



A global consensus life cycle impact assessment method - GLAM: impacts on ecosystem quality

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Abstract

Purpose The aim of this paper is to report and document the models integrated into the ecosystem quality part of the first life cycle impact assessment (LCIA) version of the GLAM (Global Guidance for Life Cycle Impact Assessment Indicators and Methods) project. The focus is on endpoint models, and all included models provide characterization factors related to the loss of species richness, indicated in potentially disappeared fraction of species (PDF·yr).

Methods In the scoping phase eight impact categories have been identified as being of relevance and provided recent methodological developments that were mature enough to be included in the consensus model within GLAM. These include ecotoxicity, land use, water consumption, eutrophication (individually for marine and freshwater ecosystems), aquatic microplastic pollution, terrestrial acidification and climate change (individual models for terrestrial, freshwater and marine ecosystems). Apart from harmonizing and developing these models, aspects of vulnerability have been included by further developing and applying the global extinction probability (GEP) concept.

Results and discussion The eight impact categories provide in total more than 500 000 characterization factors (CFs) at country and global scale for the GLAM research version 1.1.2025.11, representing potential global species loss. Five of the impact categories (land use, water consumption, marine and freshwater eutrophication and terrestrial acidification) provide values at country levels as well as global averages. The other three (ecotoxicity, climate change and aquatic microplastics pollution) provide global CFs only. Climate change and marine eutrophication provide average CFs only, terrestrial acidification only marginal while all the others provide average and marginal CFs.

Conclusions The covered impact categories for the first time consistently represent potential global species losses in terms of PDF.

Keywords Ecosystem quality · Potentially disappeared fraction of species (PDF) · Impact assessment

1 Introduction to the area of protection “ecosystem quality”

In life cycle impact assessment (LCIA), there are currently three active Areas of Protection (AoP), namely human health, natural resources and ecosystem services, as well as ecosystem quality (Verones et al. 2017a). Human health (indicating impacts to human well-being) and natural

resources (indicating impacts on resource availability) are not part of this paper. The focus of this paper is to present the developments within “ecosystem quality”, which assesses damages on the intrinsic values of nature. This biodiversity loss is measured as a potential decline in species richness.

In the last decades, impact assessment in this area of protection has seen a large development, both in terms of

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Table 1 Overview of the covered impact categories and their specification. All methods are fully included in GLAM3 (i.e. recommended both for the practitioner version and researcher version)

Impact category	Modeling approach	Taxonomic coverage	Species considered	Realm	Included effects	Type of data used for effect	Native impact level	Native scale	Indicator	Time horizon
Ecotoxicity	marginal and average	freshwater species as available in test data used for USEtox. No marine test data. Terrestrial test data and extrapolations from freshwater to terrestrial effect.	Lab-based	Freshwater and terrestrial	ecotoxicological impact of chemicals on freshwater and terrestrial species complemented with extrapolations for terrestrial species	Ecotoxicological effect data	global	Fate modeling into 24 regions, two soil archetypes (agricultural and natural) 5 environmental compartments at continental emission scale: freshwater, coastal seawater, agricultural soil, natural soil, rural air	PAF·m ³ -d/kg emitted and PDF/kg emitted	Infinite (steady state), plus 100 years for metals
Land use	marginal and average	plants, amphibians, birds, mammals, reptiles	All present species	terrestrial	land occupation, land transformation	meta-analysis	regional	terrestrial ecoregions	PDF·yr/m ² (land occupation) and PDF/m ² (land transformation)	occupation: depending on occupation time from inventory Transformation: including regeneration time (Curran et al. 2014)
Freshwater eutrophication	marginal and average	freshwater fish		freshwater	P and N enrichment	modelled	local	0.5 × 0.5 arc degree resolution	PAF·yr/kg, PAF/m ² and PDF·yr/kg, PDF/m ²	depending on residence time
Marine eutrophication	average	Cartilaginous fish; Ray-finned fishes; Crustaceans; Cnidarians; Echinoderms	All present species	marine	Species loss (through e.g., growth, reproduction, mobility issues) due to hypoxia	modelled	local	Large marine ecosystems	PDF·yr/kg	infinite (steady-state)
Climate change	average	freshwater fish, amphibians, birds, terrestrial and marine mammals, marine fish, terrestrial and marine reptiles, ben-thic marine invertebrates, and corals & seagrasses	Native species	Freshwater, marine, terrestrial	Weekly river discharge and water temperature changes (freshwater); average air temperature (terrestrial, marine)	Niche limit data, modelled	Freshwater: global Marine and terrestrial: local	5 arcminutes (freshwater), 2 arcminutes (marine, terrestrial)	PDF·yr/kg	freshwater: 100 and 1000 years marine and terrestrial: specifically for impacts until 2050 and 2100
Water consumption	marginal and average	freshwater fish	Native species	freshwater	river flow reduction	modelled	local	entire river basin	PDF·yr/m ³	infinite (steady-state)

Table 1 (continued)

Impact category	Modeling approach	Taxonomic coverage	Species considered	Realm	Included effects	Type of data used for effect	Native impact level	Native scale	Indicator	Time horizon
Aquatic microplastics	marginal and average	aquatic vertebrates, invertebrates, algae	Lab-based	marine	Impact of microplastics on growth, reproduction, and mortality on water- and sediments-dwelling organisms	Ecotoxicological effect data	global	N/A (only global CFs)	PAF-y/kg emitted and PDF-y/kg emitted	infinite (steady-state)
Terrestrial acidification	marginal	Vascular plants	Native species	terrestrial	decline in vascular plant species richness due to a lower soil pH	Plant occurrence, modelling	local	2 × 2.5° for the fate side and terrestrial ecoregions for the effect side	PDF-yr/kg	infinite (steady-state)

impact categories that are covered and in terms of model sophistication. In the Eco-Indicator 99 method (Goedkoop and Spriensma 2014), for example, one of the earlier, multi-impact methods at endpoint level, four driver of biodiversity impacts were covered: ecotoxic effects, land occupation and conversion, and impacts caused by nutrients and pH changes (as a combination of impacts from acidification and eutrophication (Goedkoop et al. 2000; Dreyer et al. 2003)). Ecotoxicity effects were characterized based eventually on laboratory toxicity test data, extrapolated to impacts in the field, whereas the other impacts were mostly characterized based on field data. None of them was spatially differentiated (i.e., no geographic differentiation in the extent of the impacts) and plant species were the only taxonomic group considered in characterizing the magnitude of impacts. Recent LCIA methods (e.g., (Huijbregts et al. 2017; Bulle et al. 2019; Verones et al. 2020)), in contrast cover around 10 impact categories related to ecosystem quality, often distinguishing impacts between different realms (freshwater, marine, terrestrial) and in most cases also providing spatially differentiated models.

Despite these efforts, there are still inconsistencies between impact categories and existing models can be refined to include, for example, more recent data, more spatial detail or more sub-categories (e.g., land use intensities). In addition, impact categories are missing, such as the effects of plastic pollution or other ocean-related impacts, which have been historically understudied in the Life Cycle Assessment (LCA) literature (Woods et al. 2016, 2021). Finally, the fact that some species are more globally threatened with extinction than others, e.g., the potential different impact on endemic species, small-ranged species, and critically endangered species versus widespread species that are classified as “least concern” by the IUCN Red List (IUCN, International Union for Conservation of Nature and Natural Resources 2023), has so far been inconsistently included in LCIA methods.

In 2020, the third phase of the global LCIA guidance project of the Life Cycle Initiative hosted by the UN Environment Programme (GLAM3) was launched. We refer to GLAM3 as the third phase but note that the versioning of the Characterization factors starts at GLAM V1. GLAM3 task force members first carried out scoping work to identify improvement potentials to be achieved during this phase. Specifically for impacts on biodiversity, the ecosystem quality task force identified three main tasks, all of which are presented and discussed in this paper, namely 1) harmonization of existing impact categories, 2) integration of new impact categories at endpoint level, and 3) inclusion of vulnerability aspects into the models.

Concerning harmonization, aspects that were identified as important were comparability and compatibility across

impact categories. A problem related to this is that the spatial scale of methods can vary from regional impacts to global impacts (e.g., impacts on ecoregion-level in land use vs global impacts of climate change), making comparisons inconsistent (as discussed in Curran et al. (2011)). As a result, the task force worked on creating a scaling factor to harmonize the impacts between different categories.

After a thorough discussion within the task force, several impact categories were identified as being important to be addressed. These are detailed in the following sections.

Land use, freshwater and marine eutrophication, as well as ecotoxicity have been part of earlier GLAM recommendations at midpoint level or for hotspot analysis (Frischknecht and Jolliet 2016, 2019). The task in the current phase of GLAM was to review these methods and recommend updates and replacements to represent the state-of-the-art at endpoint level. It is important to stress that the focus of the ecosystem quality task force was on endpoint level methods only in this phase of GLAM (with impacts being translated into damages measures in terms of PDF, potentially disappeared fraction of species, and PAF, potentially affected fraction of species, indicators). Midpoint development is covered in the GLAM overarching paper (Jolliet in preparation). GLAM3 includes models and ongoing efforts that the sub-tasks were aware of and deemed relevant to be included. It does by no means imply that no other methods in the same impact categories are currently under development outside of the framing of GLAM. The impact of biomass removal by fisheries (Stanford-Clark et al. 2024) initially proposed in the scoping document, was not included in the final version. This decision was taken because of inconsistencies between its abundance-based metric and the disappearance-based damage indicator selected in GLAM. In addition, it was decided that GLAM3 would provide characterization factors at country and global levels only, disregarding spatial units smaller than country level. These native scale CFs are only available in the underlying publications of each individual impact category.

2 Overview of the covered impact categories

The ecosystem quality task force worked to develop recommendations for eight impact categories (Table 1), plus one conversion factor from regional to global impacts (global extinction probability – GEP). More information on each impact category is available in the following sections and the Supporting Information (SI). This overview refers to the CFs included in the GLAM research version, a (Sheet “Iciamethods_CF”), which brought all CFs into the same data format. Flow name and compartment nomenclature and

additional steps for software implementation are handled in the GLAM overall and the implementation paper (Dorber in preparation).

3 Choice of endpoint indicator

We use potentially disappeared fraction of species (PDF) as the indicator of biodiversity loss (and ecosystem quality), as previously recommended (Verones et al. 2017a; Woods et al. 2018). We quantify global PDFs (i.e., fractions of species expected to go extinct) by combining regional PDFs (i.e., fractions of species expected to be extirpated) with the vulnerability of species to global extinction by using the global extinction probability (GEP). These regional CFs are modelled with specific models particular to each impact category (see Sect. 5 and SI for details). However, in general, the models follow one of three main approaches. They either employ some form of species-area-relationship (where a loss of area is related to a corresponding reduction in species richness), use a species-discharge relationship (where a change in river discharge leads to a change in species richness), or use a species-sensitivity distribution (describing how different species vary in their sensitivity to a stressor; often a pollutant).

Some impact categories (e.g., ecotoxicity) may in the first instance quantify the toxic pressure of exposure to chemicals, expressed as the potentially affected fractions of species (PAF) based on ecotoxicity test data collected under laboratory conditions, the observation that ecotoxicity test data collected under laboratory conditions are commonly log-normally distributed. Upon translating exposure concentrations into dimensionless PAF-values, there is a need for this impact category to convert the dimensionless PAF to the preferred PDF-metric of field species loss by calibration. More specifically, the GLAM3-recommended PAF is based on 10% effect-levels in the laboratory tests, summarized as EC10-values (Effect Concentration causing 10% effect on vital characteristics under chronic exposure). For the GLAM3 selected “working point” to characterize ecotoxicity impacts, the 20th percentile of the across-species distribution of EC10s, it appeared that a predicted EC10-effect in 20% of the species calibrates to approx. 20% species loss in contaminant-exposed field species assemblages of 0.2. This led to an approximate PAF-to-PDF association of 1:1 to extrapolate from PAF under laboratory conditions to PDF under field conditions (Oginah et al. 2025)). This represents a change compared to previous studies assuming larger species abundance losses compared to species richness losses (Schipper et al. 2014; Kuipers et al. 2025). This difference might be explained by the fact that these studies focused on net species change defined as true loss (species present in

non-exposed conditions but lost due to chemical exposure) compensated by increased presence of some opportunistic species. In opposition, Oginah et al. (2025) accounted for the neutralizing effect of opportunistic species, potentially explaining the differences in findings. The apparently sensitive response of field species assemblages to chemical pollution, concluded from the recent calibration observations, likely relates to the fact that field species are commonly exposed to other stressors too. Thus, all impact categories that used PAF in their development, used the 1:1 conversion to arrive at PDF. This decision reflects the current status of research and might change as studies with larger geographical or species coverage are conducted.

Some impact categories use one species group (e.g., terrestrial acidification) in their model, while others use several species groups (e.g., land use) or mixed species sets (e.g., ecotoxicity). The impact categories within the AoP “ecosystem quality” are meant to represent impacts on the health of the “ecosystem”. If there is data for more than one species group available, we used all of them to calculate CFs across several groups to represent more aspects of the variety of a whole ecosystem than single-species-group assessments would. Most original publications make species-group-specific CFs available as well. These are, however, not the recommended CFs to be used.

4 Cross-cutting aspects

4.1 Global extinction probability (GEP)

In the previous phase of GLAM it was recommended to consider vulnerability aspects of species more comprehensively (Woods et al. 2018). The GEP developed under the GLAM3 initiative (Verones et al. 2022) is an expansion of the study by Kuipers et al. (2019) (see SI for more information on the calculation procedure). Multiplying a local or regional CF with the GEP of the corresponding species group and spatial resolution results in a relative global species loss indicator. The GEP uses information on species ranges, their IUCN Red List conservation status, and species richness in a region to estimate the extent to which species loss in one area (e.g., pixel, watershed, country) potentially contributes to global extinctions. We updated and expanded this GEP with additional species (Verones et al. 2022) in order to cover as many relevant species groups for the different impact categories as possible (see calculation procedure in SI). The GEP is based on data for over 90,000 species across 25 species groups at 0.5° resolution. For each impact category, we aggregated available species groups across relevant domains (e.g., terrestrial, aquatic, marine) and calculated category-specific GEP factors to preserve the

GEP property that the sum of GEP = 1. That means that if all species in a group were extirpated from every cell, 100% of species of this group would disappear globally.

It is a prerequisite for the use of the GEP that its values (per species group and spatial scale) always add up to one. Therefore, the GEP needs to match the spatial resolution of the local or regional characterization factor (e.g., ecoregion or country scale). Grid-scale GEPs can be spatially aggregated into larger geographic features by summing the grid-level GEPs contained in the larger feature. If CFs are provided at various spatial scales (e.g., ecoregions, countries and continents), local or regional CFs need to be spatially aggregated before they are multiplied with the corresponding GEPs. The GEP can also be calculated for any relevant species assemblage that is relevant for the impact category in question. It can contain one species group (e.g., freshwater fish) or several species groups (e.g., amphibians, reptiles, birds, terrestrial mammals and vascular plants). One assumption is that species used in the CF models act as proxies for their environment, meaning that if the CF model considers a selection of freshwater fish species, the freshwater fish GEP will consider all freshwater fish available. There may be a certain mismatch in individual species due to a lack of spatial data or data for the impact category. The unit of the recommended damage indicator is thus the fraction of species that is expected to go extinct globally (global PDF). The selection of species as proxies was purely data driven. For the GEP, this means that only species that are listed on the IUCN Red List with a threat level and have a range map (from IUCN or other sources) available, are included in the calculations. This includes species that are classified from “least concern” to “critically endangered”, while data deficient and already extinct species are excluded.

The GEP is applied by multiplication to a regional CF, to scale the impacts from local or regional losses (in PDF) to potential global extinctions (in global PDF). In previous LCIA methods, many have mixed regional and global impacts (e.g., impacts from climate change are calculated at global level while e.g., land use is calculated regionally). This hampers their comparability, because regional and global losses of species are not equivalent: species that are extirpated in one region may still persist in other regions of the world (and may thus in theory be reintroduced), while species that are extinct at a global level have completely disappeared from our planet and are irreversibly lost. By applying GEPs to the CFs of the regional methods, all impact categories now quantify global PDFs, enabling their comparability. The criterion for applying the GEP in an impact category was that the CFs were available at regional scale in the first place. That means that impacts that were modelled globally (climate change, aquatic microplastics) or used nested models resulting in a global CF (ecotoxicity),

did not or could not implement the GEP, since their impacts are assumed to already be global. We want to stress that regional and global CFs serve distinct purposes, and we strongly believe that both should be used, but that consistent comparisons of species loss impacts between impact categories are only possible using global CFs.

4.2 Aggregation within impact categories

Some impact categories consider a single species group (e.g., water use), some use mixed-species models (e.g., ecotoxicity), and others derive CFs for individual species groups (e.g., land use with models for amphibians, reptiles, terrestrial mammals, birds and vascular plants individually). For footprint assessment practitioners, it may be inconvenient to have to deal with multiple impact indicators within one impact category, since the greatest interest lies in the overarching impact on the ecosystem as a whole. However, when interested in specific species groups, practitioners can use species specific CFs, available for research purposes. We therefore need an approach to aggregate between different species groups within one impact category. There are several ways to aggregate impacts across species groups (as discussed in Verones et al. (2015)). After discussions in the task force and in expert workshops we recommend a three-stage process for aggregation within one impact category to arrive at global total impacts; these three stages are applied in the CFs provided in GLAM3:

- 1 Multiply CFs of taxa and plants individually with GEP at the correct spatial resolution (see SI)
- 2 Arithmetic average across the animal species groups included (e.g., (reptiles+birds)/2).
- 3 Arithmetic average between kingdoms, if required ((Animal average CF from previous step+plant CF)/2).

4.3 Aggregation across impact categories

We recommend distinguishing the results of impact categories within the same AoP. By consistently using the global PDF values for the CFs, impact assessment results can be compared more easily between impact categories. Aggregating impacts into a single indicator reduces the level of information that can be provided (e.g., which share of the impact comes from category x?). In addition, the large differences between the ecosystem types and realms may make a simple sum uninformative. Human pressures and species responses differ substantially between marine, freshwater, and terrestrial realms. We therefore advocate to keep results from these different realms separate. However, we acknowledge that value and wish to have the option to aggregate the results to one final value for ecosystem quality.

How and whether to aggregate across impact categories is ultimately a value choice. For the GEP, we have recommended an arithmetic mean between groups of different kingdoms (see section 4.2). We argue that to be consistent, aggregations across different realms should also follow the same logic and propose to use equal weights for the three realms (marine, freshwater and terrestrial). This way we value marine, freshwater, and terrestrial ecosystems equally, independent of the number of species that these environments host.

5 Category specific indicators, models, characterization factors and main recommendations

5.1 Ecotoxicity

5.1.1 Background and scope

The increasing production of chemicals and releases into the environment are drivers of Environ. Pollut (Bernhardt et al. 2017; Persson et al. 2022). contributing to biodiversity loss (Lemm et al. 2021). The ecotoxicity impact category in LCIA aims at quantifying the impacts of toxic chemical releases associated with products and product chains or services and organizations on ecosystems.

The calculation of ecotoxicity impacts at the PAF level starts from the inventory of chemicals in use (identity and mass) and the chemical emission fractions to determine chemical amounts emitted to the environment, followed by assessments of environmental fate and exposure. These assessments account for removal processes and mechanisms determining the bioavailability of the chemical in the exposure compartment, and eventually quantify the estimated PAF integrated over the exposure compartment volume and time. At the endpoint (i.e., damage) level, the estimated PAF is extrapolated to PDF using a severity factor (SF), which aims to consider how morbidity and mortality affect overall survival.

The SF for the GLAM3-consensus ecotoxicity impact metric (HC20EC10, the Hazardous Concentration at which 20% of the species in a species assemblage is exposed to a concentration level that causes 10% impact in such exposed species), derived from a Species Sensitivity Distribution (SSD) of chronic EC10 values, has the value of 1 based on calibration studies with this metric. HC20 stands for the hazardous concentration at which 20% of the ecosystem analysed shows an effect and EC10 for a concentration that causes a reduction of 10% of a vital characteristic of a species, such as growth or reproduction. Even though the CFs are based on nested continental scales, they are ultimately

not regionalized, so no GEPs could be included (see also the discussion).

5.1.2 Impact pathway and selected framework and model

The impact pathway for ecotoxicity covers chemical emissions to the environment, environmental fate and exposure processes, bioavailability in the receiving compartment, and the resulting impacts on ecosystem quality at the endpoint level (Fig. 1).

The characterization factors (CFs) used in LCIA to estimate ecotoxicological damage are defined based on Eq. 1 (Owsianiak et al. 2023). Data used in the modelling are listed in Table S4.1 in the Supporting Information.

$$CF_c = TF_c^{\text{cum}} \times \frac{1}{k^{\text{loss}}} \times XF \times \overbrace{CRF \times SF}^{EF} \quad (\text{Eq. 1})$$

Where TF_c^{cum} is the cumulative chemical mass transfer fraction from the emitting to the receiving compartment, k^{loss} is the removal rate constant and its inverse represents the first-order residence time in the receiving compartment, XF is the exposure factor (bioavailable mass fraction), CRF is a concentration response function for the respective ecosystem and SF is a severity factor for translating affected species to disappeared species. CRF and SF combined are also called the effect factor (EF). These factors are, in principle, specific for each substance in each of the different exposure compartments (freshwater, marine, terrestrial), given that bioavailable fractions differ amongst compartments due to physico-chemical interactions between chemicals and environmental matrices, as well as differences in species sensitivity. Furthermore, the fate factor (FF) is emission-compartment specific as it depends on the fraction of chemical transferred from the emission compartment to the exposure compartment.

Unless reported otherwise, the fate, exposure and effect factor modeling follow the recommendations of Owsianiak et al. (2023). The fate and exposure modelling steps rely on the USEtox consensus model (Fantke et al. 2018; Owsianiak et al. 2023). The ecotoxicity effect modelling was adapted to better reflect environmentally relevant exposure levels and to include chronic test data to a larger extent, while the exposure modelling does not consider bioaccumulation as an additional removal mechanism. Instead of the previous consensus metric HC50-EC50, which represents relatively high and uncommon ambient exposure levels, the new HC20-EC10 metric selected as LCIA working point relates more closely to contemporary ambient exposure levels. Still, Rorije et al. (2022) showed that most field mixtures sit below a 5% msPAF, which would argue for setting the working point even lower at the HC5 at concentration ranges organisms encounter. The HC5 is, however, also known to vary more than other working points as confidence intervals widen in the extreme tail of the SSD (Aldenberg and Jaworska 2000). Choosing the HC20-EC10 is therefore a compromise between environmental representativeness and relative statistical robustness. This trade-off might be revisited as new evidence and more robust modelling approaches become available.

The update of the ecotoxicity impact category carried out in the GLAM3 phase had three aims: (1) provide a consistent approach to address experimental data-poor chemicals using in silico methods; (2) revise how CFs for terrestrial and marine ecotoxicity are derived; and (3) recalibrate the PAF to PDF relationship with refined data assessment methods for the HC20-EC10 impact metric.

Data-poor chemicals are defined as chemicals with fewer than five measured data points, here EC10-equivalents from three different species groups. Without in silico methods, which are based on statistical patterns in the ecotoxicity of chemicals across species, the number of chemicals with associated CFs would remain low, implying no

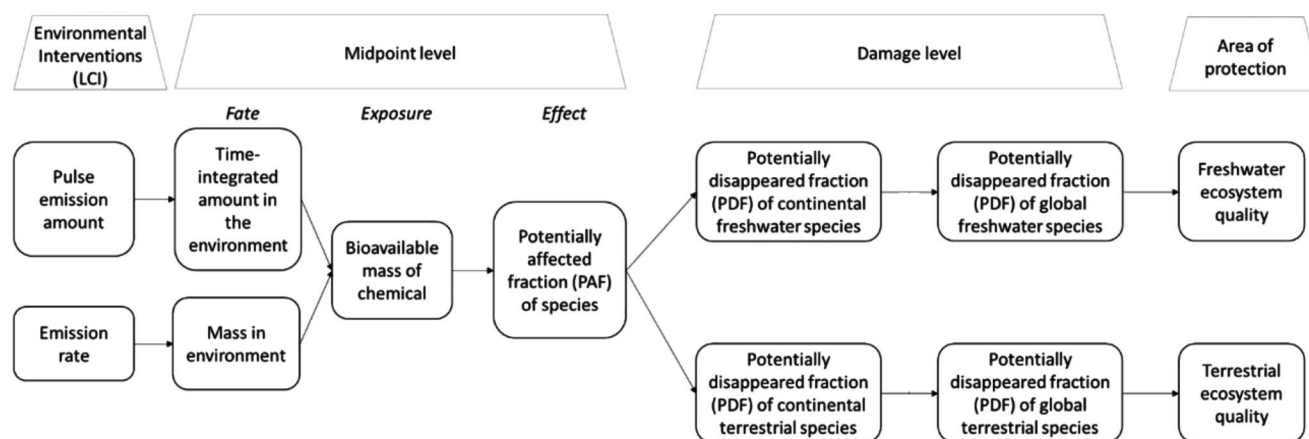


Fig. 1 Impact pathways in the impact category ecotoxicity, up till the endpoint-level 'ecosystem quality'

characterization of those compounds in LCIA. The GLAM3 approach therefore aimed to derive robust SSDs for a substantially larger number of compounds based on accepted and validated *in silico* methods. Given current data availability, the use of *in silico* methods was possible only for surface freshwater systems.

5.1.3 Resulting characterization factors

The CFs for freshwater ecotoxicity do not distinguish spatially explicit impacts because the background data used to derive toxic pressure (PAF) from ecotoxicity test assemblages are not spatially specific. Consequently, the EFs are available at the global scale. We recommend treating all emissions as global unless a USEtox-specific region has been specified. Freshwater CFs are available for more than 9,000 chemicals for continental emissions to freshwater. The uncertainty of the freshwater EFs was derived based on Oginah et al. (2023). The CFs are available in the Supporting Information of Douziech et al. (2024).

For terrestrial ecotoxicity characterization, a six-step approach detailed in the Supporting Information was applied. In brief, the existing fate and exposure factors implemented in USEtox were mapped to newly derived EFs. These EFs were derived from the curation and harmonization of collected effect test data and from newly defined extrapolation factors converting different exposure durations and effect endpoints towards chronic EC10 equivalents, in line with the recommendations of Owsianiak et al. (2023) to derive HC20 from chronic EC10 equivalents.

For marine ecotoxicity characterization, environmental fate and exposure factors can be derived from the general USEtox model (Rosenbaum et al. 2008), while marine-species specific effect factors require further collection and curation of relevant effect test data before possible implementation into GLAM. No marine CFs were therefore derived as part of this GLAM task force.

Given the low environmental concentrations and the assumption of linearity, the approach is considered valid for both marginal and average CFs, and both are therefore assumed equal.

5.1.4 Evaluation and applicability

The approach proposed in GLAM3 to derive freshwater EFs was developed based on an array of data-rich substances (Douziech et al. 2024). Evaluation of the derived EFs showed a close covariation between the earlier HC50-EC50-based and the new HC20-EC10-based effect factors, although the latter were derived using various intra- and inter-species extrapolation methods (Douziech et al. 2024). Combined with the fact that HC20-EC10 corresponds

more closely to contemporary exposures at polluted field sites, whereas HC50-EC50 does not (Rorije et al. 2022), the overall evaluation of the new consensus principle and associated consensus effect factors is positive. It is therefore recommended to use the novel effect factors derived under GLAM3.

It is recommended to base effect factors on measured ecotoxicity data. When multiple measured effect data are available for one species and chemical, the following order of preference is recommended:

- 1 EC10 as the geometric mean of measured chronic EC10 values, if no chronic NOEC values are available.
- 2 EC10 as the geometric mean of measured chronic NOEC extrapolated to chronic EC10 and measured chronic EC10 values, if both chronic NOEC and chronic EC10 values are available.
- 3 EC10 as the geometric mean of measured chronic EC50 extrapolated to chronic EC10, if no chronic EC10 or chronic NOEC values are available.
- 4 EC10 as the geometric mean of all acute effect data extrapolated to chronic EC10, if neither chronic EC10, chronic NOEC nor chronic EC50 values are available.

The recommendation is to collect sufficient test data to derive SSD-EC10 values. Whenever at least five data points from three different species groups representative of the considered environmental compartment are available, the approach of Owsianiak et al. (2023) can be followed. However, given the limited availability of test data for many compounds, the derivation of EFs for data-poor compounds proceeds differently. Complementing measured effect data with Interspecies Correlation Estimates (ICE; (Lilavois et al. 2024)) is not recommended according to Douziech et al. (2024). Instead, a hierarchical approach is recommended when the minimum number of five data points from at least three species groups is not reached.

First, an HC20-based approach using measured data complemented with QSAR estimates is recommended to reach five data points from at least three species groups. The QSARs are used to add species-specific effect data to the pool of measured data. No specific QSAR is recommended, but criteria for selecting an appropriate QSAR are provided in the Supporting Information. Second, an HC20-based approach using the geometric mean of all measured effect data and an average slope of 0.7 (log µg/L) can be applied. No recommendation can currently be made regarding pure prediction tools in the absence of measured effect concentrations.

Research carried out in parallel to the GLAM task force has also demonstrated the importance of considering taxonomically specific effect factors, enabling impact prediction

based on taxonomically specific SSDs (e.g., HC20-EC10 for algae, invertebrates, or fish). This improves the accuracy of impact predictions particularly for data-rich compounds where the split SSDs themselves are robust (Oginah et al. 2023). However, additional work is still required before a recommendation regarding this approach can be made.

The final step is the derivation and use of the severity factor linking PAF-HC20EC10 and PDF. Based on recent detailed calibration study results (Oginah et al. 2025), it is recommended to use $1 \text{ PDF} = 1 \text{ PAF(HC20EC10)}$, as explained in Sect. 2.

5.2 Land use

5.2.1 Background and scope

Land use is the main driver of terrestrial biodiversity loss (Brondizio et al. 2019; Jaureguiberry et al. 2022). In the first phase of GLAM, experts gave an interim recommendation for an indicator of land use impacts on ecosystem quality (Jolliet et al. 2018). The recommended model was developed by (Chaudhary et al. 2015). Experts additionally stressed the importance of considering land use intensity levels and habitat fragmentation (Jolliet et al. 2018). Subsequent characterization models considered these aspects separately (Chaudhary and Brooks 2018; Kuipers et al. 2021b), whereas the model developed within GLAM phase 3 considers both simultaneously (Scherer et al. 2023). The GEP combined species data on mammals, reptiles, amphibians, birds and vascular plants.

5.2.2 Impact pathway and selected framework and model

The impact category of land use encompasses two pressures: land occupation and land transformation. The inventory,

expressed as land area, is directly translated into impacts on biodiversity at the endpoint / damage level (Fig. 2). Terrestrial ecoregions (Olson et al. 2001) represent the native scale.

The characterization model uses the species-habitat relationship from Kuipers et al. (2021a), in which the total land use area is replaced with the equivalent connected area by considering habitat loss, habitat fragmentation and the ability of species to disperse across habitat patches. Dispersal distances are estimated based on species traits from Kattge et al. (2020) for plants and Wilman et al. (2014) for birds and mammals, whereas a universal dispersal distance is assumed for amphibians and reptiles. The more limited dispersal is, the more challenging it becomes for species to move between disconnected habitat patches, making the equivalent connected area smaller than the total suitable habitat within an ecoregion.

Land use intensities are considered within the habitat affinities using data mainly from Gallego-Zamorano et al. (2022) and Hudson et al. (2017). Compared to the model recommended in GLAM phase 1, the spatial land use data have been updated and now represent the year 2015 based on HILDA+ as the base map (Winkler et al. 2021).

5.2.3 Resulting characterization factors

The resulting characterization factors (SI) show that marginal CFs indicate larger impacts than average CFs. Relative species losses tend to be higher for animals than for plants, although this depends on the land use type and intensity (Scherer et al. 2023). More intensive land use generally leads to larger impacts, although differences between intensity levels can be small.

Uncertainties stem, among others, from uncertainty in local relative species losses. In addition, the model choice

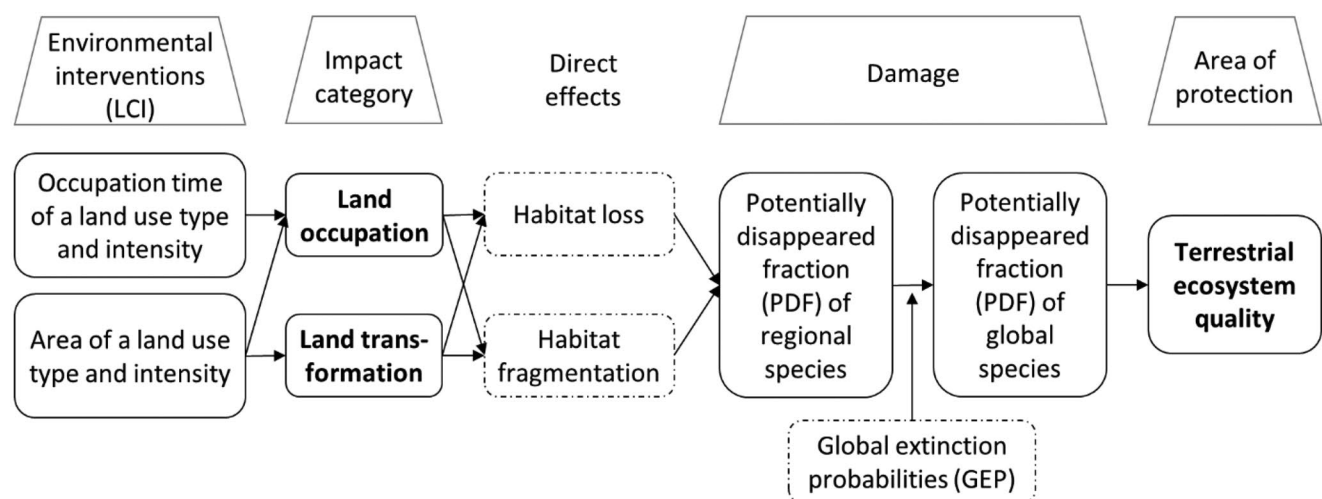


Fig. 2 Impact pathway covered for land use

to explicitly consider land use intensities and habitat fragmentation influences the results, as confirmed through sensitivity analyses (Scherer et al. 2023). To convert the native scale to country and global scales, the respective ecoregion CFs were averaged by weighting them according to their area shares or, alternatively at the global scale, according to land use shares (Scherer et al. 2023).

5.2.4 Evaluation and applicability

Land use is a highly relevant impact category for terrestrial ecosystem quality and provides comparatively broad coverage by considering multiple species groups globally across terrestrial ecoregions. The CFs build on a modified countryside species-area relationship, which is well recognized. Responses to local land use pressures are based on species-specific IUCN expert judgements (IUCN, International Union for Conservation of Nature and Natural Resources 2023) and empirical data (Hudson et al. 2014).

Uncertainty ranges are currently not available due to the computational requirements involved, especially for the quantification of fragmentation effects. However, multiple sensitivity analyses have been conducted to reflect uncertainty in the underlying data.

Land occupation and transformation are long-standing impact categories with which LCA practitioners are familiar. A matching of land use classes between life cycle inventory databases and characterization factors has been conducted to facilitate application of the developed CFs (Scherer et al. 2021). Scherer et al. (2023) additionally provide guidance on the application of the CFs.

Because large data gaps exist in the CFs, particularly where a certain land use type at a given intensity level did not occur in a given ecoregion in 2015, proxy values have also been estimated to support analyses involving land use change or future scenarios (Scherer et al. 2023).

Overall, land use features high relevance, broad species and spatial coverage, and strong applicability. However, the unquantified uncertainties and the difficulty of validating the CFs should be noted.

5.3 Freshwater and marine eutrophication

5.3.1 Background and scope

Eutrophication occurs when ecosystems receive excess inputs of limiting nutrients (Vitousek et al. 1997; Schulte-Uebbing et al. 2022). If the input of limiting nutrients to a freshwater or marine system exceeds the assimilative capacity of that system, ecosystem structure and functioning may change due to phytoplankton growth, changes in plant composition in the photic zone, altered predator-prey

relationships, habitat changes, respiration of organic matter, and reductions in dissolved oxygen concentrations in the water column.

In current LCIA practice, phosphorus is assumed to be the limiting nutrient for freshwater systems, while nitrogen is assumed to be the limiting nutrient in marine systems. These assumptions have mainly been driven by modelling parsimony. However, co-limitation by nitrogen (N) and phosphorus (P) may occur in both systems, and other substances such as silica may also be limiting (Garnier et al. 2010; Azevedo et al. 2015b; Henderson 2015; Payen and Ledgard 2017).

In the second phase of GLAM, P damages (PDF) to freshwater ecosystems and N damages (PDF) to marine ecosystems were recommended. The selected methods showed spatial variation, although only to a limited extent. In GLAM phase 3, freshwater eutrophication was further developed by investigating the inclusion of N damages and a more spatially refined effect component based on expanded datasets. In addition, the GEP was linked to both freshwater and marine eutrophication. The GEP for freshwater eutrophication included freshwater fish and for marine eutrophication the species groups considered were cartilaginous fish, ray-finned fishes, lobsters (for crustaceans), cnidarians and sea cucumbers (for echinoderms).

5.3.2 Freshwater eutrophication: impact pathway and selected framework and model

The characterization factors (CFs) for freshwater eutrophication were developed at 0.5×0.5 degree resolution for phosphorus (P) and nitrogen (N) from direct emissions, diffuse emissions (unit: PDF·year/kg P or N), and excessive erosion due to land use (unit: PDF·year/(m²·year)) (Fig. 3). The impact pathway includes nutrient fate until reaching freshwater systems and nutrient processes within freshwater systems (Zhou et al. 2022a), effects on freshwater fish species richness (Zhou et al. 2023), and the use of GEPs to translate regional species loss to global species loss (Veronesi et al. 2022).

The fate factors (FFs) were calculated using the spatially explicit and dynamic nutrient model IMAGE-GNM (Integrated Model to Assess the Global Environment – Global Nutrient Model) (Beusen et al. 2015). Marginal and average effect factors (EFs) were derived from species sensitivity distributions at the level of freshwater ecoregions, considering species occurrence data from (Barbarossa et al. 2020, 2021). Since only one nutrient may be limiting at a given location, the limiting nutrient was determined at the grid-cell level following McDowell et al. (2020). This information can guide the choice between CFs for P or N where the

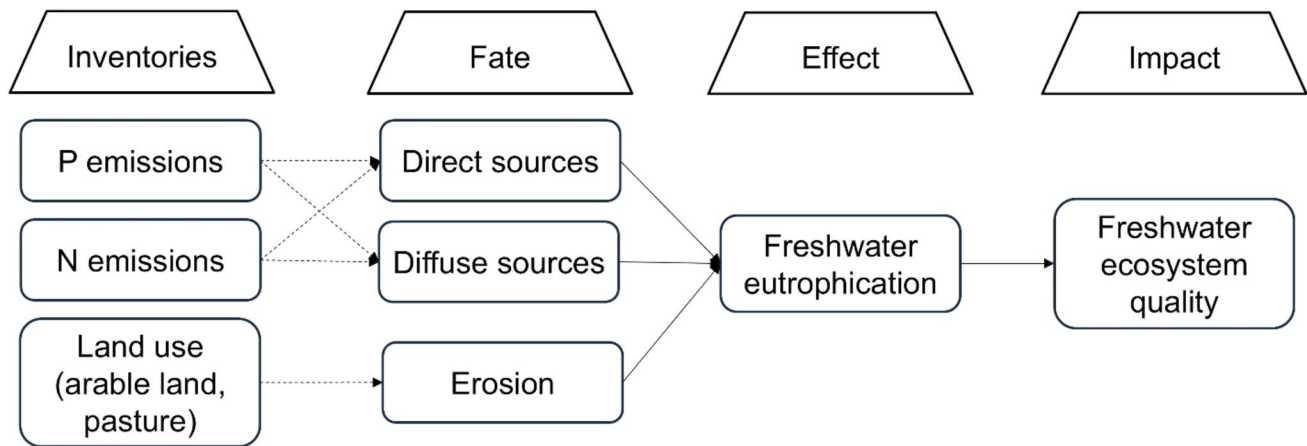


Fig. 3 Schematic diagram of the impact pathways for freshwater eutrophication

location is known. When aggregating to the country scale, the relative share of limitation by P or N is considered.

5.3.3 Freshwater eutrophication: resulting characterization factors

In total, 16 sets of CFs were developed, differentiating between P versus N, average versus marginal CFs, and direct emissions, diffuse emissions, arable land and pasture. At the global scale, CFs for P are generally higher than those for N, while average CFs are higher than marginal CFs. In addition, CFs for direct emissions are higher than those for diffuse emissions, and CFs for erosion on arable land are higher than those for erosion on pasture.

The CFs at country and global scales were aggregated by weighting with emission data for direct emissions and diffuse sources and with land use areas for erosion, either considering only P- or N-limited regions or considering the entire region (Zhou et al. 2024).

Zhou et al. (2022b) validated the underlying IMAGE-GNM model against thousands of global river stations and found moderate correlations and root mean square errors (RMSE) larger than the average, with slightly better performance for N than for P. All species sensitivity distributions with sufficient data (367 ecoregions for N and 366 for P) showed a good fit, with 97% presenting a Pseudo- $R^2 > 0.8$ and normalized RMSE < 0.5 (Zhou et al. 2023).

5.3.4 Freshwater eutrophication: evaluation and applicability

As a widespread water quality issue, freshwater eutrophication is a highly relevant impact category for freshwater ecosystem quality. The framework is relatively complete by considering multiple emission routes, multiple removal processes, and both total phosphorus and total nitrogen

emissions. However, it currently only considers impacts on a single species group: freshwater fish.

The use of the mechanistic IMAGE-GNM model for fate modelling and the inclusion of more than 13,000 fish species in the effect modelling are important strengths. However, limitations include the independence of the datasets used for nutrient concentrations and fish species occurrences, as well as the consideration of nutrient limitation only at the source cell rather than throughout all downstream cells. The CFs provide global coverage at 0.5° spatial resolution and have additionally been aggregated to the country scale.

Freshwater eutrophication is a well-established impact category familiar to LCA practitioners. Following workshop discussions, conversion coefficients have been provided for some P- and N-containing compounds to facilitate links with inventory databases. To avoid complications related to nutrient limitation, an additional set of country-level CFs has been developed that already incorporates weighting according to the probability of limitation by P or N.

If water is unspecified, meaning it is unclear whether it is freshwater or marine water, we recommend assuming that half is freshwater. If land is unspecified for erosion-related flows, we recommend assuming that half is agricultural land, with equal proportions between arable land and pasture.

Overall, relevance, spatial coverage and applicability are high. However, validation of the CFs remains difficult. While IMAGE-GNM has been validated for fate modelling (Zhou et al. 2022a) and the performance of the species sensitivity distributions has been evaluated for effect modelling (Zhou et al. 2023), uncertainty ranges have not been provided.

5.3.5 Marine eutrophication: impact pathway and selected framework and model

The fate, exposure and effect factor modeling follow the recommendations of Payen et al. (2019). The impact modelling includes fate factors for atmospheric emissions (Bjørn et al. 2020; Henderson et al. 2021) and inland and marine emissions (Cosme and Hauschild 2017), relating emissions to steady-state nitrogen concentrations in large marine ecosystems (LMEs) (Sherman and Duda 1999).

Exposure factors account for primary production, meta-zoan consumption and bacterial degradation in benthic waters to relate nitrogen enrichment to reductions in dissolved oxygen concentrations in the marine benthos (Cosme et al. 2015). Effect factors use species-level regional hypoxia sensitivity to estimate a PAF (Cosme and Hauschild 2016). Finally, GEPs (Verones et al. 2022) were added to the characterization factors. This impact pathway schematic is shown in Fig. 4 (see also SI for more details).

5.3.6 Marine eutrophication: resulting characterization factors

Characterization factors for marine eutrophication were calculated at the scale of large marine ecosystems and countries and can additionally be aggregated to the global scale (SI).

5.3.7 Marine eutrophication: evaluation and applicability

The CF model used in this work is based on (Cosme and Hauschild 2017; Payen et al. 2019; Bjørn et al. 2020; Henderson et al. 2021).

The marine eutrophication CFs provide additional sophistication, but also additional challenges for LCA software, because they distinguish between agricultural, non-agricultural and unspecified sectors. At present, we recommend using the unspecified CFs, which combine agricultural and

non-agricultural emissions, for background LCA calculations. Sector-specific CFs should be used when practitioners have foreground data and the ability to apply specific CFs to inventory flows.

The application of GEPs to the effect factors required restricting taxonomic coverage to those groups represented in both the effect factors and the GEPs. Expanding taxonomic group and species coverage remains an important area for future work.

The freshwater/soil transport modelling is based on the NEWS 2 framework (Mayorga et al. 2010) while atmospheric transport modelling is based on earlier work by Roy et al. (2012b). The NEWS 2 framework operates at watershed resolution, whereas the atmospheric transport model is based on atmospheric conditions representative of the year 2005. Both underlying models could therefore be evaluated for future updates.

Part of the framework separates freshwater and marine eutrophication into phosphorus- and nitrogen-limited systems. However, co-limitation, including by other substances such as iron or silica, should be explored further.

5.4 Climate change

5.4.1 Background and scope

Environmental change triggered by climate change is one of the major threats to the world's ecosystems (Hoegh-Guldberg et al. 2018; Brondizio et al. 2019). Currently, GLAM provides recommendations only for midpoint indicators related to climate change (Frischknecht and Jolliet 2016, 2019). In the LCIA literature, recommendations to consistently translate midpoint climate change impacts to endpoint impacts on ecosystem quality across freshwater, terrestrial and marine realms are still missing.

Here, newly developed characterization factors (CFs) are presented for the impacts of climate change on freshwater,

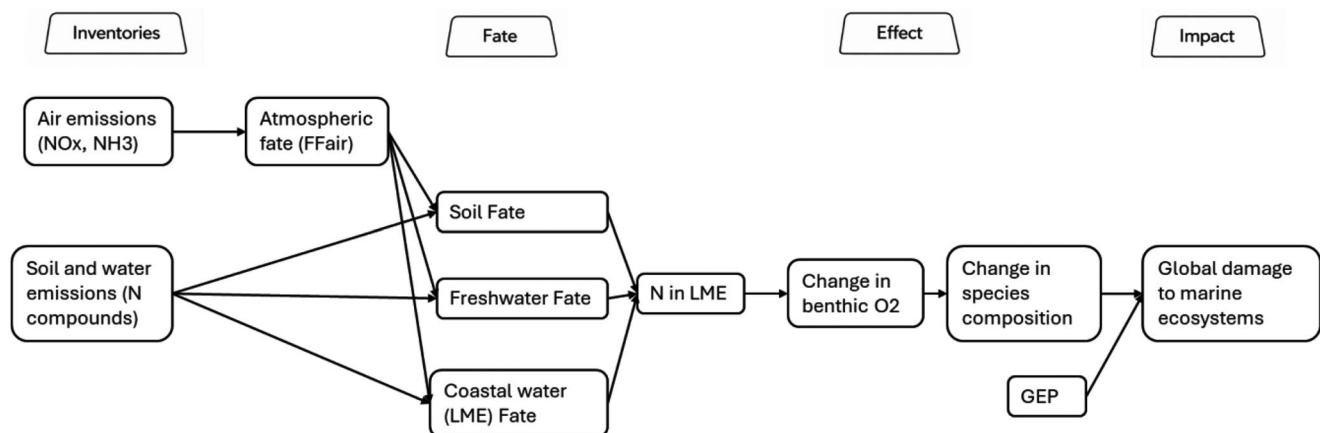


Fig. 4 Marine eutrophication impact pathway

terrestrial and marine ecosystems at the endpoint level. The framework covers various climate-related categories of impact, namely global warming / temperature potential and multiple climate tipping points potentials. Since climate change represents a global phenomenon, no GEP was included.

5.4.2 Impact pathway and selected framework and model

The PDF corresponding to a unit of greenhouse gas (GHG) emission is calculated according to the impact pathways illustrated in Fig. 5. For freshwater species, CFs [PAF·yr/kg or PDF·yr/kg] are derived through three main modelling steps. First, a global hydrological model converts changes in future climate into changes in streamflow and water temperature (Bosmans et al. 2022). (Second, a niche envelope model translates these changes into changes in the geographic ranges of freshwater fish species (Barbarossa et al. 2021). Third, area changes are converted into global extinction risk (global PDF) for approximately 11,500 freshwater fish species based on species-area relationships and linked to a unit of GHG emission (de Visser et al. 2023).

For terrestrial and marine species, air temperature niche limits are used for approximately 26,500 species (Trisos et al. 2020) to calculate unsuitable geographic range areas based on climate model projections. Species ranges are then stacked to calculate PDFs at the pixel level and linked to GHG emissions to derive global CFs (Iordan et al. 2023).

Temperature niche limits were calculated for temperature changes between 1850 and 2005, while the starting point for the 5-year average calculations was 2010. This information relates to GLAM V1.0.2024.10. For GLAM V1.1.2025.11, the fate factors (FFs) were updated based on AR6 to ensure consistency with endpoint climate change impacts on human health as well as with midpoint indicators (see SI).

5.4.3 Resulting characterization factors

The resulting CFs (SI) for freshwater, terrestrial and marine ecosystems are provided at different aggregation levels. For terrestrial and marine ecosystems, CFs are available for different representative concentration pathways (RCPs) and for two time horizons, 2050 and 2100, corresponding to the absolute global temperature change potential.

For freshwater ecosystems, one mean CF value per GHG is provided, representing long-term impacts at the end of the century. In addition, one value per GHG, RCP and time horizon (2050 and 2100) is provided corresponding to the absolute global temperature change potential. Finally, CFs corresponding to multiple climate tipping points potential (MCTP) are also provided for each year and RCP.

5.4.4 Evaluation and applicability

The CFs are evaluated in the respective development papers (de Visser et al. 2023; Iordan et al. 2023). Freshwater CFs have already been applied in a case study assessing the impacts of different biofuels on ecosystem quality (de Visser et al. 2023). Differences in magnitude, consistently across GHGs, were observed compared to previous well-established CFs for the same impact pathway.

The CFs for terrestrial and marine ecosystems, as well as the MCTP-based CFs, are available for different representative concentration pathways (RCP2.6, RCP4.5 and RCP8.5; and RCP4.5, RCP6 and RCP8.5, respectively). We recommend the use of RCP4.5 values, as this pathway is available consistently across methods and is closest to the currently most plausible scenario corresponding to RCP3.4. However, when more detailed information is available, we recommend using the RCP-specific values. The freshwater CFs are not RCP-dependent.

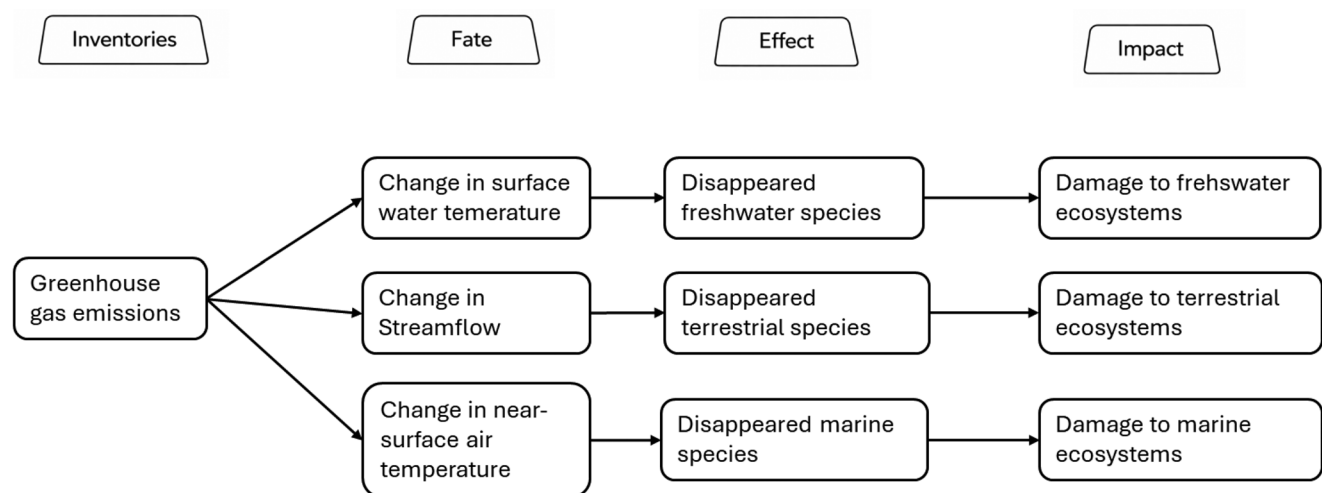


Fig. 5 Impact pathway schematic overview

Overall, we recommend the use of these newly developed CFs because of the modelling improvements introduced for the effect factors, the increased temporal detail, and the availability of multiple representative concentration pathways.

5.5 Water consumption

5.5.1 Background and scope

Water consumption is the use of water in a way that removes water from the ecosystem, either through evaporation, incorporation into products or transfer to other basins. Water consumption was included in earlier GLAM phases at the midpoint level to address in a general way the impacts of water scarcity on the three areas of protection simultaneously, including ecosystem quality, with the indicator AWARE (Boulay et al. 2018, 2020). However, this indicator is not a true midpoint on the ecosystem quality endpoint pathway. Hence, the conversion from midpoint impact to damage is not possible, and the endpoint indicators discussed below do not build upon the AWARE methodology.

Multiple regionalized CFs have been developed to characterize the potential damage of water consumption on freshwater ecosystem quality (Hanafiah et al. 2011; Tendall et al. 2014; Verones et al. 2017b; Dorber et al. 2019) yet with restricted spatial coverage and including only few species. These methods rely on species-discharge relationships (SDR) (or species-wetland area relationships) to estimate species loss associated with river flow reduction (or wetland surface reduction) due to water consumption. Such empirical relationships assume that there is a positive correlation between fish species richness and river flow in a catchment (Oberdorff et al. 2011; Schipper and Barbarossa 2022; Pierrat et al. 2023a). Pierrat et al. (2023a) further developed the SDR concept, including more predictors important for riverine biodiversity in addition to water discharge (e.g. regional climate, habitat heterogeneity) and using them as the basis to provide updated CFs covering 76% of the global landmass. The GEP focused on freshwater fish.

5.5.2 Impact pathway and selected framework and model

The impact pathway covers the consequences of water consumption (from surface water and groundwater) on freshwater habitat reduction, i.e. river discharge reduction (FF), and the resulting reduction of freshwater fish species richness (EF, see impact pathway diagram available in Fig. 6). Four sets of CFs expressed in $\text{PDF} \cdot \text{yr} \cdot \text{m}^{-3}$ were developed for 2320 river basins globally distributed (marginal regional, marginal global, average regional and average global CFs). The FFs (Pierrat et al. 2023b) represent the historical effects of surface and groundwater consumption on river discharge and were derived from a global hydrological model for the period 1960–2000 (Sutanudjaja et al. 2018; de Graaf et al. 2019). The EFs represent the effect of small (marginal EFs) and large (average EFs) streamflow depletion on freshwater fish species richness. They were derived from a SDR (Pierrat et al. 2023a), which was built upon an up-to-date fish species richness dataset (Schipper and Barbarossa 2022), simulated river discharge, elevation, and climate zones. Finally, FFs and EFs were combined into CFs representing potential impacts on regional biodiversity and with the GEP (Verones et al. 2022) for potential impacts on global biodiversity.

5.5.3 Resulting characterization factors

The analysis of the complete dataset of CFs (SI) exhibited 150 outlier values in basins representing 6.5% of all river basins and 2% of the landmass in scope (Table S2 and S3). Outliers were identified using the modified z-score on the fate factor values and attributed to global hydrological model artifacts (Salgado et al. 2016). These outliers caused the country scale CFs for 49 countries to be inconsistently high, therefore the outliers were excluded from the dataset to maintain consistency in the country and global CFs.

Table S2 in the SI for water consumption shows the CFs distribution at the native scale without outliers. The low and high values correspond to the uncertainty introduced by the EFs only, hence not including the uncertainty on the FFs and GEPs. Overall, the regional CFs vary by 11 orders of magnitude (IQR: 1 OM) with higher values concentrated in small and low discharge river basins due to the influence of

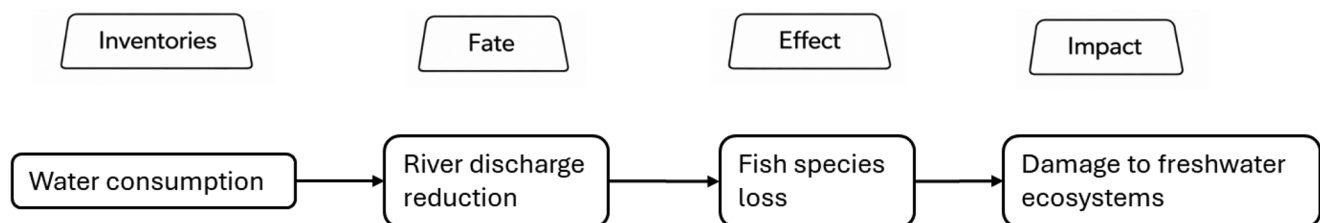


Fig. 6 Impact pathway covered by the characterization factors

the EFs (Pierrat et al. 2023a). In contrast, global CFs vary by 12 OM (median IQR: 1 OM) and are higher in large river basins with endemic and threatened species due to the influence of the GEP (Pierrat et al. 2023a). The regional CFs are always higher (on average 5 orders of magnitude - OM) than the global CFs due to the introduction of the GEP, because local damages may not always result in global extinctions (Pierrat et al. 2023a). The average CFs are also slightly lower than the marginal ones, due to the definition of the EFs and the form of the SDR (see Figure S4.5 in the SI for water consumption).

5.5.4 Evaluation and applicability

The CFs are available at the river basin, country and global scale and operational (see illustrative case study in Pierrat et al. (2023a)). The global geographical coverage, the up-to-date species data, the refined SDR model, and the spatial differentiation at river basin scale are advantages over existing LCIA methods. Therefore, we recommend using these CFs, however without the outliers and default values. The geographical coverage remains satisfactory, with approx. 76% of the global landmass with an original CF. In outlier river basins and where default values were proposed, the global CFs are recommended for use. Moreover, CFs in river basins where the FF indicated no discharge depletion should be considered null. The adjusted CFs are available in the GLAM CF files.

The CFs are compatible with generic consumptive freshwater water flow inventories and the CFs already include the source of the water consumed (from surface and ground-water bodies). For example, they can be used with LCI elementary flows of water withdrawal minus water emission from unspecified source. They are also appropriate when the average regional withdrawal mix is a reasonable assumption (Leão et al. 2018). These complement the CFs from Verones et al. (2017b), which cover other taxa than freshwater fish. CFs based on SDRs have been commonly used in LCA previously (Hanafiah et al. (2011) is used in Recipe 2016), modelled FFs and GEPs are new and results should be compared with those from applying alternative methods or complement with methods external to LCA for the identified hotspots.

5.6 Aquatic microplastic

5.6.1 Background and scope

Plastics are abundant and pose a hazard to marine and freshwater biota, which has not yet been integrated into LCIA methodologies (Woods et al. 2021). This limits the applicability of LCA for assessing the potential environmental

benefits of decisions based on plastic bans or substitution initiatives (Suh et al. 2024), which can sometimes lead to unintended consequences on ecosystems and/or human health. To tackle this gap, the MarILCA (MARine Impacts in LCA) workgroup was founded in 2018 (Boulay et al. 2021) supported by the Life Cycle Initiative hosted by UN Environment Programme (marilca.org) and with the objective to develop a methodology for the GLAM recommendations. The MarILCA framework aims at addressing the potential impacts of macro-, micro- and nanoplastic emissions in different environmental compartments (Woods et al. 2021). While some of the impacts from plastic debris can be characterized within existing impact categories such as ecotoxicity (e.g., for the release of additives), the impacts associated with the physical effects of plastics on biota belong to a new impact pathway. The corresponding category, called “physical effects on biota”, characterizes impacts linked with entanglement, smothering, ingestion and related loss of food intake, etc.

The MarILCA models that are ready to be integrated into the GLAM recommendations cover the *physical effects on biota* impacts of micro- and nanoplastic emissions into aquatic (freshwater and marine) compartments, accounting for impacts on the marine environment. Work for developing a methodology for macroplastic emission impacts (Høi-berg et al. 2022, 2024) has also been ongoing, but was not ready at the time of integration into GLAM. Due to the lack of spatial differentiation of the CF, the GEP could not be applied.

5.6.2 Impact pathway and selected framework and model

Figure 7 and the SI on aquatic microplastics describe the impact pathway of *physical effects on biota* from micro- and nanoplastic emissions to aquatic compartments. Fate represents the distribution and longevity of plastic particles in the different aquatic compartments (i.e., water and sediments), exposure occurs through ingestion of plastic particles by aquatic organisms or other physical interferences (such as entanglement or smothering), and effect is related to the damage caused (e.g. effects on health, reproduction, and growth) (Woods et al. 2021). Details on the models for the fate, exposure and effect factors can be found in the SI, in Corella-Puertas et al. (2023), and (Saadi et al. 2025). Together, they can be combined to obtain the endpoint CF (Eq. 2).

$$CF = FF \times XF \times EF \times HF \times SF = FF \times EEF \times \frac{SF}{V} \quad (2)$$

Where FF is the fate factor matrix, EEF is the exposure and effect factor matrix (containing the water and sediments

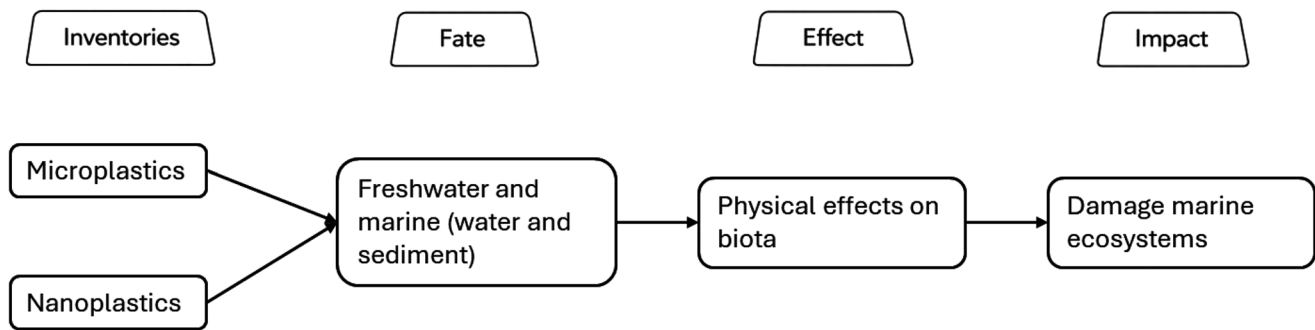


Fig. 7 Impact pathway for aquatic plastic impacts (see also SI for a more detailed version)

effect factors), HF is the harmonization factor (to arrive at the endpoint in $[\text{PDF} \cdot \text{year}]$ as proposed by GLAM, using the water and sediments volumes) and SF is the severity factor. All the parameters of Eq. 2 and their data sources are described in the SI. The application of the GEP is done with a value of 1, as the CF are global and not regional-based. The integration of sediments was done with a species distribution factor (SDF) (Saadi et al. 2025).

5.6.3 Resulting characterization factors

CFs at ecosystem level expressed as a potentially affected/disappeared fraction of marine species ($\text{PAF}_{\text{mar}} \cdot \text{year} / \text{kg}_{\text{emitted}}$ or $\text{PDF}_{\text{mar}} \cdot \text{year} / \text{kg}_{\text{emitted}}$) that consider potential impacts in the water column and sediments are proposed for eleven different polymers (see SI), three shapes (sphere/microplastic bead/fragments of unspecified shape, cylinder/microfiber, microplastic film fragments) and five sizes (1, 10, 100, 1000, 5000 μm). So far, CFs for emissions into freshwater account for impacts in the marine environment only. As for the ecotoxicity impact category, the low concentrations and the linearity assumption lead to marginal and average CFs that are assumed to be equal.

For nanoplastics, CFs for 1 μm size are proposed as interim factors. Furthermore, default CFs are recommended in case LCA practitioners lack an exact description of the microplastics emitted. Since Corella-Puertas et al. (2023) and (Saadi et al. 2025) observed that the polymer density had a major influence on the micro- and nanoplastic FFs and CFs, the default CFs are categorized by density. The particle size significantly influences the CFs of all polymers. In case the size is unknown, the default CFs provided are based on the commonness of microplastic sizes found in the environment and industry. Finally, CFs are similar for different particle shapes. In a nutshell, if the LCA practitioner only has time to collect one piece of information on the plastic particles emitted, the density should be prioritized.

5.6.4 Evaluation and applicability

CFs are currently provided at the global scale only, as the fate modelling of microplastics could not be regionalized so far. The present implementation focuses on impacts on the marine environment, while ongoing work aims to develop regionalized CFs across the three realms, following USEtox spatial parameters and introducing regional GEPs, although this could not be finalized in time for inclusion in GLAM3. For microplastics, sediments are included as an additional compartment compared to USEtox, given the accumulation of microplastics in that compartment and the strong interconnection of marine water and sediments (known as pelagic-benthic coupling) (Saadi et al. 2025). This is in line with LCIA methodological recommendations highlighting that sediment compartments are essential for persistent pollutants, given their potential to accumulate and create important exposure for benthic organisms (Fantke et al. 2018). Yet, this highlights the need for future developments to ensure a more consistent modelling in the microplastics and ecotoxicity impact categories, in terms of compartments considered and the aggregation of impacts between them.

The CFs were aligned to match the plastics inventory provided by the Plastic Leak Project (Quantis 2020), which has recently evolved into the Plastic Footprint Network (plasticfootprint.earth). The combination of the Plastic Leak Project inventory and the marine plastic CFs was tested in case studies of to-go and supermarket food packaging (Corella-Puertas et al. 2022, 2023; UN Environment 2022) and textiles (Pellengahr et al. 2025; Saadi et al. 2025; UN Environment (in preparation)). Given the uncertainty associated with the CFs (up to three orders of magnitude for certain polymers), best-, average- and worst-case CF scenarios were tested. In some case studies, the impacts from marine plastics showed significant contributions to ecosystem quality damage, especially in the textile sector or in the case of low-density plastics, such as expanded polystyrene from food containers (Corella-Puertas et al. 2022). The case studies confirmed the applicability of the proposed aquatic plastic methodology and put into perspective the impacts

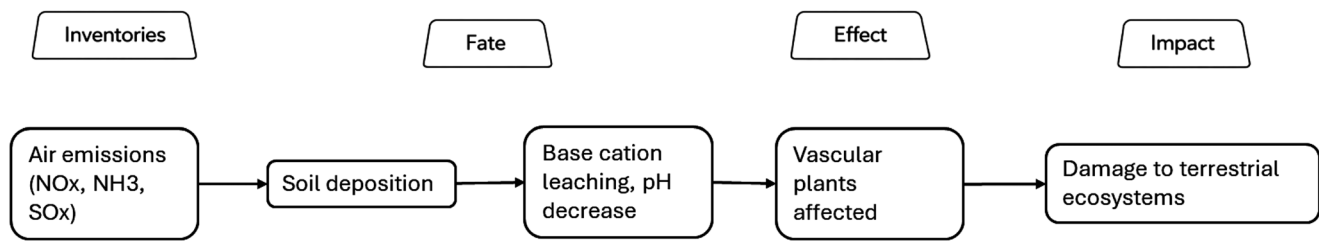


Fig. 8 Impact pathway for terrestrial acidification (see also SI for a more detailed version)

of plastic pollution compared with other impacts across the life cycle of plastic products. Yet, the use of the proposed CFs for nanoplastics may be limited, as current analytical techniques may lack the resolution required to detect and quantify such particles, thus preventing the development of robust LCI data.

5.7 Terrestrial acidification

5.7.1 Background and scope

Acidification is the reduction of base cations or an increase in proton (H^+) supply in terrestrial systems (Norton and Vesely 2003). Inputs of substances with acid-base chemistry, such as sulfur and nitrogen oxides, contribute to the acidification of terrestrial and aquatic systems, including freshwater and marine systems. While natural sources of these acidifying compounds exist, such as volcanic eruptions and emissions from the oceans, most emissions are anthropogenic. Major anthropogenic sources include fossil fuel combustion for power production, industrial activities, mobile combustion engines and agriculture (Bouwman et al. 2002; van Zelm et al. 2015).

Terrestrial acidification is largely related to atmospheric deposition of nitrogen and sulfur derived from reactions involving emissions of nitrogen oxides (NO_x), ammonia (NH_3) and sulfur dioxide (SO_2), and to a lesser extent from compounds such as HCl , H_2SO_4 and other acids (Psenner 1994; Bouwman et al. 2002).

The characterization factors (CFs) presented here represent an update of the terrestrial acidification modelling framework developed by Roy et al. (2014). While the source-receptor matrices (SRMs) from Roy et al. (2012b) remained unchanged, the remaining model components benefited from recent updates improving transparency and species coverage (Gade et al. 2021; Lebrun et al. 2025). In particular, the new species sensitivity distribution (SSD) curves developed by Gade et al. (2021) increased vascular plant species coverage from 0.6% to 49% of known plant species and refined the spatial resolution from biome scale to ecoregion scale. The GEP included vascular plant species. Note that the impact for terrestrial acidification happens at

the place of reception, not the place of origin of the emission (i.e. where the emission deposits). The GEP included is therefor the one of the reception area, not the place of origin.

5.7.2 Impact pathway and selected framework and model

The fate, exposure and effect factor modeling follow Payen et al. (2019) (see Fig. 8). The modeling framework includes fate factors for atmospheric emissions of NO_x , NH_3 , and SO_x (Roy et al. 2012b), soil response factors describing soil responses to acidifying inputs (originally developed by Roy et al. (2012a) and updated by Lebrun et al. (2025)), effect factors for vascular plants (Gade et al. 2021), and integration of the global extinction probability (GEP) (Verones et al. 2022).

The fate factor (FF) models the transport and atmospheric reactions of emitted substances and tracks the formation of acidifying dissociation products that are subsequently deposited onto terrestrial systems. The locations and quantities of deposited substances depend on atmospheric conditions, including temperature, precipitation and wind patterns, as well as atmospheric chemistry and topography (Roy et al. 2012; van Zelm et al. 2015).

Following deposition of acidifying substances, biogeochemical processes determine the pH response of the receiving soil ecosystem. This step is represented through the soil response factor (RF) (Lebrun et al. 2025). The extent of buffering depends on the chemical properties of the receiving system, which vary globally (Blaser et al. 1999; Dangles et al. 2004; Clair et al. 2007). Areas with unreactive geology, base-poor soils, and highly permeable or shallow soils are particularly vulnerable because they lack sufficient buffering capacity against acidic inputs (Driscoll 1985).

Following calculation of the RF, the resulting pH change may affect nutrient regulation in terrestrial systems, with effects ranging from biomass loss and metabolic changes to competitive exclusion by acid-tolerant species (Falkengren-Grerup 1986; Roem et al. 2000; Zvereva et al. 2008). The effect factor (EF) translates soil pH changes into local declines in vascular plant species richness (Gade et al. 2021). Finally, the application of the GEP converts local

biodiversity loss into global extinction risk (Verones et al. 2022).

Additional discussion of the framework, calculations and limitations is provided in the Supporting Information.

5.7.3 Resulting characterization factors

Resulting CFs are provided at both regional and global scales for the three substances considered (NO_x, NH_x and SO_x; see SI). In total, 3690 country-level CFs and 18 global average CFs were calculated. Global CF values were derived as averages of emission-weighted country values. This approach reflects an explicit decision to treat all ecoregions equally at the global scale rather than assigning additional weight to country CFs based on emission magnitude.

The CF values span approximately nine orders of magnitude, ranging from 10^{-14} to 10^{-5} at the regional scale and from 10^{-20} to 10^{-11} at the global scale, and are consistent with the ranges observed for other impact categories.

5.7.4 Evaluation and applicability

Terrestrial acidification is an important impact category for assessing terrestrial ecosystem quality. Given the recent updates to the corresponding CFs, their inclusion in the default GLAM method is recommended. However, because uncertainties remain unquantified and validation of the CFs remains challenging, the CFs should be applied with caution.

The framework and fate model applied in this work were previously published by Payen et al. (2019). The soil response factors have been newly updated by Lebrun et al. (2025), the effect factors are based on recent work of Gade et al. (2021), and the framework additionally incorporates the newly developed GEP approach. Consequently, the model as a whole represents a substantial update of previous terrestrial acidification frameworks.

The CFs provide additional sophistication, but also additional challenges for LCA software, because sector-specific factors are provided for agricultural, non-agricultural and unspecified emissions. At present, we recommend using the unspecified CFs, which combine agricultural and non-agricultural emissions, for background LCA calculations. Sector-specific CFs should be applied when practitioners possess foreground data and are able to assign specific CFs to specific inventory flows.

The atmospheric transport model is based on the seminal work of Roy et al. (2012b) and reflects atmospheric conditions representative of the year 2005. Evaluating the sensitivity of the overall CF framework to the fate model is beyond the scope of the present work. However, additional

work is recommended to investigate the influence of climate variability on terrestrial acidification characterization.

Because the effect factors are currently restricted to vascular plants, alignment with the GEP framework is straightforward. Nevertheless, impacts on additional species groups should be evaluated and incorporated in future work.

The GEP framework proposed by Kuipers et al. (2019) recommends converting regional CFs into global CFs as the final step of the global CF calculation. This implies applying the local-to-global biodiversity loss conversion factor at the location of the elementary flow emission rather than at the receiving soil system. However, this recommendation cannot be directly followed when the impact pathway includes substance transport. Lebrun et al. (2025) therefore proposed transforming the GEP vector into a matrix summing to one to address this issue. Nevertheless, challenges remain regarding the use of the GEP framework for transport-based impact categories, including maintaining the probabilistic framework and impact allocation, and these should be addressed in future work.

6 Overall impacts, limitations, conclusion and future research and development

GLAM3 includes eight impact categories with more than 500 000 characterization factors at country and global level to quantify different impact categories related to ecosystem quality. The country values have the benefit of easier software implementation and use by LCA practitioners, while the native scales (e.g. watersheds or ecoregions) would make more sense in ecological impact assessment studies. For the first time, all impact categories indicate impacts at both regional scale (if relevant) and global scale (i.e. global extinction). This is the first set of impact categories, and CFs, that follows a consistent approach and aims to not mix regional and global impacts on biodiversity. This allows assessing each impact category's contribution to the total impact at the endpoint level.

However, the use of a single metric (PDF) at endpoint level is a limitation for the method. As pointed out in earlier work (Curran et al. 2011; Marques et al. 2021) a suite of different metrics may allow to catch the complexity of the natural environment and biodiversity impacts better. Other biodiversity indicators (for species and for other biodiversity levels) may lead to different, complementary results and will have to be developed for a comprehensive assessment of impacts on ecosystem quality. Woods et al. (2018) suggest in their proposed way forward to further develop the AoP ecosystem quality to include indicators for both PDF (to represent compositional aspects) and functional diversity (to represent functional aspects of an ecosystem). Such

a multi-level impact assessment for ecosystem quality so far only exists in LIME (Itsubo and Inaba 2012). It is important to notice that while we included as many species groups (and species) as possible, gaps still remain. Ideally, future CFs will expand the species groups (e.g. invertebrates are currently not included) and number of species included (e.g. of the roughly described 308,000 vascular plant species, it was only possible to gather data on median dispersal distances and global extinction probabilities for 27,000). Table 1 also highlights that some impact categories used native species only in their assessments, while others used all present species without filtering for natives only. Others rely on studies from labs, which in most cases does not include location-specific presence information. This means that, often due to data availability, underlying species data is not completely consistent and should be improved in the future.

The development of the GLAM models was carried out over an extended period and involved multiple workshops aimed at achieving methodological consensus among authors. As a part of this process, it was necessary to define a practical scope and timeline to ensure completion and finding a viable compromise.

Given the highly dynamic nature of LCIA research, where new developments and updates occur continuously, it is not feasible to include all emerging approaches within a single assessment framework. We therefore acknowledge that certain methodological aspects and missing impact categories warrant further investigation, and we encourage future work to build on and refine the approaches presented here.

As examples, impact categories such as photochemical ozone formation and marine ecotoxicity were omitted due to time limitations. For photochemical ozone formation no clear roadmap exists, as currently no task force member is engaged in this area. We therefore encourage method developers outside the task force to notify the task force of any relevant new developments that could be incorporated in future versions of GLAM.

A detailed roadmap is suggested to derive marine ecotoxicity CFs (see SI on ecotoxicity). The roadmaps foresee a first data gathering step followed by data curation, and data analysis. Extrapolations within the marine compartment to get to chronic EC10 equivalents should be derived as well as extrapolations between the marine and freshwater compartments. An additional aspect to be explored and to increase consistency between impact categories is the coverage of compartments. Aquatic microplastics, for example, includes a sediment compartment, which may be relevant to include for marine ecotoxicity as well, in order to aim for an even more harmonized method.

The GEP is a step forward towards a more harmonized characterization of impacts. However, also the GEP can nevertheless profit from improvements. Apart from the

issues mentioned in terrestrial acidification with transport-related difficulties, including the GEP in nested models, such as ecotoxicity, or using them in global models, such as climate change, would be a step forward, since impacts of climate change, for example, are not equally distributed across the world, nor are toxic impacts. However, the continental models are primarily driven by differences on the fate and exposure side, not effect factor side. The species pool used in ecotoxicity is global, not leading to a continental distinction between species presence and threat status, but the range area per continent may nevertheless lead to differences between the continents.

Other impact categories that were not included due to time constraints in development and making them fully compatible with GLAM include, but are not limited to, overexploitation in fisheries (Hélias et al. 2023) and entanglement in macroplastics (Høiberg et al. 2024), ocean acidification (Azevedo et al. 2015a; Bach et al. 2016; Anderson et al. 2025) and noise impacts. The omission of certain impact categories inevitably results in an incomplete assessment framework. The practical relevance of such omissions depends on the specific goal and scope of the assessment. For instance, assessments of fishing activities are likely to benefit from the inclusion of impacts such as plastic pollution (Askham et al. 2026) and overexploitation, whereas these may be of comparatively lesser importance for agricultural products. Given the wide range of pressures on the natural environment and their inherent complexity, it is currently not feasible to capture all impact pathways within a single assessment. Nevertheless, GLAM contributes to narrowing these gaps, and ongoing methodological developments are expected to progressively further reduce these gaps, representing incremental steps toward more comprehensive impact assessment.

Additional work could involve further integrated testing of the newly developed GLAM methods, including comparative analyses with established LCIA methods to better demonstrate their relative performance. GLAM will also benefit from a clear comparative analysis with established LCIA methods to better demonstrate the relative performance, strengths, and added value of the proposed approach. Future work should also include uncertainty quantification across impact categories and provide guidance on robustness of the results. Future work is also needed to bring the work developed in the LCIA area closer to relevant policy frameworks such as the Kunming-Montreal Global Biodiversity Framework, and particularly the indicators used therein (<https://www.gbf-indicators.org/>). The work developed in GLAM3 and future updates would be particularly relevant to, and benefit from data compiled from, indicator 7.1 (Index of coastal eutrophication potential); and indicator 7.2 (Aggregated Total Applied Toxicity).

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Data availability All CFs can be downloaded here <https://www.lifecycleinitiative.org/activities/life-cycle-assessment-data-and-methods/global-guidance-for-life-cycle-impact-assessment-indicators-and-methods-glam/>.

Declarations

Competing interests There are no competing interests.

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