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RAINFOREST PROJECT SUMMARY

Food and biomass production systems are among the most prominent drivers of biodiversity loss worldwide. Halting and reversing the loss of biodiversity therefore requires transformative change of food and biomass systems, addressing the nexus of agricultural production, processing and transport, retailing, consumer preferences and diets, as well as investment, climate action and ecosystem conservation and restoration. The RAINFOREST project will contribute to enabling, upscaling and accelerating transformative change to reduce biodiversity impacts of major food and biomass value chains. Together with stakeholders, we will co-develop and evaluate just and viable transformative change pathways and interventions. We will identify stakeholder preferences for a range of policy and technology-based solutions, as well as governance enablers, for more sustainable food and biomass value chains. We will then evaluate these pathways and solutions using a novel combination of integrated assessment modelling, input-output modelling and life cycle assessment, based on case studies in various stages of the nexus, at different spatial scales and organizational levels. This coproduction approach enables the identification and evaluation of just and viable transformative change leverage points, levers and their impacts for conserving biodiversity (SDGs 12, 14-15) that minimize trade-offs with targets related to climate (SDG13) and socioeconomic developments (SDGs 1-3). We will elucidate leverage points, impacts, and obstacles for transformative change and provide concrete and actionable recommendations for transformative change for consumers, producers, investors, and policymakers.

EXECUTIVE SUMMARY

RAINFOREST aims to explore pathways and interventions to achieve transformative change for reducing biodiversity impacts. To evaluate effectiveness of these pathways and interventions to achieve transformative change, RAINFOREST develops a model toolbox that considers climate, biodiversity, and socioeconomic impacts along entire value chains. The toolbox contains a set of environmental-economic and impact assessment models that are linked to each other to enable the quantification of a comprehensive and complementary set of impact indicators relevant for evaluating progress towards targets defined in international agreements.

The toolbox includes three environmental-economic models: (i) the partial equilibrium model GLOBIOM, which is specialised in land use-based activities; (ii) the monetary environmentally extended multi-regional input-output (EEMRIO) model EXIOBASE that assesses sector-level environmental footprints of the whole economy (partially) based on national supply and use tables; and (iii) the physical EEMRIO model FABIO that assesses environmental footprints of agriculture and food products (partially) based on FAO statistics. In addition, the toolbox includes three impact assessment models: (i) the life cycle impact assessment (LCIA) model LC-IMPACT that quantifies impacts of several pressures on species richness and human health; (ii) the LCIA model ReCiPe that quantifies multiple environmental impacts, such as global warming, as a function of several pressures; and (iii) the global biodiversity model GLOBIO, which evaluates impacts of several pressures on ecosystem intactness.

This report describes the set-up of the model toolbox and how it is applied in RAINFOREST. In Section 2, the environmental-economic models are described; in section 3, the impact assessment models are described; in Section 4, the methods for quantifying climate, biodiversity, and socioeconomic impact indicators are described; and in Section 5 the application of the model toolbox is discussed. Section 6 contains a summary and outlook.

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1. INTRODUCTION

RAINFOREST aims to explore pathways for transformative change to reduce biodiversity impacts of major food and biomass value chains. This includes the development of broad-scale pathways (Work Package 1), but also case-studies of interventions that may achieve transformative change such as improving fishmeal production technologies (WP3), changing food consumption patterns (WP3), considering environmental footprints in investment portfolio decisions (WP4), and consuming novel foods (WP5). To evaluate the transformative potential of these pathways and interventions, RAINFOREST assesses the spatially- and sector-explicit environmental and socio-economic impacts associated with the pathways and interventions along entire value chains.

The model toolbox is a set of environmental-economic and impact assessment models that can be used to quantify climate, biodiversity, and socioeconomic responses to socioeconomic and policy pathways and interventions. As such, the model toolbox enables the quantification of corresponding climate, biodiversity, and socioeconomic impacts in terms of a set of complementary impact indicators. By quantifying effects of interventions to reduce environmental impacts, the toolbox can be used to evaluate the implications of transformative change for reaching climate, biodiversity, and socio-economic targets, such as those defined in the Paris Climate Agreement, EU Green Deal, Kunming-Montreal Global Biodiversity Framework, and Sustainable Development Goals (UNFCCC 2016; EC 2019; UN 2019; CBD 2022).

The toolbox includes an integrated assessment model to quantify pathways for transformative change and their implications for greenhouse gas emissions (GHG) and land use (GLOBIOM; (Havlík et al. 2014)); a monetary environmentally extended multiregional input-output (EEMRIO) model to quantify, e.g., GHG and land use footprints as well as socio-economic impacts related to national sectors across the global economy (EXIOBASE; (Stadler et al. 2018)); a physical EEMRIO model to quantify, e.g., GHG and land use footprints related to agricultural and food products (FABIO; (Bruckner et al. 2019)); and models to quantify climate and biodiversity responses to, e.g., GHG emissions and land use change (LC-IMPACT, ReCiPe, and

GLOBIO; (Huijbregts et al. 2017; Schipper et al. 2020; Verones et al. 2020)). The toolbox establishes links between individual models to allow for a comprehensive assessment of climate, biodiversity, and socioeconomic footprints of a variety of activities and actors (Figure 1). In addition, the toolbox aims to further develop the individual models to better represent human influence on the environment. Hence, the toolbox fulfils a key function in the RAINFOREST project.

In this report, we describe the set-up of the model toolbox and its planned application in RAINFOREST. First, we describe the environmental-economic and impact assessment models (Sections 2 and 3, respectively). Second, we describe how the environmental-economic models are linked to the impact assessment models to quantify climate, biodiversity, and socioeconomic impact indicators (Section 4). Finally, we describe how the toolbox will be applied in the case-studies that explore interventions aimed to achieve transformative change (Section 5).

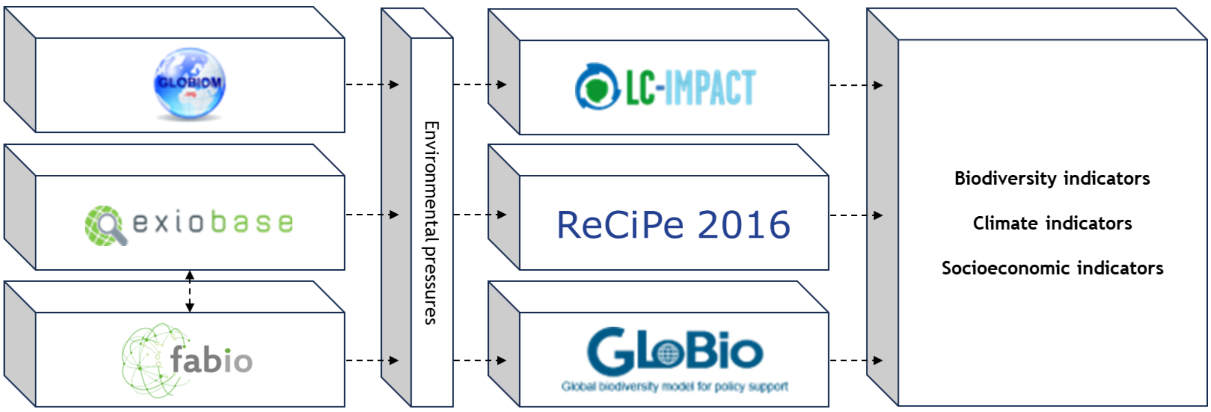

Figure 1. Illustration of the model toolbox and the planned soft links between them.

2. ENVIRONMENTAL-ECONOMIC MODELS

2.1 GLOBIOM

GLOBIOM is a bio-economic model designed to address various land use related topics (bioenergy policy impacts, deforestation dynamics, climate change adaptation and mitigation from agriculture, long term agricultural prospect) (IBF-IIASA 2023). It belongs to the family of partial equilibrium models, as it focuses on a few economic sectors to represent them at a high level of detail. As a model specialized in land use-based activities, GLOBIOM benefits from a detailed coverage for the agriculture, forestry and bioenergy sectors, with an explicit representation of production technologies, a geographically explicit allocation of land cover and land use and their related carbon stocks and GHG emission flows.

GLOBIOM provides projections from the year 2000 onwards, with a ten-year time step up to 2100. Commodity markets and international trade are modelled at the level of 59 aggregate economic regions (the aggregation is flexible and can be adapted to the users' needs) at a global coverage. The spatial resolution of the supply side relies on the concept of Simulation Units that are aggregates of 5 to 30 arcmin pixels belonging to the same altitude, slope, and soil class, and following country borders. Within each spatial unit, forests are distinguished between unmanaged and managed forests (including optional coupling to the G4M model for a more detailed representation of various forest managements), managed grassland used for livestock feeding is detailed at the level of livestock species and systems, while cropland use is distinguished to 4 input levels (subsistence, low input rainfed, high input rainfed, high input irrigated) (Kindermann et al. 2006). The agricultural sector in GLOBIOM includes the production of 18 major crops that are globally cultivated, representing more than 70% of the total harvested area and 85% of the crop-derived calorie supply, according to data reported by FAOSTAT. In addition, the GLOBIOM model features a comprehensive and detailed representation of the global livestock sector. The model distinguishes between different animal species (bovines, small ruminants, pigs, and poultry), covering 7 animal source products (bovine meat and milk, small ruminant meat and milk, pig meat, poultry meat, and eggs). GLOBIOM has detailed representation of the forest sector and its supply chain.

The model includes five primary wood products (pulplogs, sawlogs, ither industrial roundwood, fuel wood, and logging residues) that can be used as inputs for material or energy production processes. The current version of the model includes eight final products (sawnwood, plywood, fiberboard, chemical pulp, mechanical pulp, other industrial roundwood, fuelwood, and energy wood). GLOBIOM also explicitly covers biomass feedstocks from energy plantations and existing forests for energy use.

The model takes as input a large range of spatially explicit datasets. These include remote sensing, biophysical model, socioeconomic, and tradeflow data to estimate land and water use related to the production of various agricultural and forestry goods. Future projections are driven by additional, scenario-specific, assumptions about population, GDP, dietary preferences, trade costs, climate change impacts on crop and managed grassland yields, that are translated into model parameters such as product- and region-specific demand, crop and livestock productivity and trade costs. It can also consider nature and climate interventions such as increased protection and restoration efforts, limitations to nutrient surplus or water consumption in the agricultural sector as well as additional biomass demand or carbon taxes. The detailed representation of land use and land cover allows for customizable indicators related to land occupation in the reporting, ranging from main land covers at regional level to detailed land use at 5 arcminutes. In the latter case, the outputs of the GLOBIOM model are often combined with a Bayesian downscaling framework (Krisztin et al. 2022), as is for example done in Leclère et al. (2020).

GLOBIOM covers all major GHG emissions from Agriculture, Forestry and Other Land Use (AFOLU) based on IPCC accounting guidelines including N_2O from application of synthetic fertilizer and manure to soils, N_2O from manure dropped on pastures, CH_4 from rice cultivation, N_2O and CH_4 from manure management, and CH_4 from enteric fermentation, and CO_2 emissions/removals from above- and below-ground biomass changes for other natural vegetation. CO_2 emissions and removals from afforestation, deforestation, and wood production in managed forests are estimated by the geographically explicit (0.5x0.5 degree) model G4M that is linked to GLOBIOM. The GLOBIOM model can be also coupled to the MESSAGE energy model, to quantify the GHG emissions associated to the broader climate mitigation pathways for the full economy (Fricko et al. 2017).

In addition, GLOBIOM endogenously represents a comprehensive set of mitigation technologies for the crop- and livestock sectors including technological options (based on the US EPA dataset of non-CO_2 abatement technologies), structural options (e.g. transition in production systems, changes in regional product mix, international trade), and demand side (alternative diets, consumer response to price signals) mitigation options (EPA 2019).

Beyond land occupation, land transformation and GHG emissions related to the Agriculture, Forestry and Other Land Use (AFOLU) sector, the GLOBIOM model can provide indicators related to various environmental impacts. Impacts related to climate change impacts on the productivity of crops and managed grassland, available water for irrigation as well as subsequent changes in production, consumption, trade and prices including adaptation through changes in farming practices (e.g., adoption of irrigation) and reallocations of land use with and across regions including trade can be reported upon (Leclère et al. 2014; FAO 2015; Janssens et al. 2020), and are based on estimates of climate change impacts on the productivity of crops and managed grassland and the water cycle from biophysical (e.g., EPIC) and/or hydrological (e.g., LPJML, CWAT-M) models for various climate change scenarios and models from the Climate Model Intercomparison (CMIP5 and CMIP6) and Inter-Sectoral Impacts Model Intercomparison (ISIMIP1, ISIMIP3b) projects.

The use of surface water and groundwater in the agricultural sector (based on exogenous data on water availability and endogenous modelling of irrigation water use including scarcity costs and irrigation technology adoption) and in other sectors (based on external projections from hydrological models) can be reported upon, as well as resulting water scarcity, including under climate change (Palazzo et al. 2019). In addition, based on external data and endogenous modelling of water use, shortfall in environmental flows within surface water systems can be reported upon (Pastor et al. 2019).

Reactive nitrogen flows within land systems including surplus and nitrogen losses from the agricultural sector and human settlements can be reported upon, based on external data (e.g., deposition, assumed trends in nitrogen use efficiency for cropland and managed grassland) and endogenous variables (e.g., crop area and yield, fertilizer and manure application), following the methodology detailed in Chang et al (2021). In RAINFOREST, developments are ongoing to represent the phosphorous cycle (Section 4.1.2).

Various metrics of biodiversity (area of habitat, wildlife population trends, intactness, regional and global extinction risks) can be projected, based on endogenous land use projections as well as biodiversity models based on various approaches (Di Fulvio et al. 2019; Leclère et al. 2020). Additional policies in terms of conservation and restoration can also be implemented. GLOBIOM can also be coupled to biodiversity models, to estimate biodiversity impacts associated with land use projections (Leclère et al. 2020). In RAINFOREST, indicators will be generated through the coupling to LC-IMPACT (terrestrial and freshwater ecosystems quality; Section 4.1.2), ReCiPe (global warming potential; Section 4.1.3), and GLOBIO (Mean Species Abundance; Section 4.1.4), including the development of a novel indicator on pesticide input use (Section 4.1.2).

The GLOBIOM model will be used to quantify land use change, GHG emissions, nitrogen flows and biodiversity indicators in relation to transformative pathways (WP1) for the agriculture and forestry sectors and could provide estimates of GHG emissions associated to the rest of the economy through already existing MESSAGE simulations. Dedicated modules will also be used to quantify additional indicators, such as population at risk of hunger, or added value in the agricultural sector. Furthermore, the GLOBIOM model is currently being developed to provide health indicators associated with a per capita food consumption at product level (Section 4.1.1).

2.2 EXIOBASE

EXIOBASE 3 provides a time series of environmentally extended multi-regional input-output (EEMRIO) tables for 44 countries (28 EU member plus 16 major economies) and five rest of the world regions. EXIOBASE 3 builds upon the previous versions of EXIOBASE by using rectangular supply-use tables (SUT; covering 163 industries by 200 products) as the main building blocks. The tables are provided in current basic prices (Million EUR). EXIOBASE is compatible with the System of Environmental-Economic Accounting (SEEA) (Stadler et al. 2018). EXIOBASE 3 contains time series of EEMRIO tables ranging from 1995 to 2022 (extrapolated for the most recent years).

EXIOBASE3 updates are released regularly on the Open Science Data repository Zenodo. The latest EXIOBASE version is publicly available at the Zenodo repository: https://doi.org/10.5281/zenodo.3583070. Currently, EXIOBASE 3 is released under a CC-BY-SA 4.0 license, with some extensions (in particular land use) inheriting the stricter license from FAO (CC-BY-SA-NC).

Hybrid LCA-MRIO models have combined country- and sector-aggregated EXIOBASE data with actor-specific data (Nakamura & Kondo 2002). For example, Sen et al. (2019) combined EXIOBASE data to evaluate footprints of passenger vehicles. The combination of EEMRIO and more detailed data enables the consideration of complete international value chains while maintaining a high-resolution of activities related to certain processes (Beylot et al. 2020). Although EEMRIO models are particularly useful to trace pressures and impacts along supply chains, quantifying the biodiversity losses associated with the pressures and resource uses remains a challenge (Wiedmann 2016). Coupling EXIOBASE to the LC-IMPACT life cycle impact assessment model has proven to be an effective way of translating the environmental pressures to biodiversity loss (Verones et al. 2017).

2.3 FABIO

The Food and Agriculture Biomass Input-Output (FABIO) model, provides a set of multiregional supply, use and input-output tables of 123 agricultural and food products for 186 countries (and one rest-of-the-world region) (Bruckner et al. 2019). The tables are provided in physical units and the product flows are primarily based on publicly available FAOSTAT crop production and trade statistics data (https://www.fao.org/faostat/en/#data). FABIO data comprises supply, use, and input-output tables from 1986-2013 (FABIO v1.2 covers data until 2020 but is not publicly available yet),and is currently released under a CC-BY-NC-SA 4.0 license and publicly available at http://dx.doi.org/10.5281/zenodo.2577067.

Compared to other MRIO databases, FABIO provides more detailed information on agricultural products, documenting country- and sector-specific inputs and outputs in terms of physical product flows (Bruckner et al. 2019). Using physical instead of monetary data reduces uncertainty regarding the link between agricultural land use area to agricultural product trade flows (Bruckner et al. 2015).

FABIO has been increasingly used to quantify agricultural related environmental footprints. For example, Vanham et al. (2023) used FABIO to calculate the land and water footprint of food consumption for the EU. They identified that livestock grazing was a major contributor to variation in EU land and water footprint. Sun et al. (2022b) employed FABIO to compute the biomass carbon and GHG emissions driven by food consumption changes in high-income countries and found that the dietary shift from animal-based food to plant-based food in high-income nations could reduce GHG emissions from direct agricultural production and increase carbon sequestration. FABIO has also been linked to other models and data. For example. Kortleve et al. (2024) combined FABIO with public subsidy data to evaluate how the EU's Common Agricultural Policy influences the EU food system through agricultural subsidies. Furthermore, FABIO and EXIOBASE have been integrated to assess global biodiversity loss driven by land use within key biodiversity areas (Sun et al. 2022a).

2.4 FABIO-EXIOBASE hybrid model

In the RAINFOREST project, the *FABIO-EXIOBASE* hybrid model, developed by Rasul et al. ((2024), under review), is used to quantify the biodiversity footprint from land use, water use, and freshwater eutrophication.

FABIO-EXIOBASE hybrid model is a tiered hybrid EEMRIO model, that analyses the agrifood system of 123 biomass commodities in 186 countries in a consistent and comparable framework from 1995 to 2020, i.e. those products that are native in the FABIO model (Bruckner et al. 2019). The model fully accounts for intermediate inputs to the FABIO production activities by adding non-biomass inputs from EXIOBASE. Specifically, FABIO models the internal flows and outputs of the agrifood system, and EXIOBASE models the energy inputs from the rest of the economy (including both the direct and indirect energy demand), as well as food processing. The upstream impacts calculated with EXIOBASE can then be used as environmental accounts for FABIO. The coupled model links the consumption of products within a region with its environmental impact caused both directly in the agricultural system and in the corresponding upstream value chain.

In RAINFOREST, EXIOBASE (v3.8.2) and FABIO (v1.2) are combined. The FABIO-EXIOBASE hybrid model will be further coupled to the LCIA method of LC-IMPACT, for conversion of environmental impact and quantify the biodiversity footprint. The model can consider four biodiversity-related environmental indicators, including climate change, land use, water use, and freshwater eutrophication. The FABIO-EXIOBASE hybrid model will be applied to evaluate the biodiversity footprint for several novel food products.

3. IMPACT ASSESSMENT MODELS

3.1 LC-IMPACT

LC-IMPACT is a spatially differentiated life cycle impact assessment method at endpoint level. It contains currently 12 impact categories (climate change, ionizing radiation, ozone depletion, photochemical ozone formation, particulate matter, toxicity, freshwater and marine eutrophication, terrestrial acidification, land use, water use and mineral resources scarcity; Table 5). Within the impact categories both impacts on human health and ecosystem quality are included (e.g., human toxicity and ecotoxicity on freshwater, marine and terrestrial systems). The indicator for human health damage is DALY (disability adjusted life years) and the one for ecosystem quality is global PDF (global extinction, expressed as potentially disappeared fraction of species). What makes LC-IMPACT different from other LCIA methods is the comparatively high spatial resolution of characterization factors (especially for ecosystem quality) and the consistent consideration of global extinction. This is done by integrating a so called “vulnerability factor” that includes both information on the endemism of species and the already existing threats. LC-IMPACT is at the moment in the process of being updated and expanded (a little bit in RAINFOREST, but most in the BAMBOO and PATTERN projects and with the help of an additional PhD student funded by NTNU). The aim is to eventually be able to also use the updated LC-IMPACT version in the model toolbox.

The input for LC-IMPACT is a life cycle inventory, i.e., amounts of resources used/emissions released per functional unit. In addition, the geographical location of the process needs to be known, if the spatially-differentiated factors should be used (rather than the global average). LC-IMPACT is implemented in the SimaPro software and can be linked to the Brightway software package.

The output of LC-IMPACT itself is characterization factors, i.e. damages per unit of intervention/release of emission. Multiplied with an inventory (or coupled to an environmental extension from EXIOBASE or ecoinvent) it will result in a coefficient, reflecting the damage at endpoint level per functional unit.

Table 1. Characterisation factors of LC-IMPACT. The spatial coverage of all indicators native to LC-

IMPACT is global (Verones et al. 2020).

Aspect	Indicator	Unit	Taxa coverage	Pressure coverage	Spatial resolution	Description	Model the indicator links to
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Mammals, birds, reptiles, amphibians, and plants	Land use (6 categories)	Ecoregion level (804 ecoregions), national level (189 countries), global average	Indicator for global species extinctions due to habitat conversion (via the countryside-SAR)	LC-IMPACT
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Mammals, birds, frogs, reptiles, butterflies, and plants	Climate change (GHGs)	Generic	Indicator for global species extinctions due to temperature change (via GHG emissions)	LC-IMPACT
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Mammals, birds, reptiles, and amphibians and plants	Water use (m^3 water consumption)	watersheds, national level (189 countries), global average	Indicator for global species extinctions due to surface water consumption and groundwater reduction	LC-IMPACT
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Freshwater fish	Freshwater eutrophication (kg P emissions to freshwater and soil, and km^2 erosion)	Ecoregion level (449 freshwater ecoregions), national level (189 countries), continental level (6 continents), global average	Indicator for global species extinctions due to eutrophication (via P emissions to freshwater and soil and erosion ending up in freshwater)	LC-IMPACT
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Fish, crustaceans, molluscs, chinoderms, annelids, and cnidarians	Marine eutrophication (kg N emissions to freshwater and soil)	Large marine ecosystems, basin, national level (189 countries), continental level (6 continents), global average	Indicator for global species extinctions due to eutrophication (via N emissions to freshwater and soil ending up in oceans)	LC-IMPACT
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Plants	Terrestrial acidification (kg NO_x, NH_3, SO_x)	2.0°x2.5°, national level (189 countries), continental level (6 continents), global average	Indicator for global species extinctions due to acidification (via kg NOx, NH3, SO_x emissions)	LC-IMPACT
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Freshwater: fish; marine: lobsters, chondrichth	Toxicity (kg toxicant emitted to freshwater, marine, and	Subcontinental level (17 regions), continental level (7	Indicator for global species extinctions due to	LC-IMPACT

			yes, actinopterygii, and sea cucumbers	terrestrial air, water, and soil)	continents), global average	toxicity (via SSD curves linked to toxicants emitted to freshwater, marine, and terrestrial environments)	
Biodiversity	Potential disappeared fraction of species (PDF)	PDF·years	Plants	Photochemical ozone formation (kg NO_x, NMVOC)	Regional level (56 TM5-FASST regions), national level (189 countries), continental level (6 continents), global average	Indicator for global species extinctions due to photochemical ozone formation (via kg NO_x and NMVOC emissions)	LC-IMPACT
Human health	Disability-adjusted life years (DALY)	DALY	Humans	Climate change (kg GHG emission)	Generic	Indicator for the reduction in a healthy life in years due to climate change (via GHG emissions)	LC-IMPACT
Human health	Disability-adjusted life years (DALY)	DALY	Humans	Water use (m^3 water consumption)	Watershed level (11050 watersheds), national level (189 countries), global average	Indicator for the reduction in a healthy life in years due to water use (via water availability)	LC-IMPACT
Human health	Disability-adjusted life years (DALY)	DALY	Humans	Particulate matter (kg $PM_{2.5}$, NH_3, NO_x, SO_2)	Regional level (56 TM5-FASST regions), national level (189 countries), global average	Indicator for the reduction in a healthy life in years due to PM emissions (via kg $PM_{2.5}$, NH_3, NO_x, SO_2 emissions)	LC-IMPACT
Human health	Disability-adjusted life years (DALY)	DALY	Humans	Toxicity (kg toxicant)	Subcontinental level (17 regions), continental level (7 continents), global average	Indicator for the reduction in a healthy life in years due to toxicity	LC-IMPACT
Human health	Disability-adjusted life years (DALY)	DALY	Humans	Photochemical ozone formation (kg NO_x, NMVOC)	Regional level (56 TM5-FASST regions), national level (189 countries), continental level (6 continents), global average	Indicator for the reduction in a healthy life in years due to photochemical ozone formation (via kg NO_x, NMVOC emissions)	LC-IMPACT

Human health	Disability-adjusted life years (DALY)	DALY	Humans	Ozone depletion (kg ODS)	Generic	Indicator for the reduction in a healthy life in years due to ozone depletion (via kg ODS emissions)	LC-IMPACT
Human health	Disability-adjusted life years (DALY)	DALY	Humans	Ionizing radiation (kBq)	Generic	Indicator for the reduction in a healthy life in years due to ionising radiation	LC-IMPACT

Planned updates for LC-IMPACT that are relevant for RAINFOREST, especially the fishmeal case study, include:

1. Climate change: to be updated with two models for impacts on marine and terrestrial ecosystems (Iordan et al. 2023), as well as freshwater ecosystems (Li et al. 2022), replacing the current spatially-generic model that only considers terrestrial species;
2. Land use: to be updated to a new model that accounts for impacts on 5 taxa, 5 land use types (previously 6) and 3 land use intensity levels (not considered before), including both land use and fragmentation of the land, which was not considered before (Scherer et al. 2023);
3. Ocean acidification: this is a model that is currently developed in BAMBOO. The deliverable for the model is August 2024 and the development is on track, so we expect that we can use this model in RAINFOREST;
4. Seabed damage: the development of that impact assessment model has just started in BAMBOO. The goal is to expand a European model for global coverage. If successful, that impact category will be added later in the project, after the final Toolbox deliverable;
5. Overexploitation: this task will start in BAMBOO later and will build on work that is currently ongoing in another PhD thesis in Montpellier. This can only be added towards the end of the RAINFOREST project.

3.2 ReCiPe

Like LC-IMPACT, ReCiPe is a spatially differentiated life cycle impact assessment method (Huijbregts et al. 2017). In addition to endpoint impacts (e.g., biodiversity loss), ReCiPe also quantifies midpoint impacts (e.g., global warming). ReCiPe can be linked to the models in the model toolbox in the same way as LC-IMPACT, and will allow for the quantification of climate impacts (via the global warming potential indicator). The global warming potential (GWP) characterisation factors translate GHGs into CO_2-equivalents based on the atmospheric warming potential per kg GHG and the atmospheric degradation rate relative to the warming potential and degradation per kg CO_2. ReCiPe contains GWP characterisation factors for 207 GHGs (Huijbregts et al. 2017).

Table 2. Characterisation factors of ReCiPe. The spatial coverage of all characterisation factors is global (Huijbregts et al. 2017).

Aspect	Indicator	Unit	Pressure coverage	Spatial resolution	Description	Model the indicator links to
Environmental state	Land use	m^2 cropland eq.	Land use (m^2 cropland eq.)	Generic	Indicator for the amount of land used	ReCiPe
Environmental state	Climate change	kg CO_2 eq.	Climate change (kg CO_2 eq.)	Generic	Indicator for the infrared radiative forcing	ReCiPe
Environmental state	Water use	m^3 water consumer eq.	Water consumption (m^3 water eq.)	Generic, national level (220 countries)	Indicator for increase in water consumption	ReCiPe
Environmental state	Freshwater eutrophication	kg P eq.	Freshwater eutrophication (kg P eq. emission to freshwater)	Generic, national level (220 countries)	Indicator for phosphorus increase in freshwater	ReCiPe
Environmental state	Terrestrial acidification	kg SO_2 eq.	Terrestrial acidification (kg SO_2 eq. emission to air)	Generic, national level (220 countries)	Indicator for proton increase in natural soils	ReCiPe
Environmental state	Toxicity	kg 1,4-DCB eq.	Terrestrial, freshwater, marine ecotoxicity and human toxicity potential (kg 1,4-DCB eq. to soil, freshwater, marine water, and urban air, respectively)	Generic	Indicator for hazard-weighted increase in toxicants	ReCiPe
Environmental state	Photochemical oxidant formation	kg NO_x eq.	Photochemical oxidant formation (kg NOx eq. to air)	Generic, national level (220 countries)	Indicator for tropospheric ozone increase	ReCiPe
Environmental state	Ozone depletion	CFC-11 eq.	Ozone depletion (CFC-11 eq. to air)	Generic	Indicator stratospheric ozone	ReCiPe

					decrease	
Environmental state	Ionising radiation	kBq Co-60 eq.	Ionising radiation (kBq Co-60 eq. to air)	Generic	Indicator for absorbed dose increase	ReCiPe
Environmental state	Particulate matter formation	kg PM2.5 eq.	Particulate matter formation (kg PM2.5 eq. to air)	Generic, national level (220 countries)	Indicator for PM2.5 population intake	ReCiPe

3.3 GLOBIO

The GLOBIO model calculates local terrestrial species-assemblage intactness expressed by the mean species abundance (MSA) indicator (Schipper et al. 2020). MSA pressure-response relationships are derived from meta-analyses of empirical local pairwise comparisons of species populations in natural reference and impacted conditions. The GLOBIO model is typically combined with the IMAGE integrated assessment model (Schipper et al. 2020; Kok et al. 2023), but it has also been combined with the GLOBIOM model (Leclère et al. 2020).

In RAINFOREST, two pressures that impact MSA are considered: climate change and land use. The pressure-response relationship for climate impacts on MSA relate global mean temperature change to change in MSA. Global mean temperature change can be related to GHG emissions to enable linking GLOBIO to GLOBIOM, EXIOBASE, and FABIO. There are pressure-response relationships for land use impacts on MSA for seven land use types (intensive cropland, low intensity cropland, intensive pasture, extensive pasture, forest plantations, urban areas, and secondary vegetation).

4. IMPACT INDICATORS

4.1 GLOBIOM

4.1.1 Native GLOBIOM indicators

The GLOBIOM model will provide health indicators associated with a per capita food consumption at product level, linking the risk of disease to the consumption of specific food based on the Global Burden of Disease (GBD) database. Years of life lost and the disability adjusted life years lost due to increased risk of non-communicable diseases (esophageal cancer, colon and rectum cancer, breast cancer, ischemic stroke, intracerebral hemorrhage, subarachnoid hemorrhage, tracheal, bronchus, and lung cancer, ischemic heart disease, diabetes mellitus type 2), associated to specific dietary risks (diet too low in fruits, vegetables, nuts and seeds, milk or legumes; diet too high in red meat) will be quantified for each dietary change scenario. Quantification of the burden of disease attributable to each dietary factor-disease pair will be based on the following parameters: mean per capita food consumption at product level (GLOBIOM output), standard deviation of intake by country, risk exposure definitions (e.g. exposure to a diet low in fruits is defined as average daily consumption of less than 250 grams per day of fruits), as well as the effect size of the dietary factor on disease endpoint (Stanaway et al. 2018).

Furthermore, the GLOBIOM model will provide assessment of prevalence of undernourishment (PoU) impacts in each scenario. PoU is calculated using three key factors: the mean dietary energy availability (kcal per person per day), the mean minimum dietary energy requirement (MDER) and the coefficient of variation of the domestic distribution of dietary energy availability in a country (Hasegawa et al. 2019). The food distribution in a country is assumed to follow a log-normal distribution, which is defined by the mean food calorie availability and the equity of the food distribution. The proportion of the population under the cut-off point (MDER) is then defined as the prevalence of under-nourishment. The calorie-based food consumption (kcal per person per day) output from the GLOBIOM model is used for the mean food calorie availability.

Finally, the GLOBIOM model will also provide an assessment of the value added in the agricultural sector. The value added indicator provides for livestock and crop sub-sectors and for the model 59 regions an information on the economic output of these sectors, in USD2000. The projections rest on the combination of GLOBIOM projections for the market value of production (based on price and production volume projections in primary product equivalents, further aggregated across products) with GTAP data for year 2000 (ratio of value added to value of production, based on data for the year 2000 and assumed constant in projections).

Regarding the impact on biodiversity, GLOBIOM estimations are expressed through the Biodiversity Intactness Index (BII) and Fraction Globally Remaining Species (FGRS) related to the Land use pressure. Linking GLOBIOM to impact models such as GLOBIO or LC-IMPACT will not only allow to reflect on a different aspect of biodiversity, but also to estimate the biodiversity impacts related to additional pressures (Schipper et al. 2020; Verones et al. 2020).

4.1.2 GLOBIOM and LC-IMPACT

GLOBIOM will first be linked to LC-IMPACT to calculate impact on freshwater and ecosystem quality in terms of PDF, using the characterisation factors provided by LC-IMPACT. LC-IMPACT characterisation factors can be linked to the following GLOBIOM pressures related to agricultural and forestry activities: climate change, land use, ecotoxicity, freshwater eutrophication, and water stress. Using characterisation factors (impact per unit of elementary flow) instead of coefficients (impact per ton of product) allows to estimate an impact while staying consistent with GLOBIOM's modelling on the link between productivity and emissions (i.e., ton of environmental flow per ton of product), which can be affected by scenario-specific assumptions and endogenous modelling on changes in production technologies.

PDF characterisation factors for climate change and water stress pressures will be linked respectively to the GHG emissions and to water used for irrigation. The land use characterisation factors refer to the land occupation and transformation per land use type. To enable the linkage with GLOBIOM land use information, the land use categories of GLOBIOM will be linked to the land use categories of LC-IMPACT. Regarding the freshwater eutrophication impact, the LC-IMPACT characterisation factors are related to the Phosphorus emissions. Before the linkage with LC-IMPACT, GLOBIOM's Phosphorus balance will first be developed, following a similar methodology than for reactive nitrogen (Chang et al. 2021). To quantify terrestrial and freshwater ecotoxicity impacts, ecotoxic emissions are required. As these are currently not covered by GLOBIOM, a first step to enable the quantification of ecotoxicity impacts is to add the ecotoxic flows covered by LC-IMPACT to GLOBIOM.

Finally, for additional pressures, such as photochemical ozone formation, or terrestrial acidification, as well as for impacts unrelated to agriculture systems, downstream or upstream of the value chain, additional data would be needed since GLOBIOM does not estimate the emissions or environmental flows associated to it. This additional information could be provided, for example, via life cycle inventory datasets, such as Ecoinvent (Wernet et al. 2016), or EEMRIO datasets, such as EXIOBASE (Stadler et al. 2018), which, combined with LC-IMPACT characterisation factors, could provide an impact per ton of product. To consider impacts of such additional pressures, we will explore whether these coefficients could be linked to GLOBIOM's production output and possibly integrate GLOBIOM's assumptions.

4.1.3 GLOBIOM and ReCiPe

GLOBIOM uses the ReCiPe provides pressure-response factors translating emissions of specific GHG emissions to global warming. GLOBIOM and ReCiPe are linked by applying the ReCiPe's GHG-specific pressure-response factors to GLOBIOM's GHG-specific emissions.

4.1.4 GLOBIOM and GLOBIO

GLOBIOM will be linked dynamically to GLOBIO in order to estimate impacts on ecosystem integrity in Mean Species Abundance (MSA). The GLOBIOM model produces spatially-explicit land use maps that can be directly linked to the GLOBIO model to quantify cell-level MSA (Leclère et al. 2020), related to the Land use impact. Due to the spatial resolution of such linkage, as well as lack of dynamic information on some pressure drivers (e.g., roads and urban area expansion), it remains difficult to link more pressures. However, we will improve the the land use pressure between the two models, by refining the representation of management intensity of different land uses through aligning the land use categories. Additionally, we will explore the possibility to estimate an MSA impact due to climate change based on GLOBIO's pressure impact relationship, linked to global mean temperature increase. This increase would first need to be estimated within GLOBIOM based on the calculated GHG emissions.

4.1.5 GLOBIOM and agricultural employment data

The agricultural sector remains a cornerstone of global employment, serving as a vital source of livelihood for millions of people worldwide, albeit with varying degrees of prominence across regions. According to the Food and Agriculture Organization (FAO 2023), the employment share in agriculture, including forestry and fishery, ranges from 48% in Africa to 5% in Europe as of 2021. This significant variation underscores the diverse economic structures and levels of development across different regions. Notably, in low- and middle-income economies, primary production dominates employment, often resulting in relatively low wages and incomes (Davis et al. 2023). Even if representing a low share of total employment in developed countries, the employment and income in the agricultural sector can be important determinants of sustainability transitions.

As global agricultural production undergoes a transition towards sustainability and efficiency, understanding the dynamics of labour utilization, productivity, and their implications for food production, as well as societal transformation, becomes crucial. This task endeavours to develop comprehensive employment indicators within the agricultural sector. Specifically, it aims to measure the number of workers, wage structures, and value-added metrics stratified by crop and livestock activities on a global scale, with a particular focus on the European Union (EU) at the NUTS2 resolution.

An essential consideration in this endeavour is the varying intensity of labour use across different production technologies, capturing the heterogeneity of labour requirements within the sector. To address this complexity, a database delineating labour requirements per agricultural activity, production system (i.e., high input intensive, low input extensive systems), and country, along with corresponding wage and value-added metrics, is being developed. These metrics will be integrated into the GLOBIOM model to facilitate scenario analyses pertaining to employment and sectoral effects.

A preliminary study by Vittis et al. (2022) endeavours to quantify labour requirements across 12 major crop and livestock productions globally while accounting for variations in farm sizes. Bodirsky et al. (2023) describe the methodology used in the MAGPIE model, which entails the computation of crop- and livestock-specific capital and labour requirements using FAOSTAT and USDA datasets. Within this framework, the allocation of factor requirements between capital and labour is determined based on labour-to-capital ratios. Moreover, potential integration with EXIOBASE is envisaged to capture upstream and downstream sectors, enabling dynamic responses to scenario changes such as alterations in commodity production. Our estimation approach involves calculating country- and activity-specific labour requirements, drawing inspiration from both studies and extending the methodology to incorporate heterogeneity in production technologies. To achieve these objectives, two primary data streams are being utilized. **Error! Reference source not found.** presents an overview of indicators used in the estimation. Firstly, at a global scale, data from sources like FAOSTAT and ILOSTAT labour statistics serve as foundational inputs. FAOSTAT provides essential employment indicators annually, supplemented by ILOSTAT-modelled estimates to enhance coverage, particularly in rural areas. Key indicators from FAOSTAT relevant to this task include employment in agriculture, agricultural wages, forestry, and fishing, agriculture value added per worker, and the share of agricultural employment in total employment. Additionally, a comprehensive assessment of wages in agriculture is undertaken globally, incorporating data from global sources.

Secondly, Eurostat data is leveraged to estimate and quantify labour requirements at a finer resolution, specifically at the NUTS2 level within the EU. This dataset offers multiple employment indicators (Nomenclature of Territorial Units for Statistics, level 2 corresponds to regions/states/provinces within an EU member state), encompassing various labour characteristics such as employment by age, gender, family vs. non-family employment and regular vs. irregular labour arrangements. This data source offers an advantage due to its disaggregated nature, enabling the generation of regionally diverse metrics. Additionally, there is potential for validation through the Farm Accountancy Data Network (FADN) database. Moreover, insights from the United States Department of Agriculture (USDA), the Austrian Federal Institute of Agricultural Economics, and the German KTBL are considered to benchmark or refine the estimation methodology based on activity-level costs.

In summary, this initiative seeks to comprehensively analyse labour dynamics within the agricultural sector, providing valuable insights for policy formulation, resource allocation, and sustainable development efforts globally and within the EU. The final product comprises a database detailing labour requirements per agricultural activity, management systems, and region, alongside associated wages. This database will be integrated into GLOBIOM to analyse employment scenarios and sectoral effects further.

Table 3. Labour indicators in the agricultural sector.

EU and Global Sources	Indicator	Temporal Resolution	Spatial Resolution	Data Source
Global	Employment in agriculture, forestry, and fishery (ILOSTAT)	Yearly	Country	FAOSTAT ILOSTAT
	Monthly earnings per employee (agriculture, forestry, fishery) (FAOSTAT)	Yearly	Country	FAOSTAT
	Agricultural Value Added (FAOSTAT)	Yearly	Country	FAOSTAT
EU	Employment in Agriculture	Yearly	NUTS2	EUROSTAT
	Hours Worked	Yearly	NUTS2	EUROSTAT
	Wages and Earnings	Yearly	NUTS2	EUROSTAT
	Agricultural Value Added (Eurostat)	Yearly	Country	EUROSTAT

4.1.6 Impact indicators related to GLOBIOM

Table 4. Current impact indicators native to GLOBIOM and quantifiable via model links. The spatial coverage of all indicators native to GLOBIOM is global, the spatial resolution captures GLOBIOM regions (individual countries or aggregates, likely in the range of 60 regions), the temporal coverage ranges from 2000 to 2100 in a temporal resolution of 10 years (Havlík et al. 2014; Leclère et al. 2020; Chang et al. 2021).

Aspect	Indicator	Unit	Taxa coverage	Pressure coverage	Sectoral/ product coverage	Description	Model the indicator links to
Biodiversity	Biodiversity Intactness Index (BII)	fraction	All terrestrial taxonomic groups	Land use	Agriculture, forestry, conservation	Indicator for global species extinctions due to habitat conversion (via the countryside-SAR)	GLOBIOM
Biodiversity	Fraction of globally remaining species (FGRS)	fraction	Mammals, birds, reptiles, amphibians, and plants	Land use	Crop, livestock, forestry, land use change (further detail within crop and livestock products possible, as well as split CO_2, CH_4, N_2O)	Indicator for global species extinctions due to habitat conversion (via the countryside-SAR)	GLOBIOM
Biodiversity	Mean Species Abundance (MSA	MSA.ha	Terrestrial plants, birds, and mammals	Land use	Agriculture, forestry	Indicator measuring the intactness of the local species composition	GLOBIO
Biodiversity	Potentially Disappeared Fraction (PDF)	PDF.y	Mammals, birds, reptiles, amphibians, and plants	Land use, climate change, freshwater eutrophication, ecotoxicity	Agriculture, forestry	Indicator for global species extinctions	LC-IMPACT
Climate	Greenhouse gas (GHG) emissions	tons of CO_2 equivalent	na	Climate	AFOLU, land use change	Indicator for anthropogenic pressure on climate system	ReCiPe
Socio-economic	Land use	hectares	na	Land use	Crop bioenergy, crop others, livestock, forestry, conservation (protection & restoration), unmanaged ecosystems (forest and non-forest)	Indicator for the amount of land used	GLOBIOM
Socio-economic	Production, Consumption and Trade physical flows	tons of fresh matter of primary product equivalent	na	na	18 crop products, 5 livestock products, 1st generation biofuels, 2nd generation biofuels, a few aggregated forest products	Indicator for biomass supply chains	GLOBIOM
Socio-economic	Price index	ratio, from 0 to very large number, with 1	na	na	Crop and livestock sectors, some intermediate level between	Indicator for food access and producer revenue	GLOBIOM

		when price = reference price			individual commodities and sector aggregate		
Socio-economic	Value Added	USD2000	na	na	Crop and livestock sectors	Indicator for biomass supply chains	GLOBIOM
Socio-economic	Number of people at risk of hunger	number of people	na	na	Agriculture	Indicator for food security	GLOBIOM
Socio-economic	Nitrogen balance (inputs, outputs, surplus) for agricultural sector (cropland soils, pasture soils and livestock)	tons of nitrogen	na	na	Crop and livestock sectors	Indicator for nutrient cycle	GLOBIOM

4.2 EXIOBASE

4.2.1 Native EXIOBASE indicators

EXIOBASE includes environmental extensions such as GHG emissions and land use. By linking these to impact assessment models, such as LC-IMPACT, these environmental extensions can be aggregated into environmental impacts, such as global warming potential and biodiversity loss. In addition, EXIOBASE includes several (country- and sector-level) socioeconomic indicators (from which other macroeconomic indicators such as GDP can be calculated):

- Final consumption (per household, non-profit organizations serving households, government and capital formation)
- Imports/Exports
- Operational surplus
- Taxes/subsidies of production
- Value added

In addition, EXIOBASE includes the following labour indicators per sector:

- Compensation of employees in Million Euro per skill level (low-, medium- and high-skilled)
- Employment in both, number of persons and working hours, per skill level and gender (male/female)

- Total vulnerable employment (in hours worked)

4.2.2 Linking EXIOBASE to LC-IMPACT

LC-IMPACT can be applied to either life cycle inventories for a bottom-up LCA or it can be coupled to an EEMRIO like EXIOBASE for more large-scale assessments. This has been done previously for land and water impacts (Verones et al. 2017). Linking EXIOBASE and LC-IMPACT enables the quantification of national production and consumption biodiversity footprints.

The linking of EXIOBASE and the combined FABIO/EXIOBASE database to LC-IMPACT follows a soft linking approach. The soft linking allows the models to stay separated, while we provide software modules for the linking. The linking is implemented in Pymrio as a new characterization method, based on a bridging table that links the elementary flow names in the LC-IMPACT to the stressor names in EXIOBASE (Stadler 2021). To increase reusability and follow the latest developments in the field, we decided to implement the linking through the elementary flow names proposed by the GLAM (Global Guidance on Environmental Life Cycle Impact Assessment Indicators) initiative of the life cycle initiative hosted by UN Environment. The new version of LC-IMPACT will use the same elementary flow names as the default naming convention. EXIOBASE stressor names will be translated to the GLAM elementary flow names, which will then facilitate the linking to LC-IMPACT (Figure 1).

The current status of the Pymrio code development can be followed under the “char_update” branch of the pymrio github online repository (https://github.com/IndEcol/pymrio/tree/char_update), which will be merged into the main code upon finalization.

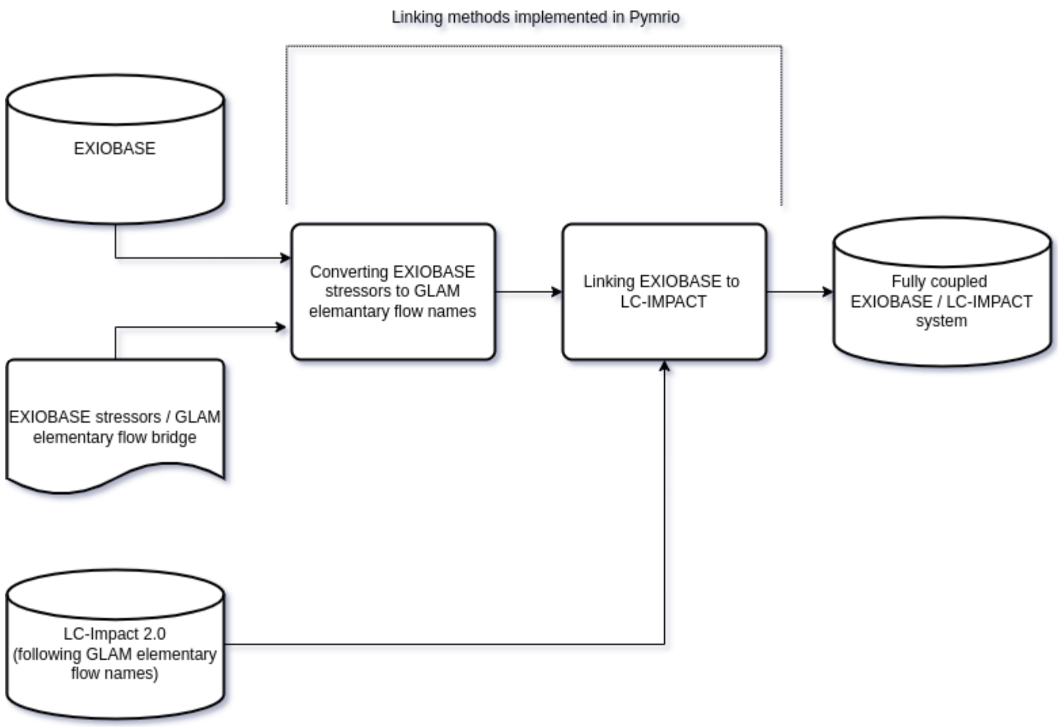

Figure 2. Linking approach for EXIOBASE and LC-IMPACT via GLAM elementary flow names.

4.2.3 EXIOBASE and ReCiPe

Because EXIOBASE contains built-in environmental extensions for climate impacts (Table 3), no link with ReCiPe will be established.

4.2.4 EXIOBASE and GLOBIO

EXIOBASE provides detailed data on the global economy and its interactions with the environment, while GLOBIO provides information on the impacts of human activities on biodiversity and ecosystems. The sources of these models are publicly available and can be accessed through their repositories: https://doi.org/10.5281/zenodo.3583070 and https://globio.info.

Similar to the EXIOBASE and LC-IMPACT linking, we have opted for a soft/dynamic linking approach that keep the model pipelines independent as well as their file formats. The linking is done through the MRIO python module Pymrio, and other additional modules as needed.

The first linking step involves GLOBIO providing characterisation factors in the

EXIOBASE regional classification. Then, the GLOBIO and EXIOBASE team will establish a correspondence table for stressor matching. Pymrio/EXIOBASE will establish a data pipeline to obtain these factors and use them to characterize EXIOBASE stressors (Figure 3).

For the code development we follow an open source approach. The current status of the code development can be followed under the "char_update" branch of the pymrio github repository (https://github.com/IndEcol/pymrio/tree/char_update), which will be merged into the main code upon finalization), which will be merged into the main code upon finalization.

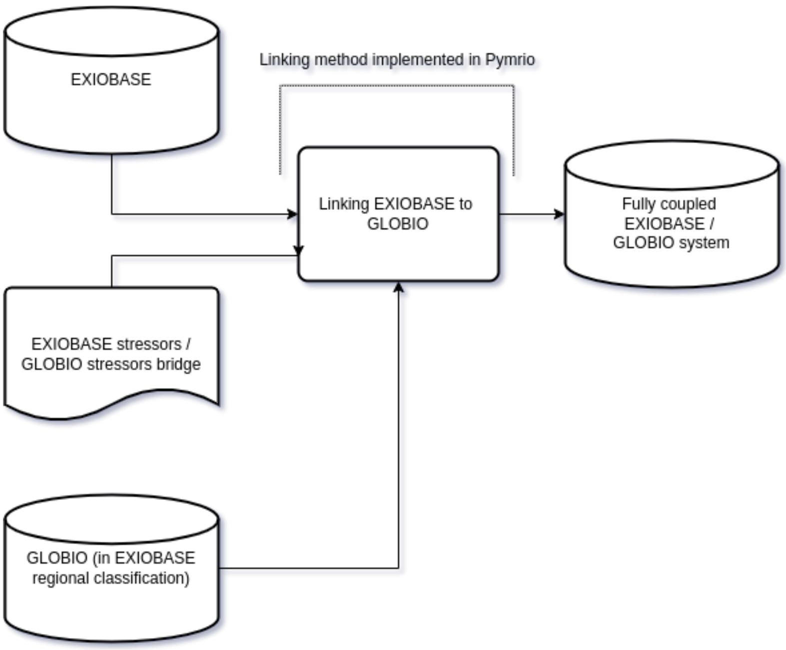

Figure 3: Simplified EXIOBASE / GLOBIO linking flow chart.

4.2.5 Impact indicators related to EXIOBASE

Table 5. Current impact indicators native to EXIOBASE and quantifiable via model links. All indicators native to EXIOBASE cover 200 products/ 163 industries, have a global coverage, a spatial resolution of 44 countries and RoW regions and a temporal coverage from 1995 – 2022 (Stadler et al. 2018).

Aspect	Indicator	Unit	Model the indicator links to
Climate	GHG emissions (GWP100) | Problem oriented approach: baseline (CML, 2001) | GWP100 (IPCC, 2007)	kg CO2 eq.	EXIOBASE

Climate	Carbon dioxide (CO2) IPCC categories 1 to 4 and 6 to 7 (excl land use, land use change and forestry)	Gg	EXIOBASE
Climate	Methane (CH4) IPCC categories 1 to 4 and 6 to 7 (excl land use, land use change and forestry)	Gg	EXIOBASE
Climate	Nitrous Oxide (N2O) IPCC categories 1 to 4 and 6 to 7 (excl land use, land use change and forestry)	Gg	EXIOBASE
Climate	Carbon dioxide (CO2) CO2EQ IPCC categories 1 to 4 and 6 to 7 (excl land use, land use change and forestry)	Gg CO2-eq	EXIOBASE
Climate	Methane (CH4) CO2EQ IPCC categories 1 to 4 and 6 to 7 (excl land use, land use change and forestry)	Gg CO2-eq	EXIOBASE
Climate	Nitrous Oxide (N2O) CO2EQ IPCC categories 1 to 4 and 6 to 7 (excl land use, land use change and forestry)	Gg CO2-eq	EXIOBASE
Climate	Carbon dioxide (CO2) Fuel combustion and cement	Gg	EXIOBASE
Climate	Carbon dioxide (CO2) Fuel combustion	Gg	EXIOBASE
Climate	GHG emissions (GWP100) | Problem oriented approach: baseline (CML, 1999) | GWP100 (IPCC, 2007)	kg CO2 eq.	EXIOBASE
Climate	GHG emissions (GWP100min) | Problem oriented approach: non baseline (CML, 1999) | net GWP100 min(Houghton et al., 2001)	kg CO2 eq.	EXIOBASE
Climate	GHG emissions (GWP100max) | Problem oriented approach: non baseline (CML, 1999) | net GWP100 max(Houghton et al., 2001)	kg CO2 eq.	EXIOBASE
Climate	GHG emissions (GWP20) | Problem oriented approach: non baseline (CML, 1999) | GWP20 (IPCC, 2007)	kg CO2 eq.	EXIOBASE
Climate	GHG emissions (GWP500) | Problem oriented approach: non baseline (CML, 1999) | GWP500 (IPCC, 2007)	kg CO2 eq.	EXIOBASE
Climate	GHG emissions AR5 (GWP100) | GWP100 (IPCC, 2010)	kg CO2 eq.	EXIOBASE
Environ-mental state	EPS | Damage Approach | EPS (Steen, 1999)	elu	EXIOBASE
Environ-mental state	Damage to Ecosystem Quality caused by ecotoxic emissions (H.A) | ECOINDICATOR 99 (H.A) | Damage to Ecosystem Quality caused by ecotoxic emissions (H.A)	PDF*m2*yr	EXIOBASE
Environ-mental state	Damage to Ecosystem Quality caused by the combined effect of acidification and eutrophication (H.A) | ECOINDICATOR 99 (H.A) | Damage to Ecosystem Quality caused by the combined effect of acidification and eutrophication (H.A)	PDF*m2*yr	EXIOBASE
Environ-mental state	Damage to Ecosystem Quality caused by ecotoxic emissions (E.E)) | ECOINDICATOR 99 (E.E) | Damage to Ecosystem Quality caused by ecotoxic emissions (E.E)	PDF*m2*yr	EXIOBASE
Environ-mental state	Damage to Ecosystem Quality caused by the combined effect of acidification and eutrophication (E.E) | ECOINDICATOR 99 (E.E) | Damage to Ecosystem Quality caused by the combined effect of acidification and eutrophication (E.E)	PDF*m2*yr	EXIOBASE
Environ-mental state	Damage to Ecosystem Quality caused by ecotoxic emissions (I.I) | ECOINDICATOR 99 (I.I) | Damage to Ecosystem Quality caused by ecotoxic emissions (I.I)	PDF*m2*yr	EXIOBASE
Environ-mental state	Damage to Ecosystem Quality caused by the combined effect of acidification and eutrophication (I.I) | ECOINDICATOR 99 (I.I) | Damage to Ecosystem Quality caused by the combined effect of acidification and eutrophication (I.I)	PDF*m2*yr	EXIOBASE
Environ-mental state	Unused Domestic Extraction	kt	EXIOBASE

Environ-mental state	Water Consumption Green - Agriculture	Mm3	EXIOBASE
Environ-mental state	Water Consumption Blue - Agriculture	Mm3	EXIOBASE
Environ-mental state	Water Consumption Blue - Livestock	Mm3	EXIOBASE
Environ-mental state	Water Consumption Blue - Manufacturing	Mm3	EXIOBASE
Environ-mental state	Water Consumption Blue - Electricity	Mm3	EXIOBASE
Environ-mental state	Water Consumption Blue - Domestic	Mm3	EXIOBASE
Environ-mental state	Water Consumption Blue - Total	Mm3	EXIOBASE
Environ-mental state	Water Withdrawal Blue - Manufacturing	Mm3	EXIOBASE
Environ-mental state	Water Withdrawal Blue - Electricity	Mm3	EXIOBASE
Environ-mental state	Water Withdrawal Blue - Domestic	Mm3	EXIOBASE
Environ-mental state	Water Withdrawal Blue - Total	Mm3	EXIOBASE
Environ-mental state	ozone layer depletion (ODP steady state) | Problem oriented approach: baseline (CML, 1999) | ODP steady state (WMO, 2003)	kg CFC-11 eq.	EXIOBASE
Environ-mental state	Freshwater aquatic ecotoxicity (FAETP inf) | Problem oriented approach: baseline (CML, 1999) | FAETP inf. (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Marine aquatic ecotoxicity (MAETP inf) | Problem oriented approach: baseline (CML, 1999) | MAETP inf. (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Freshwater sedimental ecotoxicity (FSETP inf) | Problem oriented approach: non baseline (CML, 1999) | FSETP inf. (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Marine sedimental ecotoxicity (MSETP inf) | Problem oriented approach: non baseline (CML, 1999) | MSETP inf. (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Terrestrial ecotoxicity (TETP inf) | Problem oriented approach: baseline (CML, 1999) | TETP inf.(Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Freshwater aquatic ecotoxicity (FAETP20) | Problem oriented approach: non baseline (CML, 1999) | FAETP 20 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Marine aquatic ecotoxicity (MAETP20) | Problem oriented approach: non baseline (CML, 1999) | MAETP 20 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Freshwater sedimental ecotoxicity (FSETP20) | Problem oriented approach: non baseline (CML, 1999) | FSETP 20 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Marine sedimental ecotoxicity (MSETP20) | Problem oriented approach: non baseline (CML, 1999) | MSETP 20 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Freshwater aquatic ecotoxicity (FAETP100) | Problem oriented approach: non baseline (CML, 1999) | FAETP 100 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Marine aquatic ecotoxicity (MAETP100) | Problem oriented approach: non baseline (CML, 1999) | MAETP 100 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Freshwater sedimental ecotoxicity (FSETP100) | Problem oriented approach: non baseline (CML, 1999) | FSETP 100 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE

Environ-mental state	Marine sedimental ecotoxicity (MSETP100) | Problem oriented approach: non baseline (CML, 1999) | MSETP 100 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Terrestrial ecotoxicity (TETP100) | Problem oriented approach: non baseline (CML, 1999) | TETP 100 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	human toxicity (HTP500) | Problem oriented approach: non baseline (CML, 1999) | HTP 500 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Freshwater aquatic ecotoxicity (FAETP500) | Problem oriented approach: non baseline (CML, 1999) | FAETP 500 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Marine aquatic ecotoxicity (MAETP500) | Problem oriented approach: non baseline (CML, 1999) | MAETP 500 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Freshwater sedimental ecotoxicity (FSETP500) | Problem oriented approach: non baseline (CML, 1999) | FSETP 500 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Marine sedimental ecotoxicity (MSETP500) | Problem oriented approach: non baseline (CML, 1999) | MSETP 500 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	Terrestrial ecotoxicity (TETP500) | Problem oriented approach: non baseline (CML, 1999) | TETP 500 (Huijbregts, 1999 & 2000) TETP 500	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environ-mental state	photochemical oxidation (high NOx) | Problem oriented approach: baseline (CML, 1999) | POCP (Jenkin & Hayman, 1999; Derwent et al. 1998; high NOx)	kg ethylene eq.	EXIOBASE
Environ-mental state	photochemical oxidation (low NOx) | Problem oriented approach: non baseline (CML, 1999) | POCP (Andersson-Skï¿½ld et al. 1992; low NOx)	kg ethylene eq.	EXIOBASE
Environ-mental state	photochemical oxidation (MIR; very high NOx) | Problem oriented approach: non baseline (CML, 1999) | MIR 1997; very high NOx (Carter, 1994, 1997, 1998;Carter, Pierce, Luo & Malkina, 1995	kg formed ozone	EXIOBASE
Environ-mental state	photochemical oxidation (MOIR; high NOx) | Problem oriented approach: non baseline (CML, 1999) | MOIR; high NOx (Carter, 1994, 1997, 1998;Carter, Pierce, Luo & Malkina, 1995)	kg formed ozone	EXIOBASE
Environ-mental state	photochemical oxidation (EBIR; low NOx) | Problem oriented approach: non baseline (CML, 1999) | EBIR; low NOx (Carter, 1994, 1997, 1998;Carter, Pierce, Luo & Malkina, 1995)	kg formed ozone	EXIOBASE
Environ-mental state	acidification (incl. fate, average Europe total, A&B) | Problem oriented approach: baseline (CML, 1999) | AP (Huijbregts, 1999; average Europe total, A&B)	kg SO2 eq.	EXIOBASE
Environ-mental state	acidification (fate not incl.) | Problem oriented approach: non baseline (CML, 1999) | AP (Hauschild & Wenzel (1998)	kg SO2 eq.	EXIOBASE
Environ-mental state	eutrophication (fate not incl.) | Problem oriented approach: baseline (CML, 1999) | EP (Heijungs et al. 1992)	kg PO4--- eq.	EXIOBASE
Environ-mental state	eutrophication (incl. fate, average Europe total, A&B) | Problem oriented approach: non baseline (CML, 1999) | EP (Huijbregts, 1999; average Europe total, A&B)	kg NOx eq.	EXIOBASE
Environ-mental state	odour | Problem oriented approach: non baseline (CML, 1999) | 1/OTV	m3	EXIOBASE
Environ-mental state	Climate change midpoint | ILCD recommended CF | Global warming potential 100 years	kg CO2-Equivalents	EXIOBASE
Environ-mental state	Climate change endpoint, human health | ILCD recommended CF | Disability Adjusted Life Years (DALY)	DALY	EXIOBASE
Environ-mental state	Climate change endpoint, ecosystems | ILCD recommended CF | Potentially Disappeared Fraction of species (PDF)	PDF	EXIOBASE
Environ-mental state	Particulate matter/Respiratory inorganics midpoint | ILCD recommended CF | emission-weighed average PM2.5 equivalent	kg PM2.5-eq	EXIOBASE
Environ-mental state	Particulate matter/Respiratory inorganics endpoint | ILCD recommended CF | Disability Adjusted Life Years (DALY)	DALY	EXIOBASE

Environ-mental state	Photochemical ozone formation midpoint, human health | ILCD recommended CF | Photochemical ozone creation potential (POCP)	kg-C2H4 equivalents	EXIOBASE
Environ-mental state	Photochemical ozone formation endpoint, human health | ILCD recommended CF | Disability Adjusted Life Years (DALY)	DALY	EXIOBASE
Environ-mental state	Acidification midpoint | ILCD recommended CF | Accumulated Exceedance (AE)	Accumulated Exceedance (AE)	EXIOBASE
Environ-mental state	Acidification endpoint | ILCD recommended CF | Change in potentially not occuring fraction of plant species per change in base saturation	PDF	EXIOBASE
Environ-mental state	Eutrophication terrestrial midpoint | ILCD recommended CF | Accumulated Exceedance (AE)	Accumulated Exceedance (AE)	EXIOBASE
Environ-mental state	Eutrophication marine midpoint | ILCD recommended CF | Potentially Disappeared Fraction of species (PDF)	kg-N equivalent	EXIOBASE
Environ-mental state	Ecotoxicity freshwater midpoint | ILCD recommended CF | Comparative Toxic Unit for ecosystems (CTUe)	CTUe = PAF.m3.year	EXIOBASE
Environ-mental state	Ecotoxicity freshwater endpoint | ILCD recommended CF | Potentially Disappeared Fraction of species (PDF)	PDF.m3.year	EXIOBASE
Environ-mental state	Nitrogen	kg	EXIOBASE
Environ-mental state	Phosphorous	kg	EXIOBASE
Environ-mental state	PM10[1]	kg	EXIOBASE
Environ-mental state	PM25[1]	kg	EXIOBASE
Environ-mental state	SOx[1]	kg	EXIOBASE
Environ-mental state	NOx[1]	kg	EXIOBASE
Environ-mental state	Domestic Extraction Used - Crop and Crop Residue	kt	EXIOBASE
Environ-mental state	Domestic Extraction Used - Grazing and Fodder	kt	EXIOBASE
Environ-mental state	Domestic Extraction Used - Forestry and Timber	kt	EXIOBASE
Environ-mental state	Domestic Extraction Used â“ Fisheries	kt	EXIOBASE
Environ-mental state	Domestic Extraction Used - Non-metalic Minerals	kt	EXIOBASE
Environ-mental state	Domestic Extraction Used - Iron Ore	kt	EXIOBASE
Environ-mental state	Domestic Extraction Used - Non-ferous metal ores	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Crop and Crop Residue	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Grazing and Fodder	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Forestry and Timber	kt	EXIOBASE

Environ-mental state	Unused Domestic Extraction â“ Fisheries	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Coal and Peat	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Oil and Gas	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Non-metalic Minerals	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Iron Ore	kt	EXIOBASE
Environ-mental state	Unused Domestic Extraction - Non-ferous metal ores	kt	EXIOBASE
Environ-mental state	Land use Crop, Forest, Pasture	km2	EXIOBASE
Environ-mental state	Fresh water Ecotoxicity (USEtox) | USEtox2008 | CTUe (Rosenbaum et al., 2008)	PAF m3.day	EXIOBASE
Environ-mental state	Terrestrial ecotoxicity (TETP20) | Problem oriented approach: non baseline (CML, 1999) | TETP 20 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Environmental state	Potentially disappeared fraction of species (PDF)	PDF.yr	LC-IMPACT
Environmental state	Mean species abundance (MSA)	MSA.ha	GLOBIO
Human health	Human toxicity (USEtox) | USEtox2008 | CTUh (Rosenbaum et al., 2008)	cases	EXIOBASE
Human health	Carcinogenic effects on humans (H.A) | ECOINDICATOR 99 (H.A) | Carcinogenic effects on humans (H.A)	DALY	EXIOBASE
Human health	Respiratory effects on humans caused by organic substances (H.A) | ECOINDICATOR 99 (H.A) | Respiratory effects on humans caused by organic substances (H.A)	DALY	EXIOBASE
Human health	Respiratory effects on humans caused by inorganic substances (H.A) | ECOINDICATOR 99 (H.A) | Respiratory effects on humans caused by inorganic substances (H.A)	DALY	EXIOBASE
Human health	Damages to human health caused by climate change (H.A) | ECOINDICATOR 99 (H.A) | Damages to human health caused by climate change (H.A)	DALY	EXIOBASE
Human health	Carcinogenic effects on humans (E.E) | ECOINDICATOR 99 (E.E) | Carcinogenic effects on humans (E.E)	DALY	EXIOBASE
Human health	Respiratory effects on humans caused by organic substances (E.E) | ECOINDICATOR 99 (E.E) | Respiratory effects on humans caused by organic substances (E.E)	DALY	EXIOBASE
Human health	Respiratory effects on humans caused by inorganic substances (E.E) | ECOINDICATOR 99 (E.E) | Respiratory effects on humans caused by inorganic substances (E.E)	DALY	EXIOBASE
Human health	Damages to human health caused by climate change (E.E) | ECOINDICATOR 99 (E.E) | Damages to human health caused by climate change (E.E)	DALY	EXIOBASE
Human health	Carcinogenic effects on humans (I.I) | ECOINDICATOR 99 (I.I) | Carcinogenic effects on humans (I.I)	DALY	EXIOBASE
Human health	Respiratory effects on humans caused by organic substances (I.I) | ECOINDICATOR 99 (I.I) | Respiratory effects on humans caused by organic substances (I.I)	DALY	EXIOBASE
Human health	Respiratory effects on humans caused by inorganic substances (I.I) | ECOINDICATOR 99 (I.I) | Respiratory effects on humans caused by inorganic substances (I.I)	DALY	EXIOBASE
Human health	Damages to human health caused by climate change (I.I) | ECOINDICATOR 99 (I.I) | Damages to human health caused by climate change (I.I)	DALY	EXIOBASE

Human health	human toxicity (HTP inf) | Problem oriented approach: baseline (CML, 1999) | HTP inf. (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Human health	human toxicity (HTP20) | Problem oriented approach: non baseline (CML, 1999) | HTP 20 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Human health	human toxicity (HTP100) | Problem oriented approach: non baseline (CML, 1999) | HTP 100 (Huijbregts, 1999 & 2000)	kg 1,4-dichlorobenzene eq.	EXIOBASE
Human health	Human toxicity midpoint, cancer effects | ILCD recommended CF | Comparative Toxic Unit for human (CTUh)	CTUh/kg = cases	EXIOBASE
Human health	Human toxicity midpoint, non-cancer effects | ILCD recommended CF | Comparative Toxic Unit for human (CTUh)	CTUh = cases	EXIOBASE
Human health	Human toxicity endpoint, cancer effects | ILCD recommended CF | Disability Adjusted Life Years (DALY)	DALY	EXIOBASE
Human health	Human toxicity endpoint, non-cancer effects | ILCD recommended CF | Disability Adjusted Life Years (DALY)	DALY	EXIOBASE
Socio-economic	Value Added	M.EUR	EXIOBASE
Socio-economic	Employment	1000 p.	EXIOBASE
Socio-economic	Employment hour	hr	EXIOBASE

4.3 FABIO

4.3.1 Native FABIO indicators

Focusing on the agricultural sector and using FAO data, FABIO includes the harvested crop area and area covered by pastureland as key environmental extinctions. In addition, FABIO includes primary biomass extraction as well as blue and green water use (Bruckner et al. 2019). Linking crop and pasture area environmental extensions to LC-IMPACT and GLOBIO impact assessment models enables the quantification of land-based species extinctions (LC-IMPACT), and ecosystem intactness (GLOBIO).

4.3.2 FABIO and LC-IMPACT

In the RAINFOREST project, FABIO is linked to LC-IMPACT to quantify land use impacts on global species extinctions, quantified by the potentially disappeared fraction of species (PDF) (Verones et al. 2020). To link FABIO land use footprints to LC-IMPACT land use impact factors PDF, the FABIO land use extension needs to be converted from harvested to physical area. We converted the FABIO land use extension from harvested area to physical area, considering that crops can be harvested more than once a year using the same area (Marquardt et al. 2019). Although most crops are harvested once a year (in 88% of the global cropland area), some are harvested more than once in specific regions (in 12% of the global cropland area (Waha et al. 2020; Liu et al. 2021). Converting harvested area to physical area ensures a more accurate assessment of biodiversity footprint by avoiding double counting of land use impacts.

We use Spatial Production Allocation Model (SPAM) data to derive country-average conversion ratios from harvested to physical area, matching the 42 crops in SPAM to the 60 primary crop commodities in FABIO (Table S3) (Yu et al. 2020). Finally, to maintain consistency with FAOSTAT we corrected the resulting crop- and country-specific physical areas so that the sum of the crop physical area matches the country-total physical cropland area according to FAOSTAT.

Impact factors for global species extinctions per unit of land use area are derived from LC-IMPACT (Verones et al. 2020). Because MRIO data corresponds to the land use of a single year, we consider land occupation impacts only. We use impact factors for temporary crops, permanent crops, and pastures and link temporary and permanent crop impact factors to FABIO agricultural products based on the Indicative Crop Classification data compiled for FAOSTAT (https://www.fao.org/statistics/caliper/tools/download/en) (Table S4). Multiplying corresponding LC-IMPACT factors with physical area land use footprints results in the global species extinction footprint (in PDF).

4.3.3 FABIO and ReCiPe

Because FABIO focuses on the agricultural sector and not other economic sectors such as the energy sector and because FABIO does not include GHG environmental extensions, FABIO will not be linked to ReCiPe to quantify climate impacts.

4.3.3 FABIO and GLOBIO

In the RAINFOREST project, FABIO is linked to GLOBIO to quantify land use impacts of local ecosystem intactness, quantified by the mean species abundance (MSA)

(Schipper et al. 2020). To link FABIO land use footprints to GLOBIO land use impact factors for MSA, the FABIO land use extension needs to be converted from harvested to physical area (see section 3.3.2). GLOBIO captures local ecosystem intactness by pressure-response relationships of human pressures and mean species abundance (MSA) (Schipper et al. 2020). The GLOBIO land use pressure-response relationships distinguish impacts of specific land use classes on plants and warm-blooded vertebrates. Multiplying the corresponding GLOBIO impact factors with physical area land use footprints results in the local ecosystem intactness footprint (in MSA·ha).

4.3.4 Impact indicators related to FABIO

Table 6. Current impact indicators native to FABIO and quantifiable via model links (Bruckner et al. 2019).

Aspect	Indicator	Unit	Sectoral/ product coverage	Spatial coverage	Spatial resolution	Temporal coverage	Model the indicator links to
Resource	Primary biomass extraction	tons	123 commodities	global	191 countries/1 ROW region	1986-2020	FABIO
Resource	Land use	ha	123 commodities	global	191 countries/1 ROW region	1986-2020	FABIO
Resource	Blue water use	m^3	123 commodities	global	191 countries/1 ROW region	1986-2020	FABIO
Resource	Green water use	m^3	123 commodities	global	191 countries/1 ROW region	1986-2020	FABIO
Resource	Biodiversity	PDF	123 commodities	global	191 countries/1 ROW region	1986-2020	LCIMPACT
Resource	Biodiversity	MSA	123 commodities	global	191 countries/1 ROW region	1986-2020	GLOBIO

4.4 FABIO-EXIOBASE hybrid model

The FABIO-EXIOBASE hybrid model of FABIO and EXIOBASE includes the same impact indicators as those defined in EXIOBASE (Section 4.2) and FABIO (Section 4.3), including the indicators quantifiable via model links with LC-IMPACT and GLOBIO.

4.5 Indicators and international goals and targets

The impact indicators native to the models or quantifiable via model links might be relevant to estimate progress towards international goals and targets for biodiversity, climate, and people. Biodiversity is a multifaceted concept, studied through a variety of indicators that each capture an aspect of biodiversity. The biodiversity intactness index (BII), a measure of the intactness of the local species composition and the fraction of globally remaining species (FGRS), an estimate of global species extinctions, both quantifiable with GLOBIOM, as well as the mean species abundance (MSA), quantifiable with GLOBIO, and the potential disappeared fraction of species (PDF), native to LC-IMPACT, measure aspects of the state of biodiversity under different environmental pressures such as land use, climate change or eutrophication and relate to goal A (protect and restore nature) of the Kunming-Montreal Global Biodiversity Framework (GBF) and the Sustainable Development Goals (SDG) 14 and 15 on protecting life below water and on land. These indicators also allow assessing the biodiversity effects of progress towards targets addressing drivers of biodiversity change, for example, GBF targets 1, 2, 3 and 10, all related to different aspects of land use, target 7 related to pollution including from nutrients, and target 8, related to climate change (Table S2). Some impact indicators directly measure environmental pressures and direct drivers of biodiversity change, for instance, GLOBIOM can quantify different types of land use (GBF targets 1,2 & 3) and nitrogen balances for the agricultural sector (GBF target 7). EXIOBASE can quantify a long list of indicators describing environmental states including land use for cropland, pasture and forests (GBF target 1). GLOBIOM and EXIOBASE quantify GHG emissions, which relate to the ambitions of the Paris Agreement to limit global warming to well below 2°C and to pressures of climate change on biodiversity (e.g., GBF target 8; Table S1). Moreover, LC-IMPACT and EXIOBASE can quantify various aspects of human health, which link to SDG 3 on good health and well-being. The number of people at risk of hunger, native to GLOBIOM, is an indicator related to food security (SDG 2) and indicators such as value added or employment (both for different sectors/products/industries), quantifiable via GLOBIOM and EXIOBASE, relate to SDG 8 on decent work and economic growth.

5. TOOLBOX APPLICATION

5.1 Fishmeal production case study

The case study in Peru is centred on understanding the environmental impacts of the production of fishmeal and fish oil (FMFO) from Peruvian anchoveta (*Engraulis ringens*) in the city of Chimbote. Chimbote harbours the main fishing port and FMFO production hub of Peru. For this, an LCA perspective is followed in which "conventional" and "emerging" environmental impact categories are applied to extend the spectrum of environmental indicators that are used to measure the environmental sustainability of this type of production system. In fact, it should be noted that there is an important lack of datapoints in the scientific literature linked to the production of FMFO, and only the studies by Avadí et al. (2014) and Fréon et al. (2017) have delved into the life cycle impacts of FMFO production in Peru, the world leader for these two commodities.

The results of this study, which are currently underway, aim to update FMFO production environmental impacts in Peru, which are yet to be brought up to date as compared to the abovementioned studies. The update is considered important as technological improvements have been introduced in FMFO production, especially in terms of using cleaner fossil fuels in the heating and drying processes, and it is also important to consider the changes in the health of the anchoveta fishing stock, one of the most abundant worldwide, but also widely fished, and subject to illegal, unregulated and unreported (IUU) landings. In this sense, we aim to provide a full quantification of environmental impacts using one of the most recent and up to date assessment methods available in the LCA literature, LC-IMPACT, for the "conventional" environmental impacts. Moreover, additional indicators linked to marine resources and ocean conservation, named earlier "emerging" impact categories, will be included in the computation. For the latter, a full review has been elaborated identifying all the methodological proposals that have been published in the literature linked to seabed impact, depletion of targeted biotic resource, marine plastics, following some of the most recent publications related to the Marilca and ATLANTIS projects, among others.

Data has been collected for purse seining fishing fleets targeting the anchoveta fishery within the Peruvian EEZ for years 2019 and 2021. Similarly, data on FMFO production is available for 5 FMFO reduction plants across the Peruvian coast, most of them operating in or in the vicinity of the city of Chimote. Life cycle modelling is currently on the way, for which methodological assumptions on allocation (considering the multifunctional nature of the production system) have been considered. In this sense, we are currently finalizing the life cycle inventory for FMFO production in terms of "conventional" impact categories. For the remaining impact categories, it was decided that the biotic resources characterization factors developed by Hélias et al. (2023) were the most appropriate methodological basis, but they are being modified to account for the semi-cyclical behaviour of El Niño-Southern Oscillation (ENSO), which highly affects the catchability of anchoveta stocks in the Peruvian EEZ. These computations are still underway and are expected to provide site-specific data related to the assessment of this stock from an LCA perspective. The remaining "emerging" impact categories are still under analysis to understand their applicability with the data quality available for the system under analysis. Another action which is under development at the time of this report is linking the wide spectrum of categories considered in the modelling with the transformative pathways recommended in D1.1, with the aim of identifying how the upcoming results can help in policymaking within the Peruvian FMFO sector, and the worldwide aquaculture sector that obtains an important portion of its feed from Peruvian reduction plants.

5.2 Food consumption case study

The food consumption scenarios case-study aims to quantify the implications of alternative national food consumption scenarios in the Netherlands, the United Kingdom, and the United States of America on climate and biodiversity. Consumer surveys will inform the development of national food consumption scenarios and the model toolbox will be applied to quantify climate and biodiversity footprints of the corresponding national food consumption scenarios. The Food and Agriculture Biomass Input-Output model (FABIO) will be combined with LC-IMPACT and GLOBIO to quantify national consumption climate and biodiversity footprints (i.e., national consumption scenarios will tweak the FABIO data in 'what-if' scenarios).

5.3 Investment portfolio case study

The investment portfolio case-study aims to quantify climate and biodiversity footprints of investment portfolios (typically consisting of ~100 company investments spread over several economic sectors). Quantifying climate and biodiversity footprints of portfolios requires a hybrid approach between company-specific foreground life cycle inventory (scope 1 and possibly scope 2) data and sector average data to quantify upstream impacts along company value chains (scope 3 data). Scope 1 impacts refer to the direct impacts caused by company activities. Scop2 2 impacts refer to the indirect impacts caused by the energy production that is directly consumed by the company. Scope 3 impacts refer to the indirect impacts caused upstream by the production of resources and intermediate products that the company uses. Hence, the investment portfolio case-study will build upon an integration of company-specific data (to quantify direct company-level impacts) and input-output data (e.g., EXIOBASE, to quantify indirect average upstream environmental impacts of company value chains). Subsequently LC-IMPACT and GLOBIO will be used to quantify the climate and biodiversity footprints corresponding to the investment portfolios. The application of EXIOBASE also allows for the quantification of socio-economic impacts.

5.4 Novel food case study

This case study focuses on assessing the biodiversity footprint associated with novel foods, which utilize new production technologies and are primarily derived from agricultural products and waste biomass already existing within the FABIO database. The development of novel alternatives for meat and milk (hereafter referred to as novel food) these years has been identified as a viable alternative for reducing animal-source food consumption. These novel foods are normally made from non-animal-based ingredients (e.g. plants, mycelium), with the taste mimicking animal products. These years, novel foods have already gained popularity in food market, especially plant-based novel food alternatives, which accounted for 15% of the milk market in the USA and 1.4% and 1.3% of the meat markets in the USA and Germany in 2020, respectively.

Diverse plant-based meat alternatives have been developed and evaluated these years. For example, Saget et al. (2021) compared plant-based (Legume-derived) burger patties and beef burger patties and found that plant-based patties have a smaller environmental impact across most categories, especially a 77% smaller climate change burden. Kozicka et al. (2023) found that replacing 50% of key animal products with plant-based alternatives by 2050 can nearly halt deforestation and cut agriculture and land use GHG emissions by 31% from 2020 levels.

Although innovative alternatives offer advantages to local environments, their broader biodiversity implications within the intricate global food system remain inadequately comprehended. In this study, the evaluation of these novel food products' biodiversity footprints will employ the FABIO-EXIOBASE hybrid model, from an input-output-based life cycle assessment approach (IO-LCA) approach. The FABIO-EXIOBASE hybrid model allows for a comprehensive analysis by leveraging the input-output framework of FABIO and the environmental impact upstream data from EXIOBASE. The IO-LCA approach integrates IO analysis into conventional process-based LCA, leveraging macroeconomic data from background systems to enhance efficiency and accuracy. This method accelerates the LCA process, streamlines inventory collection, and optimizes resource allocation (Mattila 2018).

The purpose of the study is to evaluate the broader biodiversity implications of novel food within the intricate global food system and to determine to what level the consumption of the designated planted-based novel food is associated with a lower biodiversity impact than that of corresponding animal-based products. Through this approach, we aim to provide valuable insights into the biodiversity impacts of emerging food technologies and their implications for food production system's sustainability.

5.5 Food case study for the touristic value chain

This case study focuses on assessing the environmental and socio-economic impacts of the food chain in the tourism industry in Cyprus and developing alternative pathways for transformative change that benefit biodiversity. The development of a sustainable food chain is underway with system mapping of the current situation in the Cyprus tourism sector. For this purpose, secondary data covering a range of tourist statistics (demographics, arrivals, accommodation, length of stay, expenditure, and revenue) from the Cyprus Statistical Service (CYSTAT) has been collected. Additionally, secondary datasets on tourists' food consumption in Cyprus have been compiled to identify consumption patterns and changes in dietary preferences over the last decade (up to 2019), as well as the origins of food items consumed by tourists. To this end, Food Balance Sheets (FBS) and Supply Utilization Accounts (SUA) from FAOSTAT have been collected. Trade data of food commodities for Cyprus has also been gathered from the annual trade matrix available in FAOSTAT.

Regarding primary data, a survey of hotels will be conducted to investigate tourists' food consumption patterns and the perceptions of stakeholder groups within Cyprus's tourist food supply chain. Specifically, data will be collected using a comprehensive questionnaire and semi-structured interviews with hoteliers and food and beverage managers, aiming to enhance our understanding of the dynamics surrounding food supply, consumption patterns, and food loss management. This information will serve as the basis for refining the scenarios and pathways developed in RAINFOREST towards a more sustainable food supply in the tourism industry and will be enriched by utilizing relevant models and metrics from the RAINFOREST model toolbox.

Considering the objective of this case study, the FABIO model is the most appropriate tool that can be used, as it facilitates tracking the impact of dietary changes and food wastage. While changes within individual countries can be monitored, the data provided also allows for tracking the impact in countries from which goods are imported. This is very relevant for Cyprus, as a large share of food commodities are imported. By integrating the global physical flows of commodities and the embodied nutrients, land, water, and energy data provided by FABIO with the comprehensive EXIOBASE database, it becomes possible to translate environmental impacts into biodiversity loss assessments. This capability enables the evaluation of the impacts of each commodity used in the tourism hospitality industry, making it essential for understanding the broader context of food consumption and for making informed and targeted decisions.

Overall, the purpose of this study is to identify food consumption patterns within the tourism sector of Cyprus that could mitigate biodiversity loss and contribute to meeting the targets outlined in the EU Biodiversity Strategy 2030. Additionally, it aims to determine the effectiveness of mitigation measures targeting food waste reduction and actions to minimize the environmental footprint of food served, in comparison to a business-as-usual scenario. Through this analysis, valuable insights will be gained towards sustainable food consumption patterns in the tourism sector and the development of appropriate strategies.

6. SUMMARY AND OUTLOOK

RAINFOREST's model toolbox combines a set of environmental-economic and impact assessment models. The toolbox includes a set of impact indicators native to the individual models or quantifiable via tailored model linking. Specifically, the toolbox covers GLOBIOM, a bio-economic model to address various land use related topics, EXIOBASE, providing a time series of environmentally extended multi-regional input-output (EEMRIO) tables, FABIO, a physical EEMRIO focusing on the agricultural sector, Life Cycle Impact Assessment methods such as LC-IMPACT, and biodiversity models such as GLOBIO. The toolbox allows us to comprehensively assess socio-economic, climate, and biodiversity impacts related to transformative change within the EU's agri-food sector, establishing quantitative insights related to internationally agreed-upon goals and targets for biodiversity, climate, and people.

The next step in RAINFOREST is to establish the model links by linking environmental flows of the environmental-economic models to the pressure-response factors from the impact assessment models. These links, in terms of tables and/or code will be made available in a subsequent RAINFOREST deliverable.

We have highlighted how the toolbox will subsequently be applied to diverse case studies conducted in the course of RAINFOREST, such as case studies on fishmeal production, food consumption scenarios, investment portfolios, and biodiversity footprints of novel foods. In addition to these case studies, the model toolbox will also be utilized to quantify aspects of pathways of transformative change developed in WP1. Moreover, future developments of the toolbox include the integration of additional impact indicators related to socio-economic, climate and biodiversity aspects. Furthermore, in addition to establishing links between models, RAINFOREST aims to further develop the individual models in the model toolbox. For example, GLOBIOM can be expanded by adding a phosphorus balance; and the representation of land use and climate impacts on biodiversity can be improved in LC-IMPACT based on novel impact indicator developments.

REFERENCES

Avadí Á, Vázquez-Rowe I, Fréon P. 2014. Eco-efficiency assessment of the Peruvian anchoveta steel and wooden fleets using the LCA+DEA framework. Journal of Cleaner Production **70**:118–131. Available from https://linkinghub.elsevier.com/retrieve/pii/S0959652614000602.

Beylot A, Corrado S, Sala S. 2020. Environmental impacts of European trade: interpreting results of process-based LCA and environmentally extended input-output analysis towards hotspot identification. International Journal of Life Cycle Assessment **25**:2432–2450. The International Journal of Life Cycle Assessment.

Bodirsky B, Humpenöder F, Crawford M, Chen D, Springmann M, Nicholls Z, Lewis J. 2023. A food system transformation can enhance global health , environmental conditions and social inclusion. Research Square:1–32.

Bruckner M, Fischer G, Tramberend S, Giljum S. 2015. Measuring telecouplings in the global land system: A review and comparative evaluation of land footprint accounting methods. Ecological Economics **114**:11–21. Elsevier B.V. Available from http://dx.doi.org/10.1016/j.ecolecon.2015.03.008.

Bruckner M, Wood R, Moran D, Kuschnig N, Wieland H, Maus V, Börner J. 2019. FABIO—The Construction of the Food and Agriculture Biomass Input–Output Model. Environmental Science & Technology **53**:11302–11312. Available from https://pubs.acs.org/doi/10.1021/acs.est.9b03554.

CBD. 2022. Kunming-Montreal Global Biodiversity Framework. Montreal, Canada. Available from https://www.cbd.int/doc/c/e6d3/cd1d/daf663719a03902a9b116c34/cop-15-l-25-en.pdf.

Chang J, Havlík P, Leclère D, de Vries W, Valin H, Deppermann A, Hasegawa T, Obersteiner M. 2021. Reconciling regional nitrogen boundaries with global food security. Nature Food **2**:700–711. Available from https://www.nature.com/articles/s43016-021-00366-x.

Davis B et al. 2023. Estimating global and country-level employment in agrifood systems. 23–34, FAO Statistics Working Paper Series. Rome.

Di Fulvio F, Forsell N, Korosuo A, Obersteiner M, Hellweg S. 2019. Spatially explicit LCA analysis of biodiversity losses due to different bioenergy policies in the European Union. Science of The Total Environment **651**:1505–1516. Elsevier B.V. Available from https://doi.org/10.1016/j.scitotenv.2018.08.419.

EC. 2019. Communication from the commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions: the European Green Deal. European Commission **(Brussels)**. Brussels. Available from https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52019DC0640&from=EN.

EPA. 2019. Global Non-CO_2 Greenhouse Gas Emission Projections & Mitigation Potential: 2015-2050. U.S. Environmental Protection Agency (EPA):1–84. Available from https://www.epa.gov/global-mitigation-non-co2-greenhouse-gases/global-non-co2-greenhouse-gas-emission-projections.

FAO. 2015. Climate change and food systems: global assessments and implications for food security and trade. Food Agriculture Organization of the United Nations (FAO). Page Climate Change and Food Systems: Global Analysis and

Implications for Food Security and Trade. Available from https://www.cabdirect.org/cabdirect/abstract/20173038228.

FAO. 2023. Employment indicators 2000-2021. July 2023 update. No.67, FAOSTAT Analytical Briefs Series. Rome.

Fréon P, Durand H, Avadí A, Huaranca S, Orozco Moreyra R. 2017. Life cycle assessment of three Peruvian fishmeal plants: Toward a cleaner production. Journal of Cleaner Production **145**:50–63. Available from https://linkinghub.elsevier.com/retrieve/pii/S0959652617300446.

Fricko O et al. 2017. The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. Global Environmental Change **42**:251–267. Elsevier Ltd. Available from http://dx.doi.org/10.1016/j.gloenvcha.2016.06.004.

Hasegawa T, Havlík P, Frank S, Palazzo A, Valin H. 2019. Tackling food consumption inequality to fight hunger without pressuring the environment. Nature Sustainability **2**:826–833.

Havlík P et al. 2014. Climate change mitigation through livestock system transitions. Proceedings of the National Academy of Sciences of the United States of America **111**:3709–3714.

Hélias A, Stanford-Clark C, Bach V. 2023. A new impact pathway towards ecosystem quality in life cycle assessment: characterisation factors for fisheries. The International Journal of Life Cycle Assessment **28**:367–379. Springer Berlin Heidelberg. Available from https://doi.org/10.1007/s11367-023-02136-2.

Huijbregts MAJ, Steinmann ZJN, Elshout PMF, Stam G, Verones F, Vieira M, Zijp M, Hollander A, van Zelm R. 2017. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. International Journal of Life Cycle Assessment **22**:138–147. The International Journal of Life Cycle Assessment. Available from http://dx.doi.org/10.1007/s11367-016-1246-y.

IBF-IIASA. 2023. Global Biosphere Management Model (GLOBIOM) Documentation 2023 - Version 1.0. International Institute for Applied Systems Analysis (IIASA). Available from https://iiasa.github.io/GLOBIOM/.

Iordan CM, Kuipers K, Huang B, Verones F, Cherubini F. 2023. Spatially and taxonomically explicit characterisation factors for greenhouse gas emission impacts on biodiversity. Resources, Conservation and Recycling **198**:107159. Elsevier B.V. Available from https://doi.org/10.1016/j.resconrec.2023.107159.

Janssens C et al. 2020. Global hunger and climate change adaptation through international trade. Nature Climate Change **10**:829–835. Springer US. Available from http://dx.doi.org/10.1038/s41558-020-0847-4.

Kindermann GE, Obersteiner M, Rametsteiner E, McCallum I. 2006. Predicting the deforestation-trend under different carbon-prices. Carbon Balance and Management **1**:15. Available from https://cbmjournal.biomedcentral.com/articles/10.1186/1750-0680-1-15.

Kok MTJ et al. 2023. Assessing ambitious nature conservation strategies in a below 2-degree and food-secure world. Biological Conservation **284**:110068. Elsevier Ltd. Available from https://doi.org/10.1016/j.biocon.2023.110068.

Kortleve AJ, Mogollón JM, Harwatt H, Behrens P. 2024. Over 80% of the European Union's Common Agricultural Policy supports emissions-intensive animal products. Nature Food **11**. Available from https://www.nature.com/articles/s43016-024-00949-4.

Kozicka M et al. 2023. Feeding climate and biodiversity goals with novel plant-based meat and milk alternatives. Nature Communications **14**:5316. Springer US. Available from https://www.nature.com/articles/s41467-023-40899-2.
Krisztin T, Piribauer P, Wögerer M. 2022. A spatial multinomial logit model for analysing urban expansion. Spatial Economic Analysis **17**:223–244. Available from https://doi.org/10.1080/17421772.2021.1933579.
Leclère D et al. 2020. Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature **585**:551–556.
Leclère D, Havlík P, Fuss S, Schmid E, Mosnier A, Walsh B, Valin H, Herrero M, Khabarov N, Obersteiner M. 2014. Climate change induced transformations of agricultural systems: Insights from a global model. Environmental Research Letters **9**. IOP Publishing.
Li D, Dorber M, Barbarossa V, Verones F. 2022. Global characterization factors for quantifying the impacts of increasing water temperature on freshwater fish. Ecological Indicators **142**:109201. Elsevier Ltd. Available from https://doi.org/10.1016/j.ecolind.2022.109201.
Liu X, Zheng J, Yu L, Hao P, Chen B, Xin Q, Fu H, Gong P. 2021. Annual dynamic dataset of global cropping intensity from 2001 to 2019. Scientific Data **8**:283. Available from https://www.nature.com/articles/s41597-021-01065-9.
Marquardt SG, Guindon M, Wilting HC, Steinmann ZJN, Sim S, Kulak M, Huijbregts MAJ. 2019. Consumption-based biodiversity footprints – Do different indicators yield different results? Ecological Indicators **103**:461–470. Elsevier.
Mattila TJ. 2018. Use of Input-Output Analysis in LCA. Pages 349–372 Life Cycle Assessment. Springer International Publishing, Cham. Available from http://link.springer.com/10.1007/978-3-319-56475-3_14.
Nakamura S, Kondo Y. 2002. Input-Output Analysis of Waste Management. Journal of Industrial Ecology **6**:39–63. Available from http://doi.wiley.com/10.1162/108819802320971632.
Palazzo A, Valin H, Batka M, Havlík P. 2019. Investment Needs for Irrigation Infrastructure along Different Socioeconomic Pathways. World Bank, Washington, DC, Washington D.C. Available from https://openknowledge.worldbank.org/handle/10986/31307.
Pastor A V., Palazzo A, Havlik P, Biemans H, Wada Y, Obersteiner M, Kabat P, Ludwig F. 2019. The global nexus of food–trade–water sustaining environmental flows by 2050. Nature Sustainability **2**:499–507. Springer US. Available from http://dx.doi.org/10.1038/s41893-019-0287-1.
Rasul K, Bruckner M, Mempel F, Trsek S, Hertwich E. 2024. Once and energy source, always an energy source? A regional net energy analysis of the global agrifood system. Page PNAS Nexus (under review).
Saget S, Porto Costa M, Santos CS, Vasconcelos M, Styles D, Williams M. 2021. Comparative life cycle assessment of plant and beef-based patties, including carbon opportunity costs. Sustainable Production and Consumption **28**:936–952. Elsevier B.V. Available from https://doi.org/10.1016/j.spc.2021.07.017.
Scherer L, Rosa F, Sun Z, Michelsen O, De Laurentiis V, Marques A, Pfister S, Verones F, Kuipers KJJ. 2023. Biodiversity Impact Assessment Considering Land Use Intensities and Fragmentation. Environmental Science & Technology **57**:19612–19623. Available from https://pubs.acs.org/doi/10.1021/acs.est.3c04191.
Schipper AM et al. 2020. Projecting terrestrial biodiversity intactness with GLOBIO 4. Global Change Biology **26**:760–771.

Sen B, Onat NC, Kucukvar M, Tatari O. 2019. Material footprint of electric vehicles: A multiregional life cycle assessment. Journal of Cleaner Production **209**:1033–1043. Elsevier Ltd. Available from https://doi.org/10.1016/j.jclepro.2018.10.309.

Stadler K et al. 2018. EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. Journal of Industrial Ecology **22**:502–515.

Stadler K. 2021. Pymrio – A Python Based Multi-Regional Input-Output Analysis Toolbox. Journal of Open Research Software **9**:8. Available from https://openresearchsoftware.metajnl.com/article/10.5334/jors.251/.

Stanaway JD et al. 2018. Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Stu. The Lancet **392**:1923–1994. Available from https://linkinghub.elsevier.com/retrieve/pii/S0140673618322256.

Sun Z, Behrens P, Tukker A, Bruckner M, Scherer L. 2022a. Global Human Consumption Threatens Key Biodiversity Areas. Environmental Science & Technology **56**:9003–9014. Available from https://pubs.acs.org/doi/10.1021/acs.est.2c00506.

Sun Z, Scherer L, Tukker A, Spawn-Lee SA, Bruckner M, Gibbs HK, Behrens P. 2022b. Dietary change in high-income nations alone can lead to substantial double climate dividend. Nature Food **3**:29–37. Springer US. Available from https://www.nature.com/articles/s43016-021-00431-5.

UN. 2019. The Sustainable Development Goals Report. Page United Nations Publications. New York, USA. Available from https://unstats.un.org/sdgs/report/2019/.

UNFCCC. 2016. The Paris Agreement. Page United Nations Framework Convention on Climate Change.

Vanham D, Bruckner M, Schwarzmueller F, Schyns J, Kastner T. 2023. Multi-model assessment identifies livestock grazing as a major contributor to variation in European Union land and water footprints. Nature Food **4**:575–584. Springer US.

Verones F et al. 2020. LC-IMPACT: A regionalized life cycle damage assessment method. Journal of Industrial Ecology **24**:1201–1219.

Verones F, Moran D, Stadler K, Kanemoto K, Wood R. 2017. Resource footprints and their ecosystem consequences. Nature Scientific Reports **7**:40743. Nature Publishing Group. Available from http://www.nature.com/articles/srep40743.

Vittis Y, Godfray C, Obersteiner M. 2022. Agricultural mechanisation could reduce global labour requirements by hundreds of millions of agri-food workers. Research Square.

Waha K, Dietrich JP, Portmann FT, Siebert S, Thornton PK, Bondeau A, Herrero M. 2020. Multiple cropping systems of the world and the potential for increasing cropping intensity. Global Environmental Change **64**:102131. Elsevier Ltd. Available from https://doi.org/10.1016/j.gloenvcha.2020.102131.

Wernet G, Bauer C, Steubing B, Reinhard J, Moreno-Ruiz E, Weidema B. 2016. The ecoinvent database version 3 (part I): overview and methodology. International Journal of Life Cycle Assessment **21**:1218–1230. The International Journal of Life Cycle Assessment. Available from http://dx.doi.org/10.1007/s11367-016-1087-8.

Wiedmann T. 2016. Impacts embodied in global trade flows. Pages 159–180 in R. Clift and A. Druckman, editors. Taking Stock of Industrial Ecology. Springer.

Yu Q, You L, Wood-sichra U, Ru Y, Joglekar AKB, Fritz S, Xiong W, Lu M, Wu W, Yang P. 2020. A cultivated planet in 2010: 2. the global gridded agricultural production maps. Earth System Science Data **11**:1–40.

SUPPLEMENTARY TABLES

Table S1. Selection of international climate targets and potential indicators (EU Green Deal, Paris Agreement)

Body*	Type	N	Description	Potential indicator**
EGD	Target		Reduce net GHG emissions by at least 55% by 2030, compared to 1990 levels.	GHG kg CO2-eq
EDG	Target		Reduce net GHG emissions by 90% by 2040 relative to 1990	GHG kg CO2-eq
EGD	Target		Achieve net zero emissions by 2050	GHG kg CO2-eq
PA	Article	2.1	Holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels (*to limit global warming to 1.5°C, GHG emissions must peak before 2025 and decline 43% by 2030*)	GHG kg CO2-eq

* EU Green Deal (EGD), Paris Agreement (PA)
** Greenhouse gas (GHG)

Table S2. Selection of international biodiversity targets and potential indicators (Global Biodiversity Framework, EU Biodiversity Strategy, Sustainable Development Goals, Planetary Boundaries)

Body*	Type	N	Description	Potential indicator**
GBF	Goal	A	The integrity, connectivity and resilience of all ecosystems are maintained, enhanced, or restored, substantially increasing the area of natural ecosystems by 2050; Human induced extinction of known threatened species is halted, and, by 2050, the extinction rate and risk of all species are reduced tenfold and the abundance of native wild species is increased to healthy and resilient levels The genetic diversity within populations of wild and domesticated species, is maintained, safeguarding their adaptive potential.	MSA, FGRS, BII, PDF
GBF	Goal	B	Biodiversity is sustainably used and managed and nature's contributions to people, including ecosystem functions and services, are valued, maintained and enhanced, with those currently in decline being restored, supporting the achievement of sustainable development for the benefit of present and future generations by 2050.	MSA
GBF	Target	7	Reduce pollution risks and the negative impact of pollution from all sources, by 2030, to levels that are not harmful to biodiversity and ecosystem functions and services, considering cumulative effects, including: reducing excess nutrients lost to the environment by at least half including through more efficient nutrient cycling and use; reducing the overall risk from pesticides and highly hazardous chemicals by at least half including through integrated pest management, based on science, taking into account food security and livelihoods; and also preventing, reducing, and working towards eliminating plastic pollution.	Kg N/ha/yr application; PDF; MSA
GBF	Target	8	Minimize the impact of climate change and ocean acidification on biodiversity and increase its resilience through mitigation, adaptation, and disaster risk reduction actions, including through nature-based solution and/or ecosystem-	PDF, MSA

			based approaches, while minimizing negative and fostering positive impacts of climate action on biodiversity.	
GBF	Target	10	Ensure that areas under agriculture, aquaculture, fisheries and forestry are managed sustainably, in particular through the sustainable use of biodiversity, including through a substantial increase of the application of biodiversity friendly practices, such as sustainable intensification, agroecological and other innovative approaches contributing to the resilience and long-term efficiency and productivity of these production systems and to food security, conserving and restoring biodiversity and maintaining nature's contributions to people, including ecosystem functions and services .	MSA, PDF
EBS	Target	6	The risk and use of chemical pesticides is reduced by 50%, and the use of more hazardous pesticides is reduced by 50% by 2030	Kg/ha/yr pesticide application; PDF; MSA
PBF	Boundary	2.1	90% biodiversity intactness index (BII)	BII or MSA

* Kunming-Montreal Global Biodiversity Framework (GBF), EU Biodiversity Strategy (EBS), Sustainable Development Goal (SDG), and Planetary Boundary Framework (PBF).
** Mean species abundance (MSA), Potentially Disappeared Fraction of Species (PDF), and Biodiversity Intactness Index (BII)

Table S3. Mapping relationship of primary crops in FABIO and SPAM

FABIO_code	FABIO_name	SPAM_name
c001	Rice and products	rice
c002	Wheat and products	whea
c003	Barley and products	barl
c004	Maize and products	maiz
c005	Rye and products	ocer
c006	Oats	ocer
c007	Millet and products	pmil/smil
c008	Sorghum and products	sorg
c009	Cereals, Other	ocer
c010	Potatoes and products	pota
c011	Cassava and products	cass
c012	Sweet potatoes	swpo
c013	Roots, Other	orts
c014	Yams	yams
c015	Sugar cane	sugc
c016	Sugar beet	sugb
c017	Beans	bean
c018	Peas	opul
c019	Pulses, Other and products	opul
c020	Nuts and products	rest
c021	Soyabeans	soyb
c022	Groundnuts	grou
c023	Sunflower seed	sunf
c024	Rape and Mustardseed	rape
c025	Seed cotton	cott
c026	Coconuts - Incl Copra	cnut

c027	Sesame seed	sesa
c028	Oil, palm fruit	oilp
c029	Olives (including preserved)	ooil
c030	Oilcrops, Other	ooil
c031	Tomatoes and products	vege
c032	Onions	vege
c033	Vegetables, Other	vege
c034	Oranges, Mandarines	trof
c035	Lemons, Limes and products	trof
c036	Grapefruit and products	trof
c037	Citrus, Other	trof
c038	Bananas	bana
c039	Plantains	plnt
c040	Apples and products	temf
c041	Pineapples and products	trof
c042	Dates	trof
c043	Grapes and products (excl wine)	temf
c044	Fruits, Other	trof/temf
c045	Coffee and products	acof/rcof
c046	Cocoa Beans and products	coco
c047	Tea (including mate)	teas
c048	Hops	rest
c049	Pepper	rest
c050	Pimento	rest
c051	Cloves	rest
c052	Spices, Other	rest
c053	Jute	ofib
c054	Jute-Like Fibres	ofib
c055	Soft-Fibres, Other	ofib
c056	Sisal	ofib
c057	Abaca	ofib
c058	Hard Fibres, Other	ofib
c059	Tobacco	toba
c060	Rubber	rest
c061	Fodder crops	
c062	Grazing	

Table S4. Crop classification of primary crops in FABIO

FABIO_code	FABIO_name	Crop type
c001	Rice and products	T
c002	Wheat and products	T
c003	Barley and products	T
c004	Maize and products	T
c005	Rye and products	T
c006	Oats	T
c007	Millet and products	T
c008	Sorghum and products	T

c009	Cereals, Other	T
c010	Potatoes and products	T
c011	Cassava and products	T
c012	Sweet potatoes	T
c013	Roots, Other	T
c014	Yams	T
c015	Sugar cane	T
c016	Sugar beet	T
c017	Beans	T
c018	Peas	T
c019	Pulses, Other and products	T
c020	Nuts and products	P
c021	Soyabeans	T
c022	Groundnuts	T
c023	Sunflower seed	T
c024	Rape and Mustardseed	T
c025	Seed cotton	T
c026	Coconuts - Incl Copra	P
c027	Sesame seed	T
c028	Oil, palm fruit	P
c029	Olives (including preserved)	P
c030	Oilcrops, Other	T
c031	Tomatoes and products	T
c032	Onions	T
c033	Vegetables, Other	T
c034	Oranges, Mandarines	P
c035	Lemons, Limes and products	P
c036	Grapefruit and products	P
c037	Citrus, Other	P
c038	Bananas	P
c039	Plantains	P
c040	Apples and products	P
c041	Pineapples and products	P
c042	Dates	P
c043	Grapes and products (excl wine)	P
c044	Fruits, Other	P
c045	Coffee and products	P
c046	Cocoa Beans and products	P
c047	Tea (including mate)	P
c048	Hops	P
c049	Pepper	P
c050	Pimento	P
c051	Cloves	P
c052	Spices, Other	P
c053	Jute	T
c054	Jute-Like Fibres	T
c055	Soft-Fibres, Other	T

c056	Sisal	P
c057	Abaca	P
c058	Hard Fibres, Other	P
c059	Tobacco	T
c060	Rubber	P
c061	Fodder crops	P
c062	Grazing	Pasture

T = temporary, P = permanent.