Impacts of global food supply on biodiversity via land use and climate change

Abstract

Land-use change is currently the greatest driver of biodiversity change, with climate change predicted to match or surpass its impacts by mid-century. The global food system is a key driver of both these anthropogenic pressures, thus the development of sustainable food systems will be critical to halting and reversing biodiversity loss. Previous studies of the biodiversity footprint of food tend to focus on land use alone. We use the multi-regional input-output model EXIOBASE to estimate the impacts of biodiversity embedded within the global food system. We build on prior analyses, calculating the impacts of both agricultural land-use and greenhouse gas (GHG) emission footprints for the same two metrics of biodiversity: local species richness and rarity-weighted species richness. Our biodiversity models capture regional variation in the sensitivity of biodiversity both to land-use differences and to climate change. We find that the footprint of land area does not capture the biodiversity impact embedded within trade that is provided by our metric of land-driven species richness change, and that our metric of rarity-weighted richness places a greater emphasis on the biodiversity costs in Central and South America. We show that the climate contributions of food production are accumulating rapidly over time, particularly in North America and Western Europe. The measures we present are simple to calculate and could be incorporated into decision making and environmental impact assessments by governments and businesses.

Keywords

Multi-regional input-output model; impacts embodied in trade; biodiversity footprint; consumption-based accounting; agriculture; food system sustainability

1. Introduction

Anthropogenic pressures continue to drive biodiversity loss despite increasing conservation efforts[1]. Land use is currently the greatest driver of biodiversity change[1,2], and has thus been the focus of much previous conservation research. However, the impacts of climate change on biodiversity are expected to increase considerably[3], and, by 2070, climate may match or surpass land use as the greatest driver of biodiversity change[4,5]. Agricultural land used for food production covers an estimated 38-55% of Earth's habitable land[6,7], while the global food system is responsible for 21-

32 37% of anthropogenic greenhouse gas (GHG) emissions[8-10]. The development of sustainable food
33 systems will be critical in halting/reversing land-driven[11]. and climate-driven biodiversity loss[12].

34 Increasingly, food grown in one country is traded internationally to satisfy demand
35 elsewhere[13-15]. The associated biodiversity impact of this international consumption is driven by
36 upstream economic activities that are often geographically distant from the locations of biodiversity
37 loss[16]. Reducing the environmental impacts of food therefore requires both supply-side and
38 demand-side changes[16].

39 Understanding the separate contributions of agricultural land use and greenhouse gas
40 emissions to biodiversity loss is an important step toward developing a sustainable international
41 trade in food. A strategy which considers land use alone might well differ from one that incorporates
42 GHG-driven biodiversity loss. Importantly, the land and GHG footprint per tonne of crops arising
43 from N_2O tend to be negatively correlated – intensive farming uses less land than extensive
44 farming, but has higher GHG emissions (N_2O) arising from higher fertilizer use[17]. Moreover, land use
45 and climate differ in their spatial impacts on biodiversity loss. Land use affects biodiversity that is
46 local to the land conversion. In contrast, climate change affects biodiversity globally, no matter the
47 location of the emissions source.

48 Environmentally-extended multi-regional input-output models (EEMRIOs) are used to link
49 downstream environmental impacts to upstream drivers, allowing the 'footprints' of commodities to
50 be followed back through complex supply chains[18]. The footprint of a hamburger, for example,
51 would contain impacts not only from cattle but from cattle feed, fertilizer, machinery, water,
52 packaging, fuel etc. [19]. Summing the impacts associated with each upstream product would, in
53 theory, give the hamburger's total footprint. However, in reality this simple addition process is
54 impossible given the complications of tracking supply chains, double counting of recycled products,
55 and infinite loops, for example electricity production requiring water which requires electricity to
56 pump it. EEMRIOs resolve these problems by using input-output tables to infer production recipes,
57 allocating environmental costs to sectors to avoid double counting and approximating infinite sums
58 with the Leontief inverse matrix[19]. Regional production data and their associated environmental
59 costs are combined with information on international trade, allowing the calculation of a variety of
60 consumption footprints, e.g. land use[20], GHG emissions[21] and water[22].

61 EEMRIO models have been used to follow the effects of international trade along supply
62 chains, to estimate biodiversity footprints. Lenzen et al. [23] performed the first global biodiversity
63 footprint analysis, using the IUCN Red List to count species' threats within trade regions. This
64 method assumes that species are equally threatened across their ranges, and excludes non-

threatened species. Other methods use a similar philosophy to calculate footprints based on biodiversity threat hotspots[24], bird ranges and the number of individual birds lost from an area[16]. An alternative method, derived from land-use data, uses the countryside species-area relationship to estimate the potential number of extinctions caused by land conversion and international trade[15,25,26]. Since many of the extinctions have yet to be realized, it is unclear how these extinctions would be allocated to different actors across time[16]. Wilting et al. [27] take a step further, deriving biodiversity footprints from GHG emissions as well as land use, using the biodiversity metric Mean Species Abundance (although climate impacts are based on model predictions of changes in species richness, so land-use and climate impacts are not entirely comparable). The GLOBIO biodiversity model[28], on which Wilting et al.'s [27] analysis was based, assumes that effects of land use and climate change are even across all terrestrial regions; in reality, biodiversity tends to be more sensitive to land use and climate change in tropical regions[29,30].

We build on these prior analyses, calculating the impacts of agricultural land use and GHG-emission footprints using models that directly output the same two metrics of terrestrial biodiversity: change in local species richness and local rarity-weighted species richness, relative to an unimpacted baseline. Species richness, although easy to measure, captures only one of the many dimensions of biodiversity, and does not always decline with global biodiversity loss[31]. Rarity-weighted richness gives greater weight to species with small geographic range size (range size correlates with species extinction risks[32]) and so declines if rare species are replaced by more common ones. Furthermore, we use biodiversity models that allow us for the first time to capture regional variation in the sensitivity of biodiversity both to land-use differences and to climate change[29]. We base our biodiversity metrics on local measures of biodiversity in the relevant agricultural areas as opposed to a value averaged across an entire trade region, meaning that we account for the wide variation in species richness that occurs within regions.

We examine the international production and consumption footprints of food-related commodities in terms of: a) land area; b) species richness (land-driven and GHG-driven); and c) rarity-weighted species richness (land-driven and GHG-driven). We calculate footprints for 33 food-related products that span food's journey from field to farm gate to household to waste in 49 regions (44 countries and 5 "rest of world" regions). We ask whether the different footprints would give the same conclusions with respect to sustainable production, consumption and trade. We identify the regions and food groups with the highest biodiversity footprints, examining the contributions of land use and GHG emissions to these footprints. We explore biodiversity footprints per km^2 and per capita for each region and look at the proportion of regions' footprints which are imported. Our analysis provides a detailed examination into the pathways by which regions'

consumption of particular food-related products affects biodiversity worldwide, giving insight into the trade-offs between land use and GHG emissions, and into priorities for demand-side changes.

2. Methods

2.1 EEMRIO analysis

Input-output analysis is a top-down approach that uses sectoral transactions data (either in financial terms or units of product) to account for the complex interdependencies of industries. An input-output table can be environmentally extended by adding information on exchanges with the environment, e.g. GHG emissions or land use, by each industry sector. EEMRIO analysis traces the production and supply chain of traded goods and services and their associated materials back to the source of primary extraction, thus capturing the direct and indirect environmental pressures associated with a country's final consumption[19]. Full details of the calculations underlying EEMRIO analysis can be found in Kitzes[19] and Miller and Blair[18].

We used the standard environmentally-extended Leontief model to calculate the effects of consumption on biodiversity loss

$$\boldsymbol{E} = \boldsymbol{f} \cdot (\boldsymbol{I} - \boldsymbol{A})^{-1} \cdot \boldsymbol{Y}$$

(Equation 1)

Where, for *i* regions and *m* economic sectors:

E is a $(1 \times i)$ matrix, representing the environmental impacts associated with the final demand of each region (GHG emissions, in kg CO_2-eq, and agricultural area, in km^2).

f is the $(1\ x\ im)$ direct intensity vector, representing the environmental pressures (e.g. area of land, mass of CO_2 emissions) associated with one unit (€1M) of production for each product sector in each region.

I is the $(im \times im)$ identity matrix.

A is the $(im \times im)$ technical coefficient matrix which gives the amount of input (€1M) that every sector must receive from every other sector in order to produce one unit (€1M) of output.

Y is the $(im \times i)$ matrix of final demand given in monetary terms (€1M).

The direct intensity vector ***f*** allows the MRIO to be extended to include environmental costs of production and consumption. Sections 2.2 and 2.3 describe our environmental 'characterisation factors' based on species richness, rarity-weighted richness, land use and GHG emissions. The vector relating to land use is a sparse vector populated in the entries for production activities that involve use of cropland or pasture.

We use the EEMRIO database EXIOBASE3.8.1 (product by product version) [33], because of its superior balance of sectoral and regional disaggregation relative to other MRIOs. EXIOBASE3 provides a harmonized time-series of MRIO tables and environmental extensions over the period 1995-2022, covering 200 products, 44 countries (EU countries and other major economies), plus 5 'Rest of World' (RoW) regions. We chose 2011 as our year for analysis since land use data are available up to 2011 only and spatial crop data were not available after this date (see below).

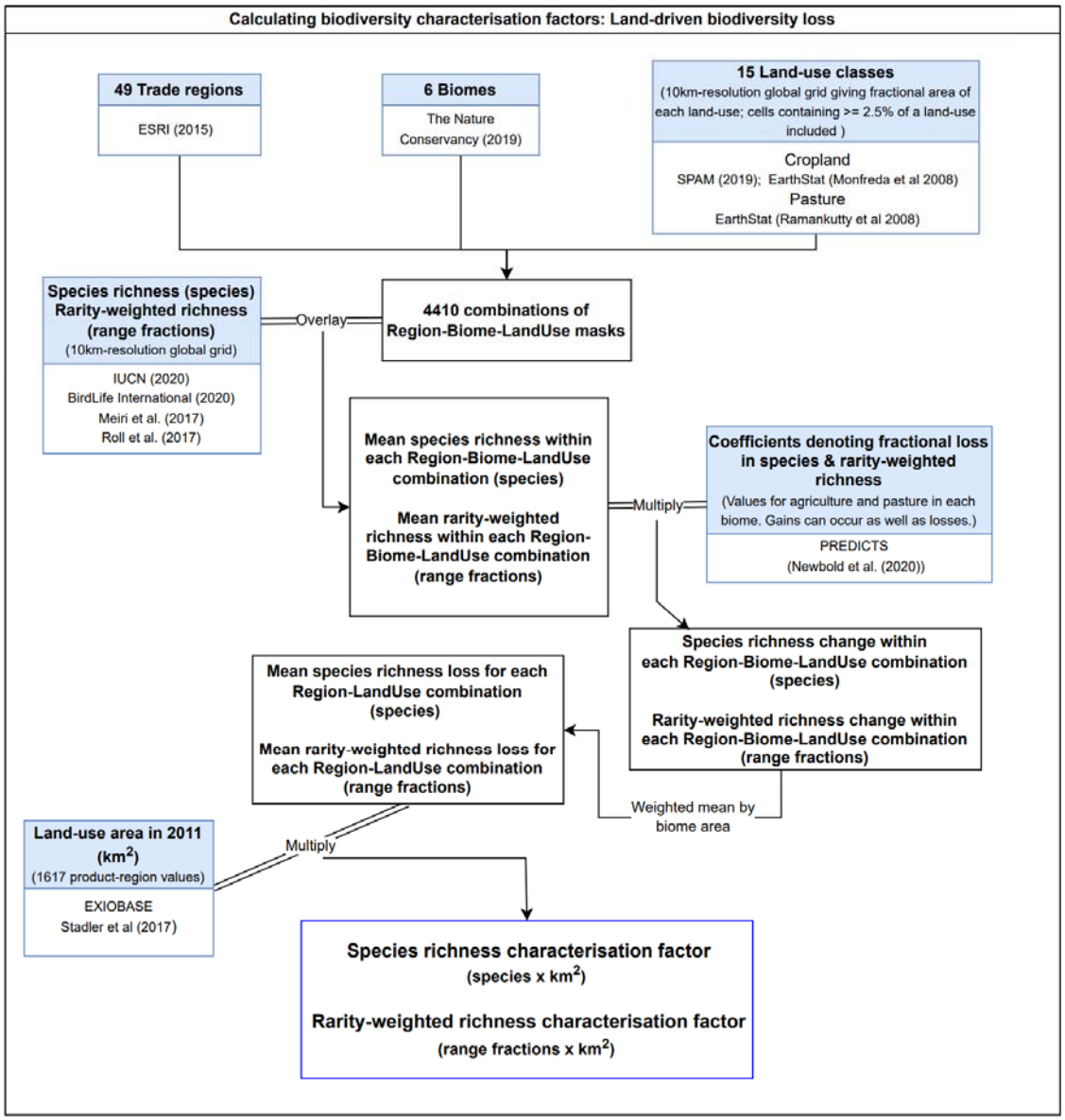
Our analysis focuses on the production and consumption of the 33 product-sectors associated with food (Supplementary Table 1) in the year 2011, including fertiliser production and food waste processing. 'Hotel and restaurant services' was excluded since it encompasses energy and materials, for example, as well as food. Full details of EXIOBASE's land-use and emissions accounts are given in Stadler et al. [33]. Our land-driven biodiversity footprints are based on agricultural land, and exclude impacts of forestry, infrastructure or other uses. Emissions from crops derive from nitrogen and phosphorous fertilisers, while emissions from livestock derive from the animals, the manure excreted and the cultivation of feed crops. Impacts of fertiliser refer to the production of the fertiliser only and impacts of food waste do not include the production impacts of the wasted food. For simplicity, we regard land use as a one-off cost that results in a change in biodiversity and we assume that once land has been converted, it can be used repeatedly without the biodiversity cost increasing. In contrast, GHG-driven biodiversity loss accrues year on year. GHG emissions that are released during land conversion are not considered, because, without detailed land-history knowledge, we cannot estimate the proportion of emissions that have dissipated since conversion, nor apportion food-production emissions across years. To put this gap in our coverage of GHGs into context, direct emissions from agriculture contribute 5.1-6.1 Pg CO_2-eq,/yr while the clearing of native land for agriculture contributes around 5.9 (SD 2.9) Pg CO_2-eq/yr[34].

2.2 Characterisation factors for land-driven biodiversity impacts

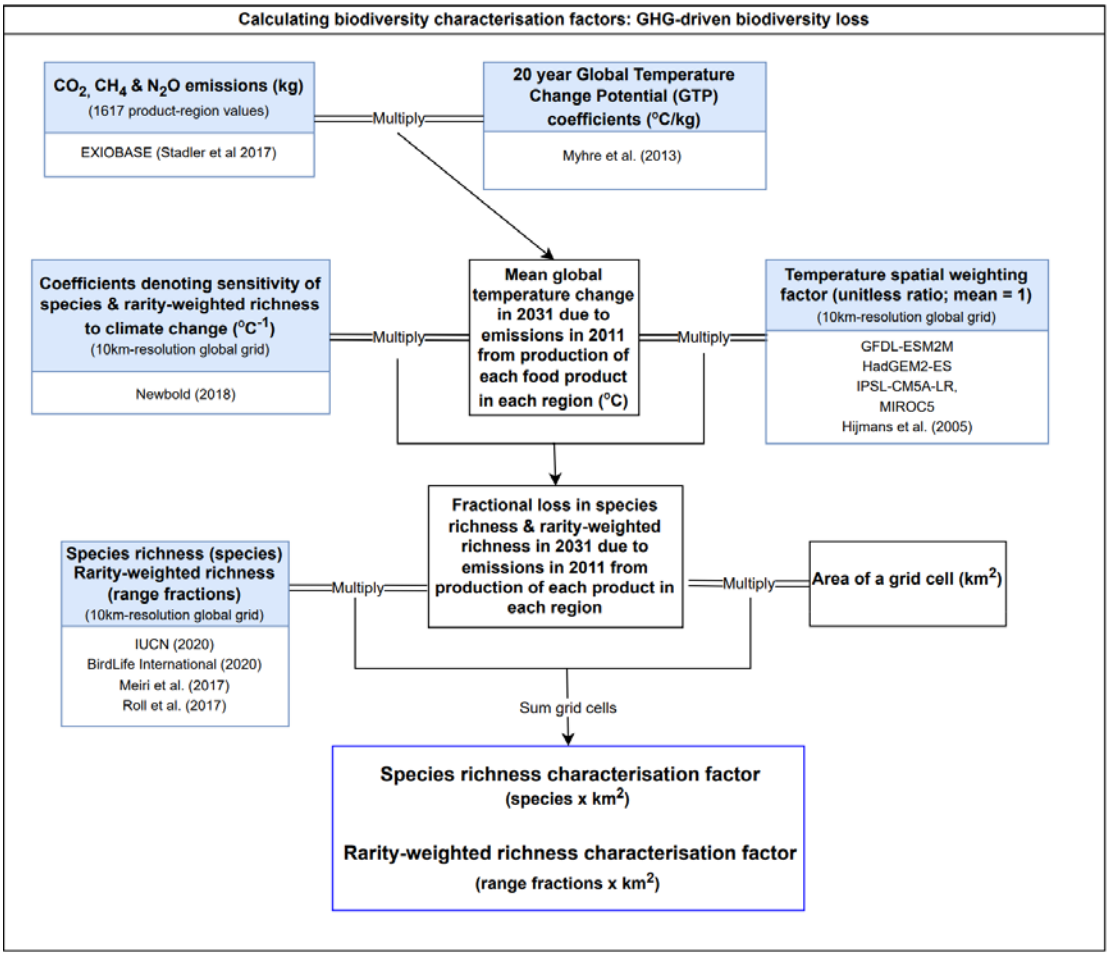
Maps for a) the 49 EXIOBASE trade regions, b) the six biomes used in Newbold et al. [29] (but here also including boreal forest within the temperate-forest grouping), and c) the 15 EXIOBASE

agricultural land-use categories were identified, and map masks for each unique 3-way combination were generated. Shapefiles mapping the borders of individual countries[35] were aggregated and rasterised to match EXIOBASE's 49 regions. Biomes were obtained from The Nature Conservancy[36] and were aggregated into tropical forest, temperate/boreal forest, tropical grassland, temperate/montane grassland, Mediterranean, and drylands (tundra, mangroves, flooded grasslands, inland water and rock & ice were excluded; Supplementary Table 2). Cropland data were obtained from the Spatial Production Allocation Model (SPAM) [37] and from EarthStat[38] and pasture data from EarthStat[39]. All spatial data were reprojected to an equal-area Behrmann grid. A summary schematic is given in Figure 1a and further details of the preparation of datasets are given in the Supplementary Information.

a)


Calculating biodiversity characterisation factors: Land-driven biodiversity loss
49 Trade regions
ESRI (2015)
6 Biomes
The Nature Conservancy (2019)
15 Land-use classes
(10km-resolution global grid giving fractional area of each land-use; cells containing >= 2.5% of a land-use included)
Cropland
SPAM (2019); EarthStat (Monfreda et al 2008)
Pasture
EarthStat (Ramankutty et al 2008)
Species richness (species)
Rarity-weighted richness (range fractions)
(10km-resolution global grid)
IUCN (2020)
BirdLife International (2020)
Meiri et al. (2017)
Roll et al. (2017)
Overlay
4410 combinations of Region-Biome-LandUse masks
Mean species richness within each Region-Biome-LandUse combination (species)
Mean rarity-weighted richness within each Region-Biome-LandUse combination (range fractions)
Multiply
Coefficients denoting fractional loss in species & rarity-weighted richness
(Values for agriculture and pasture in each biome. Gains can occur as well as losses.)
PREDICTS
(Newbold et al. (2020))
Species richness change within each Region-Biome-LandUse combination (species)
Rarity-weighted richness change within each Region-Biome-LandUse combination (range fractions)
Mean species richness loss for each Region-LandUse combination (species)
Mean rarity-weighted richness loss for each Region-LandUse combination (range fractions)
Weighted mean by biome area
Land-use area in 2011 (km2)
(1617 product-region values)
EXIOBASE
Stadler et al (2017)
Multiply
Species richness characterisation factor
(species x km2)
Rarity-weighted richness characterisation factor
(range fractions x km2)

171 b)



172

173 Figure 1. Schematics summarising the characterisation factor calculations. Characterisation
174 factors for a) land-driven biodiversity loss and b) GHG-driven biodiversity loss. The methods allow for
175 biodiversity gain which would be represented as a negative loss.

176 Mapped spatial estimates of species richness and rarity-weighted richness for terrestrial
177 vertebrates were obtained by stacking species geographical distributions at a 10-km equal-area
178 resolution. Extent-of-occurrence distribution maps were obtained from the IUCN[40], BirdLife
179 International[41], Meiri et al. [42], and Roll et al. [43]. We selected only areas where species are extant or
180 probably extant, and resident during the breeding season. As in Etard et al. [44], we further excluded
181 areas outside the known elevational limits of species[40]. Species richness was calculated as the
182 number of species occurring within a grid cell. Rarity-weighted species richness weights were
183 calculated as the inverse of a species' estimated range size, and rarity-weighted richness as the sum
184 of these weights across species occurring within a grid cell. Mean species richness and rarity-

weighted richness were calculated for each land-use type within each biome within each trade region.

We estimated the sensitivity of biodiversity to land use using models of the PREDICTS database[45,46], following the methods given in Newbold et al. [29] (see Supplementary Information). The PREDICTS database contains 3.25 million samples of biodiversity in six different land uses from 26, 114 locations and 47,044 different species. For the purposes of this study, we modelled biodiversity differences among four land-use classes: primary vegetation, secondary vegetation, agriculture (including both plantations and herbaceous cropland) and pasture, allowing the response of biodiversity (i.e. species richness and rarity-weighted richness) to these land-use categories to vary among the six broad biome groupings listed above. For further details, see the Supplementary Information.

Characterisation factors for species richness were calculated as follows. We used the species richness map to estimate the mean species richness $S_{i,j,k}$ that would occur in undisturbed land across the area covered by each EXIOBASE land-use type *i*, within each biome *j* and each EXIOBASE trade region *k*. The change in species richness $\Delta S_{i,j,k}$ due to land-use was calculated as:

$$\Delta S_{i,j,k} = S_{i,j,k} \times P_{j,l}$$

(Equation 2)

where $P_{j,l}$ is the proportional change in species richness in PREDICTS land-use type l and biome j, compared to primary vegetation in that biome (see Supplementary Table 3 for the correspondence between EXIOBASE and PREDICTS land-use types, and Supplementary Tables 4 and 5 for values of $P_{j,l}$). The change in species richness $\Delta S_{i,k}$ within each EXIOBASE land-use type *i* and each region *k* was calculated as:

$$\Delta S_{i,k} = \sum_{j=1}^{J_{i,k}} (\Delta S_{i,j,k} \times B_{i,j,k})$$

(Equation 3)

where $J_{i,k}$ is the number of biomes covered by the EXIOBASE land use type *i* within the region *k* and $B_{i,j,k}$ is the proportion of the EXIOBASE land-use type *i* within the region *k* that is covered by the biome *j*. The characterisation factor $CF_{i,k}$ was then calculated as:

$$CF_{i,k} = \Delta S_{i,k} \times A_{i,k}$$

(Equation 4)

212 where $A_{i,k}$ is the area of agricultural land used to produce €1M of product in land-use type *i* in
213 region *k*). Characterisation factors for rarity-weighted richness were calculated using the same
214 method, but using the map of rarity-weighted species richness, and corresponding modelled
215 estimates of land-use sensitivity (for characterisation factor values, see Supplementary Tables 6 and
216 7).

217 The characterisation factors for species richness have units of number of species × km^2 and
218 can be thought of as the count of the species lost, with this loss extending over a certain area (i.e.,
219 the area of land use given in EXIOBASE). Rarity-weighted richness characterisation factors are less
220 intuitive, but can be thought of as having a unit of species range fractions × km^2.

221

222 *2.3 Characterisation factors for GHG-driven biodiversity loss*

223 We calculated GHG-driven biodiversity loss in a three-step process. First, we calculated the
224 GHG emissions associated with each region's 2011 final demand for the 33 different food-related
225 products. Second, we calculated the warming that would result from these emissions. Third, we
226 calculated the biodiversity loss that would result from this warming. A summary schematic is given in
227 Figure 1b.

228 EXIOBASE gives emissions for six GHGs: carbon dioxide (CO_2), methane (CH_4), nitrous oxide
229 (N_2O), and three fluorinated gases. We calculated footprints using the first three gases only. Their
230 contribution to warming via food-related emissions is much greater than that of the fluorinated
231 gases. We summed methane emissions over the four categories given by EXIOBASE ('Combustion –
232 air', 'non-combustion', 'agriculture' and 'waste').

233 We calculated the increase in global surface temperature due to GHG emissions using the
234 Global Temperature Change Potential (GTP), a metric designed to be an intuitive measure of climate
235 response[47]. The GTP is defined as the ratio between the global mean surface temperature change at
236 a given future time horizon following an emission (pulse or sustained) of a compound relative to a
237 reference gas[47]. We chose a 20-year time horizon, to capture warming due to the relatively short-
238 lived methane emissions, and to represent a time that is tangible to today's policy and decision-
239 makers. GTP values in units of degrees of warming (°C) per kilogram of emissions were taken from
240 the AR5 IPCC report[48], Table 8.A.1 (CO_2 6.84×10^{-16} °C /kg, CH_4 4.62×10^{-14} °C /kg, N_2O 1.89×10^{-13}
241 °C /kg). The warming in °C that would result by 2031 $\Delta T_{p,k}$ due to the emissions $E_{g,p,k}$ associated
242 with each gas *g* due to the production of €1M of each product *p* in each region *k* was calculated as:

$$\Delta T_{p,k} = \sum_g (E_{g,p,k} \times C_g)$$

(Equation 5)

where C_g is the GTP value for each gas *g*.

We estimated the sensitivity of biodiversity to climate change based on future projections of changes in the distributions of terrestrial vertebrates under the Representative Concentration Pathways (RCP) climate-change scenarios[5]. It is necessary to use future projections rather than observed responses of species to climate change, because we do not yet have enough data for a wide range of species from locations that have experienced extensive historical climate change[29]. Full details are given in the Supplementary Information.

To account for the non-uniformity of warming across the globe, we calculated a grid of spatial weighting factors to up or down weight temperature change depending on the difference between the projected local and mean global temperature change. The projected temperature change ΔT_x in each cell *x* between 2011 and 2031 under RCP8.5 was calculated by averaging the projections of four different climate models (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC5[49]). The temperature weighting factor F_x for each cell *x* was calculated as

$$F_x = \Delta T_x / \overline{\Delta T_x}$$

(Equation 6)

where $\overline{\Delta T_x}$ is the mean global temperature change. The fractional loss in species richness $\Delta S_{x,p,k}$ in 2031 due to $\Delta T_{p,k}$, the temperature increase from emissions from food production of each product *p* in each region *k*, was calculated as:

$$\Delta S_{x,p,k} = F_x \times H_x \times \Delta T_{p,k}$$

(Equation 7)

where H_x is the grid estimating sensitivity of species richness to climate change.

This fractional loss in species richness $\Delta S_{x,p,k}$ was then multiplied by our species richness grid and by the area of each grid cell to give a characterisation factor for GHG-driven biodiversity loss, $CF_{p,k}$, with a unit of species × km^2 that is comparable to our metric for land-driven biodiversity loss. This characterisation factor was calculated as:

$$CF_{p,k} = \Delta S_{x,p,k} \times S_x \times A_x$$

(Equation 8)

where S_x is the species richness in undisturbed vegetation under a natural climate in grid cell x and A_x is the area of grid cell x. The same basic method was used to calculate the characterisation factors for change in rarity-weighted richness (see Supplementary Information for details). The GHG-driven characterisation factors for change in species and rarity-weighted richness are directly correlated (for characterisation factor values, see Supplementary Tables 8 and 9.)

Global maps illustrating the proportional richness changes that would occur due to land-driven and GHG-driven processes are given in Supplementary Figure 3. Our metrics of land-driven and GHG-driven biodiversity loss are modelled and presented in the same units, and hence are comparable. However, there are differences in the way that the two drivers impact biodiversity, and in the methods we used to model these impacts. We consider land use as a one-off cost that has already occurred, but GHG emissions as repeated annual costs that occur 20 years after emission. We would expect the biodiversity loss caused by a single year of emissions to be much lower than that caused by the one-off cost of total land conversion. We calculate the ratio of land-driven to GHG-driven biodiversity loss for products and regions. We can crudely approximate a ratio of 100, for example, to mean that within a century, assuming the same emissions repeat annually, the global biodiversity loss caused by emissions from a region's food production will equal the biodiversity loss due to total land conversion in that region. In reality, this may be an underestimate since we do not consider the emissions released by land conversion.

2.4 Per land area and per capita footprints

The regions within EXIOBASE have unequal land areas and human populations. To make a fairer comparison of footprints between regions, we converted production footprints to footprint per km^2 and consumption footprints to footprint per capita. Per-km^2 footprints were calculated using EXIOBASE trade regions' areas (Supplementary Table 10), which were calculated in R from ESRI country shapefiles[35]. Per-capita footprints were calculated using population data for the year 2011 for the EXIOBASE trade regions (Supplementary Table 11), which were obtained from CountryEconomy.com[50] (Taiwan) and the World Bank[51] (all other regions).

3. Results

3.1 Regional production and consumption-based footprints for total food

298 For all footprints, regions with a high production-based footprint tend to have a high
299 consumption-based footprint. Our land-driven biodiversity footprints show a different picture from a
300 simple land-area footprint. Important information is missed if the area of agricultural land alone is
301 used as a proxy for the impact of food production on biodiversity (Figure 2). Differences between
302 land-associated footprints are driven in part by differences in species richness between regions'
303 agricultural areas but also by our characterisation factors allowing for biome-specific sensitivity to
304 land use. Furthermore, footprints also vary according to the measure of biodiversity used. The
305 regions with the greatest land-area footprints in 2011 were Rest of World (RoW) Africa, China, and
306 RoW Asia & Pacific (Figure 2a). However, while RoW Africa also has the highest land-driven species
307 richness footprint, Brazil and RoW Central & South America (RoW CS America) have the second and
308 third highest species richness footprints, respectively (Figure 2b). RoW CS America hosts many
309 narrow-ranged species, which is reflected in its high rarity-weighted richness footprint (Figure 2c).
310 Decisions regarding land use and food production should therefore consider not only the land area
311 involved but also the land-driven loss of different facets of biodiversity (see Supplementary Figure 4
312 and Supplementary Table 12 for the footprints of individual products within regions).

313 GHG-driven biodiversity loss shows a different pattern from the land-driven footprints
314 (Figure 2) with China, the US and India having the highest production-based footprints. RoW Africa is
315 notable for having a much lower GHG-driven footprint relative to its land-driven biodiversity
316 footprint. The ratio of land-driven to GHG-driven biodiversity loss varied by region from 54 for rarity-
317 weighted richness production footprint in Russia to the order of 10,000 for production in RoW
318 Africa, for example. Finding ratios as low as 50-100 is concerning as it shows that direct emissions
319 from a single year of a region's food production will cause biodiversity loss equivalent to 1-2% of the
320 biodiversity loss caused by that region's total historic land use. Furthermore, we substantially
321 underestimate biodiversity losses from GHG emissions since our analysis does not include emissions
322 from land clearance.

323 Some regions are net importers of land-driven biodiversity loss but net exporters of GHG-
324 driven biodiversity loss, e.g. China, or *vice versa*, e.g. Australia. RoW Asia & Pacific, RoW CS America,
325 Brazil, Mexico and South Africa are all net exporters of both land-driven and GHG-driven biodiversity
326 losses whilst Russia, RoW Middle East and Japan are net importers (Figure 2).

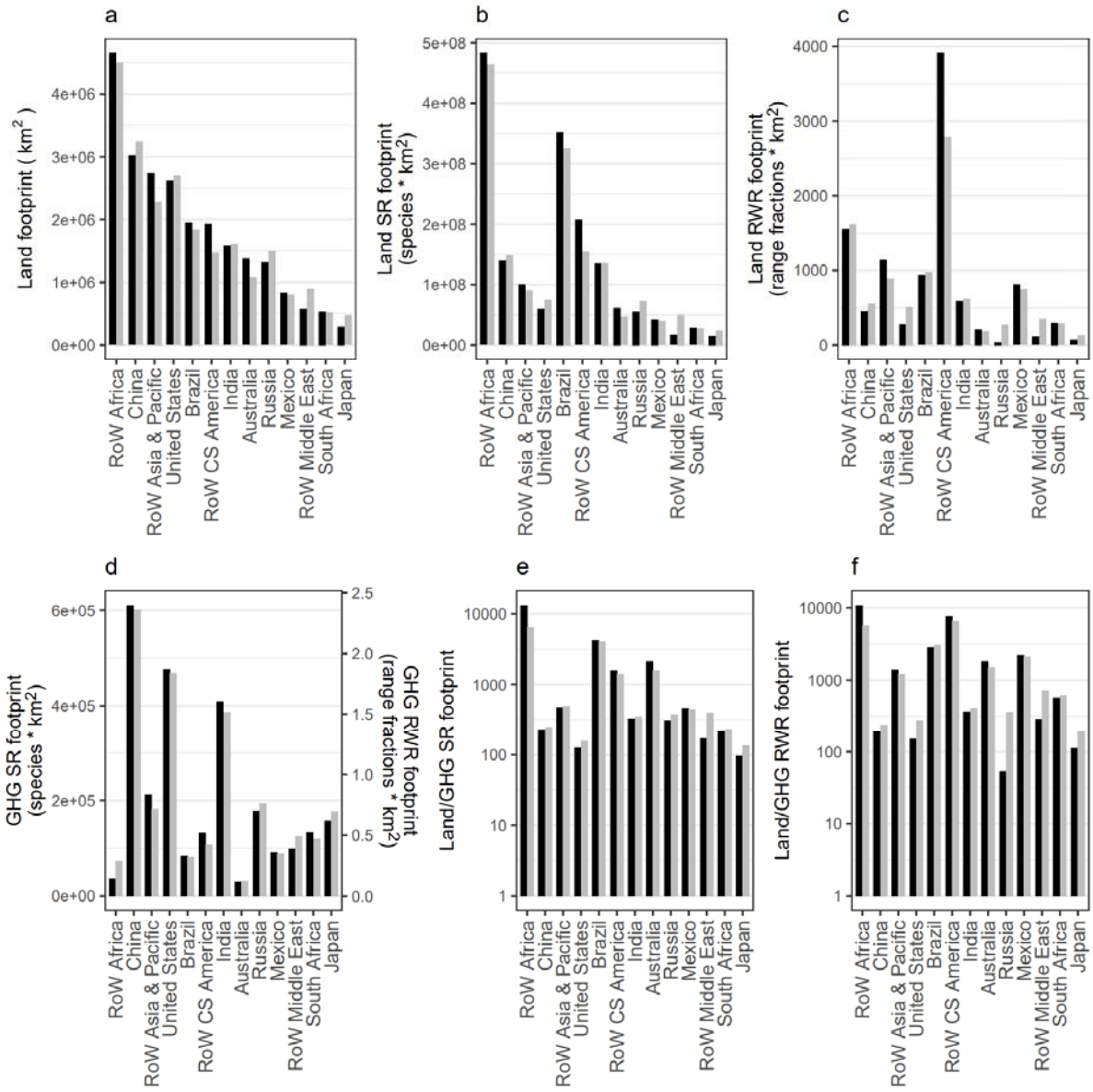


Figure 2. Total production and consumption-based footprints of food-related products. Footprints relate to a) land area, b) land-driven species richness (SR) loss, c) land-driven rarity-weighted richness (RWR) loss, d) GHG-driven biodiversity loss (right-hand axis – species richness; left hand axis – rarity-weighted richness), e) the ratio of land-driven species richness loss to GHG-driven species richness loss and f) the ratio of land-driven rarity-weighted richness loss to GHG-driven rarity-weighted richness loss. Black bars show production-based and grey bars consumption-based footprints. Regions which are in the highest ten for any footprint are shown.

3.2 Production-based footprints for world regions aggregated by food-related sector

Production-based footprints vary considerably among food-related groups and, within food-related groups, among world regions (Figure 3). As for total food footprints, land-driven biodiversity footprints do not mirror land-area footprints, and the relative size of biodiversity footprints is affected by the richness metric. Using animal-derived products as an example, Asia & Pacific has a land footprint 60% higher than CS America's (and Africa's, Figure 3a), but its land-driven species-richness footprint is less than half (Figure 3b), and its rarity-weighted richness footprint less than a third that of CS America (Figure 3c). This result reflects Asia & Pacific's lower average natural species richness compared to CS America's and the lower biodiversity sensitivity of some of its biomes to land use.

Again, GHG-driven and land-driven biodiversity footprints show different patterns, with tropical regions no longer having consistently higher footprints. Although Asia & Pacific has the highest GHG-driven footprints for all food groups but waste, production in Western Europe and North America also drives high GHG-driven biodiversity loss. With land-driven to GHG-driven ratios in the order of 100, Western and Eastern Europe's animal-derived and 'other food' products stand out as areas for which emissions reductions would have a large benefit for biodiversity alongside reductions in land area used for agriculture.

Animal-derived products tend to have higher footprints than plant-derived (i.e. crops), although Asia & Pacific is a notable exception for both land-driven and GHG-driven biodiversity footprints, in part due to production of paddy rice in India and fruit/vegetables/nuts in China (for individual product footprints see Supplementary Table 13). GHG-driven biodiversity loss from fertiliser production and the processing of food waste is much lower than that stemming from the production of food itself. Land-driven biodiversity loss from these two food-related groups is very low since their production uses very little agricultural land.

The 'Other Food' category has the highest production-based GHG-driven biodiversity footprint for almost all world regions (Figure 3d). The ratio of land-driven:GHG-driven footprints for this category is in the order of 100 for non-tropical world regions (Figure 3e,f), indicating that reducing GHG emissions from this sector would be a priority for reducing biodiversity loss. Other Food includes 'Food products not elsewhere classified (nec)' (coded in EXIOBASE as 'OFOD') and beverages ('BEVR'). 'Food products nec' contributes the vast majority of the Other Food footprint and covers a broad range of processed foods such as soups, sandwiches and sauces. The EXIOBASE land-use types that contribute most to the Food Products nec land-driven footprints are cereal

369 grains nec, cattle pasture, wheat, oil seeds, raw milk pasture and fruit/vegetables/nuts

370 (Supplementary Figure 5).

371

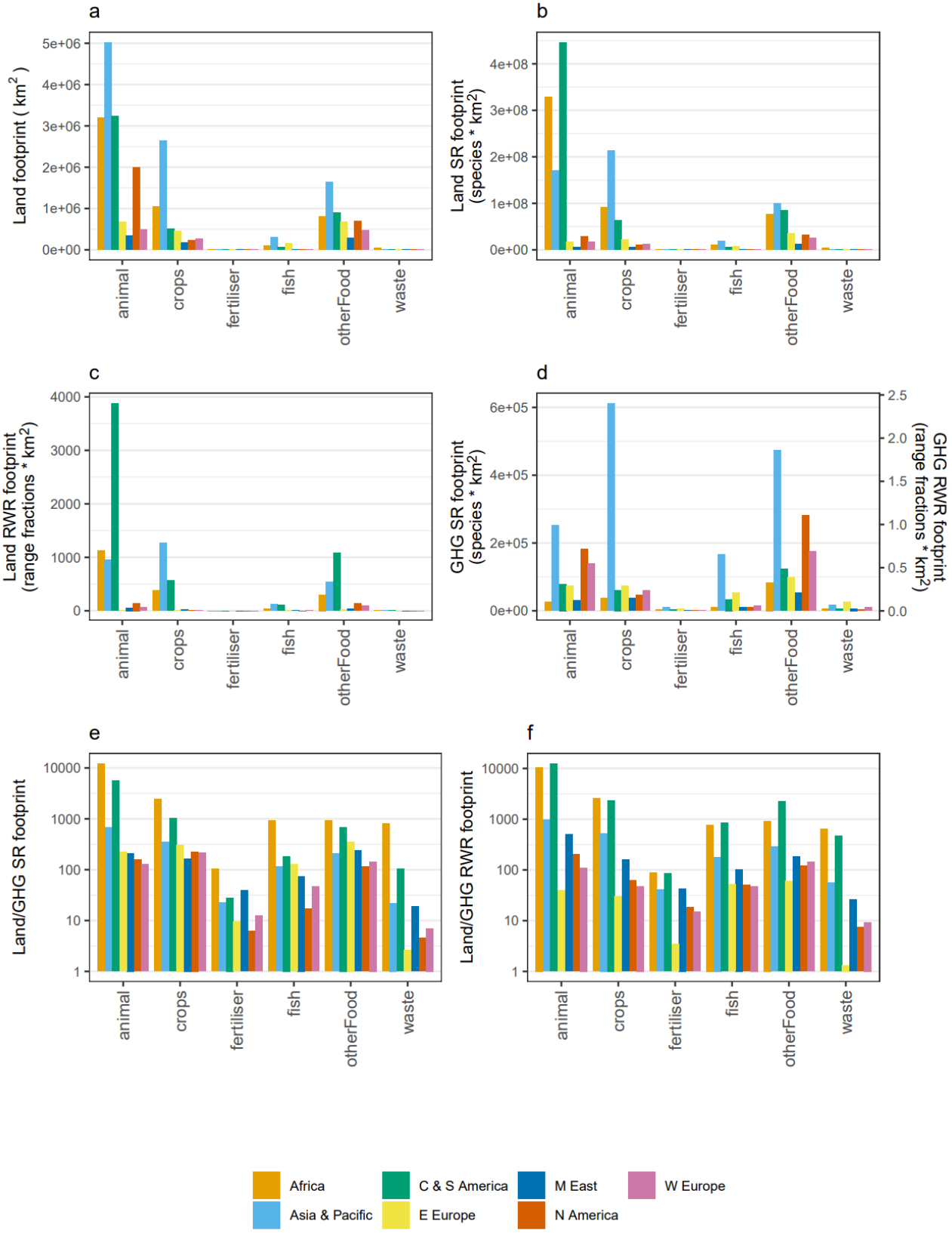

a
Land footprint (km^2)
5e+06
4e+06
3e+06
2e+06
1e+06
0e+00
animal
crops
fertiliser
fish
otherFood
waste
b
Land SR footprint (species * km^2)
4e+08
3e+08
2e+08
1e+08
0e+00
c
Land RWR footprint (range fractions * km^2)
4000
3000
2000
1000
0
d
GHG SR footprint (species * km^2)
6e+05
4e+05
2e+05
0e+00
GHG RWR footprint (range fractions * km^2)
2.5
2.0
1.5
1.0
0.5
0.0
e
Land/GHG SR footprint
10000
1000
100
10
1
f
Land/GHG RWR footprint
Africa
Asia & Pacific
C & S America
E Europe
M East
N America
W Europe

Figure 3. Production-based footprints of aggregated food-related groups within world regions. Footprints relate to a) land area, b) land-driven species richness (SR) loss, c) land-driven rarity-weighted richness (RWR) loss, d) GHG-driven biodiversity loss (right-hand axis – species richness; left-hand axis – rarity-weighted richness), e) the ratio of land-driven species richness loss to GHG-driven species richness loss and f) the ratio of land-driven rarity-weighted richness loss to GHG-driven rarity-weighted richness loss.

3.3 Per-area and per-capita footprints

Taiwan stands out as having the highest per-area land-related production-based footprints (Figure 4). The agriculturally dense but biodiversity poor UK is an example of a region with a relatively high per-area land-use footprint but lower per-area land-driven biodiversity footprints (Figure 4). In contrast, the species-rich Brazil has a lower per-area land-use footprint but a relatively higher per-area land-driven species richness footprint. Some regions (e.g. Brazil, India, South Africa) have both high total production-based footprints (Figure 2) and high per-area production-based footprints (Figure 4). The other regions with high per-area production tend to be smaller regions with wide agricultural coverage, for example the Netherlands and Belgium. Small agricultural regions have the highest per-area production-based GHG-driven footprints, for example Taiwan, Belgium and Malta.

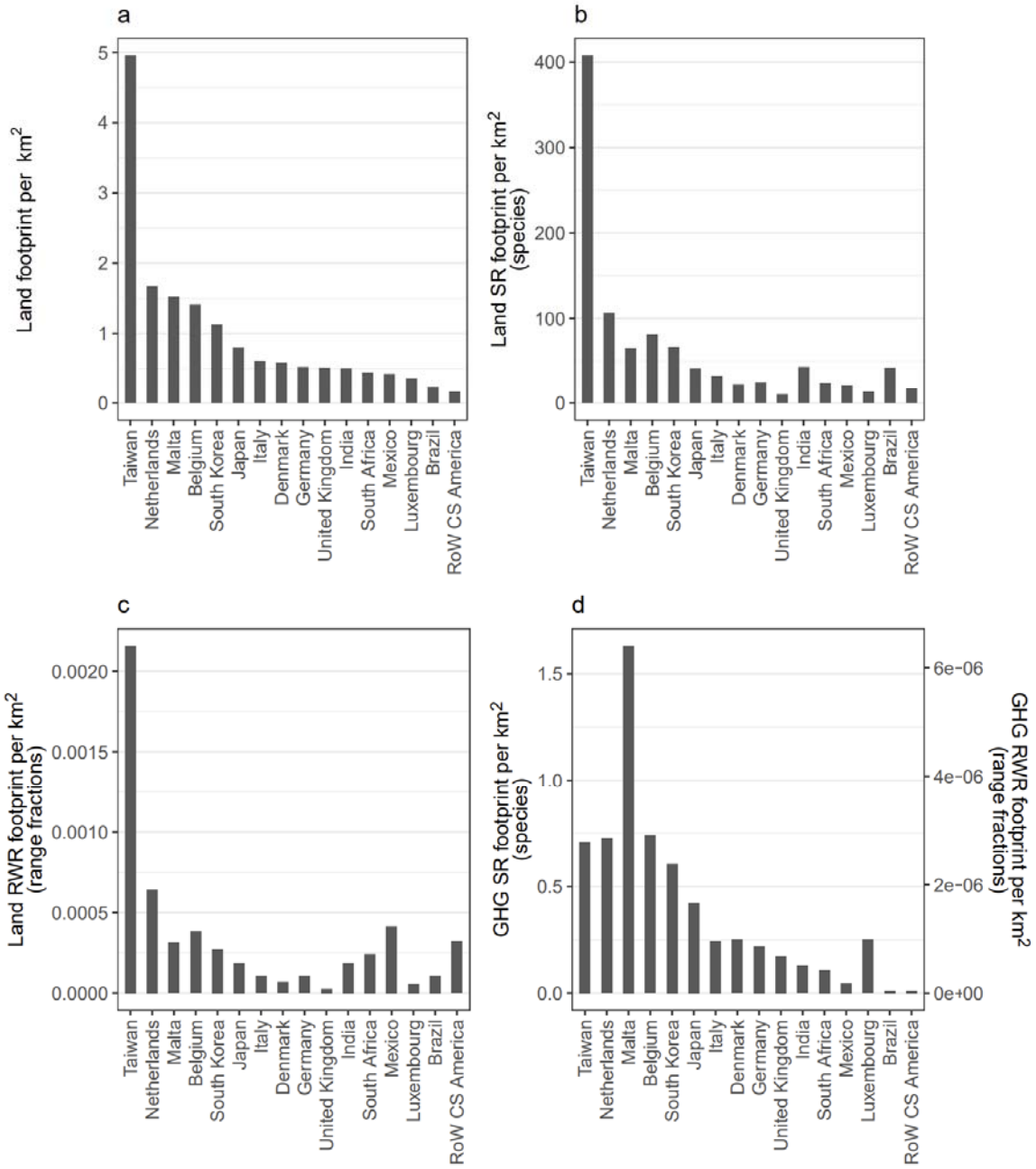


Figure 4. Total per-area production-based footprints of food-related products. Footprints relate to a) land use, b) land-driven species richness (SR) loss, c) land-driven rarity-weighted richness (RWR) loss and d) GHG-driven biodiversity loss (right-hand axis - species richness; left-hand axis - rarity-weighted richness). Regions which are in the highest ten for any footprint are shown.

Australia is notable for having extremely high per-capita land-driven consumption-based footprints (Figure 5), driven particularly by animal-based products (notably 'Products of Cattle'), but also by plant-based products and 'Other Food' (Supplementary Figure 7). Luxembourg also has consistently high per-capita consumption-based footprints, probably in part due its highly affluent population[51]. In contrast to Australia, Luxembourg's consumption-based footprint is primarily driven by plant-derived products (fruit/vegetables/nuts, oil seeds and crops nec (i.e., coffee, cocoa, spices)'). China, India and RoW Asia & Pacific are not within the top ten highest per-capita consumption-based footprints for any category, despite having high total consumption due to their large populations (Figure 2). However, some regions with high total biodiversity consumption also have high per-capita footprints (Australia, Brazil, Japan, Mexico, Russia, the United States, RoW Africa, RoW CS America and South Africa.) Again, we see contrasts between different footprint types. For example, Brazil's per-capita land-driven species richness consumption-based footprint is much larger than RoW CS America's, but the latter's per-capita rarity-weighted footprint is almost twice that of Brazil. Regions with relatively low species richness can have high per-capita land-driven biodiversity consumption-based footprints as a result of importing food.

The products underpinning high per-capita consumption-based GHG-driven biodiversity footprints vary among regions. Belgium's high footprint, for example, is largely driven by other foods nec (e.g. pizza, ready-meals, sauces) and dairy products, Canada's by beverages and dairy products, Estonia's by dairy products, raw milk and other foods nec, Luxembourg's by fruit/vegetable/nuts, crops nec (i.e., coffee, cocoa, spices) and chemical fertiliser, and South Africa's by fruit/vegetable/nuts and other foods nec (see also Supplementary Figures 7 & 14 for further breakdowns).

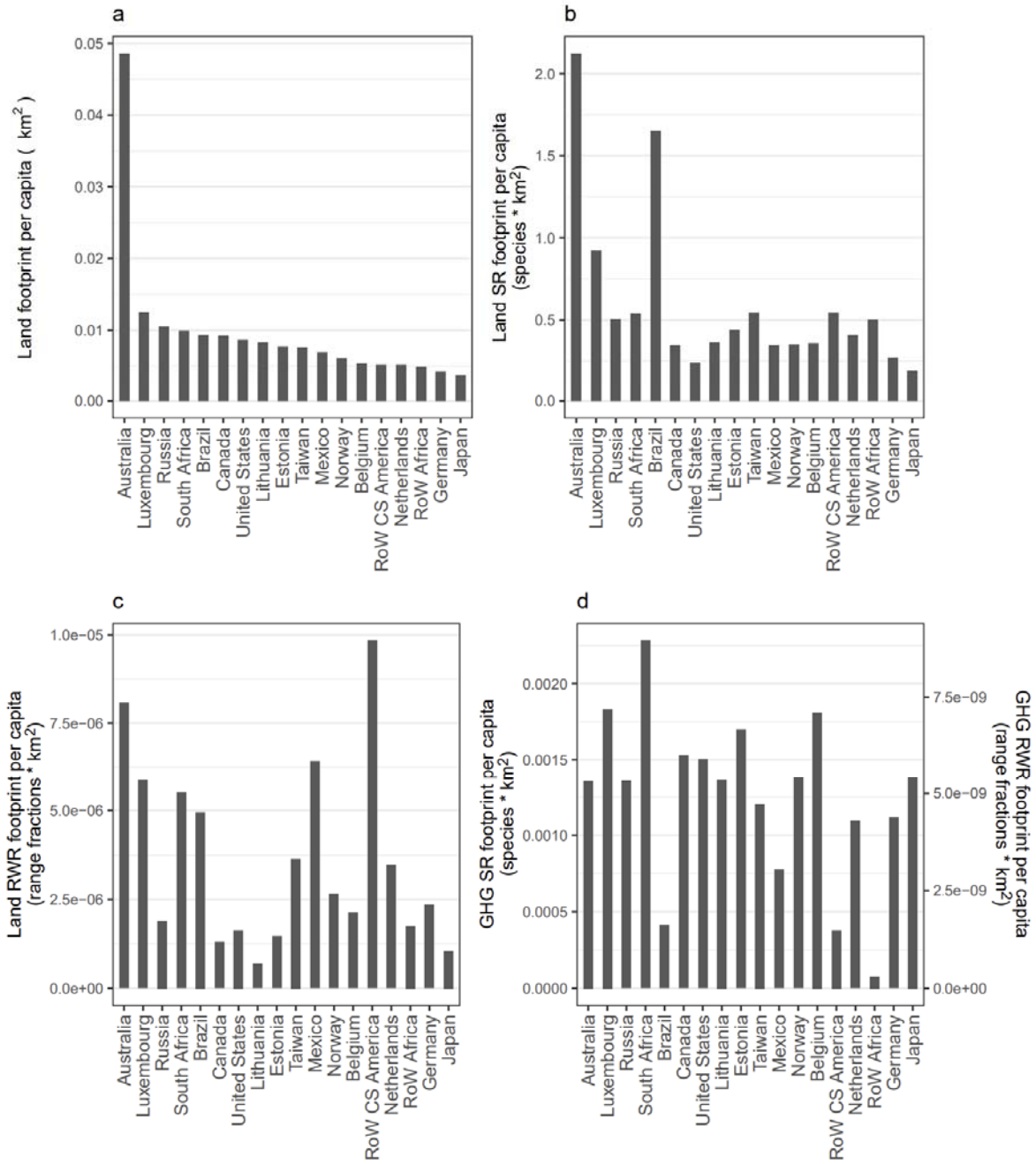


Figure 5. Total per-capita consumption-based footprints of food-related products. Footprints are in terms of a) land use, b) land-driven species richness (SR) loss, c) land-driven rarity-weighted richness (RWR) loss and d) GHG-driven biodiversity loss (right-hand axis – species richness; left-hand axis – rarity-weighted richness). Regions which are in the highest ten for any footprint are shown.

3.4 Biodiversity loss embedded in export/import trade

We found a near-reversal of net trade flows for land-driven versus GHG-driven biodiversity footprints (Figure 6, Supplementary Figure 8). The United Kingdom, Germany, Russia, Japan and RoW Middle East are all net importers of land-driven biodiversity loss but net exporters of GHG-driven biodiversity loss. The different land-driven footprints also show different messages. For example, RoW CS America exports a similar land-area footprint to that exported by RoW Asia & Pacific but approximately four times RoW Asia & Pacific's exported rarity-weighted richness footprint. RoW Africa is a net exporter of land-driven species richness impacts but a net importer of land-driven rarity-weighted richness impacts. The three greatest net importers of both land-driven biodiversity footprints are RoW Middle East, Russia and the United States.

.

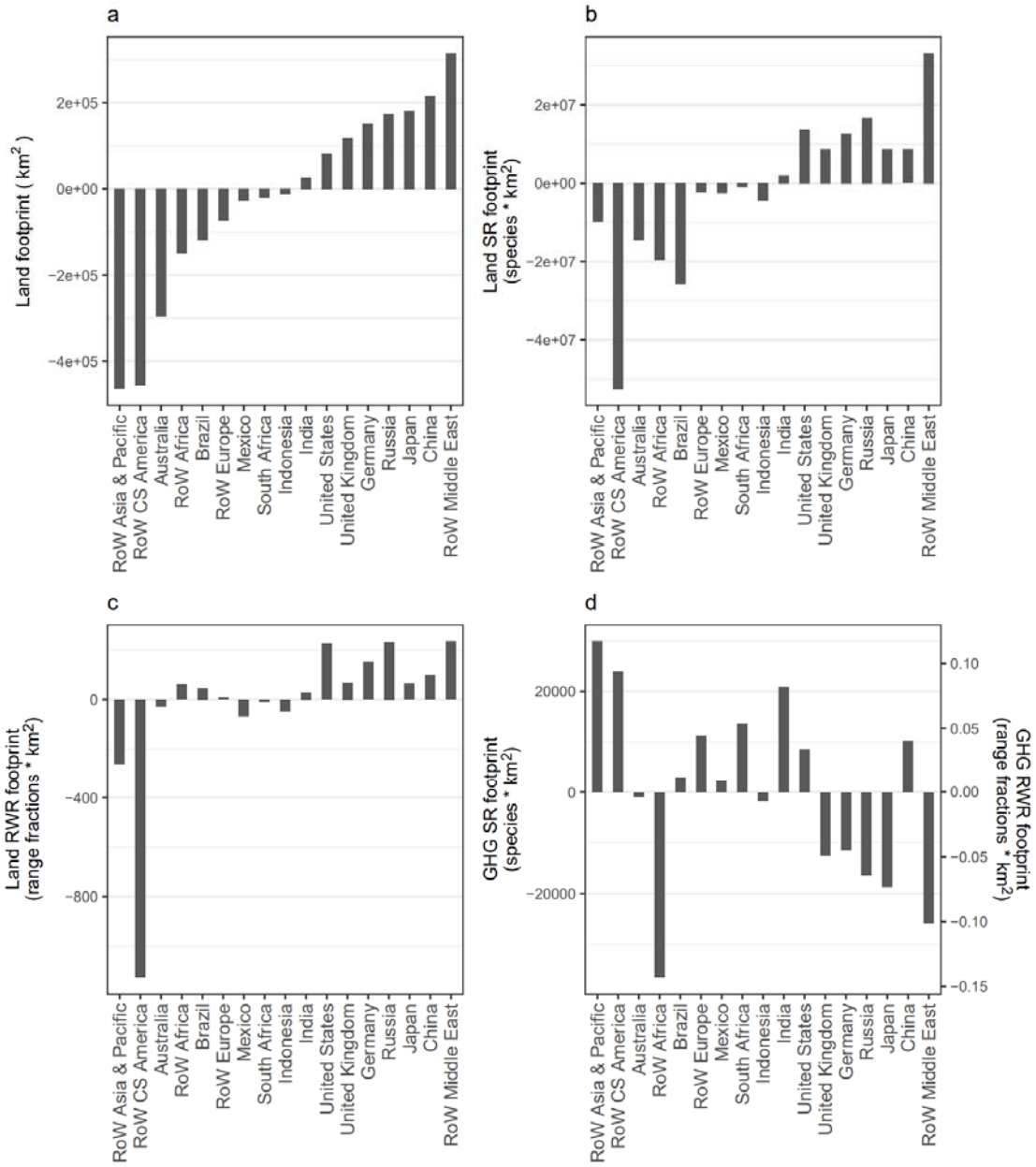


Figure 6. Regions' net import/export footprints for food-related products. Footprints are in terms of a) land use, b) land-driven species richness (SR) loss, c) land-driven rarity-weighted richness (RWR) loss and d) GHG-driven richness loss. Regions which are in the highest five for any of the import (+ve)/export (-ve) footprints are shown.

Understanding the percentage of a region's footprint that is imported is important in devising policies to reduce footprints. Imports make up 5% or less of land-driven species richness footprints for highly biodiverse regions such as Mexico and RoW CS America (Figure 7); reducing

domestic consumption in these regions might actually lower their consumption-based footprints. In contrast, the regions with the highest percentages of imported footprints are European. Luxembourg, the Republic of Ireland and the United Kingdom import 98%, 88% and 82% of their land-driven species richness footprints respectively. These high percentages will in part be due to the regions' relatively low domestic food production footprints but may also reflect imports grown in highly biodiverse regions, which could potentially be sourced more sustainably.

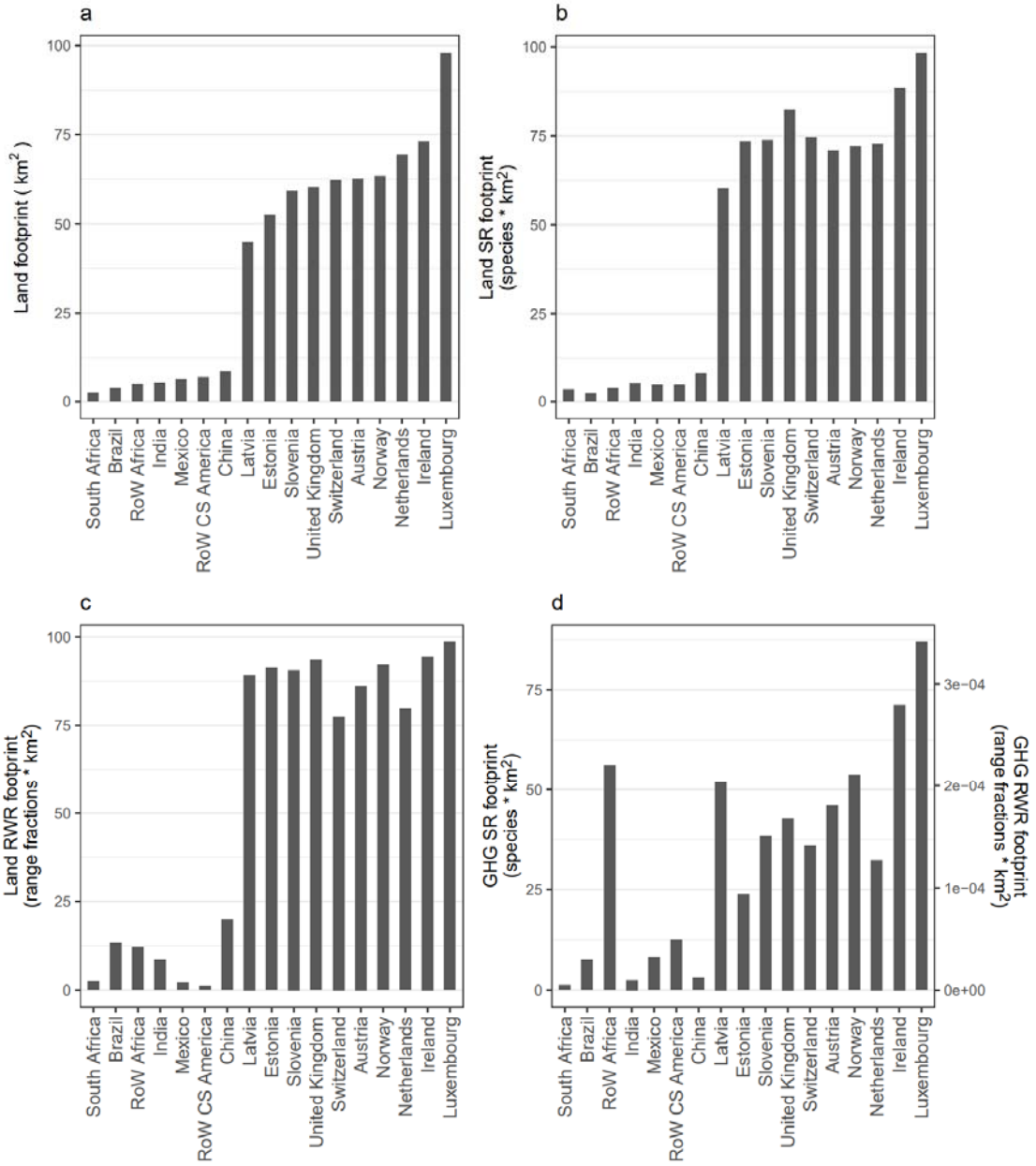


Figure 7. The percentage of a region's food-related footprint that is imported. Footprints are in terms of a) land use, b) land-driven species richness (SR) loss, c) land-driven rarity-weighted richness (RWR) loss and d) GHG-driven richness loss. Regions which are in the 5 lowest or highest percentage for any footprint are shown.

10%, 15% and 9% respectively of land-driven species richness, land-driven rarity-weighted richness and GHG-driven richness footprints are embedded within trade between world regions (Supplementary Figure 10), with patterns differing between the footprint types, and between animal and plant-derived foods (Supplementary Figures 10-12). Although the total footprints of animal-derived products are higher than plant-derived, a greater percentage of the plant-derived footprint is traded between world regions (approximately 8%, 15%, 6% (animal-derived) versus 17%, 21%, 12% (plant-derived) of the total footprint for land-driven species richness, land-driven rarity-weighted richness and GHG-driven species richness respectively). These results are discussed in more detail in the Supplementary Information.

4. Discussion

Our metric of land-driven species richness change captures the higher biodiversity footprint of products from more species-rich regions and from biomes in which biodiversity is more sensitive to land-use change. The metric thus provides a more accurate footprint of the biodiversity impact embedded within food than would be obtained using land area alone. Weighting richness by species' range area further changes assessment of embedded biodiversity footprint. Rarity-weighted richness places a greater emphasis on the biodiversity costs in areas containing a higher proportion of narrow-ranged species, which are of greater conservation concern than wider-ranging species, notably parts of CS America. Our analysis also shows the need to consider GHG-driven biodiversity loss, particularly in assessing longer term future impacts of food production. We find that the climate contributions of food production are accumulating rapidly over time – in some regions, annual GHG-driven production footprints are as high as 1% of the total historic land-use footprint, meaning that just a decade's worth of emissions (not including land conversion emissions) will add an additional 10% to the biodiversity loss that has already occurred due to wholesale conversion of land to agriculture.

4.1 Comparison with other studies

Our study incorporated the novel combination of: (i) allowing sensitivity to land use to vary by land-use type and biome; (ii) allowing for the natural variation of species richness across political

492 regions; and (iii) allowing for spatial variation in future temperature change and in species'
493 responses to that temperature change. The models we used to capture land-use and climate impacts
494 output the same biodiversity metrics, allowing us to compare these two major drivers of biodiversity
495 change. Comparing the results of our study with those of previous analyses of the embedded
496 biodiversity footprints of food is not straightforward since studies generally differ in resolution with
497 respect to regions and/or products. Where comparisons can be made, we find both common ground
498 and divergence. In line with Marques et al. [26], we show that production in Africa, CS America and
499 Asia & Pacific regions has the highest overall biodiversity footprints, and that cattle products have a
500 particularly high impact on biodiversity globally. Marques et al. [26] use a biodiversity metric of
501 number of impending extinctions of bird species and, in common with our land-driven species
502 richness metric, identify almost equally high impacts of cattle in Africa as in CS America. However, it
503 is only by using our rarity-weighted richness measure that the particularly high cost to narrow-
504 ranged species from cattle products in CS America is revealed. Chaudhary and Kastner[15] use a metric
505 of the number of species committed to extinction. Their study had greater spatial disaggregation
506 than ours meaning we cannot compare regions included within our RoW regions. Nevertheless, our
507 results broadly support each other with respect to highlighting particularly high consumption
508 footprints in India, China, Brazil and the US. However, Chaudhary and Kastner found Indonesia to
509 have the second highest consumption footprint, whereas it does not appear in our top ten
510 consumption footprints for any metric. The relative magnitude of the regions with the greatest
511 consumption footprints in Chaudhary et al.'s [52] study differs from our results. These discrepancies
512 are likely to result from the biodiversity metric used as well as differences in trade models, and
513 further support our finding that different biodiversity metrics lead to different conclusions. Sun et al.
514 [53] also use a metric of the number of species committed to extinction at a greater spatial
515 disaggregation than our study. Their results show strong agreement with ours with respect to
516 consumption per capita, both studies finding high footprints in Central America, Brazil, South Africa
517 and Australia. Lenzen et al. [23] look at the biodiversity footprint, as measured by number of threats to
518 species, of all commodities, not just those associated with food. Both Lenzen et al.'s [23] and our
519 studies find the US, Germany, the UK and Japan to be among the greatest importers of embedded
520 biodiversity but our study has Russia as a major importer of embedded biodiversity whereas Lenzen
521 et al. [23] find it to be one of the greatest net exporters.

522 Our estimates of the impacts of food-related GHGs on biodiversity are much lower than
523 those of Wilting et al. [27] which is at least in part due to differences in methodology. We predicted the
524 temperature rise in 2031 due to an emissions pulse in 2011 using the global temperature potential
525 (GTP). Wilting et al. [27] used the integrated GTP over a 100 year time horizon, thus summing the

526 warming that occurred in every year following the emission pulse, as opposed to calculating the
527 temperature of the hundredth year only. We would therefore expect Wilting et al.'s [27] GHG-driven
528 footprint to be two orders of magnitude greater than ours, as was the case. Wilting et al. [27] analysed
529 the land-driven and GHG-driven biodiversity loss from all economic sectors using an indicator of
530 Mean Species Abundance and estimated that GHGs contributed to an average of 18% of the
531 biodiversity loss associated with food although contributions varied by region from 7% (Africa) to
532 45% (rest of Oceania). Accounting for the different metrics of global warming used, our results were
533 relatively similar, with our GHG-driven footprints estimated to contribute from the order of 0.01% –
534 1% of biodiversity loss for food products and up to 10% for fertiliser. Wilting et al.'s [27] study further
535 differed from ours since it used a different biodiversity metric and MRIO, and assumed agricultural
536 land was evenly distributed across regions. Our studies support each other in suggesting current
537 GHG-driven emissions from the food-related products will play a very significant role in future
538 biodiversity loss. Reducing emissions associated with food is therefore a high priority, particularly in
539 Europe, North America and Asia & Pacific.

540

541 *4.2 Policy implications*

542 Our study shows that measurements of trade-related impacts of biodiversity differ
543 considerably depending on the metric used. Whilst detailed discussion of the merits and relevance
544 of different biodiversity metrics may be appropriate in the scientific literature, it is unlikely to be
545 helpful to businesses and policy makers who require succinct and readily interpretable biodiversity
546 footprints. This leads to the question of which measure(s) should be recommended to the public and
547 private sectors to aid them in reducing their environmental footprints. What might the
548 consequences be of one metric being chosen over others? Our study suggests that a metric of land
549 area, whilst easy to measure and interpret, will over inflate the cost of biodiversity in biodiversity-
550 poor areas and under-estimate it in biodiversity-rich areas, and thus is not recommended when the
551 focus is biodiversity conservation. Species richness is preferable in this case, and is still relatively
552 easy to interpret, particularly if used in relative rather than absolute terms. However, species
553 richness has been criticised as a biodiversity metric, since it does not decline if rare species are
554 replaced with common species (see Hillebrand et al. [31]). Weighting for species rarity overcomes this,
555 and highlights the higher losses of smaller-ranged species from CS America. Using rarity-weighted
556 richness over a simple species richness measure would likely lead to different decisions with respect
557 to sustainable trading.

We must also consider whether GHG-driven biodiversity loss adds value or unnecessary complexity to footprint estimates. Our study has shown that it is fairly simple to calculate GHG-driven biodiversity loss and to aggregate it with the land-driven impact. The annual GHG-driven biodiversity impact of food produced in the US and Western Europe is not insignificant and, in livestock sectors, is equivalent to approximately 1% of land-driven biodiversity loss. Importantly, this equates to 10% of the biodiversity impact of complete land conversion within the timespan of just one decade. For some individual products, at a level of disaggregation finer than that used in this study, the ratio of GHG to land-driven impacts could be even higher. Including the GHG-driven losses in estimates of the food industry's impact on biodiversity would therefore seem worthwhile.

The biodiversity footprints that we present could be used to inform policies and trade agreements targeted at reducing biodiversity loss. Policies which encourage a reduction of high-income countries' consumption of beef, for example, could be used to target biodiversity loss in Australia and CS America, regions which dominate exported biodiversity footprint embedded in cattle products. Trade deals which lead to an increase in imports from these regions (e.g. the 2021 UK-Australia trade deal, the European Union's 'New Green Deal') will likely lead to an increase in biodiversity loss and offshoring of yet more of Europe's environmental footprint[54] unless strict and enforceable environmental regulations are included in the agreements. Decisions on future trade deals must take embedded environmental costs into account and use appropriate metrics of biodiversity. If impacts are based on land use alone they will severely underestimate biodiversity impacts in CS America.

The examination of production-based footprints per-area (which facilitate comparisons of production between different-sized regions) allows for an increased understanding of the implications of regional/national agricultural policies. Regions with high per-area production-based footprints are targets for policies that reduce the environmental impact of farming. There is considerable overlap of high per-area land-driven and GHG-driven production impacts and it is interesting that the Netherlands and Belgium, both less species-rich temperate countries, have some of the highest per-area production-based footprints, even for rarity-weighted richness (Figure 4). Taiwan is notable for all three of its per-area land-driven production-based footprints being extremely high (Figure 4), with impacts being driven by a variety of products including fruit/vegetables/nuts, animal products nec (e.g., eggs, honey), fish, pork products, sugar, and food products nec (e.g., pizza, soups, sauces) (Supplementary Figure 6). India stands out as having very high paddy rice production per area for all footprints (Supplementary Figure 6).

590 Per-capita consumption-based footprints (which facilitate comparisons of consumption
591 between regions with different population sizes) also allow for targeting of agricultural and trade
592 policies. We found China, the US and India had the highest overall GHG-driven biodiversity
593 footprints, but once population size was considered, only the US remained in the top ten per-capita
594 footprints. Identifying the products that lead to regions' high per-capita footprints is the first step
595 towards reducing those footprints. For example, extremely high per-capita consumption-based
596 footprints from raw milk and dairy products contribute to Estonia's place in the top ten for GHG-
597 driven biodiversity loss (see Figure 5 and Supplementary Figure 7). Whilst we recognise that
598 changing cultural norms can be very difficult, reducing Estonia's per-capita footprint would be
599 relatively straight forward from a policy perspective, since it involves only one food group and could
600 perhaps be tackled via a combination of dietary shifts, source-shifting and change in dairy-farming
601 practices. Australia, in contrast, has particularly high per-capita land-driven consumption-based
602 footprints for a wide variety of products spanning cereal grains nec, fruit/vegetables/nuts, sugar
603 cane/beet, all products associated with cattle and other meat animals (e.g. sheep), rice, food
604 products nec and beverages. Reducing these footprints will likely require a more complex suite of
605 strategies.

606 We found that some regions import over 90% of their embedded biodiversity footprint,
607 further indicating the need for sustainable trade as a measure to halt biodiversity loss. Regions with
608 a high proportion of imported footprint coupled with high per-capita consumption-based footprints
609 are targets for reducing their imports and/or the biodiversity footprint embedded within those
610 imports[16]; Estonia, Luxembourg, the Netherlands and Norway all fall into this category (Figures 5 and
611 7). Conversely, regions with a low percentage of imported footprint but high per-capita consumption
612 such as Brazil, Mexico and South Africa should be lowering their domestic footprint in order to
613 reduce their biodiversity impact.

614 The main net importers of land-driven biodiversity footprint tend to be net exporters of
615 GHG-driven biodiversity footprint, and vice versa. The emissions associated with cropland largely
616 arise from fertiliser use. Low fertiliser application will be associated with low emissions but lead to a
617 smaller yield and therefore a larger land-use footprint. On the other hand, heavy fertiliser use will
618 result in more emissions but smaller land use. This negative correlation is exacerbated since areas
619 that use more fertiliser tend to be areas of lower species richness such as N America and W
620 Europe[55].

621

622 *4.3 Limitations*

623 There are several limitations of MRIOs which must be considered in interpreting our results:
624 sectoral and regional aggregation[56,57], an assumption of price homogeneity[58,59], limitations in data
625 reporting[60], and the age of input data[61]. The original EXIOBASE 3 data end in 2011 and although
626 more recent trade data are now available, land use is still limited to 2011
627 (https://zenodo.org/record/5589597#.YnkHvOjMK3A). Our results therefore reflect the biodiversity
628 impact of food production over a decade ago, and will likely underestimate the current impact due
629 to the expansion of agricultural land[62] in the intervening period.

630 In common with other footprinting studies, e.g.[25,26], our analysis only measures biodiversity
631 impacts caused by direct land-use change, and does not explicitly consider the impacts of
632 agricultural intensification. Neither does our study explicitly account for indirect biodiversity loss
633 that might occur through loss of ecosystem function, e.g. soil impoverishment. Nevertheless, the
634 PREDICTS database does sample gradients of agricultural intensity and ecosystem degradation, and
635 so these factors should be captured implicitly[29].

636 While our study highlights that the consumption of cattle products contributes considerably
637 to land-driven biodiversity loss, it is important to be aware that there is high variability in pasture
638 maps stemming from the different definitions, methods and underlying datasets used in their
639 generation[63]. However, the Ramankutty et al.[39] dataset that we used is one of the best available,
640 aligning well with other datasets[63].

641

642 *4.4 Conclusions*

643 We have presented new methods to estimate the land-driven and GHG-driven biodiversity
644 impacts embedded within the production, consumption and trade of food-related commodities. We
645 find that land-driven footprints differ depending on the metric used, and that GHG-driven
646 biodiversity impacts are more intense in regions of higher income and lower species-richness. The
647 measures we present are simple to calculate and could be incorporated into decision making and
648 environmental impact assessments by governments and businesses. Our consistent metric for
649 biodiversity impacts allows us to present multiple aspects of land-driven and GHG-driven
650 biodiversity footprints, enabling insight into priorities for reducing biodiversity costs via both global
651 and regional production and consumption.

652

References

1 IPBES. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. (Bonn, Germany, 2019).

2 Maxwell, S. L., Fuller, R. A., Brooks, T. M. & Watson, J. E. M. The ravages of guns, nets and bulldozers. *Nature* **536**, 143-145 (2016).

3 Schipper, A. M. *et al.* Projecting terrestrial biodiversity intactness with GLOBIO 4. *Glob Chang Biol* **26**, 760-771 (2020). https://doi.org:10.1111/gcb.14848

4 Di Marco, M. *et al.* Projecting impacts of global climate and land-use scenarios on plant biodiversity using compositional-turnover modelling. *Glob Chang Biol* **25**, 2763-2778 (2019). https://doi.org:10.1111/gcb.14663

5 Newbold, T. Future effects of climate and land-use change on terrestrial vertebrate community diversity under different scenarios. *Proc Biol Sci* **285** (2018). https://doi.org:10.1098/rspb.2018.0792

6 Ellis, E. C., Klein Goldewijk, K., Siebert, S., Lightman, D. & Ramankutty, N. Anthropogenic transformation of the biomes, 1700 to 2000. *Global Ecology and Biogeography*, no-no (2010). https://doi.org:10.1111/j.1466-8238.2010.00540.x

7 FAOStat. (License: CC BY-NC-SA 3.0 IGO., 2022).

8 Mbow, C. *et al.* Food Security. (2019).

9 Rosenzweig, C., N Tubiello, F., Sandalow, D., Benoit, P. & N Hayek, M. Finding and fixing food system emissions: the double helix of science and policy. *Environmental Research Letters* **16** (2021). https://doi.org:10.1088/1748-9326/ac0134

10 Crippa, M. *et al.* Food systems are responsible for a third of global anthropogenic GHG emissions. *Nature Food* **2**, 198-209 (2021).

11 Leclere, D. *et al.* Bending the curve of terrestrial biodiversity needs an integrated strategy. *Nature* **585**, 551-556 (2020). https://doi.org:10.1038/s41586-020-2705-y

12 Lynch, J., Cain, M., Frame, D. & Pierrehumbert, R. Agriculture's contribution to climate change and role in mitigation is distinct from predominantly fossil CO2-emitting sectors. *Frontiers in Sustainable Food Systems* **4**, 518039 (2021).

13 Kastner, T., Erb, K.-H. & Haberl, H. Rapid growth in agricultural trade: effects on global area efficiency and the role of management. *Environmental Research Letters* **9**, 034015 (2014).

14 FAO. *The State of Agricultural Commodity Markets 2020. Agricultural markets and sustainable development: Global value chains, smallholder farmers and digital innovations*. (FAO, 2020).

15 Chaudhary, A. & Kastner, T. Land use biodiversity impacts embodied in international food trade. *Global Environmental Change* **38**, 195-204 (2016). https://doi.org:10.1016/j.gloenvcha.2016.03.013

16 Kitzes, J. *et al.* Consumption-Based Conservation Targeting: Linking Biodiversity Loss to Upstream Demand through a Global Wildlife Footprint. *Conserv Lett* **10**, 531-538 (2017). https://doi.org:10.1111/con4.12321

17 Balmford, A. *et al.* The environmental costs and benefits of high-yield farming. *Nature Sustainability* **1**, 477-485 (2018). https://doi.org:10.1038/s41893-018-0138-5

18 Miller, R. E. & Blair, P. D. *Input-output Analysis: Foundations and Extension*. (Cambridge University Press, 2009).

19 Kitzes, J. An introduction to environmentally-extended input-output analysis. *Resources* **2**, 489-503 (2013).

20 Roux, N., Kastner, T., Erb, K.-H. & Haberl, H. Does agricultural trade reduce pressure on land ecosystems? Decomposing drivers of the embodied human appropriation of net primary production. *Ecological Economics* **181** (2021). https://doi.org:10.1016/j.ecolecon.2020.106915

21 Peters, G. & Hertwich, E. G. CO_2 embodied in international trade with implications for global climate policy. *Environmental Science and Technology* **42**, 1401-1407 (2008).
22 Hoekstra, A. Y. & Mekonnen, M. M. The water footprint of humanity. *Proceedings of the National Academy of Sciences* **109**, 3232-3237 (2012).
23 Lenzen, M. *et al.* International trade drives biodiversity threats in developing nations. *Nature* **486**, 109-112 (2012).
24 Moran, D. & Kanemoto, K. Identifying species threat hotspots from global supply chains. *Nature Ecology and Evolution* **1**, 0023 (2017).
25 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). https://doi.org:10.1021/acs.est.5b02507
26 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). https://doi.org:10.1038/s41559-019-0824-3
27 Wilting, H. C., Schipper, A. M., Bakkenes, M., Meijer, J. R. & Huijbregts, M. A. Quantifying Biodiversity Losses Due to Human Consumption: A Global-Scale Footprint Analysis. *Environ Sci Technol* **51**, 3298-3306 (2017). https://doi.org:10.1021/acs.est.6b05296
28 Alkemade, R. *et al.* GLOBIO3: A Framework to Investigate Options for Reducing Global Terrestrial Biodiversity Loss. *Ecosystems* **12**, 374-390 (2009). https://doi.org:10.1007/s10021-009-9229-5
29 Newbold, T., Oppenheimer, P., Etard, A. & Williams, J. J. Tropical and Mediterranean biodiversity is disproportionately sensitive to land-use and climate change. *Nat Ecol Evol* **4**, 1630-1638 (2020). https://doi.org:10.1038/s41559-020-01303-0
30 Martins, I. S. & Pereira, H. M. Improving extinction projections across scales and habitats using the countryside species-area relationship. *Sci Rep* **7**, 12899 (2017). https://doi.org:10.1038/s41598-017-13059-y
31 Hillebrand, H. *et al.* Biodiversity change is uncoupled from species richness trends: Consequences for conservation and monitoring. *Journal of Applied Ecology* **55**, 169-184 (2018). https://doi.org:10.1111/1365-2664.12959
32 Chichorro, F., Juslén, A. & Cardoso, P. A review of the relation between species traits and extinction risk. *Biological Conservation* **237**, 220-229 (2019).
33 Stadler, K. *et al.* EXIOBASE 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. *Journal of Industrial Ecology* https://doi.org/10.1111/jiec.12715 (2018).
34 Smith, P. & Gregory, P. J. Climate change and sustainable food production. *Proc Nutr Soc* **72**, 21-28 (2013). https://doi.org:10.1017/S0029665112002832
35 ESRI. (2015).
36 The Nature Conservancy. (2019).
37 International Food Policy Research Institute. *MapSPAM* (ed International Food Policy Research Institute) (Harvard Dataverse, 2019).
38 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 Biogeochemical Cycles* **22**, GB1022 (2008). https://doi.org:doi: 10.1029/2007GB002947
39 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 Biogeochemical Cycles* **22**, GB1003 (2008). https://doi.org:doi:10.1029/2007GB002952
40 IUCN, I. U. f. C. o. N. (2020).
41 BirdLife International. (2020).
42 Meiri, S. *et al.* (2017).

43 Roll, U. *et al.* The global distribution of tetrapods reveals a need for targeted reptile conservation. *Nat Ecol Evol* **1**, 1677-1682 (2017). https://doi.org:10.1038/s41559-017-0332-2

44 Etard, A., Morrill, S. & Newbold, T. Global gaps in trait data for terrestrial vertebrates. *Global Ecology and Biogeography* **29**, 2143-2158 (2020). https://doi.org:https://doi.org/10.1111/geb.13184

45 Hudson, L. N. *et al.* The database of the PREDICTS (Projecting Responses of Ecological Diversity In Changing Terrestrial Systems) project. *Ecol Evol* **7**, 145-188 (2017). https://doi.org:10.1002/ece3.2579

46 Hudson, L. N. *et al.* (ed Natural History Museum) (https://doi.org/10.5519/0066354, 2016).

47 Shine, K. P., Fuglestvedt, J. S., Hailemariam, K. & Stuber, N. Alternatives to the global warming potential for comparing climate impacts of emissions of greenhouse gases. *Climate Change* **68**, 281-302 (2005).

48 Myhre, G. *et al.* Anthropogenic and Natural Radiative Forcing. (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2013).

49 Hijmans, R., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* **25**, 1965-1978 (2005). https://doi.org:doi.org/10.1002/joc.1276

50 CountryEconomy.com. *https://countryeconomy.com/demography/population/taiwan?year=2011* 2021).

51 World Bank. (2021).

52 Chaudhary, A., Carrasco, L. R. & Kastner, T. Linking national wood consumption with global biodiversity and ecosystem service losses. *Sci Total Environ* **586**, 985-994 (2017). https://doi.org:10.1016/j.scitotenv.2017.02.078

53 Sun, Z., Behrens, P., Tukker, A., Bruckner, M. & Scherer, L. Shared and environmentally just responsibility for global biodiversity loss. *Ecological Economics* **194** (2022). https://doi.org:10.1016/j.ecolecon.2022.107339

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

55 Mueller, N. D. *et al.* Closing yield gaps through nutrient and water management. *Nature* **490**, 254-257 (2012). https://doi.org:10.1038/nature11420. 490:254-257

56 Steen-Olsen, K., Owen, A., Hertwich, E. G. & Lenzen, M. Effects of sector aggregation on CO_2 multipliers in multiregional input-output analyses. *Economic Systems Research* **26**, 284-302 (2014).

57 Lenzen, M. Aggregation versus disaggregation in input-output analysis of the environment. *Economic Systems Research* **23**, 73-89 (2011).

58 Merciai, S. & Heijungs, R. Balance issues in monetary input-output tables. *Ecological Economics* **102**, 69-74 (2014).

59 de Koning, A. *et al.* Effect of aggregation and disaggregation on embodied material use of products in input-output analysis. *Ecological Economics* **116**, 289-299 (2015).

60 Tukker, A. *et al.* Towards robust, authoratitive assessments of environmental impacts embodied in trade: Current state and recommendations. *Journal of Industrial Ecology* **22** (2018).

61 Chandrakumar, C., McLaren, S., Malik, A., Ramilan, T. & Lenzen, M. Understanding New Zealand's consumption-based greenhouse gas emissions: an application of multi-regional input-output analysis. *The International Journal of Life Cycle Assessment* **25**, 1323-1332 (2020).

62 FAO. How to Feed the World in 2050. (Rome, Italy, 2009).

63 Oliveira, J. *et al.* Choosing pasture maps: An assessment of pasture land classification definitions and a case study of Brazil. *International Journal of Applied Earth Observation and Geoinformation* **93** (2020). https://doi.org:10.1016/j.jag.2020.102205