijde SMRIO analyses, wat het beantwoorden van de resterende sub-vragen ondersteunde.

De eerste case studie in Hoofdstuk 3 identificeert hotspots (dat wil zeggen de belangrijkste productieregio's) voor de primaire gewassen en dierlijke producten in relatie tot internationale consumptie van voeding. Voor dit doel koppelde ik productie kaarten van landbouw en veeteelt met een hoge geografische resolutie met een GMRIO tabel (EXIOBASE). De productie van gewassen en dierlijke producten voor consumptie in landen met hoge inkomens vindt plaats in grotere gebieden dan het geval is voor landen met midden- en lage-inkomens. Dit wordt veroorzaakt door het grotere aantal en de complexiteit van handelsrelaties voor landen met een hoog inkomen naast hogere consumptievolumes per hoofd van de bevolking, met name van dierlijke producten Dit betekent dat lage- en liddeninkomenslanden voor het voeden van hun eigen bevolking meer afhankelijk zijn van hun eigen productie en grote hoeveelheden voer en voedsel exporteren voor gebruik in hoge-inkomenslanden. De laatsten hebben vaak te maken met overconsumptie van voedsel en hebben vaak ook systemen van intensieve veehouderij. Dit heeft duidelijke gevolgen voor de voedselzekerheid voor landen met lage- en middeninkomens. De hotspots die ik identificeerde kunnen consumenten en producenten helpen bij het prioriteren van samenwerking ten aanzien van het zekerstellen van wereldwijde voedselzekerheid. Methodologisch maakt het hoofdstuk de volgende stap in het verbeteren van de SMRIO benadering. Het is van belang per gridcel onderscheid te maken tussen productie voor lokale consumptie en export. Het gebruik van de verhouding hiertussen op nationaal niveau is te grof. Ik gebruikte de wegendichtheid uit het Global Roads Inventory Project (GRIP) om de verhouding tussen productie voor lokale consumptie en export beter in te schatten. Ik toetste deze aanpak met cijfers over sub-nationale handel in Brazilië, hetgeen enige overeenstemming liet zien. Kalibratie van dit soort proxybenadering op wereldschaal is echter nog steeds niet mogelijk vanwege beperkingen in voorhanden gegevens.

In de tweede casestudie presenteert Hoofdstuk 4 een uitgebreide beoordeling van het potentiële wereldwijde verlies van terrestrische soorten als gevolg van landgebruik door wereldwijde voedselconsumptie binnen belangrijke biodiversiteitsgebieden (‘Key Biodiversity Areas’ of KBA's) . Hiervoor bouwde ik een SMRIO- model gebaseerd op fysieke en monetaire input-output databases, ruimtelijk specifieke informatie over landgebruik, en ruimtelijk specifieke karakterisatiefactoren die aangeven hoe milieudruk zoals landgebruik doorwerkt op biodiversiteitsverlies. De landbouw domineert menselijk landgebruik. Traditionele GMRIO-databases hebben sterk geaggregeerde landbouwsectoren en -regio's. Om deze beperkingen te overwinnen gebruikt Hoofdstuk 4 de Food and Agriculture Biomass Input-Output (FABIO) -tabel, een consistente, gebalanceerde, fysieke input-outputdatabase op basis van statistieken van de Food- en Agricultural Organisation van de UN (‘FAOSTAT’). Die gegevens hebben betrekking op 191 landen en 130 landbouw-, voedsel- en bosbouwproducten. FABIO dekt echter alleen productie en consumptie van landbouwproducten. FABIO mist de productie en handel van niet-landbouwproducten en mist dus een deel van de wereldeconomie. Daarom verbindt hoofdstuk 4 FABIO met EXIOBASE. EXIOBASE is een zeer gedetailleerde GMRIO-database, met 200 producten en 49 landen of regio's. De analyse laat zien dat landgebruik binnen KBA's slechts 7% van het totale landgebruik uitmaakt, terwijl in vergelijking met het totale landgebruik daar 16% van het wereldwijde plantverlies en 12% van het wereldwijde verlies van gewervelde dieren plaatsvindt. De consumptie van dierlijke producten blijkt verantwoordelijk voor meer dan de helft van het verlies aan biodiversiteit binnen KBA's. Alleen al de consumptie van rundvlees droeg bij tot ongeveer 40% van het verlies aan biodiversiteit binnen KBA's. In termen van landgebruik draagt licht begraasd weiland bij aan ongeveer de helft van alle soortenverlies. Internationale handel is een belangrijke oorzaak hiervan, goed voor 25-33% van het verlies aan planten en gewervelde dieren. Deze analyse geeft handvaten hoe KBA's en de wereldwijde biodiversiteit beschermd kunnen worden.

In de derde casestudie beoordeelt Hoofdstuk 5 het potentieel voor een 'dubbel dividend' ten aanzien het klimaatprobleem door wijziging van het voedingspatroon in landen met een hoog inkomen door zowel (1) verminderde directe emissies van landbouwproductie als (2) koolstofvastlegging door vermindering van gebruik van land voor landbouwdoeleinden. Hierbij kunnen landbouwgronden voor andere doeleinden worden gebruikt. Ik pas de SMRIO-benadering toe door FABIO te koppelen aan ruimtelijk expliciete kaarten, agrarische broeikasgasemissies en van opslag van koolstof in bovengrondse biomassa (AGBC), in ondergrondse biomassa (BGBC) en als organische koolstof in de bodem (SOC). Ik analyseer hoe wijzigingen in diëten in landen met hoge inkomens landbouwgrond vrijmaakt voor andere doeleinden, met name het terugbrengen van die grond in oorspronkelijke staat (‘verwildering’). Ik neem hiervoor een scenario waarin 54 landen met hoge inkomens (goed voor 68% van het mondiale bruto binnenlands product (bbp) en 17% van de globale bevolking) een dieet gaan volgen zoals voorgesteld door de EAT-Lancet Commission. Ik vind dat dergelijke wijzigingen zouden kunnen leiden tot een verhoogde koolstofvastlegging van 115.57 Pg CO_2e op de lange termijn (vergelijkbaar met ongeveer 2,3 jaar van de wereldwijde koolstofuitstoot in 2010), en een daling van de emissies uit het voedingssysteem van 0.61 Pg CO_2 per $jaar^{-1}$. De vermindering van de consumptie van dierlijke eiwitten levert het grootste voordeel op. Ook vermindering van gebruik van voedingsmiddelen die geen deel uitmaken van het EAT-Lancet dieet kunnen tot extra reductie van koolstofemissies leiden. Bijvoorbeeld, het terugdringen van consumptie van bier en wijn in landen met hoge inkomens kan tot ongeveer 1.8 pg CO_2e koolstofvastlegging leiden. De koolstofvastlegging door landbesparing als gevolg van veranderingen in het voedingspatroon kunnen dus een significante bijdrage leveren aan het beperken van de atmosferische broeikasgasconcentraties. Het koppelen van land-, voedsel-, klimaat- en volksgezondheidsbeleid is cruciaal om de kansen op dit dubbele dividend te benutten.

Ten slotte concludeert Hoofdstuk 6 dat SMRIO-analyses in staat zijn om met nieuwe inzichten bij te dragen om de duurzaamheid van het landbouw- en voedingssysteem te vergroten. Resultaten op basis van SMRIO-analyses kunnen helpen bij het identificeren van hotspots ten aanzien van milieudruk op lokaal niveau , het stellen van prioriteiten voor reductie van impacts en het faciliteren van gerichte samenwerking tussen producenten en consumenten. Hoofdstuk 6 geeft ook een algemene discussie over SMRIO-analyse en presenteert drie mogelijke lijnen voor verbetering van de methode. Dit behelst een verdere verbetering van ruimtelijke gegevens en het toepassen op andere cases die niet in dit proefschrift zijn onderzocht. Vooral nieuwe hoge-resolutie satelliet gegevens in combinatie met machine learning benaderingen kunnen de SMRIO analyses voeden met betere en gedetailleerdere data. Vooral het ruimtelijk expliciet maken van de transactiematrix is een grote uitdaging. Het gebruik van sub-nationale handelsdata kan helpen handelsketens specifieker in kaart te brengen. Het is daarbij vooral belangrijk dat een onderscheid gemaakt kan worden voor welk deel de lokale productie van landbouwproducten wordt gebruikt voor lokale consumptie, en welk deel naar andere regio’s of landen wordt geëxporteerd. Als er geen gegevens over sub-nationale handel beschikbaar zijn, kan het gebruik van een proxy worden overwogen, zoals bijvoorbeeld de wegendichtheid die gebruikt werd in hoofdstuk 3. Een betere validatie van proxybenaderingen is echter van belang.

Over het algemeen vond elke hoofdstuk resultaten met die wetenschappelijk- en beleidsrelevant zijn. De consumptie van dierlijke producten speelde een prominente rol in elke case studie in dit proefschrift. Zoals uit deze en andere onderzoeken blijkt, is er dringend behoefte aan nieuwe vormen van eiwitproductie en verandering van het voedingspatroon. Dit soort analyses kan helpen om inzicht te krijgen in hoe we catastrofale milieuproblemen in een geglobaliseerde wereld kunnen voorkomen. Het realiseren van de kansen die dit proefschrift identificeert vergt echter een aanzienlijke mate van internationale actie en samenwerking. Die samenwerking zal ook rekening moeten houden met de lokale omstandigheden en de economische gevolgen van snelle voedselovergangen op zowel mondiaal als lokaal niveau .

Acknowledgements

It is challenging and wonderful to finalize the thesis. Foremost, I would like to express my deepest thankfulness and everlasting gratitude to my supervisors, Dr. Paul Behrens and Dr. Laura Scherer. They spent significant time and energy on every word of the thesis. They came up with suggestions whenever I met a tough problem, from algorithm design to technical issues of the software. They guided me in the road of academic research from all aspects. They inspired me how to choose an attractive topic for academic research and provided me new insights on how to explain results. They also taught me a lot about how to write an excellent academic paper how I should present my research. And beyond the academic research, they cared about my daily life. They encouraged me to take sufficient rest and I could share stressful issues and some worries with them.

I would also like to thank my promoter, Prof. Arnold Tukker for providing me a great opportunity to work in the CML. This thesis could not have been accomplished without his help and contributions. His feedbacks were always very clear and very helpful to improve the thesis.

I would thank the China Scholarship Council for the financial support that provided me with the opportunity to work at CML and live in Leiden. Special thanks to my Chinese friends for accompanying me to celebrate Chinese festivals. Your sweet parties helped me to overcome homesickness. I would thank the PhD-committee for organization of very useful workshops and other activities, such as “Managing Stress & Anxiety”, “Coaching in academic writing”, “Virtual drink”, and for circulating little presents on the occasion of the Chinese new year. I would thank my previous office mates and research partners in A3.03: Marinda van Pomeren, Bregje Brinkmann, and Henrik Barmentlo. We enjoyed the mixed Dutch and Chinese culture, and learned some words from each other. I would also thank current roommates in B2.17: Elizabeth Migoni Alejandre, and Carlos Blanco Rocha. They are both very nice and humorous friends. I was very lucky to work with them. It a pleasure to thank other colleagues in CML for all their help in both work and daily life: Susanna van den Oever, Sammy Koning, Glenn Aguilar Hernandez, Franco Donati, Leon Hauser, Paul de Hoog, Arjan de Koning, and Sidney Niccolson.

Last but not the least, I would like to express my heartfelt thanks to my family for their unconditional support. I thank my parents to encourage me to explore my curiosity. I thank my brother and his wife take care of my parents, and also thank my little nephew who brings a lot of pleasure to the whole family.

List of publications

Papers in this thesis

1. **Sun, Z.,** Tukker, A. and Behrens, P., 2018. Going global to local: connecting top-down accounting and local impacts, a methodological review of spatially-explicit input–output approaches. Environmental Science & Technology, 53(3), pp.1048-1062.
2. **Sun, Z.,** Scherer, L., Tukker, A. and Behrens, P., 2020. Linking global crop and livestock consumption to local production hotspots. Global Food Security, 25, p.100323.
3. **Sun, Z.,** Behrens, P., Tukker, A., Bruckner, M., and Scherer, L. Land use in key biodiversity areas disproportionately threatens global biodiversity. (submitted to Proceedings of the National Academy of Sciences)
4. **Sun, Z.,** Scherer, L., Tukker, A., Spawn-Lee, S., Bruckner, M., Gibbs, H., and Behrens, P. A double carbon dividend from dietary change in high-income nations. (under review in Nature Food)

Additional publications

5. Huang, J., Ridoutt, B.G., **Sun, Z.,** Lan, K., Thorp, K.R., Wang, X., Yin, X., Huang, J., Chen, F. and Scherer, L., 2020. Balancing food production within the planetary water boundary. Journal of Cleaner Production, 253, p.119900.

Curriculum vitae

Zhongxiao Sun was born on 19th September 1991, in Zaozhuang City, Shandong Province, China. He took his high school education from Zaozhuang No.2 Senior High school from 2007 to 2010. He majored in Mathematics and Applied Mathematics at China University of Geosciences (Wuhan) from 2010 to 2014 and graduated with his BSc degree in June 2014.

Between 2014 and 2017, He obtained his MSc degree in the major of Environmental Science at the School of Environment, Beijing Normal University. After graduation, he joined the Institute of Environmental Sciences (CML) with the support of the China Scholarship Council (CSC). His PhD project, under the supervision of Dr. Paul Behrens, Dr. Laura Scherer, and Prof. Arnold Tukker, aimed at the application of spatially explicit input-output analysis. He employed the approach to trace local impacts propagating globally via domestic and international demand. This thesis is the outcome of his PhD research.