Accounting for biodiversity impacts of consumption and production: current gaps and frontiers.

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Abstract

Aim and background

The way humans produce and consume material goods continues to be a primary driving force on biodiversity decline. Despite significant advances in quantifying biodiversity footprints, important differences exist across types of approaches and indicators. These include, what aspects of biodiversity are measured and how they are reported. In this scoping review, we provide an overview of biodiversity impact metrics developed to assess biodiversity impacts by human production and consumption activities.

Methods

We use systematic literature mapping to scan over 1,200,000 records sourced from OpenAlex. Using natural language processing models and a cosine similarity index, we reduce our corpus to more than 7,000 records and finally include 154 works as part of the review.

Findings

We find that biodiversity footprinting metrics have evolved substantially since their initial development in the late 1990s. Initially focused on land use as the principal driver of biodiversity loss, metrics now also address climate change, pollution, invasive species, and, in some cases, overexploitation. We propose a classification into four families of biodiversity-related metrics: impact assessment metrics dominate (64%), followed by pressure-impact metrics (12%), pressure-impact combined with impact assessment (10%), and state-based metrics (5%), alongside a minor contribution from theoretical ecology in combination with others.

Impact assessment metrics, rooted in industrial ecology, specialize around three ecological models to characterize the effects of diverse pressures on species: (i) species–area relationships and equivalent connected areas for land use, (ii) species–discharge relationships for water flow alterations, and (iii) species sensitivity distributions for pollution impacts.

Existing metrics cover terrestrial, freshwater, and marine realms, with a predominant focus on taxonomic and functional diversity. Phylogenetic diversity remains substantially underrepresented, and while many metrics operate at the species level, relatively few extend to ecosystem assessments, and none adequately capture genetic diversity. Except for amphibians, birds, mammals, reptiles, and vascular plants, species groups such as fishes, insects, bryophytes, algae, fungi, and non-insect invertebrates across realms remain largely underrepresented in current biodiversity metrics.

Outlook

Future work should focus on (1) bridging scientific disciplines like biology, ecology and conservation with industrial- and social ecology, (2) advancing and refining existing methods to include more taxa, (3) developing new methods to account for existing gaps and (4) harmonise metrics with conservation and mitigation efforts.

1 Introduction

Current production and consumption patterns are one of the major Anthropogenic drivers of biodiversity loss (Díaz et al., 2019) and pose a challenge for conservation and sustainable use of resources. Pressures due to economic activities, include ecosystem fragmentation and degradation, exposure to harmful chemicals and pollution, competing use of water sources, direct and indirect homogenisation of genetic pools, overexploitation, and the effects of climate change (Pörtner, Hans-Otto et al., 2021).

Biodiversity footprints (Lenzen et al., 2012; Marques et al., 2017; Wilting et al., 2017; Marquardt et al., 2019) allow for quantifying impacts of production and consumption on biodiversity or defined areas of protection (Consoli et al., 1993; Finnveden et al., 2009). First devised to account for the life-cycle impacts of products (Guinée et al., 2001; Pennington et al., 2004; Rebitzer et al., 2004; Hauschild, 2005), footprints can now also give an estimate of a nation's final consumption impacts on biodiversity. This is accomplished by accounting for impacts through production and supply value chains (Marques et al., 2017; Wilting et al., 2017; Marquardt et al., 2019).

Two major approaches to this quantification are Life Cycle Assessment (LCA) and Environmentally Extended Multi-Regional Input-Output Models (EEMRIO). LCA focuses on detailed, product-level analyses, tracing environmental impacts across the entire life cycle of a product, also defined as cradle-to-cradle. This life cycle includes pressures from raw material extraction to production, distribution, use, and disposal. LCA provides a granular view of the specific pressures associated with each product's life stage. In contrast, EEMRIO models operate at a broader scale, e.g., national, regional or global, assessing biodiversity impacts by linking economic activities to environmental impacts through inter-country trade relationships. On the one hand, EEMRIO models complement LCA by providing a more systemic and broad overview of impacts across multiple sectors and countries, enabling the assessment of "virtual" and telecoupled (Liu et al., 2013; Hull & Liu, 2018; Ibarrola-Rivas et al., 2020; Laroche et al., 2020) biodiversity impacts embedded in international trade flows (Kastner et al., 2011; Lenzen et al., 2012; Moran et al., 2016; Nishijima et al., 2016; Moran & Kanemoto, 2017; Kastner et al., 2021; Irwin et al., 2022; Boakes et al., 2024; Cabernard et al., 2024). On the other, LCA models provide EEMRIO with granular data to devise local impacts on biodiversity as a result of differentiated production systems (Scherer & Pfister, 2016; Marques et al., 2017; Crenna et al., 2019; Crenna et al., 2020).

Contextualising and characterising impacts on biodiversity associated with consumption and production patterns across the globe is an operational prerequisite for maintaining a "safe operating space for humanity" (Rockström et al., 2009). Globally, current anthropogenic drivers and pressures result in socioeconomically and culturally differentiated "metabolic rates" in the material and energy flows in the world's social-ecological systems, contributing to unequal ecological exchange (Hornborg, 1998; Dorninger et al., 2021; Bruckner et al., 2023). Quantifying final consumption footprints illuminates the problem of moving abroad many activities that underlie increasing consumption of high-income countries (Dorninger et al., 2021; Bruckner et al., 2023). Just accounting for local impacts might give a false sense of sustainability in such countries and a focus on how they affect local species when such countries are, in fact, contributing to biodiversity loss and increased extinction risks abroad (Lenzen et al., 2012; Nishijima et al., 2016; Moran & Kanemoto, 2017; Irwin et al., 2022; Boakes et al., 2024; Cabernard et al., 2024).

Quantifying the impacts on various aspects of biodiversity using LCAs and EEMRIOs presents significant challenges. These include the complexity of biodiversity itself and how biodiversity is accounted for, limitations in data availability, and the lack of standardised metrics that capture different facets of biodiversity loss. These challenges arise because biodiversity is inherently multi-dimensional in policy, science and practice. In the international policy context, it spans the levels of genes, species and ecosystems (CBD, 1992). The scientific treatment include taxonomic, phylogenetic and functional components. This means that our understanding of biodiversity impacts is not evenly distributed among types of ecosystems, types of biodiversity and spatial scales. For example, land use systems have historically received more attention than marine or freshwater in their assessment, and even within terrestrial ecosystems, tropical rainforests often receive more attention due to their high species richness. This creates uneven assessments and an incomplete picture of global biodiversity impacts across regions, ecosystem types, species and their ecological functions.

This review provides an overview of the current application of biodiversity metrics in LCAs and EEMRIOs. Through a systematic literature mapping, we quantify the current application of LCAs and EEMRIOs across biodiversity realms (i.e., terrestrial, freshwater, and marine), levels of biodiversity (i.e., genetic, species, and ecosystems) across different components (i.e., phylogenetic, functional, and taxonomic) and anthropogenic pressures, covering both production- and consumption-based biodiversity metrics. We critically examine the historical development of a broad set of metrics, how they have evolved to capture the many different facets of biodiversity, and how they account for anthropogenic impacts on biodiversity to produce so-called production- and consumption-based footprints. Further, we explore the ecological and biological foundations of the metrics and how these can be improved to better account for a single or a combination of anthropogenic pressures that drive biodiversity decline.

2 Results

2.1 Biodiversity metrics use: anthropogenic characterisation

Of the **154** reviewed articles and their supporting information, 57% (88) dealt exclusively with biodiversity in terrestrial realms, followed by freshwater (22) and marine (15). Combinations across realms were less common, with terrestrial-freshwater (12), marine-freshwater (4), or all three realms (11). Of all articles, 79% (121) focused on taxonomic diversity, 16% (24) on functional diversity and none on phylogenetic diversity. Of the reviewed metrics, species richness is widely used across direct pressures and drivers of biodiversity loss. Species abundance was only studied for land use and climate change, whereas genetic diversity is absent. Ecosystem diversity is partially covered by land and water use, climate change, pollution, and (over)exploitation (Figure 1, **Supporting Tables 5-6**).

Classifying the metrics in regards to the Essential Biodiversity Variables (EBV) classes results in a broad coverage across realms for community composition (50:freshwater, 113:terrestrial, 33:marine) with a high focus on taxonomic diversity (164), followed by community abundance (31) and trait diversity (5). Species populations class shows a higher coverage for terrestrial (97), followed by freshwater (41) and marine (21) realms, of which species distributions (133) shows the higher representation and less for species abundances (26). Ecosystem structure has a broader representation for terrestrial (47), than other realms, with an even representation across ecosystem distribution (20), ecosystem vertical profile (19) and liver cover fraction (16). Ecosystem functioning is also covered by metrics for terrestrial (22), freshwater (14) and marine (10) realms, mostly associated with primary productivity (25) and ecosystem disturbances (21). Finally, EBVs related to species traits and genetic composition showed the biggest gap in their inclusion, with some marginal cases for species traits exclusively associated with terrestrial ecosystems (13) (**Supporting Figures 2-3; Supporting Table 7**).

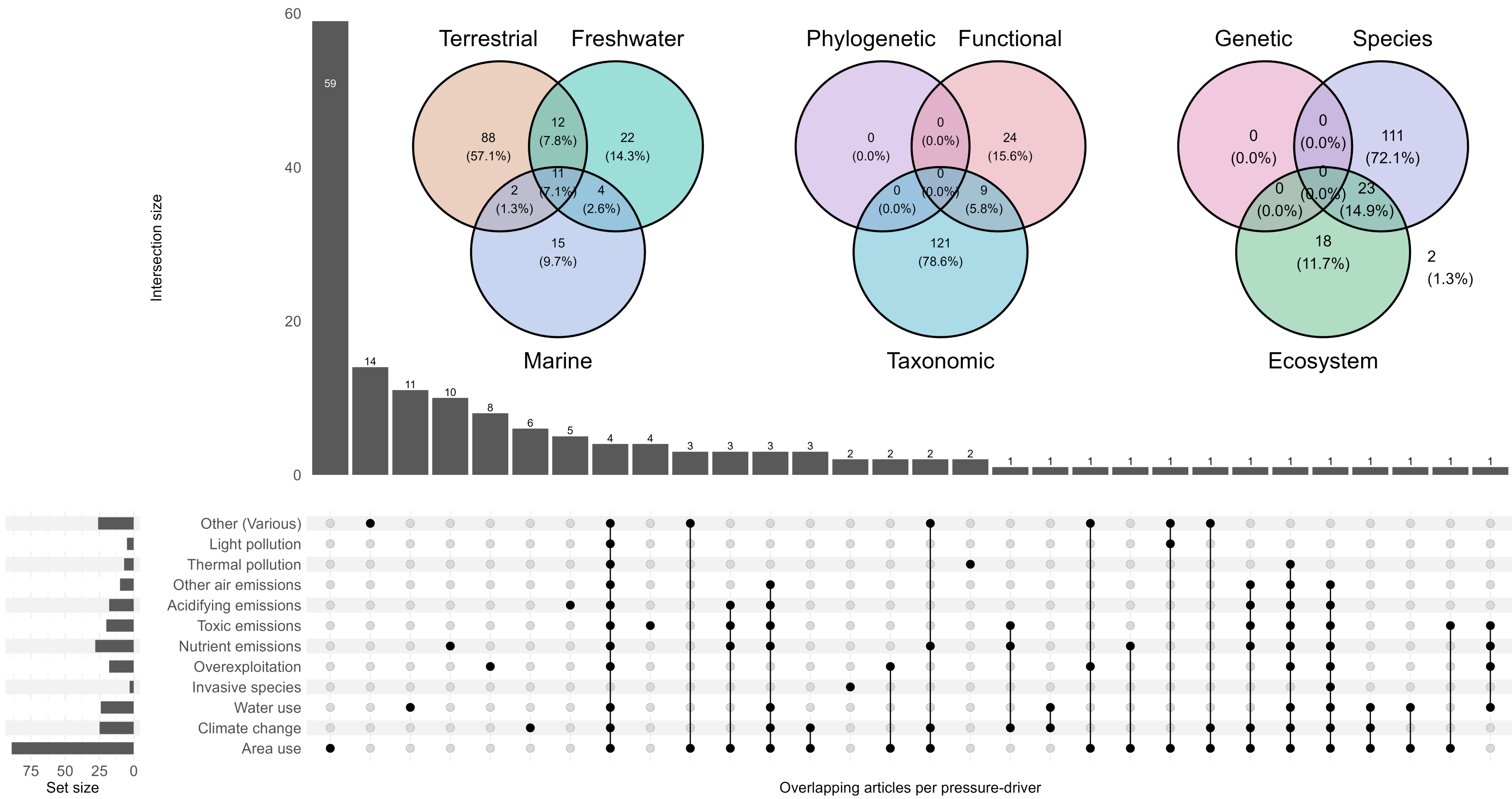

Figure 1: Articles' distribution by forms of biodiversity and pressures. UpSet plot (bottom) shows the count of articles per anthropogenic pressure and their corresponding overlaps (if any); left side: count per individual pressure, top: count per overlapping pressures. The Venn diagrams (top) show a summary of overlapping articles across biodiversity realms (A), types (B) and levels (C). N = 154

Broadly, we found that all biodiversity footprinting metrics can be classified under the umbrella of pressure-impact metrics. However, to capture meaningful distinctions within this category, we further refined the classification based on shared characteristics, including assessment focus, biodiversity reference state and interpretation, mathematical formulation, data sources, and underlying cause–effect frameworks (Table 1). Based on this, we propose four broad families of biodiversity metrics.

The first, **traditional ecology** metrics, typically describe the state of biodiversity at the species or ecosystem level and are commonly applied to single or multiple taxa. This family includes widely used indicators such as species richness, species abundance, and α-, β-, and γ-diversity. While traditionally used for ecological assessments, some of these metrics have been adapted to quantify biodiversity impacts in LCA and EEMRIO frameworks. The second family comprises **state-based/pressure-impact** metrics, which are often structured as indices and offer a static snapshot of biodiversity under specific conditions. These can be further subdivided into species-targeted and ecosystem-targeted approaches, depending on their unit of analysis. While some extend beyond taxonomic measures to incorporate ecosystem-level attributes, their integration into LCA and EEMRIO remains limited. Finally, **impact assessment** metrics, commonly used in industrial ecology, are explicitly designed to translate anthropogenic pressures into biodiversity impacts via formal cause–effect pathways and ecological models (Box 2.2; Table 2).

This classification not only organizes biodiversity metrics thematically, but also reveals how biodiversity measurement approaches have evolved both historically and methodologically. Figure 2 further illustrates these patterns through an article similarity network, revealing a great density around impact assessment metrics that span across the rest of the families. On some selected cases, articles do not share a common framework or model of assessment and perform alone, even with a single family category. In some cases, articles remain isolated, indicating either unique frameworks or limited integration with existing approaches. Only a few articles simultaneously incorporate three different metric types to characterize biodiversity impacts resulting from anthropogenic activities. The accompanying wordcloud highlights the dominant frameworks and models within each family, particularly the strong influence of cause–effect models such as Species Sensitivity Distributions (SSD) and Species Discharge Relationships (SDR) within the impact assessment family (Box 2.2; Table 2).

Quantitatively, according to our coding, **impact assessment** (IA) biodiversity metrics are the most common (98), followed by **pressure-impact** metrics (19), combinations of pressure-impact and impact assessment (15), and **state-based** metrics (7). A smaller group of articles draws from **theoretical ecology** (9), which never occurs alone but always in combination with one of the other families — most frequently impact assessment (4), state-based (3), or pressure-impact (1) (Figure 2; **Supporting Table 8**).

Among impact assessment metrics, cause–effect pathway models dominate (48), addressing pollution impacts — primarily through Species Sensitivity Distributions (SSD) (23) — and changes in water flow — through Species Discharge Relationships (SDR) (7) — across terrestrial, freshwater, and marine realms. IA metrics related to land use are largely based on Species–Area Relationships (SAR) (34) and relative species richness models (8). A smaller subset of articles simultaneously bridges impact assessment and pressure-impact categories, especially those focusing on species- and ecosystem-targeted approaches.

Overall, impact assessment metrics translate anthropogenic activities into biodiversity impacts through structured cause–effect pathways. Depending on the environmental pressure considered, these metrics typically rely on ecological models such as SAR, SDR, and SSD (Table 2). While impact assessment methods dominate the industrial ecology landscape, it is important to recognize that metrics originally developed in theoretical ecology, state-based and pressure-impact frameworks have increasingly been adapted into impact assessment families. These adaptations demonstrate that static descriptors of ecosystem condition can be recontextualized to assess dynamic, human-induced changes across time and space.

Table 1: Summary of biodiversity-related metrics categorized by type.

Type	Metric	Description	Example
Traditional ecology	Species richness	The total number of species present in a defined area.	(Geyer et al., 2010; Boakes et al., 2024)
	Species abundance	Absolute size of species populations in a defined area or community.	(Geyer et al., 2010)
	Rarity-weighted species richness	Adjusts species richness based on how rare the species are globally or locally.	(Boakes et al., 2024)
	Alpha-, beta-, gamma-diversity	Measures of diversity at different spatial scales — local (α), between sites (β), and landscape-level (γ).	(Koellner & Scholz, 2008; de Baan, Alkemade, & Koellner, 2013)
	Fisher's alpha	A diversity index based on the log-series distribution; sensitive to rare species.	(de Baan, Alkemade, & Koellner, 2013)
	Shannon's entropy (H)	Combines richness and evenness to measure community diversity.	(de Baan, Alkemade, & Koellner, 2013)
	Sørensen's similarity index (Ss)	A metric for comparing species composition between two communities.	(de Baan, Alkemade, & Koellner, 2013)
	Simpson index	Models species dominance or evenness in a community.	(Geyer et al., 2010)
	Functional diversity	Diversity in species functional traits.	(de Souza et al., 2013; Scherer et al., 2020)

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Type	Metric	Description	Example
State-based	Hemeroby	Indicates the degree of human influence or deviation from natural conditions based on vegetation structure.	(Geyer et al., 2010; Taelman et al., 2016; Rossi et al., 2018; Côté et al., 2021)
	Net Primary Production (NPP)	The rate at which plants accumulate biomass, reflecting ecosystem productivity.	(Weidema & Lindeijer, 2001; Langlois et al., 2015; Taelman et al., 2016; Weinzettel et al., 2019)
Pressure-impact	Human Appropriation of NPP (HANPP)	How much of the ecosystem's productivity is claimed by humans.	(Haberl et al., 2007, 2012; Taelman et al., 2016)
	Embodied HANPP (eHANPP)	The HANPP embodied in consumed goods, regardless of production location.	(Erb et al., 2009; Haberl et al., 2009, 2012)
	Living Planet Index (LPI)	Tracks global biodiversity trends using time series of vertebrate populations.	(Loh et al., 2005; McRae et al., 2017; Westveer et al., 2022)
	Human Footprint Index (HFI)	A composite index of spatial human pressures (e.g., roads, cropland, population).	(Sanderson et al., 2002)

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Type	Metric	Description	Example
	Ecological Footprint (EF)	Measures human appropriation of ecological capacity.	(Hanafiah et al., 2012; Mattila et al., 2012; Galli et al., 2014; Lee et al., 2015)
	Biodiversity Intactness Index (BII)	Proportion of original biodiversity remaining in an area.	(Biggs & Scholes, 2005; Newbold et al., 2016; De Palma et al., 2021; Marquardt et al., 2021)
	Mean Species Abundance (MSA)	Average abundance of species relative to undisturbed conditions.	(Alkemade et al., 2009; Janse et al., 2015; Wilting et al., 2017; Marquardt et al., 2019; Barbarossa et al., 2020; Gallego-Zamorano et al., 2020; Schipper et al., 2020)

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Type	Metric	Description	Example
	Species-threats	Associations between species and their known anthropogenic threats.	(Lenzen et al., 2012; Nishijima et al., 2016; Moran & Kanemoto, 2017; Holland et al., 2019; Mair et al., 2021; Irwin et al., 2022)
	Species/Ecosystem-targets	Targets species or ecosystems as a reference baseline and proxy indicator.	(Vogtländer et al., 2004; Emanuelsson et al., 2014; Nishijima et al., 2016; Rossi et al., 2018; Myllyviita et al., 2019; Bach et al., 2022; Alejandre et al., 2023; É. Pierrat et al., 2023)

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Type	Metric	Description	Example
Impact assessment	Area-related	Metrics that model how habitat fragmentation affect species.	(Goedkoop & Spriensma, 1999; Köllner, 2000; Jolliet et al., 2003; Koellner & Scholz, 2008; De Schryver et al., 2010; de Baan, Mutel, et al., 2013; Chaudhary et al., 2015, 2017; Knudsen et al., 2017; Chaudhary & Brooks, 2018; Chaudhary et al., 2018; C. M. Iordan et al., 2018; Chaudhary & Brooks, 2019; Marques et al., 2019; Verones et al., 2020; Kuipers, May, & Verones, 2021; Scherer et al., 2023)

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Type	Metric	Description	Example
	Cause-effect	Models linking pressures (e.g., pollution, water level change) to biodiversity impacts.	(De Schryver et al., 2009; Goedkoop et al., 2009; M. Huijbregts et al., 2016; M. A. J. Huijbregts et al., 2017; L. Tang et al., 2018; Yamaguchi et al., 2018; Bulle et al., 2019; Verones et al., 2020; E. Pierrat et al., 2023)
	Nutrient	Effects of nutrient pollution (e.g., nitrogen, phosphorus) on freshwater and marine eutrophication.	(Struijs et al., 2011; Helmes et al., 2012; Cosme et al., 2015; Cosme & Hauschild, 2016; Cosme & Hauschild, 2017; Cosme et al., 2017; Payen et al., 2021)
	Acidifying	Biodiversity effects of emissions like SO_2 and NO_x causing acidification.	(Van Zelm et al., 2007; Roy et al., 2014)

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Type	Metric	Description	Example
	Toxic	Impacts of chemical pollutants (e.g., metals, pesticides) on terrestrial and aquatic biodiversity.	(Gandhi et al., 2010; Dong et al., 2016; Woods et al., 2019; Casagrande et al., 2024)
	Thermal	Impacts of heated discharges on aquatic biodiversity.	(Pfister & Suh, 2015; Raptis et al., 2017; Li et al., 2022)
	Plastic	Damage to marine and freshwater species from plastic debris, including micro- and nanoplastics.	(Woods et al., 2019; Lavoie et al., 2022)
	Noise	Disruption of communication and behaviour in species from anthropogenic noise.	(Middel & Verones, 2017)
	Invasive species	Biodiversity loss from species invasions facilitated by human activity.	(Hanafiah et al., 2013; Borgelt et al., 2024)
	Other	Miscellaneous cause-effect pathways including salinity, suspended solids, radiation, etc.	(Quinteiro et al., 2015; Roibás-Rozas et al., 2022)

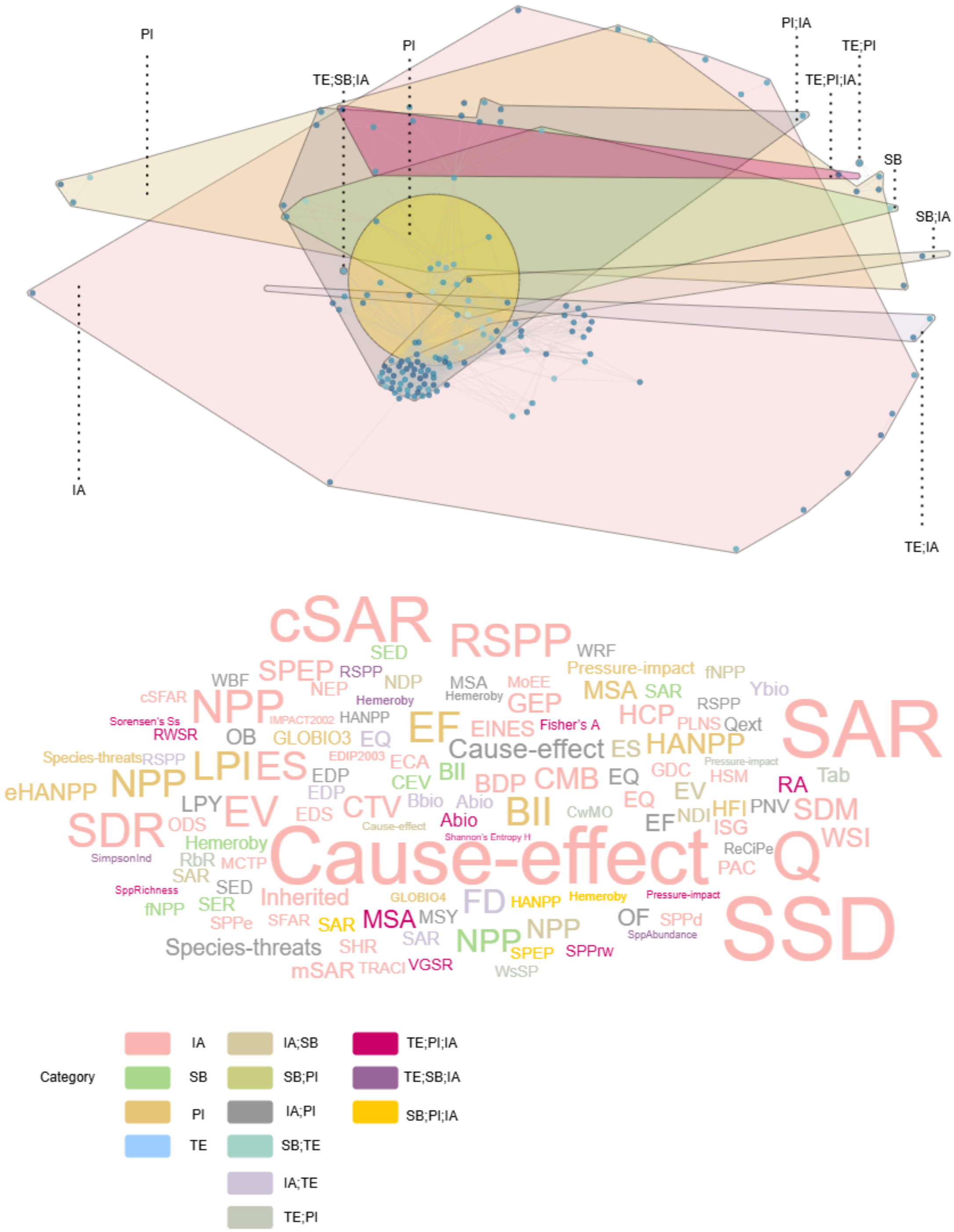

Figure 2: Biodiversity metric assessment categories and frameworks. (A) Article similarity network of 154 reviewed papers, clustered by assessment family (IA: Impact Assessment, PI: Pressure-Impact, SB: State-Based, TE: Theoretical Ecology). Node color shows publication year (lighter to darker), and position reflects shared frameworks/models. (B) WordCloud of frameworks/models colored by assessment family. See Supporting Figures 4–10 and Table 8 for detailed networks and data.

To further explore how these metric families have evolved and how they relate to one another conceptually and empirically, we constructed a co-citation network based on the reviewed literature and the literature these used as part of their methods to assemble the biodiversity metrics (**Supporting Figures 5-10**). The network reveals how different schools of thought and disciplinary clusters have shaped the development of biodiversity metrics, including a core of ecology and conservation studies (Panel A), a transition zone including global biodiversity modelling and data integration (Panel B), and an applied assessment cluster focused on those articles that effectively enable a characterization of anthropogenic impacts on biodiversity (Panel C).

These clusters also reflect differences in the ecological models employed (e.g., species–area relationships, sensitivity distributions) and the realms (terrestrial, freshwater, marine) to which the metrics are typically applied. This structure reinforces the need for interdisciplinary synthesis to ensure that biodiversity assessments fully capture ecosystem structure, function, and resilience across domains of research and application.

Overall, these findings demonstrate that although biodiversity metrics originate from diverse disciplinary backgrounds and conceptual foundations, there is a progressive convergence toward more integrative, mechanistic models linking anthropogenic activities to biodiversity impacts. However, important distinctions persist in the ecological models used, the pressures captured, and the spatial and taxonomic resolution achieved across families, which we detail further in the next sections.

2.2 Biodiversity metrics ecological models

Except for land use and partially other compound pressures-drivers (e.g., May et al. (2020); May et al. (2021) considered the disturbances and collisions of birds, and Alkemade et al. (2009); Schipper et al. (2020) who considered hunting), most of all impact assessment metrics (55) are constructed considering effect, fate, exposure, and some damage or severity factors (see Box 2.2 and Equation (1)). Regarding model selection to assemble the metrics, while some biodiversity metrics rely on expert judgement (e.g., Biggs and Scholes (2005); Jeanneret et al. (2014); Winter et al. (2018); Turner et al. (2019); Alejandre et al. (2023)), there has been a shift from qualitative (5) approaches to predominantly quantitative (144) ecological models. Some state-based/pressure-impact metrics, due to their nature, are typically unitless and designed as indices (e.g., Hemeroby with the Natural Degradation Index (Brentrup et al., 2002; Farmery et al., 2017), Biodiversity Intactness Index (Biggs & Scholes, 2005), Human Footprint Index (Sanderson et al., 2002; Venter, Sanderson, Magrach, Allan, Beher, Jones, Possingham, Laurance, Wood, Fekete, Levy, & Watson, 2016, 2016; Keys et al., 2021), or the Living Planet Index (Loh et al., 1998, 2005; McRae et al., 2017; Westveer et al., 2022)).

Box 2.2 Impact assessment (Industrial Ecology-related) metrics construction and use.

Impact assessment metrics are mostly used in LCA and EEMRIO. These metrics translate and characterize anthropogenic activities and their corresponding impacts at various stages by integrating multiple impact-chain pathways (cause-effect) and datasets (see Figure 3). For instance:

- **Anthropogenic pressures** are derived from activity inventories and translated using characterization factors with common units. For example, all greenhouse gasses (GHG) are expressed in terms of carbon dioxide equivalent per kilogram of emitted GHG.
- **Midpoint level indicators** represent intermediate environmental effects, such as terrestrial acidification, eutrophication, climate change, or land transformation, each with a specific characterization factor.
- **Damage level indicators** aggregate midpoint effects into impact categories and link them to an **Area of Protection (AoP)**, such as ecosystem quality for biodiversity via an endpoint indicator. AoPs are categories relevant to society that should be safeguarded and are consensually agreed (UNEP & SETAC Life Cycle Initiative, 2016, 2019).

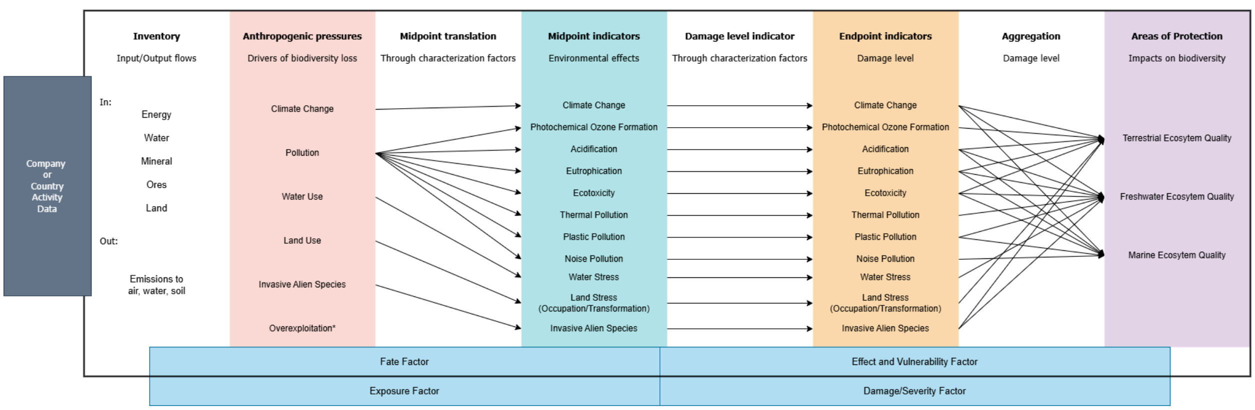

Figure 3: Industrial ecology metrics cause-effect chain with existing covered pathways for biodiversity assessment.

The construction of industrial ecology metrics varies based on the impact category and the method used to harmonize different drivers and pressures. These metrics typically include various factors (see Equation (1)).

$$CF = EF * FF * XF * (VF/SF/DF) \tag{1}$$

Factors description:

- **Effect (EF):** models how species are affected by changes in the environment caused by exposure to a pollutant.
- **Fate (FF):** describes the distribution and transformation over time of a substance in a given environmental compartment (air, soil, or water).
- **Exposure (XF):** quantifies the extent to which an ecosystem or species comes into contact with a pollutant at a given concentration.

- **Vulnerability (VF):** “translate species loss from regional to global” (Verones et al., 2020, p. 1206)
- **Damage (DF)/Severity (SF):** this translates to the midpoint impact and the resulting damage to a specific area of protection given the intensity of damage caused by a specific impact on the endpoint.

In impact assessment families, biodiversity metrics are expressed as Potentially Disappeared Fraction of species (PDF) (setaclifecycleinitiative2016GlobalGuidanceLife, UNEP & SETAC Life Cycle Initiative, 2019), a term that originated from vascular plant characterisation, and is related to Potentially Not-Occurring Fraction of species (PNOF) and Potentially Affected Fraction of species (PAF) from ecotoxicology and environmental sciences. At the midpoint level, PAF is usually used. Harmonisation occurs at endpoint categories that aggregate impacts across different pressures.

We identified several impact assessment families (methods) that cover biodiversity such as Eco-indicator 99 (Goedkoop & Spriensma, 1999), Impact World + (Bulle et al., 2019), ReCiPe (Goedkoop et al., 2009; M. Huijbregts et al., 2016; M. A. J. Huijbregts et al., 2017), LC-Impact (Verones et al., 2020), and Global Guidance for Life Cycle Impact Assessment Indicators and Methods (GLAM). These families assemble the effect factor mostly around three ecological models (Table 2; Supporting Information), with some alternating models. These models underpin biodiversity assessments by linking human activities to impacts on species. In many cases, the models are specific to assess individual pressures and include a set of unique or diversified species groups across different realms and ecosystems. Historically, vascular plants have served as proxies for biodiversity assessment across pressure and models. Nonetheless, new developments in ecological models, combined with data availability and species responses, have allowed biodiversity to be better captured and included in human activities’ characterisation and corresponding impacts.

Table 2: Ecological models used in biodiversity impact assessment, with associated pressures, realms, descriptions, references, and applications.

Model	Name	Pressures	Realms	Description	References	Applications
SAR	Species–Area Relationship	Land use and change	Terrestrial, Freshwater	Relates species richness to area and how ecosystem fragmentation alters species distribution.	Arrhenius, 1921; MacArthur and Wilson, 1967; Myers and Simon, 1994; Rosenzweig, 1995	Goedkoop and Spriensma, 1999; Köllner, 2000; Weidema and Lindeijer, 2001; Schmidt, 2008; Verones et al., 2015
cSAR	Countryside SAR	Land use and change	Terrestrial	Extends SAR to account for land use types and species' habitat affinities.	Pereira and Daily, 2006; Pereira et al., 2014	Chaudhary et al., 2015; Chaudhary and Brooks, 2018; Verones et al., 2020
mcSAR	Matrix-calibrated cSAR	Land use and change	Terrestrial	Extends SAR to incorporate species' varying sensitivities to different land use matrix arrangements.	Koh et al., 2010	de Baan, Alkemade, and Koellner, 2013; Chaudhary et al., 2015; Bulle et al., 2019
SFAR	Species-Fragmented Area Relationship	Land use and change	Terrestrial	Considers how habitat fragmentation and patch isolation can support viable population groups through metapopulation capacities.	Hanski and Ovaskainen, 2000; Hanski et al., 2013	Larrey-Lassalle, Loiseau, et al., 2018
cSFAR	Countryside-SFAR	Land use and change	Terrestrial	Refines species affinities and sensitivities to diverse landscape matrix, habitat fragmentation while incorporating metapopulation dynamics.	Larrey-Lassalle, Esnouf, et al., 2018	Larrey-Lassalle, Loiseau, et al., 2018

Model	Name	Pressures	Realms	Description	References	Applications
SHR	Species Habitat Relationship	Land use and change	Terrestrial	Combines habitat suitability (via c-SAR) and connectivity (via ECA) to assess the impacts of habitat loss and fragmentation, accounting for patch size, connectivity, and matrix quality.	Saura et al., 2011; Kuipers, Hilbers, et al., 2021	Kuipers, May, and Verones, 2021
ECA	Equivalent Connected Area	Land use and change	Terrestrial	Represents the area of a single habitat patch that provides the same probability of connectivity as the actual, potentially fragmented landscape.	Saura et al., 2011; Garcia-Ulloa et al., 2016	Scherer et al., 2023
SDR	Species Discharge Relationship	Water consumption, climate change	Freshwater	Captures the accumulation or loss of species in response to increasing or decreasing water discharge, reflecting changes in habitat availability, suitability, and dispersal along aquatic flow gradients.	Xenopoulos et al., 2005; Xenopoulos and Lodge, 2006	Hanafiah et al., 2011; Tendall et al., 2014; Dorber et al., 2019; E. Pierrat et al., 2023

Model	Name	Pressures	Realms	Description	References	Applications
SSD	Species Sensitivity Distribution	Climate change, pollution (e.g., toxic, acidifying, air, nutrient, thermal, noise, plastic)	Terrestrial, Freshwater, Marine	Models species' tolerance to environmental contaminants using dose–response curves derived from toxicity thresholds (e.g., EC50, LC50, NOEC, LOEC), providing a probabilistic estimate of the fraction of species affected.	Hamers et al., 1996; Posthuma et al., 2001; Fantke et al., 2017	Goedkoop and Spriensma, 1999; Jolliet et al., 2003; Van Zelm et al., 2007; Roy et al., 2014; Quinteiro et al., 2015; Cosme and Hauschild, 2016; M. A. J. Huijbregts et al., 2017; Verones et al., 2020; Li et al., 2022; Scherer et al., 2022; Y. Tang et al., 2022; Casagrande et al., 2024

3 Discussion

We identified contrasting differences in how biodiversity is measured and how metrics are constructed. On the one hand, some metrics assess the state of biodiversity at a given point in time (e.g. traditionally from fields such as ecology, biology, and conservation), producing indices (e.g. alpha, beta, gamma, species richness, abundance) that may or may not relate to a baseline, usually do not actively characterize anthropogenic impacts yet they have been applied to characterize impacts of land use change. On the other hand, impact-oriented metrics explicitly assess biodiversity loss due to production and consumption activities, incorporating various pressures. Given industrial ecology's focus on measuring biodiversity impacts across supply chains (e.g., LCA, EEMRIO), the field has actively developed metrics that translate and characterise anthropogenic activities as impacts on biodiversity. This has resulted in sufficient metrics to assess existing production and consumption impacts across all drivers of biodiversity loss. However, stark differences arise in what is measured, through which ecological models, and how spatio-temporal scales and biodiversity components are considered.

3.1 Biodiversity metrics gaps

Although biodiversity metrics cover many anthropogenic pressures, terrestrial and freshwater ecosystems are far larger represented, limiting the inclusion of marine biodiversity reducing its evolutionary importance. Furthermore, species richness is commonly assessed but gaps exist in how scholars report on the species used to assemble their models and species coverage, with many underrepresented groups (Figure 4).

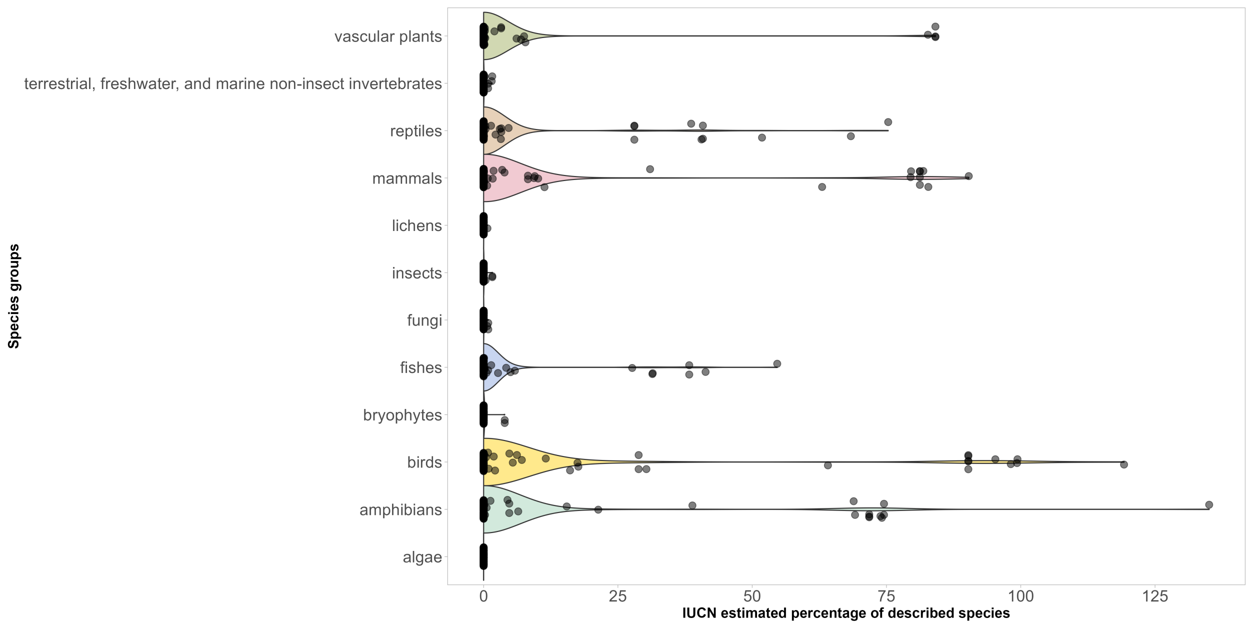

Figure 4: Percentage of species groups covered in relation to IUCN estimated percentage of described species (IUCN, 2024). Articles above 100% of described species have used subspecies.

3.1.1 Challenges in Data Availability and Harmonization

One of the most significant challenges for biodiversity metrics lies in harmonising and updating large-scale biodiversity datasets. For instance, many metrics are built at the ecoregion level using species richness data recovered from the IUCN Red List of Species (IUCN, 2024) and BirdLife International (International, 2024). Particularly for the IUCN Red List of Species, while it is an authoritative database it suffers from (i) lack of assessments for certain species groups with a large number of species (e.g., fungi, insects, vascular plants) (Bachman et al., 2019); (ii) significant delays in updating species information threat levels; and (iii) has accessibility issues (Cazalis et al., 2022, 2024).

Beyond global databases, some biodiversity metrics rely on national-level biodiversity records such as US EPA (Trottier et al., 2021) or Norwegian records (Dorber et al., 2019). However, national-level databases present additional challenges as they are limited to reported species within national jurisdictions, which might not match in name or species group classification, and accessing them may be easy only for local teams. Consequently, reliance on national databases hinders cross-regional comparisons, reducing their applicability for global biodiversity assessments.

To address some of these gaps, researchers have developed metrics using specialized biodiversity databases, such as OBIS (Ocean Biodiversity Information System) (IOC-UNESCO, 2024), WWF WildFinder (WWF, 2006), GLOBIO (Alkemade et al., 2009), and PREDICTS (Hudson et al., 2014, 2017), and while they offer focused insights, their integration into biodiversity metrics remains partial. For instance, OBIS provides extensive marine biodiversity data, but lacks species behaviour and response data, limiting its application in impact assessments. In contrast, PREDICTS and GLOBIO effectively capture species richness and abundance under specific ecosystem conditions, yet (i) are primarily focused on terrestrial ecosystems; (ii) cover only a fraction of known species per region; (iii) have significant data gaps ("blackspots") for species worldwide. Few databases comprehensively cover marine and freshwater ecosystems. Notable exceptions include GLOBIO-Aquatic (Janse et al., 2015) that incorporates pressures such as land use, flow alteration, eutrophication, and water temperature on species abundance, and Barbarossa et al. (2021) who examine climate change-induced water flow alterations. However, meta-analysis databases that integrate biodiversity responses to anthropogenic pressures across aquatic realms remain scarce, limiting the ability to align these ecosystems with existing models and metrics.

Adding to these challenges, the uneven global distribution of biodiversity data exacerbates gaps, as research is often concentrated in well-funded regions. Socio-economic factors, governance issues, and linguistic barriers further hinder biodiversity data collection and reporting (Smith et al., 2003; Christie et al., 2012; Amano & Sutherland, 2013; Turak et al., 2017; Stepping & Meijer, 2018; Hochkirch et al., 2021; Smit et al., 2022).

Overall, these limitations highlight the need for more comprehensive biodiversity databases that integrate species behaviour, ecological responses, and broader taxonomic coverage. Improving and harmonizing these datasets will enhance biodiversity impact assessments, making them more representative, globally applicable, and effective in tracking ecosystem changes.

3.1.2 Spatial-, temporal-, geographical-, gaps

Although species data remains a hurdle, other spatial, temporal, and geographically associated challenges are specific to the different pressures affecting biodiversity. For instance, terrestrial and freshwater ecosystems gaps stem from (i) the choice in land use and cover classes, (ii) the management regimes, and (iii) the ecological model choice. Particularly for terrestrial ecosystems, many methods classify land use broadly (e.g., agriculture, urban areas), while others distinguish between primary/secondary forests or intensive/extensive land use, drastically hindering the applicability and comparability of the metrics and the resulting impacts when used in biodiversity assessments (Chaudhary et al., 2015; Kuipers, May, & Verones, 2021; Scherer et al., 2023). This is further exacerbated given the inclusion or exclusion of management regimes (e.g., minimal, light, intense) across land use and cover classes **(Supporting Figure 11)**.

Another challenge stems from ecosystem recovery assumptions. Many industrial ecology metrics assume no human intervention takes place and ecosystems may or may not recover to a pristine state (de Baan et al., 2015). Meanwhile, species-targets metrics assume an active human intervention through restoration, shortening the recovery time (Irwin et al., 2022). However, research suggests that ecosystems might be better off without any active restoration unless the ecosystem is severely degraded (H. P. Jones et al., 2018). This distinction is also affected by the recovery times used for both metrics, largely differing among them, ranging from 10 to about 40 years (Curran et al., 2014; H. P. Jones et al., 2018).

Marine biodiversity metrics lag significantly behind their terrestrial and freshwater counterparts, often by more than a decade. This disparity stems from limitations in species representation, the range of pressures assessed, and the ecological models employed. Early efforts to bridge these gaps include the work of Cosme and Hauschild (2016), who compiled a dataset on species sensitivity to hypoxia, focusing on benthic, demersal, and benthopelagic species. Their subsequent model linked nitrogen pollution to its effects on marine biota, incorporating data from 91 demersal species, including fishes, crustaceans, molluscs, echinoderms, annelids, and cnidarians (Cosme & Hauschild, 2017). Similarly, Middel and Verones (2017) examined the impacts of marine noise pollution on cetaceans, while Woods et al. (2019) assessed plastic debris entanglement across 344 species (Kühn et al., 2015). Further advancing marine impact assessments, Scherer et al. (2022) included 179 species in their ocean acidification model. Despite these contributions, existing datasets capture only a fraction of marine biodiversity, covering a limited subset of the estimated 246,000 known marine species (WoRMS, 2024).

Beyond data limitations, ecological models themselves face a set of challenges. Many rely on species-level data and the regional specificity of pressures across realms, leading to inconsistencies across spatial and temporal scales. While species sensitivities, habitats, endemism, and distributions are considered (Kuipers et al., 2019; Verones et al., 2022), the metrics often assume homogeneity or linearity in species responses. Additionally, the temporal resolution of all the family metrics is similarly constrained, as they are anchored to fate models or entry datasets that define an ecosystem's baseline state at specific point in time. These reference years vary across models and are available at different resolutions, further complicating cross-study comparisons.

3.1.3 Missing biodiversity components

While existing biodiversity metrics capture certain aspects of biodiversity loss, significant gaps remain, particularly in phylogenetic, functional, genetic, and ecosystem diversity (Figure 1). Most metrics are primarily based on species richness, often neglecting evolutionary relationships, ecological roles, and genetic variability. This limitation restricts our ability to fully assess biodiversity loss and its broader ecological consequences.

Except for a few metrics on terrestrial and freshwater ecosystems that have a great species coverage for birds, amphibians, reptiles, mammals and partially vascular plants, other species groups like non-insect invertebrates, lichens, insects, fungi, fishes and bryophytes remain highly or entirely underrepresented (Figure 4. This pattern is even more pronounced in marine ecosystems, where data on fishes, algae, vascular plants, and non-insect invertebrates is scarce, fragmented, or lacks standardization, leading to their exclusion from biodiversity models. Efforts such as Chaudhary et al. (2018) have attempted to address evolutionary loss under anthropogenic pressures, but these remain limited to terrestrial ecosystems and cannot be directly linked to activity-based data for impact assessments. Similarly, de Souza et al. (2013) and Scherer et al. (2020) developed metrics based on functional diversity, focusing on species traits in birds, mammals, and plants, yet these are confined to land-use-driven changes and suffer from limited taxonomic scope.

In parallel, ecosystem-level metrics, such as those focusing on net primary productivity (NPP) (Weidema & Lindeijer, 2001; Weinzettel et al., 2019), provide insights into human-induced changes in ecosystem productivity but fail to account for species-specific contributions to productivity, thereby overlooking key aspects of ecosystem functionality. Similarly, genetic diversity, essential for population resilience and ecosystem functionality (Hughes & Stachowicz, 2004; Engelhardt et al., 2014; Salo & Gustafsson, 2016), is largely absent from current models. Species richness alone does not indicate whether populations maintain sufficient genetic variation for long-term evolutionary adaptability. Furthermore, existing evidence indicates that genetic erosion is directly attributable to anthropogenic threats on species, making species more vulnerable to environmental challenges and diseases (Shaw et al., 2025). Recent evidence from empirical and simulated data shows that anthropogenic pressures on terrestrial ecosystems first cause declines in species abundance, which in turn may lead to local extinctions. Mean Species Abundance (MSA) loss has been shown to consistently precede increases in the Potentially Disappeared Fraction of species (PDF), underscoring MSA's value as a sensitive, early-warning indicator of biodiversity change (Kuipers et al., 2025).

Emerging tools such as environmental DNA (eDNA) offer promising avenues for mapping species richness and partial abundance across terrestrial, freshwater, and marine ecosystems (Carraro et al., 2018; Beng & Corlett, 2020; Jo, 2023; Granqvist et al., 2025). However, these data are still nascent and absent from biodiversity models. Consequently, the absence of a multi-dimensional approach - incorporating phylogenetic, functional, genetic, and ecosystem diversity - limits our ability to fully assess biodiversity loss and its long-term ecological and evolutionary consequences (Burgess et al., 2024). Addressing these gaps is critical for developing more comprehensive, policy-relevant or corporate-private biodiversity assessments.

3.2 Biodiversity frontiers

We identified biodiversity frontiers on five fronts: (i) expanding taxonomic inclusion in ecological models, (ii) developing novel methods that account for the different levels and components of biodiversity across individual and cross-sectional realms, (iii) the inclusion and refinement of more and existing impact pathways to capture the full range of anthropogenic pressures, (iv) the integration of metrics with concepts of ecological carrying capacity, tipping points, stress, scarcity and thresholds, and (v) shifting from stand-alone indicators toward multi-metric approaches to communicate differentiated biodiversity impacts.

First, while biodiversity metrics have moved beyond simple species proxies to incorporate broader taxonomic groups—such as vascular plants, mammals, reptiles, amphibians, and birds in terrestrial ecosystems—many known species remain underrepresented (Figure 4). This gap is particularly stark in freshwater and marine ecosystems, where many taxa are missing. Future efforts should focus on including species with similar traits or functional dependencies across trophic levels to enhance ecological representation.

Second, although some biodiversity metrics for terrestrial ecosystems integrate functional traits of birds, mammals, and plants, their application remains largely geographically constrained. For instance, de Souza et al. (2013) focused on North America, while Scherer et al. (2020) refined plant trait assessments primarily for Europe. The recent study by Rosa et al. (2025) further highlights how land-use change alters plant functional diversity, showing that anthropogenic landscapes tend to reduce functional richness and divergence while increasing functional evenness. Their findings suggest that land-use modifications lead to functional homogenization, where dominant species in human-modified environments exhibit narrower trait distributions compared to those in natural habitats. Given advances in data availability, computational power, and novel tools like artificial intelligence filling these gaps by extrapolating species traits based on ecological similarities, enables a more comprehensive integration of functional diversity across all ecosystems. Expanding these approached beyond vascular plants and terrestrial ecosystems remains a key frontier for biodiversity metrics.

Third, biodiversity is affected by individual and multiple interacting stressors, particularly those linked to climate change. For instance, rising anthropogenic greenhouse gasses alter precipitation patterns, increase streamflow variability and water temperature (Kernan et al., 2010; Poff, 2018; Barbarossa et al., 2021). Furthermore, climate change also contributes to extreme sudden events such as floods, hurricanes, and heatwaves that cause an additional burden on biodiversity, increasing extinction risks (Teixidó et al., 2013; Liu et al., 2015; Sintayehu, 2018; Maxwell et al., 2019; Smale et al., 2019; Román-Palacios & Wiens, 2020; Trisos et al., 2020; Manes et al., 2021; Zhang et al., 2021; Sabater et al., 2023). Frontiers methods incorporate spatially explicit assessments of precipitation shifts and water flow alterations (Li et al., 2022), evaluate extinction risks driven by climate change in freshwater ecosystems (De Visser et al., 2023) , and model species-specific responses to temperature fluctuations induced by rising GHG emissions in terrestrial and marine environments (C.-M. Iordan et al., 2023).

Fourth, biodiversity metrics must integrate Earth system processes to identify thresholds where ecosystems transition from stability to decline (Mace et al., 2014; Steffen et al., 2015). This requires linking biodiversity assessments to ecological carrying capacities and tipping points, beyond which ecosystems may experience irreversible damage (Odum, 1971; Carpenter et al., 2001; Sayre, 2008; Bjørn & Hauschild, 2015). Notable advancements include Fabbri et al. (2022), who developed a metric assessing how GHG emissions contribute to surpassing tipping points in biodiversity loss, and É. Pierrat et al. (2023), who incorporated water stress and pollution thresholds to evaluate the combined impacts of multiple pressures on ecosystem resilience.

Finally, future research should prioritize the integration of multiple biodiversity metrics rather than relying on stand-alone indicators. A more comprehensive approach, combining species-based assessments, ecosystem functioning metrics, and climate-related stressors, would provide a clearer picture of how biodiversity is affected across scales and regions. Recent work by Rabeschini et al. (2025) illustrates that applying multiple, methodologically diverse indicators to the same system can reveal distinct yet complementary insights into biodiversity loss and its drivers. Such integration helps disentangle the relative influence of indicator design, input data, and spatial–temporal scale in shaping assessments. Addressing these frontiers will be essential for developing more robust, policy-relevant biodiversity assessments that effectively guide conservation and sustainability efforts.

4 Conslusion

Our review reveals that although significant advances have been made in quantifying the biodiversity impacts of human production and consumption, important challenges remain. Biodiversity footprinting metrics have diversified over the past two decades, moving from simple assessments limited in scope to land use and vascular plants as proxies for biodiversity, towards broader frameworks capturing climate change, pollution and invasive species. Nevertheless, no single metric or family of metrics comprehensively captures the full multidimensional nature of biodiversity, spanning genes, species, and ecosystems.

While industrial ecology, and its modelling tools such as LCA and EEMRIO, has been largely dominated by area-related and cause-effect impact assessment metrics, state-based, pressure-impact and theoretical ecology metrics remain essential for capturing the structure and functioning of ecosystems. Despite a convergence around certain mechanistic ecological models—such as species–area relationships, species discharge relationships, and species sensitivity distributions—there remains a fragmentation across scales, taxa, and environmental pressures under assessment. Marine and freshwater biodiversity, functional and phylogenetic diversity, and complex multiple-pressure pathways remain especially underrepresented.

Looking ahead, advancing biodiversity metrics requires deeper interdisciplinary integration between conservation biology, ecology, and industrial ecology. Expanding taxonomic coverage, enhancing existing biodiversity databases, improving pressure-specific impact modelling, incorporating spatial and temporal dynamics, and linking with ecological thresholds and planetary boundaries are crucial frontiers. Equally important is harmonizing footprinting efforts with emerging policy and corporate frameworks aimed at halting and reversing biodiversity loss.

Moving away from single indicators, while developing a next generation of complementary multi-faceted biodiversity metrics, globally representative, aligned with policy- and corporate relevant efforts, will be essential for effectively accounting for impacts of production and consumption on biodiversity.

5 Methods

5.1 Study design

Scoping reviews are suitable for studying topics spanning scientific disciplines and have yet to be reviewed in a detailed and structured manner, so that research gaps can be identified. We followed and adapted the checklist from PRISMA Extension for Scoping Reviews (PRISMA-ScR) (Tricco et al., 2018) and the Reporting Standards for Systematic Evidence Syntheses (ROSES) for Systematic Map Reports (Haddaway et al., 2017) (see Supporting Figure 1). Searches were conducted in April 2023 and retested in January 2024 using OpenAlex (Priem et al., 2022) and PyAlex (De Bruin, 2023). OpenAlex is an open-access bibliographic catalogue of scientific research including more than 250 million scholarly works. We decided on this database as it has been proven to show a good degree of scholarly records coverage, with their corresponding metadata, compared to databases behind a paywall (e.g., Scopus, Web of Science) and search engines (e.g. Google Scholar, Semantic Scholar) (Culbert et al., 2024; Delgado-Quirós & Ortega, 2024). Using Natural Language Processing and the cosine similarity index, combined with a set of benchmark articles (see Supporting Table 1), we reduced the retrieved OpenAlex corpus to titles and abstracts, which were further screened according to the eligibility criteria (see Supporting Table 2). Additionally, we included opportunistic peer-reviewed articles published while assembling this manuscript and grey literature on biodiversity metrics assessed as part of significant reviews not captured by our search terms, OpenAlex, or our methodology (see Supporting Table 1). An initial consistency check was performed independently on 50% of the benchmark articles to control for selection bias across all researchers. Once potential divergences were clarified, one researcher (DIAO) screened the reduced trained corpus on a title and abstract basis and further analysed the full text for their inclusion or exclusion.

5.2 Eligibility criteria

We included articles that assessed different biodiversity components (e.g. phylogenetic, functional, and taxonomic) at various levels (e.g. genes, species, and ecosystems). No geographic limitations were imposed for research origins or level of assessment (e.g. global, national, regional, or local). The inclusion/exclusion decisions were based on an eligibility criteria matrix (see Supporting Table 2) and reported at each screening stage (title, abstract, and full text). While this is not mandatory by the PRISMA Protocol for Scoping Reviews, it is recommended by the Collaboration for Environmental Evidence (CEE) methodological steps for systematic maps in the CEE Guidelines and Standards for Evidence Synthesis v5.1 (CEE, 2022). Primarily, we have included articles - excluding books, chapters, proceedings, editorials, etc.–only in English with quantitative results or oriented towards quantitative metrics to assess biodiversity. Direct and indirect impacts of anthropogenic activities on biodiversity have been considered in the terrestrial, marine, and freshwater realms.

5.3 Search strategy and data charting process

As a search strategy, we compiled a set of 60 articles known to be relevant to the authors, which were classified as benchmarks (see Supporting Table 1). Through iterations in the OpenAlex web interface (Priem et al., 2022), we used a single search term that captured the benchmark articles (see Table 3). We reduced our search period from 1990 to 2022. Once the articles were filtered in OpenAlex's database, they were downloaded using PyAlex (De Bruin, 2023). In Python v3.7.12, we first removed (1) all retracted articles, (2) not in English, (3) not articles (e.g. editorial, dataset, report, book, letter, etc.), (4) articles that were missing references, (5) duplicated records, and (6) articles without a DOI. It followed title and abstract screening that was done using Natural Language Processing (NLP) with text vectorisation through Term Frequency–Inverse Document Frequency (TF-IDF) (K. S. Jones, 1972; Robertson, 2004; Rajaraman & Ullman, 2011) and the cosine similarity (CS) (Singhal, 2001). First, the TF-IDF model was trained with the benchmark article titles applied to the corpus titles, setting a threshold above 15% for CS. For articles with missing abstracts, we filtered 1,000 for abstract extraction through different tools and packages, such as (1) citationchaser (Haddaway et al., 2022) and (2) crossref-commons (Tkaczyk, 2020) without success. Hence, we manually recovered all the possible abstracts. We trained a second TF-IDF exclusively on the benchmark abstracts used in the remaining articles, setting a threshold above 13% for CS. Finally, we screened the full-text articles and selected only those relevant to our scoping review. We implemented our methodology using dask v2022.2.0 (Rocklin, 2015; Dask Development Team, 2016), pandas v1.3.5 (McKinney, 2010; The pandas development team, 2020), numpy v1.21.6 (Harris et al., 2020), nltk v3.8.1 (Bird et al., 2009), and sklearn v1.0.2 (Pedregosa et al., 2011) packages. All our codes are available on a GitHub repository.

Table 3: Scoping review search term.

Database	Search term	Search hits	Date range
OpenAlex	biodiversity AND (lca OR lcia OR mrio OR eeioa OR 'life cycle' OR 'life-cycle' or 'life cycle assessment' OR impact) OR (production OR consumption)	1,186,600	1990 – 2022

Some of the reviewed biodiversity metrics were not captured by the search term in OpenAlex, particularly those from gray literature or outside the direct scope of production and consumption. Based on the reviews recovered from our search terms and the set of opportunistic articles (see Supporting Table 1), we used backward and forward citations to recover and include missing articles.

Our coding strategy consisted of retrieving all information from a standardised data extraction document based on identified and defined categories (see Supporting Table 3). Based on the benchmark articles, we identified commonalities across biodiversity metrics. However, when selecting articles to test the defined categories, we observed differences in how researchers reported their methods and study cases. Hence, we used a combined deductive and inductive approach to recover all information of interest. The coding of all articles was undertaken by one reviewer (DIAO), and whenever an article seemed trivial or challenging to code, the rest of the co-authors intervened for validation. Finally, no critical appraisal was done per PRISMA Protocol guidelines (Tricco et al., 2018). Our scoping review process and methods are summarised in Supporting Figure 1, which shows a combination of the PRISMA and ROSES flow charts.

Author Contributions

Daniel Itzamna Avila-Ortega: Conceptualization, Formal analysis, Methodology, Project administration, Data curation, Visualization, Writing – original draft, Writing – review & editing. *Peter Søgaard Jørgensen:* Conceptualization, Supervision, Writing – review & editing. *Sarah Cornell:* Conceptualization, Supervision, Writing – review & editing. *Daniel Moran:* Writing – review & editing. *Gustav Engström:* Writing – review & editing.

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Conflicts of Interest Declarations

D.I.A.O. is a Fellow of the Business and Biodiversity Assessment from IPBES. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

Data and codes product of this article are available on the following repository: . An interactive website: .

Declaration of AI use

We have used AI-assisted technologies for spell checking and code checking.

References

Arrhenius, O. (1921). Species and Area. *The Journal of Ecology*, *9*(1), 95. https://doi.org/10.2307/2255763

MacArthur, R. H., & Wilson, E. O. (1967). *The Theory of Island Biogeography*. Princeton University Press.

Odum, E. P. (1971). Fundamentals of ecology. *Printing Company Ltd*.

Jones, K. S. (1972). A Statistical Interpretation of Term Specificity and its Application in Retrieval. *Journal of Documentation*, *28*(1), 11–21.

CBD. (1992, May). Convention on Biological Diversity : Text and annexes / Secretariat of the Convention on Biological Diversity.

Consoli, F., Allen, D., Boustead, I., Fava, J., Franklin, W., Jensen, A. A., de Oude, N., Parrish, R., Perriman, R., Postlethwaite, D., Quay, B., Séguin, J., & Vigon, B. (1993, August). *Guidelines for Life-Cycle Assessment: A "Code of Practice"* (tech. rep.). Society of Environmental Toxicology and Chemistry (SETAC). Sesimbra, Portugal.

Myers, N., & Simon, J. L. (1994). *Scarcity or abundance? a debate on the environment*. W. W. Norton & Company.

Rosenzweig, M. L. (1995). *Species Diversity in Space and Time*. Cambridge University Press. https://doi.org/10.1017/CBO9780511623387

Hamers, T., Aldenberg, T., & van de Meent, D. (1996, March). *Definition Report -Indicator Effects Toxic Substances (Itox).* (RIVM Rapport No. 607128001). RIVM. Bilthoven, The Netherlands.

Hornborg, A. (1998). Towards an ecological theory of unequal exchange: Articulating world system theory and ecological economics. *Ecological Economics*, *25*(1), 127–136. https://doi.org/10.1016/S0921-8009(97)00100-6

Loh, J., Randers, J., MacGillivray, A., Kapos, V., Groombridge, B., & Jenkins, M. (1998). *Living Planet Report: 1998* (tech. rep.). WWF. Gland, Switzerland.

Goedkoop, M., & Spriensma, R. (1999). *The Eco-Indicator 99: A Damage Oriented Method for Life Cycle Impact Assessment. Methodology Report* (tech. rep. No. 1999/36A). PRé Consultants B.V. Amersfoort, the Netherlands.

Hanski, I., & Ovaskainen, O. (2000). The metapopulation capacity of a fragmented landscape. *Nature*, *404*(6779), 755–758. https://doi.org/10.1038/35008063

Köllner, T. (2000). Species-pool effect potentials (SPEP) as a yardstick to evaluate land-use impacts on biodiversity. *Journal of Cleaner Production*, *8*(4), 293–311. https://doi.org/10.1016/S0959-6526(00)00026-3

Carpenter, S., Walker, B., Anderies, J. M., & Abel, N. (2001). From Metaphor to Measurement: Resilience of What to What? *Ecosystems*, *4*(8), 765–781. https://doi.org/10.1007/s10021-001-0045-9

Guinée, J. B., Heijungs, R., Huppes, G., Kleijn, R., de Koning, A., van Oers, L., Wegener Sleeswijk, A., Suh, S., Udo de Haes, H. a., de Bruijn, H., van Duin, R., Huijbregts, M. a. J., & Gorrée, M. (2001). *Life cycle assessment: An operational guide to the iso standards. part 1, lca in perspective* (tech. rep.). Maastricht, The Netherlands. https://doi.org/10.1007/BF02978784

Posthuma, L., Suter Ii, G. W., & Traas, T. P. (Eds.). (2001, December). *Species Sensitivity Distributions in Ecotoxicology* (0th ed.). CRC Press. https://doi.org/10.1201/9781420032314

Singhal, A. (2001). Modern Information Retrieval: A Brief Overview. *Bulletin of the IEEE Computer Society Technical Committee on Data Engineering*, *24*(4), 35–43.

Weidema, B. P., & Lindeijer, E. (2001, December). *Physical impacts of land use in product life cycle assessment* (tech. rep. No. IPL-033-01). Department of Manufacturing Engineering and Management. Technical University of Denmark.

Brentrup, F., Küsters, J., Lammel, J., & Kuhlmann, H. (2002). Life Cycle Impact assessment of land use based on the hemeroby concept. *The International Journal of Life Cycle Assessment*, *7*(6), 339. https://doi.org/10.1007/BF02978681

Sanderson, E. W., Jaiteh, M., Levy, M. A., Redford, K. H., Wannebo, A. V., & Woolmer, G. (2002). The Human Footprint and the Last of the Wild. *BioScience*, *52*(10), 891. https://doi.org/10.1641/0006-3568(2002)052[0891:THFATL]2.0.CO;2

Jolliet, O., Margni, M., Charles, R., Humbert, S., Payet, J., Rebitzer, G., & Rosenbaum, R. (2003). IMPACT 2002+: A new life cycle impact assessment methodology. *The International Journal of Life Cycle Assessment*, *8*(6), 324. https://doi.org/10.1007/BF02978505

Smith, R. J., Muir, R. D. J., Walpole, M. J., Balmford, A., & Leader-Williams, N. (2003). Governance and the loss of biodiversity. *Nature*, *426*(6962), 67–70. https://doi.org/10.1038/nature02025

Hughes, A. R., & Stachowicz, J. J. (2004). Genetic diversity enhances the resistance of a seagrass ecosystem to disturbance. *Proceedings of the National Academy of Sciences*, *101*(24), 8998–9002. https://doi.org/10.1073/pnas.0402642101

Pennington, D. W., Potting, J., Finnveden, G., Lindeijer, E., Jolliet, O., Rydberg, T., & Rebitzer, G. (2004). Life cycle assessment part 2: Current impact assessment practice. *Environment International*, *30*(5), 721–739. https://doi.org/10.1016/j.envint.2003.12.009

Rebitzer, G., Ekvall, T., Frischknecht, R., Hunkeler, D., Norris, G., Rydberg, T., Schmidt, W.-P., Suh, S., Weidema, B. P., & Pennington, D. W. (2004). Life cycle assessment part 1: Framework, goal and scope definition, inventory analysis, and applications. *Environment International*, *30*(5), 701–720. https://doi.org/10.1016/j.envint.2003.11.005

Robertson, S. (2004). Understanding inverse document frequency: On theoretical arguments for IDF. *Journal of Documentation*, *60*(5), 503–520. https://doi.org/10.1108/00220410410560582

Vogtländer, J. G., Lindeijer, E., Witte, J.-P. M., & Hendriks, C. (2004). Characterizing the change of land-use based on flora: Application for EIA and LCA. *Journal of Cleaner Production*, *12*(1), 47–57. https://doi.org/10.1016/S0959-6526(02)00022-7

Biggs, R., & Scholes, R. J. (2005). A biodiversity intactness index. *Nature*, *434*(7029), 45–49. https://doi.org/10.1038/nature03289

Hauschild, M. Z. (2005). Assessing environmental impacts in a life-cycle perspective. *Environmental Science & Technology*, *39*(4), 81A–88A. https://doi.org/10.1021/es053190s

Loh, J., Green, R. E., Ricketts, T., Lamoreux, J., Jenkins, M., Kapos, V., & Randers, J. (2005). The Living Planet Index: Using species population time series to track trends in biodiversity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1454), 289–295. https://doi.org/10.1098/rstb.2004.1584

Xenopoulos, M. A., Lodge, D. M., Alcamo, J., Märker, M., Schulze, K., & Van Vuuren, D. P. (2005). Scenarios of freshwater fish extinctions from climate change and water withdrawal. *Global Change Biology*, *11*(10), 1557–1564. https://doi.org/10.1111/j.1365-2486.2005.001008.x

Pereira, H. M., & Daily, G. C. (2006). Modeling biodiversity dynamics in countryside landscapes. *Ecology*, *87*(8), 1877–1885. https://doi.org/10.1890/0012-9658(2006)87[1877:MBDICL]2.0.CO;2

WWF. (2006). WildFinder: Online database of species distributions.

Xenopoulos, M. A., & Lodge, D. M. (2006). GOING WITH THE FLOW: USING SPECIES–DISCHARGE RELATIONSHIPS TO FORECAST LOSSES IN FISH BIODIVERSITY. *Ecology*, *87*(8).

Haberl, H., Erb, K. H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., Gingrich, S., Lucht, W., & Fischer-Kowalski, M. (2007). Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. *Proceedings of the National Academy of Sciences*, *104*(31), 12942–12947. https://doi.org/10.1073/pnas.0704243104

Van Zelm, R., Huijbregts, M. A. J., Van Jaarsveld, H. A., Reinds, G. J., De Zwart, D., Struijs, J., & Van De Meent, D. (2007). Time Horizon Dependent Characterization Factors for Acidification in Life-Cycle Assessment Based on Forest Plant Species Occurrence in Europe. *Environmental Science & Technology*, *41*(3), 922–927. https://doi.org/10.1021/es061433q

Koellner, T., & Scholz, R. W. (2008). Assessment of land use impacts on the natural environment: Part 2: Generic characterization factors for local species diversity in Central Europe. *The International Journal of Life Cycle Assessment*, *13*(1), 32–48. https://doi.org/10.1065/lca2006.12.292.2

Sayre, N. F. (2008). The Genesis, History, and Limits of Carrying Capacity. *Annals of the Association of American Geographers*, *98*(1), 120–134. https://doi.org/10.1080/00045600701734356

Schmidt, J. H. (2008). Development of LCIA characterisation factors for land use impacts on biodiversity. *Journal of Cleaner Production*, *16*(18), 1929–1942. https://doi.org/10.1016/j.jclepro.2008.01.004

Alkemade, R., van Oorschot, M., Miles, L., Nellemann, C., Bakkenes, M., & ten Brink, B. (2009). GLOBIO3: A Framework to Investigate Options for Reducing Global Terrestrial Biodiversity Loss. *Ecosystems*, *12*(3), 374–390. https://doi.org/10.1007/s10021-009-9229-5

Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with Python: Analyzing text with the natural language toolkit*. " O'Reilly Media, Inc.".

De Schryver, A. M., Brakkee, K. W., Goedkoop, M. J., & Huijbregts, M. A. J. (2009). Characterization Factors for Global Warming in Life Cycle Assessment Based on Damages to Humans and Ecosystems. *Environmental Science & Technology*, *43*(6), 1689–1695. https://doi.org/10.1021/es800456m

Erb, K.-H., Krausmann, F., Lucht, W., & Haberl, H. (2009). Embodied HANPP: Mapping the spatial disconnect between global biomass production and consumption. *Ecological Economics*, *69*, 328–334. https://doi.org/10.1016/j.ecolecon.2009.06.025

Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., Koehler, A., Pennington, D., & Suh, S. (2009). Recent developments in life cycle assessment. *Journal of Environmental Management*, *91*(1), 1–21. https://doi.org/10.1016/j.jenvman.2009.06.018

Goedkoop, M., Heijungs, R., Huijbregts, M., De Schryver, A., Struijs, J., & van Zelm, R. (2009). *ReCiPe 2008. A life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level. First edition. Report I: Characterisation* (tech. rep.). Ruimte en Milieu. Ministerie van Volkshuisvesting, Ruimtelijke Ordening en Milieubeheer. Den Haag, The Netherlands.

Haberl, H., Erb, K.-H., Krausmann, F., Berecz, S., Ludwiczek, N., Martínez-Alier, J., Musel, A., & Schaffartzik, A. (2009). Using embodied HANPP to analyze teleconnections in the global land system: Conceptual considerations. *Geografisk Tidsskrift-Danish Journal of Geography*, *109*(2), 119–130. https://doi.org/10.1080/00167223.2009.10649602

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., de Wit, C. A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., ... Foley, J. A. (2009). A safe operating space for humanity. *Nature*, *461*(7263), 472–475. https://doi.org/10.1038/461472a

De Schryver, A. M., Goedkoop, M. J., Leuven, R. S. E. W., & Huijbregts, M. A. J. (2010). Uncertainties in the application of the species area relationship for characterisation factors of land occupation in life cycle assessment. *The International Journal of Life Cycle Assessment*, *15*(7), 682–691. https://doi.org/10.1007/s11367-010-0205-2

Gandhi, N., Diamond, M. L., Van De Meent, D., Huijbregts, M. A. J., Peijnenburg, W. J. G. M., & Guinée, J. (2010). New Method for Calculating Comparative Toxicity Potential of Cationic Metals in Freshwater: Application to Copper, Nickel, and Zinc. *Environmental Science & Technology*, *44*(13), 5195–5201. https://doi.org/10.1021/es903317a

Geyer, R., Lindner, J. P., Stoms, D. M., Davis, F. W., & Wittstock, B. (2010). Coupling GIS and LCA for biodiversity assessments of land use: Part 2: Impact assessment. *The International Journal of Life Cycle Assessment*, *15*(7), 692–703. https://doi.org/10.1007/s11367-010-0199-9

Kernan, M., Battarbee, R. W., & Moss, B. (Eds.). (2010, September). *Climate Change Impacts on Freshwater Ecosystems* (1st ed.). Wiley. https://doi.org/10.1002/9781444327397

Koh, L. P., Lee, T. M., Sodhi, N. S., & Ghazoul, J. (2010). An overhaul of the species-area approach for predicting biodiversity loss: Incorporating matrix and edge effects: Overhaul of the species-area approach. *Journal of Applied Ecology*, *47*(5), 1063–1070. https://doi.org/10.1111/j.1365-2664.2010.01860.x

McKinney, W. (2010). Data Structures for Statistical Computing in Python. In S. van der Walt & J. Millman (Eds.), *Proceedings of the 9th Python in Science Conference* (pp. 56–61). https://doi.org/10.25080/Majora-92bf1922-00a

Hanafiah, M. M., Xenopoulos, M. A., Pfister, S., Leuven, R. S. E. W., & Huijbregts, M. A. J. (2011). Characterization Factors for Water Consumption and Greenhouse Gas Emissions Based on Freshwater Fish Species Extinction. *Environmental Science & Technology*, *45*(12), 5272–5278. https://doi.org/10.1021/es1039634

Kastner, T., Kastner, M., & Nonhebel, S. (2011). Tracing distant environmental impacts of agricultural products from a consumer perspective. *Ecological Economics*, *70*(6), 1032–1040. https://doi.org/10.1016/j.ecolecon.2011.01.012

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Rajaraman, A., & Ullman, J. D. (2011, October). Data Mining. In *Mining of Massive Datasets* (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9781139058452

Saura, S., Estreguil, C., Mouton, C., & Rodríguez-Freire, M. (2011). Network analysis to assess landscape connectivity trends: Application to European forests (1990–2000). *Ecological Indicators*, *11*(2), 407–416. https://doi.org/10.1016/j.ecolind.2010.06.011

Struijs, J., Beusen, A., De Zwart, D., & Huijbregts, M. (2011). Characterization factors for inland water eutrophication at the damage level in life cycle impact assessment. *The International Journal of Life Cycle Assessment*, *16*(1), 59–64. https://doi.org/10.1007/s11367-010-0232-z

Christie, M., Fazey, I., Cooper, R., Hyde, T., & Kenter, J. O. (2012). An evaluation of monetary and non-monetary techniques for assessing the importance of biodiversity and ecosystem services to people in countries with developing economies. *Ecological Economics*, *83*, 67–78. https://doi.org/10.1016/j.ecolecon.2012.08.012

Haberl, H., Kastner, T., Schaffartzik, A., Ludwiczek, N., & Erb, K.-H. (2012). Global effects of national biomass production and consumption: Austria's embodied HANPP related to agricultural biomass in the year 2000. *Ecological Economics*, *84*, 66–73. https://doi.org/10.1016/j.ecolecon.2012.09.014

Hanafiah, M. M., Hendriks, A. J., & Huijbregts, M. A. (2012). Comparing the ecological footprint with the biodiversity footprint of products. *Journal of Cleaner Production*, *37*, 107–114. https://doi.org/10.1016/j.jclepro.2012.06.016

Helmes, R. J. K., Huijbregts, M. A. J., Henderson, A. D., & Jolliet, O. (2012). Spatially explicit fate factors of phosphorous emissions to freshwater at the global scale. *The International Journal of Life Cycle Assessment*, *17*(5), 646–654. https://doi.org/10.1007/s11367-012-0382-2

Lenzen, M., Moran, D., Kanemoto, K., Foran, B., Lobefaro, L., & Geschke, A. (2012). International trade drives biodiversity threats in developing nations. *Nature*, *486*(7401), 109–112. https://doi.org/10.1038/nature11145

Mattila, T., Helin, T., & Antikainen, R. (2012). Land use indicators in life cycle assessment: A case study on beer production. *The International Journal of Life Cycle Assessment*, *17*(3), 277–286. https://doi.org/10.1007/s11367-011-0353-z

Amano, T., & Sutherland, W. J. (2013). Four barriers to the global understanding of biodiversity conservation: Wealth, language, geographical location and security. *Proceedings of the Royal Society B: Biological Sciences*, *280*(1756), 20122649. https://doi.org/10.1098/rspb.2012.2649

de Baan, L., Alkemade, R., & Koellner, T. (2013). Land use impacts on biodiversity in LCA: A global approach. *The International Journal of Life Cycle Assessment*, *18*(6), 1216–1230. https://doi.org/10.1007/s11367-012-0412-0

de Baan, L., Mutel, C. L., Curran, M., Hellweg, S., & Koellner, T. (2013). Land Use in Life Cycle Assessment: Global Characterization Factors Based on Regional and Global Potential Species Extinction. *Environmental Science and Technology*, *47*(16), 9281–9290. https://doi.org/10.1021/ES400592Q

de Souza, D. M., Flynn, D. F. B., DeClerck, F., Rosenbaum, R. K., de Melo Lisboa, H., & Koellner, T. (2013). Land use impacts on biodiversity in LCA: Proposal of characterization factors based on functional diversity. *The International Journal of Life Cycle Assessment*, *18*(6), 1231–1242. https://doi.org/10.1007/S11367-013-0578-0

Hanafiah, M. M., Leuven, R. S. E. W., Sommerwerk, N., Tockner, K., & Huijbregts, M. A. J. (2013). Including the Introduction of Exotic Species in Life Cycle Impact Assessment: The Case of Inland Shipping. *Environmental Science & Technology*, *47*(24), 13934–13940. https://doi.org/10.1021/es403870z

Hanski, I., Zurita, G. A., Bellocq, M. I., & Rybicki, J. (2013). Species–fragmented area relationship. *Proceedings of the National Academy of Sciences*, *110*(31), 12715–12720. https://doi.org/10.1073/pnas.1311491110

Liu, J., Hull, V., Batistella, M., Defries, R., Dietz, T., Fu, F., Hertel, T. W., Izaurralde, R. C., Lambin, E. F., Li, S., Martinelli, L. A., Mcconnell, W. J., Moran, E. F., Naylor, R., Ouyang, Z., Polenske, K. R., Reenberg, A., De, G., Simmons, C. S., ... Zhu, C. (2013). Framing sustainability in a telecoupled world. *Ecology and Society*, *18*(2), 26. https://doi.org/10.5751/ES-05873-180226

Teixidó, N., Casas, E., Cebrián, E., Linares, C., & Garrabou, J. (2013). Impacts on Coralligenous Outcrop Biodiversity of a Dramatic Coastal Storm (S. Thrush, Ed.). *PLoS ONE*, *8*(1), e53742. https://doi.org/10.1371/journal.pone.0053742

Curran, M., Hellweg, S., & Beck, J. (2014). Is there any empirical support for biodiversity offset policy? *Ecological Applications*, *24*(4), 617–632. https://doi.org/10.1890/13-0243.1

Emanuelsson, A., Ziegler, F., Pihl, L., Sköld, M., & Sonesson, U. (2014). Accounting for overfishing in life cycle assessment: New impact categories for biotic resource use. *The International Journal of Life Cycle Assessment*, *19*(5), 1156–1168. https://doi.org/10.1007/s11367-013-0684-z

Engelhardt, K. A., Lloyd, M. W., & Neel, M. C. (2014). Effects of genetic diversity on conservation and restoration potential at individual, population, and regional scales. *Biological Conservation*, *179*, 6–16. https://doi.org/10.1016/j.biocon.2014.08.011

Galli, A., Wackernagel, M., Iha, K., & Lazarus, E. (2014). Ecological footprint: Implications for biodiversity. *Biological Conservation*, *173*, 121–132. https://doi.org/10.1016/j.biocon.2013.10.019

Hudson, L. N., Newbold, T., Contu, S., Hill, S. L. L., Lysenko, I., De Palma, A., Phillips, H. R. P., Senior, R. A., Bennett, D. J., Booth, H., Choimes, A., Correia, D. L. P., Day, J., Echeverría-Londoño, S., Garon, M., Harrison, M. L. K., Ingram, D. J., Jung, M., Kemp, V., ... Purvis, A. (2014). The PREDICTS database: A global database of how local terrestrial biodiversity responds to human impacts. *Ecology and Evolution*, *4*(24), 4701–4735. https://doi.org/10.1002/ece3.1303

Jeanneret, P., Baumgartner, D. U., Freiermuth Knuchel, R., Koch, B., & Gaillard, G. (2014). An expert system for integrating biodiversity into agricultural life-cycle assessment. *Ecological Indicators*, *46*, 224–231. https://doi.org/10.1016/j.ecolind.2014.06.030

Mace, G. M., Reyers, B., Alkemade, R., Biggs, R., Chapin, F. S., Cornell, S. E., Díaz, S., Jennings, S., Leadley, P., Mumby, P. J., Purvis, A., Scholes, R. J., Seddon, A. W., Solan, M., Steffen, W., & Woodward, G. (2014). Approaches to defining a planetary boundary for biodiversity. *Global Environmental Change*, *28*, 289–297. https://doi.org/10.1016/j.gloenvcha.2014.07.009

Pereira, H. M., Ziv, G., & Miranda, M. (2014). Countryside Species–Area Relationship as a Valid Alternative to the Matrix-Calibrated Species–Area Model. *Conservation Biology*, *28*(3), 874–876. https://doi.org/10.1111/cobi.12289

Roy, P.-O., Azevedo, L. B., Margni, M., Van Zelm, R., Deschênes, L., & Huijbregts, M. A. (2014). Characterization factors for terrestrial acidification at the global scale: A systematic analysis of spatial variability and uncertainty. *Science of The Total Environment*, *500–501*, 270–276. https://doi.org/10.1016/j.scitotenv.2014.08.099

Tendall, D. M., Hellweg, S., Pfister, S., Huijbregts, M. A. J., & Gaillard, G. (2014). Impacts of River Water Consumption on Aquatic Biodiversity in Life Cycle Assessment—A Proposed Method, and a Case Study for Europe. *Environmental Science & Technology*, *48*(6), 3236–3244. https://doi.org/10.1021/es4048686

Bjørn, A., & Hauschild, M. Z. (2015). Introducing carrying capacity-based normalisation in LCA: Framework and development of references at midpoint level. *The International Journal of Life Cycle Assessment*, *20*(7), 1005–1018. https://doi.org/10.1007/s11367-015-0899-2

Chaudhary, A., Verones, F., de Baan, L., & Hellweg, S. (2015). Quantifying Land Use Impacts on Biodiversity: Combining Species–Area Models and Vulnerability Indicators. *Environmental Science and Technology*, *49*(16), 9987–9995. https://doi.org/10.1021/ACS.EST.5B02507

Cosme, N., Koski, M., & Hauschild, M. Z. (2015). Exposure factors for marine eutrophication impacts assessment based on a mechanistic biological model. *Ecological Modelling*, *317*, 50–63. https://doi.org/10.1016/j.ecolmodel.2015.09.005

de Baan, L., Curran, M., Rondinini, C., Visconti, P., Hellweg, S., & Koellner, T. (2015). High-Resolution Assessment of Land Use Impacts on Biodiversity in Life Cycle Assessment Using Species Habitat Suitability Models. *Environmental Science & Technology*, *49*(4), 2237–2244. https://doi.org/10.1021/es504380t

Janse, J., Kuiper, J., Weijters, M., Westerbeek, E., Jeuken, M., Bakkenes, M., Alkemade, R., Mooij, W., & Verhoeven, J. (2015). GLOBIO-Aquatic, a global model of human impact on the biodiversity of inland aquatic ecosystems. *Environmental Science & Policy*, *48*, 99–114. https://doi.org/10.1016/j.envsci.2014.12.007

Kühn, S., Bravo Rebolledo, E. L., & Van Franeker, J. A. (2015). Deleterious Effects of Litter on Marine Life. In M. Bergmann, L. Gutow, & M. Klages (Eds.), *Marine Anthropogenic Litter* (pp. 75–116). Springer International Publishing. https://doi.org/10.1007/978-3-319-16510-3_4

Langlois, J., Fréon, P., Steyer, J.-P., Delgenès, J.-P., & Hélias, A. (2015). Sea use impact category in life cycle assessment: Characterization factors for life support functions. *The International Journal of Life Cycle Assessment*, *20*(7), 970–981. https://doi.org/10.1007/s11367-015-0886-7

Lee, S.-J., Hawkins, T. R., Ingwersen, W. W., & Young, D. M. (2015). Exploring the Use of Ecological Footprint in Life Cycle Impact Assessment: Findings from a Comparison of Transportation Fuels. *Journal of Industrial Ecology*, *19*(3), 416–426. https://doi.org/10.1111/jiec.12188

Liu, J., Kattel, G., Arp, H. P. H., & Yang, H. (2015). Towards threshold-based management of freshwater ecosystems in the context of climate change. *Ecological Modelling*, *318*, 265–274. https://doi.org/10.1016/j.ecolmodel.2014.09.010

Pfister, S., & Suh, S. (2015). Environmental impacts of thermal emissions to freshwater: Spatially explicit fate and effect modeling for life cycle assessment and water footprinting. *The International Journal of Life Cycle Assessment*, *20*(7), 927–936. https://doi.org/10.1007/s11367-015-0893-8

Quinteiro, P., Dias, A. C., Araújo, A., Pestana, J. L. T., Ridoutt, B. G., & Arroja, L. (2015). Suspended solids in freshwater systems: Characterisation model describing potential impacts on aquatic biota. *The International Journal of Life Cycle Assessment*, *20*(9), 1232–1242. https://doi.org/10.1007/s11367-015-0916-5

Rocklin, M. (2015). Dask: Parallel computation with blocked algorithms and task scheduling. In K. Huff & J. Bergstra (Eds.), *Proceedings of the 14th python in science conference* (pp. 130–136).

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., De Vries, W., De Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*(6223). https://doi.org/10.1126/science.1259855

Verones, F., Huijbregts, M. A., Chaudhary, A., De Baan, L., Koellner, T., & Hellweg, S. (2015). Harmonizing the assessment of biodiversity effects from land and water use within LCA. *Environmental Science and Technology*, *49*(6), 3584–3592. https://doi.org/10.1021/es504995r

Cosme, N., & Hauschild, M. Z. (2016). Effect Factors for marine eutrophication in LCIA based on species sensitivity to hypoxia. *Ecological Indicators*, *69*, 453–462. https://doi.org/10.1016/j.ecolind.2016.04.006

Dask Development Team. (2016). *Dask: Library for dynamic task scheduling*.

Dong, Y., Rosenbaum, R. K., & Hauschild, M. Z. (2016). Assessment of Metal Toxicity in Marine Ecosystems: Comparative Toxicity Potentials for Nine Cationic Metals in Coastal Seawater. *Environmental Science & Technology*, *50*(1), 269–278. https://doi.org/10.1021/acs.est.5b01625

Garcia-Ulloa, J., Giam, X., Rondinini, C., Saura, S., & Koh, L. (2016). Incorporating graph theory into species-area modelling of land use change impacts. *The Doctoral Thesis of John Garcia-Ulloa: Improving Conservation Perspectives of Land-use Change Policies in the Tropics. Department of Environmental Systems Science, ETH Zürich*, 19–47.

Huijbregts, M., Steinmann, Z., Elshout, P., Stam, G., Verones, F., Vieira, M., Hollander, A., Zijp, M., & van Zelm, R. (2016). *ReCiPe 2016 v1.1. A harmonized life cycle impact assessment method at midpoint and endpoint level. Report I: Characterization* (tech. rep.). National Institute for Public Health and the Environment. Bilthoven, The Netherlands.

Moran, D., Petersone, M., & Verones, F. (2016). On the suitability of input-output analysis for calculating product-specific biodiversity footprints. *Ecological Indicators*, *60*, 192–201. https://doi.org/10.1016/j.ecolind.2015.06.015

Newbold, T., Hudson, L. N., Arnell, A. P., Contu, S., De Palma, A., Ferrier, S., Hill, S. L. L., Hoskins, A. J., Lysenko, I., Phillips, H. R. P., Burton, V. J., Chng, C. W. T., Emerson, S., Gao, D., Pask-Hale, G., Hutton, J., Jung, M., Sanchez-Ortiz, K., Simmons, B. I., ... Purvis, A. (2016). Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. *Science*, *353*(6296), 288–291. https://doi.org/10.1126/science.aaf2201

Nishijima, S., Furukawa, T., Kadoya, T., Ishihama, F., Kastner, T., Matsuda, H., & Kaneko, N. (2016). Evaluating the impacts of wood production and trade on bird extinction risks. *Ecological Indicators*, *71*, 368–376. https://doi.org/10.1016/j.ecolind.2016.07.008

Salo, T., & Gustafsson, C. (2016). The Effect of Genetic Diversity on Ecosystem Functioning in Vegetated Coastal Ecosystems. *Ecosystems*, *19*(8), 1429–1444. https://doi.org/10.1007/s10021-016-0014-y

Scherer, L., & Pfister, S. (2016). Global Biodiversity Loss by Freshwater Consumption and Eutrophication from Swiss Food Consumption. *Environmental Science & Technology*, *50*(13), 7019–7028. https://doi.org/10.1021/acs.est.6b00740

Taelman, S. E., Schaubroeck, T., De Meester, S., Boone, L., & Dewulf, J. (2016). Accounting for land use in life cycle assessment: The value of NPP as a proxy indicator to assess land use impacts on ecosystems. *Science of The Total Environment*, *550*, 143–156. https://doi.org/10.1016/j.scitotenv.2016.01.055

UNEP & SETAC Life Cycle Initiative. (2016). *Global Guidance for Life Cycle Impact Assessment Indicators: Volume 1* (tech. rep.). United Nations Environment Programme. Paris, France.

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., & Watson, J. E. M. (2016). Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. *Nature Communications*, *7*(1), 12558. https://doi.org/10.1038/ncomms12558

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., & Watson, J. E. (2016). Global terrestrial Human Footprint maps for 1993 and 2009. *Scientific Data*, *3*(1), 160067. https://doi.org/10.1038/sdata.2016.67

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

Cosme, N., & Hauschild, M. Z. (2017). Characterization of waterborne nitrogen emissions for marine eutrophication modelling in life cycle impact assessment at the damage level and global scale. *The International Journal of Life Cycle Assessment*, *22*(10), 1558–1570. https://doi.org/10.1007/s11367-017-1271-5

Cosme, N., Jones, M. C., Cheung, W. W., & Larsen, H. F. (2017). Spatial differentiation of marine eutrophication damage indicators based on species density. *Ecological Indicators*, *73*, 676–685. https://doi.org/10.1016/j.ecolind.2016.10.026

Fantke, P., Bijster, M., Guignard, C., Hauschild, M., Huijbregts, M., Jolliet, O., Kounina, A., Magaud, V., Margni, M., Mckone, T., Posthuma, L., Rosenbaum, R. K., Van De Meent, D., Van Zelm, R., & Fantke, P. (2017). *USEtox ® 2.0 Documentation (Version 1)* (tech. rep.). UNEP/SETAC Life Cycle Initiative. Lyngby, Denmark. https://doi.org/10.11581/DTU:00000011

Farmery, A. K., Jennings, S., Gardner, C., Watson, R. A., & Green, B. S. (2017). Naturalness as a basis for incorporating marine biodiversity into life cycle assessment of seafood. *The International Journal of Life Cycle Assessment*, *22*(10), 1571–1587. https://doi.org/10.1007/s11367-017-1274-2

Haddaway, N. R., Macura, B., Whaley, P., & Pullin, A. S. (2017). ROSES for Systematic Map Reports. Version 1.0. https://doi.org/10.6084/m9.figshare.5897299

Hudson, L. N., Newbold, T., Contu, S., Hill, S. L. L., Lysenko, I., De Palma, A., Phillips, H. R. P., Alhusseini, T. I., Bedford, F. E., Bennett, D. J., Booth, H., Burton, V. J., Chng, C. W. T., Choimes, A., Correia, D. L. P., Day, J., Echeverría-Londoño, S., Emerson, S. R., Gao, D., ... Purvis, A. (2017). The database of the PREDICTS (Projecting Responses of Ecological Diversity In Changing Terrestrial Systems) project. *Ecology and Evolution*, *7*(1), 145–188. https://doi.org/10.1002/ece3.2579

Huijbregts, M. A. J., Steinmann, Z. J. N., Elshout, P. M. F., 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. *Int J Life Cycle Assess*, *22*(2), 138–147. https://doi.org/10.1007/s11367-016-1246-y

Knudsen, M. T., Hermansen, J. E., Cederberg, C., Herzog, F., Vale, J., Jeanneret, P., Sarthou, J.-P., Friedel, J. K., Balázs, K., Fjellstad, W., Kainz, M., Wolfrum, S., & Dennis, P. (2017). Characterization factors for land use impacts on biodiversity in life cycle assessment based on direct measures of plant species richness in European farmland in the 'Temperate Broadleaf and Mixed Forest' biome. *Science of The Total Environment*, *580*, 358–366. https://doi.org/10.1016/j.scitotenv.2016.11.172

Marques, A., Verones, F., Kok, M. T., Huijbregts, M. A., Pereira, H. M., Brondizio, E., Leemans, R., & Solecki, W. (2017). How to quantify biodiversity footprints of consumption? A review of multi-regional input–output analysis and life cycle assessment. *Current Opinion in Environmental Sustainability*, *29*, 75–81. https://doi.org/10.1016/j.cosust.2018.01.005

McRae, L., Deinet, S., & Freeman, R. (2017). The Diversity-Weighted Living Planet Index: Controlling for Taxonomic Bias in a Global Biodiversity Indicator (H. Doi, Ed.). *PLOS ONE*, *12*(1), e0169156. https://doi.org/10.1371/journal.pone.0169156

Middel, H., & Verones, F. (2017). Making Marine Noise Pollution Impacts Heard: The Case of Cetaceans in the North Sea within Life Cycle Impact Assessment. *Sustainability*, *9*(7), 1138. https://doi.org/10.3390/su9071138

Moran, D., & Kanemoto, K. (2017). Identifying species threat hotspots from global supply chains. *NATURE ECOLOGY & EVOLUTION*, *1*(0023). https://doi.org/10.1038/s41559-016-0023

Raptis, C. E., Boucher, J. M., & Pfister, S. (2017). Assessing the environmental impacts of freshwater thermal pollution from global power generation in LCA. *Science of The Total Environment*, *580*, 1014–1026. https://doi.org/10.1016/j.scitotenv.2016.12.056

Turak, E., Regan, E., & Costello, M. J. (2017). Measuring and reporting biodiversity change. *Biological Conservation*, *213*, 249–251. https://doi.org/10.1016/j.biocon.2017.03.013

Wilting, H. C., Schipper, A. M., Bakkenes, M., Meijer, J. R., & Huijbregts, M. A. J. (2017). Quantifying Biodiversity Losses Due to Human Consumption: A Global-Scale Footprint Analysis. *Environmental Science & Technology*, *51*(6), 3298–3306. https://doi.org/10.1021/acs.est.6b05296

Carraro, L., Hartikainen, H., Jokela, J., Bertuzzo, E., & Rinaldo, A. (2018). Estimating species distribution and abundance in river networks using environmental DNA. *Proceedings of the National Academy of Sciences*, *115*(46), 11724–11729. https://doi.org/10.1073/pnas.1813843115

Chaudhary, A., & Brooks, T. M. (2018). Land Use Intensity-Specific Global Characterization Factors to Assess Product Biodiversity Footprints. *Environmental Science & Technology*, *52*(9), 5094–5104. https://doi.org/10.1021/acs.est.7b05570

Chaudhary, A., Pourfaraj, V., & Mooers, A. O. (2018). Projecting global land use-driven evolutionary history loss (R. Cowie, Ed.). *Diversity and Distributions*, *24*(2), 158–167. https://doi.org/10.1111/ddi.12677

Hull, V., & Liu, J. (2018). Telecoupling: A new frontier for global sustainability. *Ecology and Society*, *23*(4), 41. https://doi.org/10.5751/ES-10494-230441

Iordan, C. M., Verones, F., & Cherubini, F. (2018). Integrating impacts on climate change and biodiversity from forest harvest in Norway. *Ecological Indicators*, *89*, 411–421. https://doi.org/10.1016/j.ecolind.2018.02.034

Jones, H. P., Jones, P. C., Barbier, E. B., Blackburn, R. C., Rey Benayas, J. M., Holl, K. D., McCrackin, M., Meli, P., Montoya, D., & Mateos, D. M. (2018). Restoration and repair of Earth's damaged ecosystems. *Proceedings of the Royal Society B: Biological Sciences*, *285*(1873), 20172577. https://doi.org/10.1098/rspb.2017.2577

Larrey-Lassalle, P., Esnouf, A., Roux, P., Lopez-Ferber, M., Rosenbaum, R. K., & Loiseau, E. (2018). A methodology to assess habitat fragmentation effects through regional indexes: Illustration with forest biodiversity hotspots. *Ecological Indicators*, *89*, 543–551. https://doi.org/10.1016/j.ecolind.2018.01.068

Larrey-Lassalle, P., Loiseau, E., Roux, P., Lopez-Ferber, M., & Rosenbaum, R. K. (2018). Developing characterisation factors for land fragmentation impacts on biodiversity in LCA: Key learnings from a sugarcane case study. *The International Journal of Life Cycle Assessment*, *23*(11), 2126–2136. https://doi.org/10.1007/s11367-018-1449-5

Poff, N. L. (2018). Beyond the natural flow regime? Broadening the hydro-ecological foundation to meet environmental flows challenges in a non-stationary world. *Freshwater Biology*, *63*(8), 1011–1021. https://doi.org/10.1111/fwb.13038

Rossi, V., Lehesvirta, T., Schenker, U., Lundquist, L., Koski, O., Gueye, S., Taylor, R., & Humbert, S. (2018). Capturing the potential biodiversity effects of forestry practices in life cycle assessment. *The International Journal of Life Cycle Assessment*, *23*(6), 1192–1200. https://doi.org/10.1007/s11367-017-1352-5

Sintayehu, D. W. (2018). Impact of climate change on biodiversity and associated key ecosystem services in Africa: A systematic review. *Ecosystem Health and Sustainability*, *4*(9), 225–239. https://doi.org/10.1080/20964129.2018.1530054

Stepping, K. M. K., & Meijer, K. S. (2018). The Challenges of Assessing the Effectiveness of Biodiversity-Related Development Aid. *Tropical Conservation Science*, *11*, 194008291877099. https://doi.org/10.1177/1940082918770995

Tang, L., Higa, M., Tanaka, N., & Itsubo, N. (2018). Assessment of global warming impact on biodiversity using the extinction risk index in LCIA: A case study of Japanese plant species. *The International Journal of Life Cycle Assessment*, *23*(2), 314–323. https://doi.org/10.1007/s11367-017-1319-6

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Annals of Internal Medicine*, *169*(7), 467–473. https://doi.org/10.7326/M18-0850

Winter, L., Pflugmacher, S., Berger, M., & Finkbeiner, M. (2018). Biodiversity impact assessment (BIA+) - methodological framework for screening biodiversity: Biodiversity Impact Assessment (BIA+). *Integrated Environmental Assessment and Management*, *14*(2), 282–297. https://doi.org/10.1002/ieam.2006

Yamaguchi, K., Ii, R., & Itsubo, N. (2018). Ecosystem damage assessment of land transformation using species loss. *The International Journal of Life Cycle Assessment*, *23*(12), 2327–2338. https://doi.org/10.1007/s11367-016-1072-2

Bachman, S. P., Field, R., Reader, T., Raimondo, D., Donaldson, J., Schatz, G. E., & Lughadha, E. N. (2019). Progress, challenges and opportunities for Red Listing. *Biological Conservation*, *234*, 45–55. https://doi.org/10.1016/j.biocon.2019.03.002

Bulle, C., Margni, M., Patouillard, L., Boulay, A. M., Bourgault, G., De Bruille, V., Cao, V., Hauschild, M., Henderson, A., Humbert, S., Kashef-Haghighi, S., Kounina, A., Laurent, A., Levasseur, A., Liard, G., Rosenbaum, R. K., Roy, P. O., Shaked, S., Fantke, P., & Jolliet, O. (2019). IMPACT World+: A globally regionalized life cycle impact assessment method. *The International Journal of Life Cycle Assessment*, *24*(9), 1653–1674. https://doi.org/10.1007/s11367-019-01583-0

Chaudhary, A., & Brooks, T. M. (2019). National Consumption and Global Trade Impacts on Biodiversity. *World Development*, *121*, 178–187. https://doi.org/10.1016/j.worlddev.2017.10.012

Crenna, E., Sinkko, T., & Sala, S. (2019). Biodiversity impacts due to food consumption in Europe. *Journal of Cleaner Production*, *227*, 378–391. https://doi.org/10.1016/J.JCLEPRO.2019.04.054

Díaz, S., Settele, J., Brondízio, E. S., Ngo, H. T., Agard, J., Arneth, A., Balvanera, P., Brauman, K. A., Butchart, S. H. M., Chan, K. M. A., Garibaldi, L. A., Ichii, K., Liu, J., Subramanian, S. M., Midgley, G. F., Miloslavich, P., Molnár, Z., Obura, D., Pfaff, A., … Zayas, C. N. (2019). Pervasive human-driven decline of life on earth points to the need for transformative change. *Science*, *366*(6471), eaax3100. https://doi.org/10.1126/science.aax3100

Dorber, M., Mattson, K. R., Sandlund, O. T., May, R., & Verones, F. (2019). Quantifying net water consumption of Norwegian hydropower reservoirs and related aquatic biodiversity impacts in Life Cycle Assessment. *Environmental Impact Assessment Review*, *76*, 36–46. https://doi.org/10.1016/j.eiar.2018.12.002

Holland, R. A., Scott, K., Agnolucci, P., Rapti, C., Eigenbrod, F., & Taylor, G. (2019). The influence of the global electric power system on terrestrial biodiversity. *Proceedings of the National Academy of Sciences*, *116*(51), 26078–26084. https://doi.org/10.1073/pnas.1909269116

Kuipers, K. J., Hellweg, S., & Verones, F. (2019). Potential Consequences of Regional Species Loss for Global Species Richness: A Quantitative Approach for Estimating Global Extinction Probabilities. *Environmental Science & Technology*, *53*(9), 4728–4738. https://doi.org/10.1021/acs.est.8b06173

Marquardt, S. G., Guindon, M., Wilting, H. C., Steinmann, Z. J., Sim, S., Kulak, M., & Huijbregts, M. A. (2019). Consumption-based biodiversity footprints – Do different indicators yield different results? *Ecological Indicators*, *103*, 461–470. https://doi.org/10.1016/J.ECOLIND.2019.04.022

Marques, A., Martins, I. S., Kastner, T., Plutzar, C., Theurl, M. C., Eisenmenger, N., Huijbregts, M. A., Wood, R., Stadler, K., Bruckner, M., Canelas, J., Hilbers, J. P., Tukker, A., Erb, K., & Pereira, H. M. (2019). Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. *Nature Ecology and Evolution*, *3*(4), 628–637. https://doi.org/10.1038/s41559-019-0824-3

Maxwell, S. L., Butt, N., Maron, M., McAlpine, C. A., Chapman, S., Ullmann, A., Segan, D. B., & Watson, J. E. M. (2019). Conservation implications of ecological responses to extreme weather and climate events. *Diversity and Distributions*, *25*(4), 613–625. https://doi.org/10.1111/ddi.12878

Myllyviita, T., Sironen, S., Saikku, L., Holma, A., Leskinen, P., & Palme, U. (2019). Assessing biodiversity impacts in life cycle assessment framework - Comparing approaches based on species richness and ecosystem indicators in the case of Finnish boreal forests. *Journal of Cleaner Production*, *236*, 117641. https://doi.org/10.1016/j.jclepro.2019.117641

Smale, D. A., Wernberg, T., Oliver, E. C. J., Thomsen, M., Harvey, B. P., Straub, S. C., Burrows, M. T., Alexander, L. V., Benthuysen, J. A., Donat, M. G., Feng, M., Hobday, A. J., Holbrook, N. J., Perkins-Kirkpatrick, S. E., Scannell, H. A., Sen Gupta, A., Payne, B. L., & Moore, P. J. (2019). Marine heatwaves threaten global biodiversity and the provision of ecosystem services. *Nature Climate Change*, *9*(4), 306–312. https://doi.org/10.1038/s41558-019-0412-1

Turner, P. A. M., Ximenes, F. A., Penman, T. D., Law, B. S., Waters, C. M., Grant, T., Mo, M., & Brock, P. M. (2019). Accounting for biodiversity in life cycle impact assessments of forestry and agricultural systems—the BioImpact metric. *The International Journal of Life Cycle Assessment*, *24*(11), 1985–2007. https://doi.org/10.1007/s11367-019-01627-5

UNEP & SETAC Life Cycle Initiative. (2019). *Global Guidance for Life Cycle Impact Assessment Indicators: Volume 2* (tech. rep.). United Nations Environment Programme. Paris, France.

Weinzettel, J., Vačkářů, D., & Medková, H. (2019). Potential net primary production footprint of agriculture: A global trade analysis. *Journal of Industrial Ecology*, *23*(5), 1133–1142. https://doi.org/10.1111/jiec.12850

Woods, J. S., Rødder, G., & Verones, F. (2019). An effect factor approach for quantifying the entanglement impact on marine species of macroplastic debris within life cycle impact assessment. *Ecological Indicators*, *99*, 61–66. https://doi.org/10.1016/j.ecolind.2018.12.018

Barbarossa, V., Schmitt, R. J. P., Huijbregts, M. A. J., Zarfl, C., King, H., & Schipper, A. M. (2020). Impacts of current and future large dams on the geographic range connectivity of freshwater fish worldwide. *Proceedings of the National Academy of Sciences*, *117*(7), 3648–3655. https://doi.org/10.1073/pnas.1912776117

Beng, K. C., & Corlett, R. T. (2020). Applications of environmental DNA (eDNA) in ecology and conservation: Opportunities, challenges and prospects. *Biodiversity and Conservation*, *29*(7), 2089–2121. https://doi.org/10.1007/s10531-020-01980-0

Crenna, E., Marques, A., La Notte, A., & Sala, S. (2020). Biodiversity Assessment of Value Chains: State of the Art and Emerging Challenges. *Environmental Science & Technology*, *54*(16), 9715–9728. https://doi.org/10.1021/acs.est.9b05153

Gallego-Zamorano, J., Benítez-López, A., Santini, L., Hilbers, J. P., Huijbregts, M. A. J., & Schipper, A. M. (2020). Combined effects of land use and hunting on distributions of tropical mammals. *Conservation Biology*, *34*(5), 1271–1280. https://doi.org/10.1111/cobi.13459

Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., del Río, J. F., Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Ibarrola-Rivas, M.-J., Castro, A. J., Kastner, T., Nonhebel, S., & Turkelboom, F. (2020). Telecoupling through tomato trade: What consumers do not know about the tomato on their plate. *Global Sustainability*, *3*, e7. https://doi.org/10.1017/sus.2020.4

Laroche, P. C., Schulp, C. J., Kastner, T., & Verburg, P. H. (2020). Telecoupled environmental impacts of current and alternative western diets. *Global Environmental Change*, *62*(September 2019), 102066. https://doi.org/10.1016/j.gloenvcha.2020.102066

May, R., Middel, H., Stokke, B. G., Jackson, C., & Verones, F. (2020). Global life-cycle impacts of onshore wind-power plants on bird richness. *Environmental and Sustainability Indicators*, *8*, 100080. https://doi.org/10.1016/j.indic.2020.100080

Román-Palacios, C., & Wiens, J. J. (2020). Recent responses to climate change reveal the drivers of species extinction and survival. *Proceedings of the National Academy of Sciences*, *117*(8), 4211–4217. https://doi.org/10.1073/pnas.1913007117

Scherer, L., van Baren, S. A., & van Bodegom, P. M. (2020). Characterizing Land Use Impacts on Functional Plant Diversity for Life Cycle Assessments. *Environmental Science & Technology*, *54*(11), 6486–6495. https://doi.org/10.1021/acs.est.9b07228

Schipper, A. M., Hilbers, J. P., Meijer, J. R., Antão, L. H., Benítez-López, A., de Jonge, M. M., Leemans, L. H., Scheper, E., Alkemade, R., Doelman, J. C., Mylius, S., Stehfest, E., van Vuuren, D. P., van Zeist, W. J., & Huijbregts, M. A. (2020). Projecting terrestrial biodiversity intactness with GLOBIO 4. *Global Change Biology*, *26*(2), 760–771. https://doi.org/10.1111/gcb.14848

The pandas development team. (2020, February). *Pandas-dev/pandas: Pandas* (Version 1.3.5). Zenodo. https://doi.org/10.5281/zenodo.3509134

Tkaczyk, D. (2020, January). Crossref Commons.

Trisos, C. H., Merow, C., & Pigot, A. L. (2020). The projected timing of abrupt ecological disruption from climate change. *Nature*, *580*(7804), 496–501. https://doi.org/10.1038/s41586-020-2189-9

Verones, F., Hellweg, S., Antón, A., Azevedo, L. B., Chaudhary, A., Cosme, N., Cucurachi, S., de Baan, L., Dong, Y., Fantke, P., Golsteijn, L., Hauschild, M., Heijungs, R., Jolliet, O., Juraske, R., Larsen, H., Laurent, A., Mutel, C. L., Margni, M., … Huijbregts, M. A. (2020). LC-IMPACT: A regionalized life cycle damage assessment method. *Journal of Industrial Ecology*, *24*(6), 1201–1219. https://doi.org/10.1111/jiec.13018

Barbarossa, V., Bosmans, J., Wanders, N., King, H., Bierkens, M. F. P., Huijbregts, M. A. J., & Schipper, A. M. (2021). Threats of global warming to the world's freshwater fishes. *Nature Communications*, *12*(1), 1701. https://doi.org/10.1038/s41467-021-21655-w

Côté, S., Beauregard, R., Margni, M., & Bélanger, L. (2021). Using Naturalness for Assessing the Impact of Forestry and Protection on the Quality of Ecosystems in Life Cycle Assessment. *Sustainability*, *13*(16), 8859. https://doi.org/10.3390/su13168859

De Palma, A., Hoskins, A., Gonzalez, R. E., Börger, L., Newbold, T., Sanchez-Ortiz, K., Ferrier, S., & Purvis, A. (2021). Annual changes in the Biodiversity Intactness Index in tropical and subtropical forest biomes, 2001–2012. *Scientific Reports*, *11*(1), 1–13. https://doi.org/10.1038/s41598-021-98811-1

Dorninger, C., Hornborg, A., Abson, D. J., Von Wehrden, H., Schaffartzik, A., Giljum, S., Engler, J.-O., Feller, R. L., Hubacek, K., & Wieland, H. (2021). Global patterns of ecologically unequal exchange: Implications for sustainability in the 21st century. *Ecological Economics*, *179*, 106824. https://doi.org/10.1016/j.ecolecon.2020.106824

Hochkirch, A., Samways, M. J., Gerlach, J., Böhm, M., Williams, P., Cardoso, P., Cumberlidge, N., Stephenson, P. J., Seddon, M. B., Clausnitzer, V., Borges, P. A. V., Mueller, G. M., Pearce-Kelly, P., Raimondo, D. C., Danielczak, A., & Dijkstra, K.-D. B. (2021). A strategy for the next decade to address data deficiency in neglected biodiversity. *Conservation Biology*, *35*(2), 502–509. https://doi.org/10.1111/cobi.13589

Kastner, T., Chaudhary, A., Gingrich, S., Marques, A., Persson, U. M., Bidoglio, G., Le Provost, G., & Schwarzmüller, F. (2021). Global agricultural trade and land system sustainability: Implications for ecosystem carbon storage, biodiversity, and human nutrition. *One Earth*, *4*(10), 1425–1443. https://doi.org/10.1016/j.oneear.2021.09.006

Keys, P. W., Barnes, E. A., & Carter, N. H. (2021). A machine-learning approach to human footprint index estimation with applications to sustainable development. *Environmental Research Letters*, *16*(4), 044061. https://doi.org/10.1088/1748-9326/abe00a

Kuipers, K. J., Hilbers, J. P., Garcia-Ulloa, J., Graae, B. J., May, R., Verones, F., Huijbregts, M. A., & Schipper, A. M. (2021). Habitat fragmentation amplifies threats from habitat loss to mammal diversity across the world's terrestrial ecoregions. *One Earth*, *4*(10), 1505–1513. https://doi.org/10.1016/j.oneear.2021.09.005

Kuipers, K. J., May, R., & Verones, F. (2021). Considering habitat conversion and fragmentation in characterisation factors for land-use impacts on vertebrate species richness. *Science of The Total Environment*, *801*, 149737. https://doi.org/10.1016/J.SCITOTENV.2021.149737

Mair, L., Bennun, L. A., Brooks, T. M., Butchart, S. H. M., Bolam, F. C., Burgess, N. D., Ekstrom, J. M. M., Milner-Gulland, E. J., Hoffmann, M., Ma, K., Macfarlane, N. B. W., Raimondo, D. C., Rodrigues, A. S. L., Shen, X., Strassburg, B. B. N., Beatty, C. R., Gómez-Creutzberg, C., Iribarrem, A., Irmadhiany, M., … McGowan, P. J. K. (2021). A metric for spatially explicit contributions to science-based species targets. *Nature Ecology & Evolution*, *5*(6), 836–844. https://doi.org/10.1038/s41559-021-01432-0

Manes, S., Costello, M. J., Beckett, H., Debnath, A., Devenish-Nelson, E., Grey, K.-A., Jenkins, R., Khan, T. M., Kiessling, W., Krause, C., Maharaj, S. S., Midgley, G. F., Price, J., Talukdar, G., & Vale, M. M. (2021). Endemism increases species' climate change risk in areas of global biodiversity importance. *Biological Conservation*, *257*, 109070. https://doi.org/10.1016/j.biocon.2021.109070

Marquardt, S. G., Doelman, J. C., Daioglou, V., Tabeau, A., Schipper, A. M., Sim, S., Kulak, M., Steinmann, Z. J., Stehfest, E., Wilting, H. C., & Huijbregts, M. A. (2021). Identifying regional drivers of future land-based biodiversity footprints. *Global Environmental Change*, *69*, 102304. https://doi.org/10.1016/j.gloenvcha.2021.102304

May, R., Jackson, C. R., Middel, H., Stokke, B. G., & Verones, F. (2021). Life-cycle impacts of wind energy development on bird diversity in Norway. *Environmental Impact Assessment Review*, *90*, 106635. https://doi.org/10.1016/j.eiar.2021.106635

Payen, S., Cosme, N., & Elliott, A. H. (2021). Freshwater eutrophication: Spatially explicit fate factors for nitrogen and phosphorus emissions at the global scale. *The International Journal of Life Cycle Assessment*, *26*(2), 388–401. https://doi.org/10.1007/s11367-020-01847-0

Pörtner, Hans-Otto, Scholes, Robert J., Agard, John, Archer, Emma, Arneth, Almut, Bai, Xuemei, Barnes, David, Burrows, Michael, Chan, Lena, Cheung, Wai Lung (William), Diamond, Sarah, Donatti, Camila, Duarte, Carlos, Eisenhauer, Nico, Foden, Wendy, Gasalla, Maria A., Handa, Collins, Hickler, Thomas, Hoegh-Guldberg, Ove, ... Ngo, Hien. (2021, June 24). *Scientific outcome of the ipbes-ipcc co-sponsored workshop on biodiversity and climate change* (tech. rep.). https://doi.org/10.5281/ZENODO.4659158

Trottier, G., Turgeon, K., Verones, F., Boisclair, D., Bulle, C., & Margni, M. (2021). Empirical Characterization Factors for Life Cycle Assessment of the Impacts of Reservoir Occupation on Macroinvertebrate Richness across the United States. *Sustainability*, *13*(5), 2701. https://doi.org/10.3390/su13052701

Zhang, Y., Li, Z., Ge, W., Chen, X., Xu, H., & Guan, H. (2021). Evaluation of the impact of extreme floods on the biodiversity of terrestrial animals. *Science of The Total Environment*, *790*, 148227. https://doi.org/10.1016/j.scitotenv.2021.148227

Bach, V., Hélias, A., Muhl, M., Wojciechowski, A., Bosch, H., Binder, M., & Finkbeiner, M. (2022). Assessing overfishing based on the distance-to-target approach. *The International Journal of Life Cycle Assessment*, *27*(4), 573–586. https://doi.org/10.1007/s11367-022-02042-z

Cazalis, V., Di Marco, M., Butchart, S. H., Akçakaya, H. R., González-Suárez, M., Meyer, C., Clausnitzer, V., Böhm, M., Zizka, A., Cardoso, P., Schipper, A. M., Bachman, S. P., Young, B. E., Hoffmann, M., Benítez-López, A., Lucas, P. M., Pettorelli, N., Patoine, G., Pacifici, M., ... Santini, L. (2022). Bridging the research-implementation gap in IUCN Red List assessments. *Trends in Ecology & Evolution*, *37*(4), 359–370. https://doi.org/10.1016/j.tree.2021.12.002

CEE. (2022). Guidelines and Standards for Evidence Synthesis in Environmental Management. Version 5.1.

Fabbri, S., Owsianiak, M., Newbold, T., & Hauschild, M. Z. (2022). Development of climate tipping damage metric for life-cycle assessment—the influence of increased warming from the tipping. *The International Journal of Life Cycle Assessment*, *27*(9-11), 1199–1212. https://doi.org/10.1007/s11367-022-02096-z

Haddaway, N. R., Grainger, M. J., & Gray, C. T. (2022). Citationchaser: A tool for transparent and efficient forward and backward citation chasing in systematic searching. *Research Synthesis Methods*, *13*(4), 533–545. https://doi.org/10.1002/jrsm.1563

Irwin, A., Geschke, A., Brooks, T. M., Siikamaki, J., Mair, L., & Strassburg, B. B. N. (2022). Quantifying and categorising national extinction-risk footprints. *Scientific Reports*, *12*(1), 5861. https://doi.org/10.1038/s41598-022-09827-0

Lavoie, J., Boulay, A.-M., & Bulle, C. (2022). Aquatic micro- and nano-plastics in life cycle assessment: Development of an effect factor for the quantification of their physical impact on biota. *Journal of Industrial Ecology*, *26*(6), 2123–2135. https://doi.org/10.1111/jiec.13140

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. https://doi.org/10.1016/j.ecolind.2022.109201

Priem, J., Piwowar, H., & Orr, R. (2022). OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts. *ArXiv*. https://doi.org/10.48550/arXiv.2205.01833

Roibás-Rozas, A., Núñez, M., Mosquera-Corral, A., & Hospido, A. (2022). Modeling the Impact of Salinity Variations on Aquatic Environments: Including Negative and Positive Effects in Life Cycle Assessment. *Environmental Science & Technology*, *56*(2), 874–884. https://doi.org/10.1021/acs.est.1c04656

Scherer, L., Gürdal, İ., & Van Bodegom, P. M. (2022). Characterization factors for ocean acidification impacts on marine biodiversity. *Journal of Industrial Ecology*, *26*(6), 2069–2079. https://doi.org/10.1111/jiec.13274

Smit, K. P., Van Niekerk, L., Harris, L. R., McQuatters-Gollop, A., Shannon, L. J., & Sink, K. J. (2022). A Roadmap to Advance Marine and Coastal Monitoring, Biodiversity Assessment, and International Reporting: A Developing Nation Perspective. *Frontiers in Marine Science*, *9*, 886373. https://doi.org/10.3389/fmars.2022.886373

Tang, Y., Mankaa, R. N., & Traverso, M. (2022). An effect factor approach for quantifying the impact of plastic additives on aquatic biota in life cycle assessment. *The International Journal of Life Cycle Assessment*, *27*(4), 564–572. https://doi.org/10.1007/s11367-022-02046-9

Verones, F., Kuipers, K., Núñez, M., Rosa, F., Scherer, L., Marques, A., Michelsen, O., Barbarossa, V., Jaffe, B., Pfister, S., & Dorber, M. (2022). Global extinction probabilities of terrestrial, freshwater, and marine species groups for use in Life Cycle Assessment. *Ecological Indicators*, *142*, 109204. https://doi.org/10.1016/j.ecolind.2022.109204

Westveer, J., Freeman, R., McRae, L., Marconi, V., Almond, R., & Grooten, M. (2022). *A Deep Dive into the Living Planet Index: A Technical Report* (tech. rep.). WWF. Gland, Switzerland.

Alejandre, E. M., Scherer, L., Guinée, J. B., Aizen, M. A., Albrecht, M., Balzan, M. V., Bartomeus, I., Bevk, D., Burkle, L. A., Clough, Y., Cole, L. J., Delphia, C. M., Dicks, L. V., Garratt, M. P., Kleijn, D., Kovács-Hostyánszki, A., Mandelik, Y., Paxton, R. J., Petanidou, T., ... Van Bodegom, P. M. (2023). Characterization Factors to Assess Land Use Impacts on Pollinator Abundance in Life Cycle Assessment. *Environmental Science & Technology*, *57*(8), 3445–3454. https://doi.org/10.1021/acs.est.2c05311

Bruckner, B., Shan, Y., Prell, C., Zhou, Y., Zhong, H., Feng, K., & Hubacek, K. (2023). Ecologically unequal exchanges driven by EU consumption. *Nature Sustainability*, *6*(5), 587–598. https://doi.org/10.1038/s41893-022-01055-8

De Bruin, J. (2023, March). *PyAlex* (Version 0.8).

De Visser, S., Scherer, L., Huijbregts, M., & Barbarossa, V. (2023). Characterization factors for the impact of climate change on freshwater fish species. *Ecological Indicators*, *150*, 110238. https://doi.org/10.1016/j.ecolind.2023.110238

Iordan, C.-M., Kuipers, K. J., Huang, B., Hu, X., Verones, F., & Cherubini, F. (2023). Spatially and taxonomically explicit characterisation factors for greenhouse gas emission impacts on biodiversity. *Resources, Conservation and Recycling*, *198*, 107159. https://doi.org/10.1016/j.resconrec.2023.107159

Jo, T. S. (2023). Correlation between the number of eDNA particles and species abundance is strengthened by warm temperature: Simulation and meta-analysis. *Hydrobiologia*, *850*(1), 39–50. https://doi.org/10.1007/s10750-022-05036-y

Pierrat, E., Barbarossa, V., Núñez, M., Scherer, L., Link, A., Damiani, M., Verones, F., & Dorber, M. (2023). Global water consumption impacts on riverine fish species richness in Life Cycle Assessment. *Science of The Total Environment*, *854*, 158702. https://doi.org/10.1016/j.scitotenv.2022.158702

Pierrat, É., Laurent, A., Dorber, M., Rygaard, M., Verones, F., & Hauschild, M. (2023). Advancing water footprint assessments: Combining the impacts of water pollution and scarcity. *Science of The Total Environment*, *870*, 161910. https://doi.org/10.1016/j.scitotenv.2023.161910

Sabater, S., Freixa, A., Jiménez, L., López-Doval, J., Pace, G., Pascoal, C., Perujo, N., Craven, D., & González-Trujillo, J. D. (2023). Extreme weather events threaten biodiversity and functions of river ecosystems: Evidence from a meta-analysis. *Biological Reviews*, *98*(2), 450–461. https://doi.org/10.1111/brv.12914

Scherer, L., Rosa, F., Sun, Z., Michelsen, O., De Laurentiis, V., Marques, A., Pfister, S., Verones, F., & Kuipers, K. J. J. (2023). Biodiversity impact assessment considering land use intensities and fragmentation. *Environmental Science & Technology*, *57*(48), 19612–19623. https://doi.org/10.1021/acs.est.3c04191

Boakes, E. H., Dalin, C., Etard, A., & Newbold, T. (2024). Impacts of the global food system on terrestrial biodiversity from land use and climate change. *Nature Communications*, *15*(1), 5750. https://doi.org/10.1038/s41467-024-49999-z

Borgelt, J., Dorber, M., Géron, C., Kuipers, K. J., Huijbregts, M. A. J., & Verones, F. (2024). What Is the Impact of Accidentally Transporting Terrestrial Alien Species? A New Life Cycle Impact Assessment Model. *Environmental Science & Technology*, acs.est.3c08500. https://doi.org/10.1021/acs.est.3c08500

Burgess, N. D., Ali, N., Bedford, J., Bhola, N., Brooks, S., Cierna, A., Correa, R., Harris, M., Hargey, A., Hughes, J., McDermott-Long, O., Miles, L., Ravilious, C., Rodrigues, A. R., Van Soesbergen, A., Sihvonen, H., Seager, A., Swindell, L., Vukelic, M., … Butchart, S. H. (2024). Global Metrics for Terrestrial Biodiversity. *Annual Review of Environment and Resources*, *49*(1), 673–709. https://doi.org/10.1146/annurev-environ-121522-045106

Cabernard, L., Pfister, S., & Hellweg, S. (2024). Biodiversity impacts of recent land-use change driven by increases in agri-food imports. *Nature Sustainability*. https://doi.org/10.1038/s41893-024-01433-4

Casagrande, N., Silva, C. O., Verones, F., Sobral, P., & Martinho, G. (2024). Ecotoxicity effect factors for plastic additives on the aquatic environment: A new approach for life cycle impact assessment. *Environmental Pollution*, *341*, 122935. https://doi.org/10.1016/j.envpol.2023.122935

Cazalis, V., Di Marco, M., Zizka, A., Butchart, S. H., González-Suárez, M., Böhm, M., Bachman, S. P., Hoffmann, M., Rosati, I., De Leo, F., Jung, M., Benítez-López, A., Clausnitzer, V., Cardoso, P., Brooks, T. M., Mancini, G., Lucas, P. M., Young, B. E., Akçakaya, H. R., … Santini, L. (2024). Accelerating and standardising IUCN Red List assessments with sRedList. *Biological Conservation*, *298*, 110761. https://doi.org/10.1016/j.biocon.2024.110761

Culbert, J., Hobert, A., Jahn, N., Haupka, N., Schmidt, M., Donner, P., & Mayr, P. (2024, February). Reference Coverage Analysis of OpenAlex compared to Web of Science and Scopus.

Delgado-Quirós, L., & Ortega, J. L. (2024). Completeness degree of publication metadata in eight free-access scholarly databases. *Quantitative Science Studies*, *5*(1), 31–49. https://doi.org/10.1162/qss_a_00286

International, B. (2024). Threatened Birds of the World.

IOC-UNESCO. (2024). Ocean Biodiversity Information System (OBIS).

IUCN. (2024). The IUCN Red List of Threatened Species. Version 2024-1.

WoRMS. (2024, November). World Register of Marine Species.

Granqvist, E., Goodsell, R. M., Töpel, M., & Ronquist, F. (2025). The transformative potential of eDNA-based biodiversity impact assessment. *Current Opinion in Environmental Sustainability*, *73*, 101517. https://doi.org/10.1016/j.cosust.2025.101517

Kuipers, K. J., Melki, A., Morel, S., & Schipper, A. M. (2025). Relationships between mean species abundance (MSA) and potentially disappeared fraction of species (PDF) are consistent but also uncertain. *Environmental and Sustainability Indicators*, *26*, 100652. https://doi.org/10.1016/j.indic.2025.100652

Rabeschini, G., Persson, U. M., West, C., & Kastner, T. (2025). Choosing fit-for-purpose biodiversity impact indicators for agriculture in the Brazilian Cerrado ecoregion. *Nature Communications*, *16*(1), 1799. https://doi.org/10.1038/s41467-025-57037-9

Rosa, F., Van Bodegom, P. M., Hellweg, S., Pfister, S., Biurrun, I., Boch, S., Chytrý, M., Ćušterevska, R., Fratte, M. D., Damasceno, G., Garbolino, E., Lenoir, J., Ozinga, W. A., Penuelas, J., Sabatini, F. M., Schrodt, F., Uogintas, D., Byun, C., Dolezal, J., ... Scherer, L. (2025). Land-Use Impacts on Plant Functional Diversity Throughout Europe. *Global Ecology and Biogeography*, *34*(1), e13947. https://doi.org/10.1111/geb.13947

Shaw, R. E., Farquharson, K. A., Bruford, M. W., Coates, D. J., Elliott, C. P., Mergeay, J., Ottewell, K. M., Segelbacher, G., Hoban, S., Hvilsom, C., Pérez-Espona, S., Ruņģis, D., Aravanopoulos, F., Bertola, L. D., Cotrim, H., Cox, K., Cubric-Curik, V., Ekblom, R., Godoy, J. A., ... Grueber, C. E. (2025). Global meta-analysis shows action is needed to halt genetic diversity loss. *Nature*, *638*(8051), 704–710. https://doi.org/10.1038/s41586-024-08458-x