Navigating uncertainty in LCA-based approaches to biodiversity footprinting

Authors

Talitha Bromwich[1,2]*, Thomas B. White[1,3]*, Alice Bouchez[3], Isobel Hawkins[4], Sophus zu Ermgassen[1], Joseph Bull[1,2], Harriet Bartlett[4,5], Leon Bennun[3,6], Elizabeth Biggs[3], Hollie Booth[3,4], Michael Clark[4,5], Sami El Geneidy[7,8], Graham W. Prescott[3], Laura J Sonter[3,9], Malcolm Starkey[3] & E.J. Milner-Gulland[1].

*Joint first authors. Emails: talitha.bromwich@biology.ox.ac.uk; thomas.white@biology.ox.ac.uk

Affiliations

[1]Leverhulme Centre for Nature Recovery & Department of Biology, University of Oxford, UK.

[2]Wild Business Ltd., Oxford, UK.

[3]The Biodiversity Consultancy, Cambridge, UK.

[4]Department of Biology, University of Oxford, Oxford, UK.

[5]Smith School of Enterprise and the Environment, School of Geography and the Environment, University of Oxford, Oxford, UK.

[6]Department of Zoology, University of Cambridge, Cambridge, UK.

[7] School of Resource Wisdom, University of Jyväskylä, Finland.

[8] School of Business and Economics, University of Jyväskylä, Finland.

[9] School of the Environment, The University of Queensland, St Lucia, QLD, Australia.

Abstract

The use of Life cycle assessment (LCA) methods is rapidly expanding as a means of estimating the biodiversity impacts of organisations across complex value chains. However, these methods have limitations and substantial uncertainties, which are rarely communicated in the results of LCAs.

Drawing upon the ecological and LCA literature on uncertainty and two worked examples of biodiversity footprinting, we outline where different types of uncertainty occur across multiple stages of the LCA process, from input data to the choice of biodiversity metric. Some uncertainties are epistemic, incorporating structural (e.g., the types of pressures included in models), parametric (e.g., uncertainty around conversion factors), and measurement uncertainty, as well as natural variability, stochasticity, and information gaps. Other uncertainties are linguistic (e.g., ambiguity around definitions of biodiversity) and decision-based (e.g., choices made when matching company data to inventory categories). We provide suggestions for understanding, reducing, and navigating uncertainties when using LCAs for biodiversity footprinting.

Understanding the risks posed by these uncertainties, weighing them against the costs of inappropriate action or inaction, and ensuring decisions are robust to these uncertainties, is vital for designing effective biodiversity strategies. With a full understanding of these uncertainties, opportunities exist to utilise LCAs for high-level risk screening to prioritise action and highlight areas where focused effort and more granular data are needed, to track progress towards abating impacts year-on-year and identify low risk actions. However, biodiversity strategies should not be based solely on absolute LCA impact results. Instead, LCAs should be used alongside other approaches to guide location-specific and robust action to deliver a Nature Positive future.

Keywords

Life cycle impact assessment; Value chains; Environmental impact; Biodiversity; Uncertainty; Business Strategy; Nature Positive.

Wordcount

Approx 6,002 (excluding figures & refs).

Introduction

LCA as a method for estimating organisational biodiversity impacts

The ongoing loss of biodiversity and ensuing ecosystem collapse are now recognised as major global risks to both business and society at large (WEF, 2024). Major drivers of these negative impacts on biodiversity, such as land use change and overexploitation of resources, are tied to consumptive and economic activities (Dasgupta & Levin, 2023). Robust quantification of how different activities, organisations and whole economic sectors are impacting natural systems is needed to inform more sustainable business strategies and government policies, which are crucial for realising a "Nature Positive" future (Addison et al., 2019; Zu Ermgassen et al., 2022) where organisations are no longer driving biodiversity loss but instead contributing to international goals for biodiversity recovery (CBD, 2022). To develop appropriate strategies that can contribute towards global biodiversity objectives, businesses require an understanding of how the products and activities across their entire value chain (not just direct impacts) are impacting biodiversity (Booth et al., 2024; Panwar, 2023; White, Bromwich et al., 2023).

Life cycle assessment (LCA) methods have been fundamental for environmental policy (Sala et al., 2021), enabling users to estimate and guide relative reduction of environmental impacts over the entire life cycle of materials, products, services, and activities, and avoid unforeseen or perverse trade-offs between different lifecycle stages, environmental pressures, and over different timescales (Hellweg and Mila i Canals 2014; ISO 14040 2006). As one of the only methods for assessing broad life cycle impacts and incorporating multiple drivers of biodiversity loss, LCA methods are now being used to estimate "biodiversity footprints"; a term used to refer to estimates of organisational biodiversity impacts (Bull et al., 2022; Peura et al., 2023), analogous to the "carbon footprints" of greenhouse gas emission reporting. These LCA-based methods are recommended in frameworks such as the Taskforce on Nature-related Financial Disclosures (TNFD, 2023) and Science-Based Targets Network (SBTN, 2023), and in regulation via the EU's Corporate Sustainability Reporting Directive (European Commission, 2023). Once calculated, biodiversity footprint results can be used to highlight the scale and focus of interventions needed to address an organisation's impacts, track change over time, and drive action for biodiversity impact reduction and compensation (Arlidge et al., 2018). Biodiversity footprints are thus increasingly used to guide corporate biodiversity strategy design, including by data providers for financial institutions, potentially informing large-scale economic decisions.

LCA-based biodiversity footprints begin by gathering data on company activities, purchased products and materials, and identifying existing life cycle inventories or impact assessments which can be used to estimate the environmental pressures exerted by all the inputs and outputs to a company's activities. These environmental pressures are termed "midpoints" and may include, e.g. greenhouse gas emissions, land use, water use etc. Midpoints can be estimated using process-based LCA (using data on company activities and the associated emissions, energy and materials), economic input-output (IO) LCA (using data on spending, economic flows and sector-level impact data), or hybrids of the two (Finnveden et al., 2009). The midpoints are then combined in life cycle impact assessment frameworks to estimate "endpoint" biodiversity impacts by modelling what quantity of e.g. greenhouse gas emissions, or area of land use, causes a defined amount of biodiversity loss (Crenna et al., 2020; Sanyé-Mengual et al., 2023; Verones & Dorber, 2023) (Figure 1). Often these approaches are implemented in pre-existing LCA software using harmonised LCA inventory datasets.

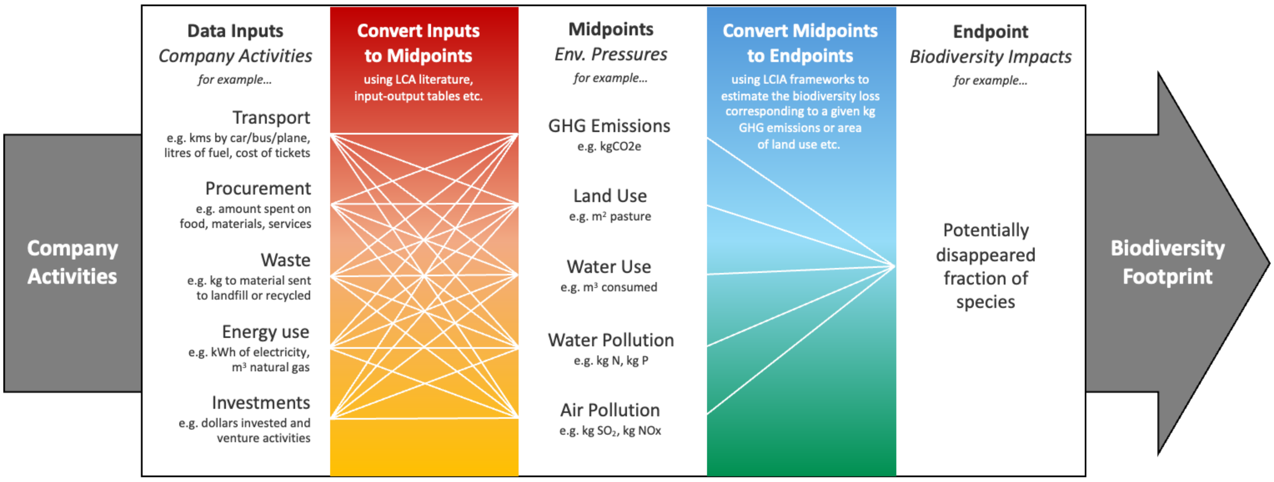


Figure 1: Schematic diagram of the LCA process for assessing biodiversity impacts, moving between three stages: data inputs; converting to midpoint environmental pressures; and converting to endpoint biodiversity impacts. *The company activities, environmental pressures, and endpoint indicators of biodiversity included are examples and not a comprehensive list of categories always included in LCA approaches to biodiversity footprints.*

However, LCA-based methods and associated models were not originally developed for biodiversity footprinting (Damiani et al., 2023; Lammerant et al., 2021). LCAs have recognised limitations in capturing the complexities of biodiversity (Crenna et al., 2020; Damiani et al., 2023), and assumptions and value choices necessarily vary between methods and practitioners. These assumptions and choices lead to differences in scope, system boundaries, aggregation of products/activities and how different pressures are weighted across different LCA analyses (Sanyé-Mengual et al., 2023). Results from LCA analyses therefore depend on the tools used and assumptions made, as well as inevitable uncertainties involved in quantifying pressure-state relationships in complex natural systems.

There is thus potential for uncertainties in i) estimated total biodiversity footprints and ii) the relative importance of different products, activity areas or environmental pathways that form part of the total footprint. These uncertainties have implications for the recommendations and biodiversity strategies that footprints are typically informing. If ignored or misinterpreted, these uncertainties could lead to misattribution of impacts, inappropriate prioritisation, and distrust by decision-makers if they suspect outcomes are too uncertain (Herrmann et al., 2014). The urgency of halting biodiversity loss means that action cannot wait for "perfect" methods. However, better understanding, awareness and accounting of the uncertainties associated with LCAs can drive collective efforts for improvement, identify opportunities for the use of LCAs, and ensure results are interpreted appropriately so business and policy actions to mitigate biodiversity impacts are effective and appropriate.

Aims & Scope

Here, we provide the first structured overview of types of uncertainties in the LCA process for assessing biodiversity footprints (recognising that there may also be significant unrecognised uncertainties) and the different analytical stages at which they occur (Figure 1). We illustrate how different sources of uncertainty influence biodiversity footprints, using worked examples, including those of more complex value chains or entire organisations.

We use this review to discuss the potential of LCA-based methods to support the design of businesses' biodiversity strategies – highlighting both risks and opportunities. We provide recommendations to better understand, reduce and navigate LCA uncertainties to increase the likelihood of appropriate and effective prioritisation of actions to conserve biodiversity.

Uncertainty in LCA biodiversity assessments

In the context of LCA, uncertainty exists wherever there is incomplete knowledge of differences between estimated and actual values (Barahmand & Eikeland, 2022; Finnveden et al., 2009), essentially "any departure from the unachievable ideal of complete determinism" (Walker et al., 2003). Typologies and methods for quantifying uncertainties are well documented in both the LCA (Bamber et al., 2020; Barahmand & Eikeland, 2022; M. A. J. Huijbregts, 1998; Igos et al., 2019; Lloyd & Ries, 2007; Walker et al., 2003) and biodiversity conservation literatures (Kujala et al., 2013; Milner-Gulland & Shea, 2017; Regan et al., 2002). However, these uncertainties and methodological differences are often not investigated (Alyaseri & Zhou, 2019; Bamber et al., 2020; Saxe et al., 2020), poorly communicated in guidelines for biodiversity footprinting (for example, TNFD, SBTN, and Finance for Biodiversity Foundation guidance on biodiversity measurement approaches mention limitations, but not explicitly uncertainties), or incompletely understood or appreciated by the organisations using LCAs to disclose impacts and design biodiversity strategies.

We therefore propose a practical categorisation of uncertainties associated with LCA-based biodiversity footprints to help locate uncertainty across the analytical process, scrutinise its severity and determine tractability for improvement. This categorisation may help highlight, for example, whether uncertainty can be reduced with improved organisational data, requires research efforts from the LCA and biodiversity conservation science community, or is due to inherent system indeterminism and fundamentally irreducible (Igos et al., 2019). Our framework divides the sources of uncertainty into three major groups: epistemic, linguistic and decision-based uncertainty (Table 1). This categorisation broadly aligns with the conservation literature, following Kujula et al. (2013), but is also informed by the LCA uncertainty taxonomy of Huijbregts (1998) and Igos et al. (2019).

Epistemic uncertainty relates to knowledge gaps in LCA methods. It includes uncertainty due to unknown or unaccounted-for spatial, temporal or activity level variation (M. A. J. Huijbregts, 1998), measurement errors and biases (for example, in both the organisational activity data used to perform the footprint and underlying ecological data supporting the LCA models), inherent stochasticity and structural and parametric limitations in LCA models versus the real-life processes and systems they represent (Kujala et al., 2013).

Linguistic uncertainties occur during the communication of information and can arise from over-generalization, context dependence, or ambiguity and vagueness in language (Regan et al., 2002). Uncertainty taxonomies in the LCA literature typically do not recognize linguistic uncertainty, but it is likely to be significant, particularly when communicating the final impact metrics of biodiversity footprints. Linguistic uncertainties can also occur when matching organisational or inventory data to appropriate LCA or input-output economic categories (Table 1). For example, is a pressure labelled "water use" in one model equivalent to water withdrawal or consumption in another, and is it "blue", "green" or "grey" water (Mekonnen & Hoekstra, 2011))? This is particularly challenging when category names are ambiguous or highly aggregated.

Lastly, some uncertainties arise due to human decisions, leading to assumptions in the LCA process often underlain by subjective values and preferences (M. A. J. Huijbregts, 1998; Kujala et al., 2013). Human decision uncertainty may relate to what to include or exclude in assessments, via both the organisational activities considered "in scope" and the environmental impact pathways modelled. For example, an organisation may only consider direct land use related to its buildings, versus considering a broader spectrum of emissions and impacts across the value chain. Other choices may lead to assumptions around incomplete data, for example, whether a petrol/diesel ratio in an organisation's fleet is better represented by company data from a previous year or by national averages from government data sets. Choices can also be made about which LCA framework or future scenario to use. For example, the ReCiPe LCA framework includes "individualistic", "hierarchic", and "egalitarian" models to choose from that reflect different assumptions around how impacts change over time, and how humanity will respond to environmental changes in the future (M. A. J. Huijbregts et al., 2017).

Epistemic, linguistic, and decision-based uncertainty can occur at many different stages of the LCA biodiversity footprinting process (Figure 1; Table 1). Where uncertainties have been investigated in detail in LCA studies, they have predominantly focussed on the epistemic uncertainty in model parameters, variability in data, and from the use of different databases and methods (e.g. Barahmand & Eikeland, 2022). However, all sources of potential uncertainty need to be acknowledged and addressed, as they will all feed into the biodiversity footprint, affecting the perceived and actual legitimacy and utility of LCA outputs.

Table 1: Examples of the three types of uncertainties at three different stages of the LCA process (see Figure 1) when calculating biodiversity impact. *A detailed list of uncertainties split by type and LCA stage is provided in Table S1 in the Supporting Information*

Type of Uncertainty	***LCA Stage (see Figure 1)***		
	Organisational Activity Data Inputs	***Midpoint Environmental Pressures***	***Endpoint Biodiversity Impact***
Epistemic	Data gaps, poor representativeness of units (e.g. spend not quantity), unknown geographic sourcing of materials, or intrinsic variability of activities not adequately captured (e.g. one month used to model entire year).	Parameter uncertainty in the conversion factors, including the assumption of linear scaling of activity units to pressures, spatial, temporal and activity-level variation, measurement error and stochasticity. Structural uncertainty due to what pressures are or are not included in the model.	Parameter uncertainty in the conversion factors, including the spatial, temporal, and context specificity of biodiversity impacts, and underlying biases, paucity and measurement error in data used to model pressure-state relationships. Structural uncertainty due to pressures (and interactions between pressures) included in the model, components of biodiversity included.
Linguistic	Unclear labelling in documentation of what the company activities are, and if they should be included, e.g. does spend labelled as "IT" include software, hardware, IT support salaries, digital services, or all of the above.	Poor matching of LCA categories, or company data to LCA inventory categories, due to ambiguity, vagueness or high degrees of aggregation. For example, is "land stress" in one model equivalent to "land occupation" or "transformation" in another, and what is included in "business services" as an LCA input-output category or as a procurement label in company data.	Linguistic uncertainty in communicating biodiversity impact scores, including their intrinsic meaning as well as what constitutes a "good" score. Linguistic uncertainties can prompt the use of simplified metrics, such as normalised "Biodiversity Impact Scores", which appear to sidestep communication issues but are not clearly related to what is being modelled or the underlying conservation issues
Decision-based	Deciding the activity data boundaries, i.e. what to include or exclude from scope of analysis, and what assumptions to make for missing or incomplete data.	Choice of life cycle impact assessment method (e.g. process-based, input-output, or hybrid LCA methods), software implementation (e.g. SimaPro, Open LCA, Brightway), and underlying data (e.g., EXIOBASE, Ecoinvent, HESTIA) and how to make them compatible with each other.	Choice of assessment framework e.g., LC-IMPACT, ReCiPe, Impact World +. Assessing adequacy of the metric for providing a proxy of overall biodiversity value and deciding what a "good" score is.

Organisational Activity Data Inputs

There are often large uncertainties associated with company activities. A lack of data hinders businesses' engagement with their biodiversity impacts (T. B. White et al., 2023). Specific activities may be completely undocumented or quantified in inappropriate or suboptimal ways. For example, purchase data may only be available as spend instead of quantities of materials purchased, or activities may be pooled in broad categories (e.g. all transportation, as opposed to driving, flying, and public transit detailed separately). Data may be inaccessible because employees or suppliers are unwilling or unable to supply information, or heterogenous in quality or completeness owing to varying standards across company business units or suppliers. This necessitates assumptions in analysis, for example, scaling one set of organisational data on the supposition it follows the same trends as another, or leaving out activities or inputs where there are data gaps. Consequently, better-documented activities may be disproportionately represented in the results simply because they are better quantified.

Company data on direct operations are often better quantified than data on the upstream and downstream value chain activities. For example, a supermarket chain may know the location of its offices and shops but have limited information on sourcing locations of ingredients in the products it buys (upstream) or how customers dispose of waste (downstream). This is problematic for footprinting, as supply chains form a major component of biodiversity impacts (Bull et al., 2022; Peura et al., 2023), and impacts on biodiversity vary substantially depending on their location. If data on sourcing locations are limited, assumptions often must be made, introducing uncertainties into the final results, which may be inconsistent across different parts of the footprint. The data available on downstream activities and approaches for modelling their impacts are often even more limited. For example, current SBTN guidance classifies downstream impacts out of scope, due to low confidence in the methods for estimating impact (SBTN, 2023). From an organisational perspective, downstream activities may also not be considered if they are deemed fully outside the organisation’s remit and control.

Converting inputs to midpoint environmental pressures (midpoints)

The numerous uncertainties within the LCA modelling process for converting inputs to midpoint environmental pressures have been well documented (M. A. J. Huijbregts, 1998; Igos et al., 2019; Walker et al., 2003). Defining the goals and scope of an individual LCA requires choices about system boundaries, functional units, and LCA indicators and methods (Igos et al., 2019). Choices regarding matching company activity data to different LCA processes, use of different inventory datasets, allocation procedures, and how all these things are combined and implemented in LCA software can all produce variation in outputs (e.g., Cherubini et al. 2018). For example, in a case study of wine production, different LCA practitioners were provided with standardised data inputs and made many different choices across an assessment of upstream, core and downstream midpoint impacts for a single Italian wine bottle (Scrucca et al., 2020).

The broad choice between using a process-based (e.g., Ecoinvent) or input-output-based (e.g., EXIOBASE) LCA model presents an "accuracy vs precision dilemma" (Perkins & Suh, 2019). Process-based LCA offers a high degree of specificity but limited system boundaries (known as "truncation errors"), which may underestimate impacts (Lenzen, 2000), whereas input-output approaches (which often estimate impacts from resource extraction up to the product leaving the factory) may be hindered by aggregation into broad economic sectors and regions (Baboulet & Lenzen, 2010). Hybrid approaches attempt to combine the best of both (Lenzen & Crawford, 2009) but should be carefully navigated to avoid combining analyses with incomparable system boundaries, which could result in misrepresenting the relative size of different impacts (Lenzen, 2002). For example, Steubing et al (2022) show how the choice of input-output or LCA databases for carbon assessments influenced the footprint results for many products and services, with more than half of the footprint estimates differing by more than a factor of two.

There can be large epistemic uncertainties in using LCAs to convert activity data to mid-point environmental pressures. Structural uncertainties include the representativeness of the materials and energy required for a given product/service (e.g. flows), the limited modelling of the relationships between activities and pathways (Igos et al., 2019), and can include key processes being missed entirely in the life cycle inventory, for example, neglecting the impacts of materials being transported or the energy required for construction. There are also parameter uncertainties in the multipliers used to convert activity data to pressures, known as "characterisation" or "conversion" factors (e.g. calculating the greenhouse gas emissions per kg of a given product produced). Uncertainties can arise from limited data on the activity-pressure relationship, stochasticity, measurement errors, and spatial, temporal and activity-level variations and assumptions (such as the assumed linear relationship between the activity and the magnitude of the impacts). Taking mining activities as an example, environmental impacts may not scale linearly with increased production, with impacts varying with mining site age or economies of scale (Franks et al., 2013). In addition, generalised conversion factors for mining activity will not capture differences between sub-sectors, mining methods, and geographies. For example, the most significant pressures per kg of nickel produced from laterite mines versus sulphide mines may be very different (Mervine et al., 2023).

Initiatives such as the United Nations Environment Programme's Global Guidance on Environmental Life Cycle Impact Assessment Indicators (UNEP-GLAM), ISO standards (ISO 14040 2006), and TNFD and SBTN, offer guidance on best practice and recommended tools and approaches. However, there is currently no standardised biodiversity equivalent to GHG protocols that clearly delimits the scope of biodiversity impact analysis, resulting in uncertainties in benchmarking both within and between companies, depending on the methods and boundaries chosen for a particular analysis.

Estimating and communicating biodiversity impact (endpoint)

Biodiversity is defined as the variety of life and can include variation in structural, functional and compositional components at various levels of organisation, from genes and species to ecosystems and land/seascapes (Bracy Knight et al., 2020; Noss, 1990). Metrics to quantify biodiversity may be developed for different reasons; for example, to assess the state of nature, to estimate the outcomes of biodiversity conservation actions or, in the case of biodiversity footprints, estimate pressures driving biodiversity declines. A single biodiversity metric may be desirable for policy and business targets (Rounsevell et al., 2020), but no one metric can capture all components and levels of biodiversity. There are therefore necessary assumptions and uncertainties imbedded in the act of including biodiversity metrics within LCA, with different models varying in which components and levels of biodiversity are considered, and uncertainties around whether the proxies for potential biodiversity loss (such as ecosystem quality decline or extinction risk) are representative enough of actual biodiversity loss to be meaningful in the specific decision context.

Various LCA frameworks have been developed to estimate endpoint biodiversity impacts (see reviews by Sanyé-Mengual et al. (2023) & Damiani et al (2023)). Although powerful in their capacity to combine different environmental impact pathways into one overall impact on biodiversity, the shoehorning of so many different processes and pressures into one metric introduces many epistemic uncertainties. Frameworks capture different threatening processes, different realms (e.g., terrestrial, freshwater, marine) and components of biodiversity, and have different levels of spatial specificity (Crenna et al., 2020; Damiani et al., 2023).

The most commonly used biodiversity LCA frameworks include ReCiPe 2016 (M. A. J. Huijbregts et al., 2017), LC-IMPACT (Verones et al., 2020), EcoScarcity 2013, and Impact World+ (Bulle et al., 2019), which all use measures of species and community composition, i.e. the predicted loss of species richness, as a proxy of ecosystem degradation under given pressures and timeframes (Damiani et al., 2023). The final impacts are usually expressed as a “Potentially Disappeared Fraction of Species” [PDF], referring to either local or regional loss (the communication of this is often unclear and definitions vary from model to model). In ReCiPe 2016 the PDF score is multiplied by an estimate of the average global species density in the three different biogeographic realms (terrestrial, freshwater and marine ecosystems) to calculate ‘species.year’; an estimate of the species loss that may occur as a consequence of an organisation’s activities (Huijbregts et al. 2017). The absence of genetic diversity, species abundance and ecosystems diversity (Crenna et al., 2020) from these frameworks means important changes in biodiversity are missed in underlying conversion factors (Scherer et al., 2023). However, metrics exist that do capture some of these different components in LCA contexts (e.g. mean species abundance; Schipper et al. 2020).

Of the major pressures to biodiversity (see IPBES 2019), only land use change, climate change, pollution and water use are currently captured in most frameworks, while research is ongoing to incorporate invasive species and overexploitation (Borgelt et al., 2024; Crenna et al., 2020; Sanyé-Mengual et al., 2023). Even within the approaches for assessing individual pressures, however, there can be significant epistemic model uncertainties. For example, species-area relationships – a fundamental ecological concept (MacArthur & Wilson, 1967) – are accounted for in some land use conversion factors via ecoregion-scale weightings that reflect the area of habitat remaining (e.g., Chaudhary et al. 2015; Chaudhary and Brooks 2018). However, the impact of land use change on species persistence probability also depends on species' affinity to different habitats, and level of habitat fragmentation – something only recently incorporated into conversion factors (Scherer et al 2023). Land use conversion factors also assume a linear relationship between the pressure and species loss, despite the non-linearity of species-area relationships. Different LCA biodiversity metrics can also make very different assumptions and choices regarding reference conditions, system boundaries and baselines (Damiani et al., 2023), and assume that the impact of different pressures on biodiversity are additive, while in reality there may be synergistic or antagonistic interactions between pressures (Brook et al., 2008).

LCA models also differ in the level of spatial specificity they provide – an important source of uncertainty given biodiversity is highly location-specific. Adding regionalisation into LCA biodiversity impact frameworks is a key priority and regional specificity has already been enhanced by LC-IMPACT and Impact World+ (Sanyé-Mengual et al., 2023). Indeed, where conversion factors have been calculated at a finer level, very large variations in outcomes has been found between different taxa and land use types globally (Scherer et al., 2023). PDF-based approaches do not always account for the differences in the significance of biodiversity in different localities (e.g. total number of species present, endemism, specific threat levels, i.e. how many species are critically endangered in a region). Metrics are emerging that could be integrated into LCA methods to make them more spatially explicit (i.e. providing increasingly granular location-specific conversion factors) and account for the significance of the biodiversity in an area (e,g, Eyres et al. 2023; Mair et al. 2021), including approaches that weight regional conversion factors with an estimate of global extinction probabilities (GEP; Verones et al 2022).

There are also many parameter uncertainties, data gaps, and biases stemming from our imperfect knowledge of the status of biodiversity and its context-specific response to pressures. There can be extreme taxonomic and geographic variation in biodiversity data availability (Cazalis et al., 2022), including the data underlying the conversion of pressures to endpoint indicators in LCA methods (Table 2). This means that conversion factors may not be representative of spatial, temporal and activity level variability in the pressure-state relationships. For example, different policy and regulatory contexts may influence the impact of different pressures on biodiversity.

As well as the epistemic biases in datasets, ecological systems have inherent variability and stochasticity that manifest as further parameter uncertainty. Whilst research is continuing to improve the robustness of our understanding and quantification of pressure-state relationships (e.g., biodiversity responses to land use change; Chaudhary and Brooks 2018; Scherer et al 2023; and water use; Pierrat et al. 2023), these parameter uncertainties and data gaps add uncertainty when biodiversity impacts are generalised across the globe or extrapolated to different taxa and geographies.

Table 2: Examples of datasets and uncertainties underlying characterisation of biodiversity impacts in LCA.

Source	***Pressure***	***Datasets used:***	***Epistemic biases in datasets***
Chaudhary & Brooks (2018)	Land Use	Chaudhary and Brooks (2018) look at differences in species richness in different land use types and intensities. The conversion factors are based on data from Chaudhary et al. 2016), and Newbold et al (2015). Newbold et al (2015) presents information on the PREDICTS database.	The PREDICTS database is one of the most comprehensive databases of species responses to different land uses and intensities, however, it still has biases in taxonomic and geographic coverage. For example, data on boreal forests, flooded grasslands, tundra, savannas, and mangroves are underrepresented (Newbold et al 2015). Metrics built on the dataset have been criticised for being unrepresentative in some land use types (e.g. urban areas) and in areas of high conservation threat (Martin et al., 2019).
ReCiPE 2016 (M. Huijbregts et al., 2016)	Eutrophication	The eutrophication data linking levels of phosphorus to PDF in freshwater ecosystems is based on data from Azevedo et al 2013.	Azevedo et al. (2013) look at impact of phosphorus (P) concentrations on species richness by compiling results from 186 studies. They show differences in responses of species richness to P concentrations between climates, habitat types, and taxa (autotrophs and heterotrophs). However, the vast majority (142) of the studies are in European and North American contexts, with very limited data from Asia, Africa and Australasia. The studies exclude wetlands and not all species groups are equally represented in each climate-habitat type. Patterns are reported above but not below an EU-defined optimal P concentration and will therefore be biased towards more P-tolerant species. Other eutrophication stressors, such as nitrogen, and variables that alter responses to P, such as chlorophyl concentration, stream width etc., are not included.
ReCiPE 2016 (M. Huijbregts et al., 2016)	Climate change	In ReCiPE 2016 the global conversion factors between GHG and impacts on terrestrial ecosystems are based on a meta-analysis of global extinction risks from climate change (Urban, 2015)	Urban (2015) identify an average of 7.9% extinction risk from climate change across studies - with extinction risk increasing non-linearly with higher global temperature. They also show a large variation around the average predicted extinction risk, including large effects of geography, biological parameters modelled (e.g. if dispersal was allowed), and model types. Indeed, extinction risk from climate change is challenging to predict, and influenced by many biological parameters i.e., dispersal potential, species interactions, evolution, physiology and demography. However such data is often lacking and not included in extinction risk studies (Urban et al., 2016) ReCiPE 2016, uses average values for extinction risk at current levels of warming (2.8%) and at 4.3 degrees C of warming (15.7%), assumes a linear trend between these values to estimate the conversion factor. This figure is then extrapolated globally, not accounting for the non-linear relationship between temp and extinction risk, the uncertainty in estimates, or variation in the impacts of global warming geographically or by taxa.

Biodiversity metrics used in LCA processes often generate very small numbers (for example, a biodiversity footprint of 1e-7, or 0.0000001 PDF.year, see worked example in Box 1) which can be very challenging to interpret and communicate (Cohen et al., 2002). This is exacerbated in area- and time-integrated PDF, which can show similar results through changes in either area, time or species loss. For example, 10 PDF.m^2.year could mean i) 10% of species have disappeared from 100m^2 over a year, or ii) 100% of species have disappeared from 10m^2 over a year, or iii) 10% of species have disappeared from 10 m^2 over 10 years (Goedkoop et al., 2022), each of which would have very different ecological consequences. In addition, the area could be associated with the first clearance of land or the pressures of ongoing land occupation, e.g. for industry or agriculture (LCA frameworks can estimate both processes). This introduces linguistic uncertainty, and often motivates biodiversity outputs being communicated in generic terms (e.g. an arbitrarily scaled biodiversity impact score (Bull et al., 2022) or a relative score within an overall biodiversity footprint) which may be interpreted differently depending on the audience and contextualisation (Kujala et al., 2013).

Worked Examples:

Although many studies have investigated uncertainties in the LCA process, it is still common for LCAs to be used for biodiversity footprinting without consideration or presentation of uncertainties in the outputs. In Boxes 1-2, we present two worked examples to show how uncertainties can affect outputs of an LCA for biodiversity footprinting. An expanded methodology is provided in the **Supporting Information.**

Box 1: Quantifying the biodiversity impact of a simple agri-food product.

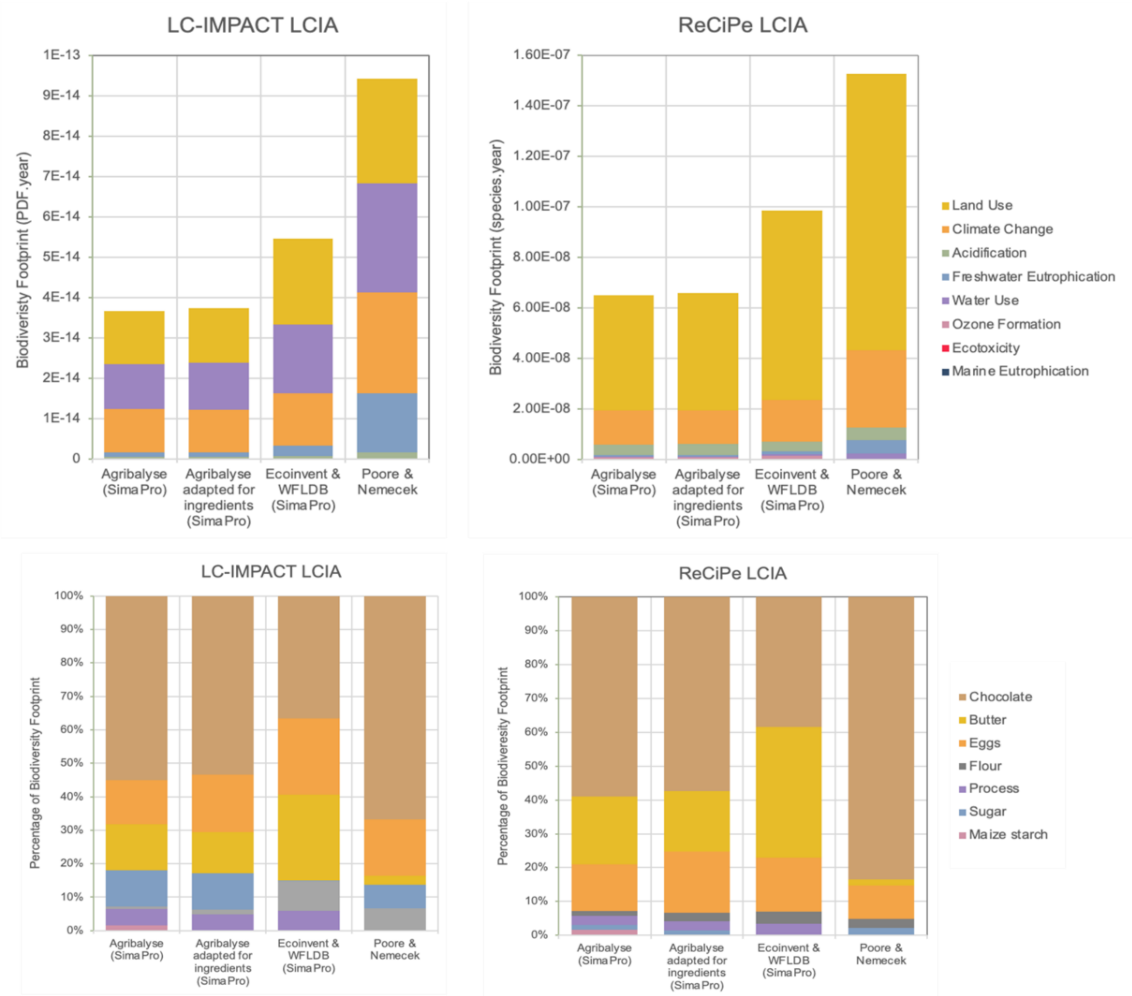


Figure 2: Biodiversity footprint results for a single chocolate cake commodity (y axis) analysed using four different LCA inventories (x axis), and two different LCA frameworks. The top row shows absolute biodiversity footprint results broken down by environmental pressure. The lower plots shows the percentage biodiversity footprint broken down by different chocolate cake ingredients.

***Aim**: This example explores the decision case of a company assessing the biodiversity impacts of a product in order to prioritise biodiversity mitigation actions. The aim is to show how different midpoint and endpoint models can introduce model uncertainties that result in both different absolute estimates of biodiversity impact, and variation in how those impacts are distributed across different ingredients and impact pathways.*

***Methods**: Figure 2 shows the biodiversity footprint of a hypothetical chocolate cake, with variation on the x-axis showing results when four different LCA inventories are used to estimate the midpoint pressures. In addition, the two sets of different plots utilise two different LCA frameworks – LC-IMPACT and ReCiPe – which were used to calculate endpoint biodiversity impacts.*

***Implications**: This case study highlights the epistemic model uncertainty in biodiversity footprinting, with all 8 methodological combinations generating both different absolute biodiversity impact values, and different distribution of impacts across environmental pathways and cake ingredients (Figure 2). This serves to emphasise that LCA alone cannot be used to justify decisions around target setting. However, agreement across most models that chocolate is responsible for the largest proportion of impacts, most likely via land use and climate change impact pathways, could be used to justify a prioritisation of further investigation into chocolate sourcing, supplementing these results with more spatially-specific biodiversity monitoring and screening in the specific geographies and processes involved.*

Box 2: Understanding the impact of a UK household's consumption on biodiversity.

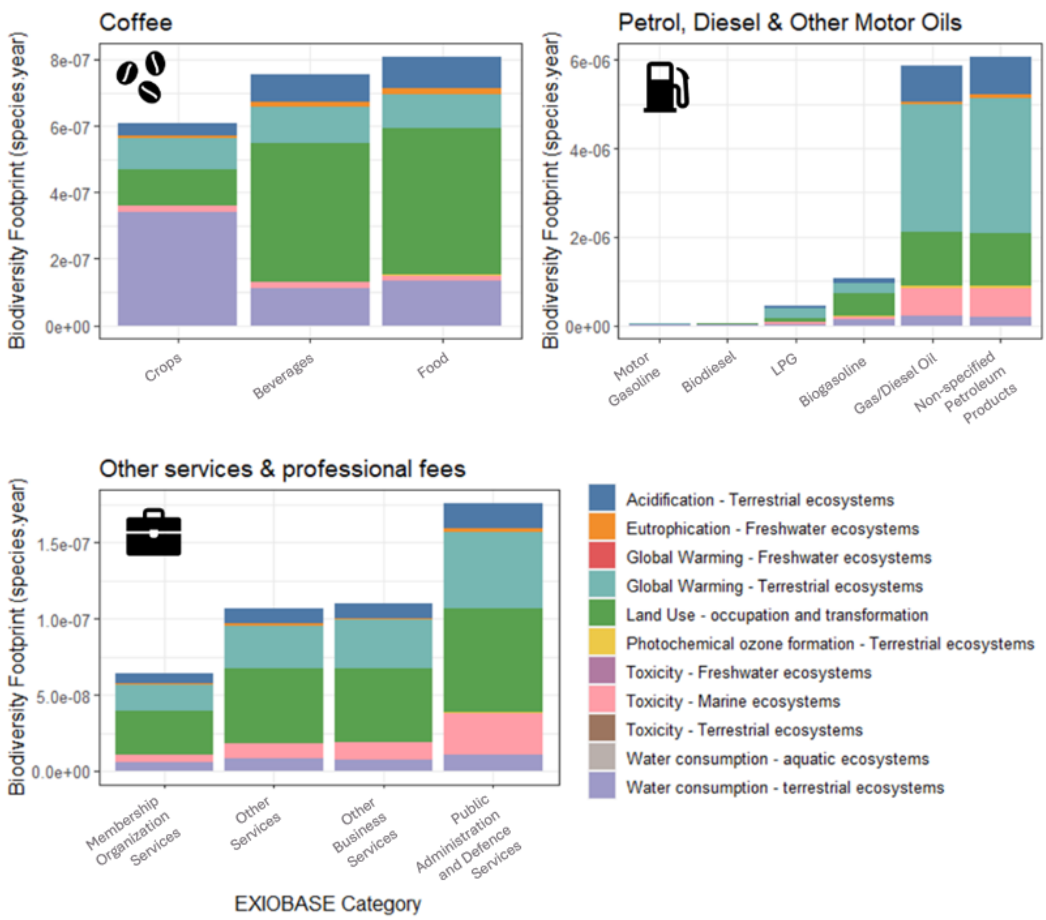


Figure 3: Biodiversity footprint results for the same quantity of expenditure on coffee [top-left], petrol [top-right] and other services and professional fees [bottom-left] (y axis), if allocated to different input-output-based LCA categories (x axis).

Aim: *This example explores the decision context of a household, organisation, or even nation, wishing to understand the relative impacts of expenditure on different activities or commodities. The goal was to highlight how decision and linguistic uncertainties can influence biodiversity impact calculations when matching activity or spend data to appropriate LCA or input-output categories, and the associated limitations of LCA analyses.*

Methods: *Figure 3 shows the calculated biodiversity impact of the average UK household spend on A) coffee, B) petrol and C) other professional services. On the x-axis, the input-output-based LCA category to which the spend was matched is varied, showing the difference in biodiversity impact that would be calculated as a result of decisions made when matching categories. The input-output framework used was EXIOBASE, a multi-regional environmentally extended input-output database used to calculate midpoint pressures. For example, expenditure on Coffee in the UK Living Costs survey could be matched to: coffee drinks captured in EXIOBASE category Beverages; roasted coffee and coffee substitutes in Food products; or unroasted coffee in Crops. Endpoint biodiversity impacts are then calculated using the ReCiPe LCA framework.*

Implications: *These examples demonstrate how linguistic uncertainty in input data – with data grouped in vaguely-named, highly aggregated categories – and subsequent decision-based uncertainty in the matching of spend to broad LCA categories, can lead to large variations in the estimates of impacts. If these matches were not representative of the actual expenditure activities and commodities they were being used to model, and these choices were not made clear when LCA-based biodiversity footprints were reported, it could lead to misattribution of impacts and inappropriately targeted biodiversity strategies.*

Reducing, understanding, and navigating uncertainty in LCAs

Reducing uncertainty

Reducing uncertainties in LCA outputs is a key approach for increasing their utility and robustness. Approaches for this include:

Reduce uncertainties in data inputs – Organisations can reduce LCA uncertainties through collecting improved data on their value chains, including more complete and accurate quantification of the volumes of specific goods and services, sourcing locations, and details of specific production processes. These data are often patchy or unavailable, meaning only generalised values are used to assess impact (T. B. White et al., 2023). Improved data inputs could substantially reduce parametric uncertainties in the biodiversity footprint process, facilitate benchmarking across sectors and tracking of trends over time. Having more accurate inventory data can also reduce decision uncertainties by providing clarity on the relevant processes and categories to match to LCA classifications (Scrucca et al., 2020). However, improving data collection can be resource and time-intensive (Halpern et al., 2006) and may only be improvable to a limited extent.

Reduce uncertainties in models – For LCA researchers, and those developing biodiversity endpoint metrics, there is an opportunity to refine impact models and conversion factors via targeted research on high uncertainty areas, including (a) building in more specific production practices to make estimates more reflective of actual company impacts, and (b) working to improve regionalisation in models. For example, the HESTIA project is working to update and improve regionalisation in conversion factors from agricultural commodities by collating and harmonizing data from peer-reviewed literature. For organisations, model uncertainties can be reduced by moving away from generic or proxy data to quantify impacts, and towards the use of better matched or extrapolated models (Canals et al., 2011), or generating context-specific LCAs from onsite measurements.

Understanding and documenting uncertainty

It is only possible to reduce uncertainty to a certain extent; the inherent stochasticity of natural systems, for example, will always be present. However, a range of approaches and tools can help better understand and document uncertainties to improve confidence in decision-making. Igos et al. (2019) outline recommended approaches at three levels of effort and technical capacity. At minimum, they recommend a qualitative description of uncertainties in the process, carefully communicated to avoid biased interpretation of results (Igos et al., 2019). Higher levels of effort involve quantitative analysis and descriptions of the uncertainties emanating from multiple sources.

Document assumptions and limitations to aid interpretation - Documenting assumptions is a key component of evidence-based practice (Salafsky et al., 2022), and can be key to reducing uncertainties caused by human decisions. LCA users should be mindful to disclose assumptions and limitations, alongside justifications for the selection of particular indicators and models (Igos et al., 2019). To reduce linguistic uncertainties, care should be taken in communication of biodiversity outcomes and associated assumptions and limitations, considering end-users' prior understanding.

Test sensitivity and use multiple LCA methods - Conducting LCAs using different LCA methods, different inventory databases and conversion factors to calculate biodiversity impacts (Box 1 and 2) can help reveal discrepancies and test the sensitivity of results to changes in model structure, parameters, biodiversity metrics, and input variables (Barahmand & Eikeland, 2022). For example, a study of the biodiversity impact of the EU's household consumption tested multiple methods, highlighting broad alignment (food, and in particular meat and chocolate consumption, were the most contributing products under most methods) but also discrepancies between methods (Sanyé-Mengual et al., 2023). More broadly, scenario analyses and sensitivity tests are used in LCA to test the impact of key assumptions on outputs (Igos et al., 2019; Martínez Ramón et al., in review). For example, LC-IMPACT provides max and min values for conversion factors that could be used to test sensitivity of results. Ideally, such sensitivity tests would allow triangulation of metrics that assess different components of biodiversity, to help prioritise robust action.

Use tools to assess uncertainty in combination with LCA - There are a range of approaches that can be used to express uncertainty (e.g. probability bounds analysis, Monte Carlo sampling and variations on these approaches; Groen et al., 2014; Halpern et al., 2006; Igos et al., 2019). In LCAs the impacts of parameter uncertainties are most frequently investigated using Monte Carlo simulations that repeatedly re-run analyses, sampling values of each parameter from probability distributions provided in LCA databases, and looking at the variation in outcomes (Barahmand & Eikeland 2022). Approaches used to assess uncertainties vary in their performance and computational requirements (Groen et al., 2014). Some LCA software has started to integrate these approaches (e.g. SimaPro; Scrucca et al. 2020), but they can be computationally demanding. Such methods will not address variation in results owing to human decisions and linguistic uncertainty. Recommendations on better navigating decision and linguistic uncertainties include enhanced inventory data with clear information on functional units, system boundaries and the environmental pathways considered to aid with choices of representative processes, and external peer review of the LCAs (Scrucca et al., 2020).

Navigating uncertainty

Uncertainty is inherent in LCAs, but once acknowledged can be navigated to ensure that decisions made are robust to these uncertainties. Options to help navigate uncertainties include:

Deploy tools for aiding decision making in high-uncertainty contexts - Several approaches are available to make decisions in high-uncertainty contexts. For example, info-gap theory looks at possible variation in initial estimates that would influence the outcomes of decisions made (Hayes et al., 2013). In the case of LCA, this may involve assessing the biodiversity impacts of different sourcing materials and seeing how much variation in parameters would be required to alter the prioritisation of business mitigation effort. There are numerous examples from the ecological literature where these approaches have been used to help guide decisions about conservation strategies, often focussed on parameter uncertainties (Hayes et al., 2013).

Get started, and plan to update – Given the urgency of the need to engage with biodiversity, limitations and uncertainties in LCA methods may need to be embraced to some extent – having a first go at estimating impacts, alongside transparent reporting of the approach used and a plan to update and improve analyses, would demonstrate a willingness to reduce uncertainty over time. Decision-support and evaluation frameworks that allow for adaptive management may be useful here (Addison et al., 2020). Businesses should be aware that analytical refinements and data improvements may result in changes in the estimated impacts that are not associated with actual changes in business activity, just their quantification. Care should therefore be taken to separate changes in footprint calculations due to company action across the mitigation hierarchy, and those resulting from improved data and model refinements. When LCA models are improved and updated, re-baselining will be required to enable meaningful comparisons over time and assess progress towards biodiversity goals. In general, LCA methods are most appropriate for comparing relative differences in estimated impacts for products and activities that are assessed with exactly the same methods. Used in this way, the uncertainties at least remain relatively consistent, allowing for a meaningful relative comparison.

Take a conservative approach - One simple approach for navigating uncertainty is to use conservative estimates when possible. This leans towards overestimating impacts, which might be unattractive to businesses but reduces the risks associated with inadvertently underestimating impact and incentivises investment in improving datasets and models. If reporting over time, businesses should be careful to avoid accusations of greenwashing by being very clear when reductions in their biodiversity impacts are due to genuine action to address them, rather than improvements in the estimates of impacts. In some contexts, there could be a strong rationale for taking other approaches, which must be clearly articulated. For instance, there may be large discrepancies in uncertainties between pressures e.g., ecotoxicity impacts may have higher uncertainty than land use impacts. If a precautionary approach is taken in these situations it could lead to prioritisation of effort towards mitigating potentially insignificant, but highly uncertain pressures.

Implications for estimating biodiversity impact and strategy design

LCAs provide a tractable approach for estimating biodiversity impacts across complex value chains and considering multiple pressures on biodiversity - a necessary foundation for Nature Positive commitments (Panwar, 2023). Yet, uncertainties in LCA results pose potential conservation and business risks when the results are used for designing biodiversity strategies, including inappropriate prioritisation of actions and subsequent misallocation of resources to abate biodiversity impacts. It is therefore important to understand the risks posed by these uncertainties in strategy design, weigh them against the costs of inappropriate action or inaction, and ensure decision-making is robust to these uncertainties – a balance explored in the climate change literature (e.g., Wiens et al. 2009).

LCA approaches are well suited for risk screening to estimate the potential biodiversity impacts of different products and activities across value chains, identify the possible scale of action required to address those impacts, and prioritise key issue areas (e.g., pressures, activities, products, locations, commodities) for further investigation, target setting and action. This use case corresponds to multiple steps in TNFD's LEAP framework (TNFD, 2023), the 'Assess' step of SBTN (SBTN, 2023) and the ACT-D framing. Used in this way, with carefully defined system boundaries, methodologies and assumptions, LCAs can also help organisations explore the relative benefits of and trade-offs between different products, processes and sourcing or production decisions. However, the time and resources required to gather data, complete analyses, and interpret LCA results must be proportionate to where it is needed to support robust decisions (e.g. Pilgrim et al., 2013), and should not substantially divert efforts from implementing low-risk actions to start reducing negative impacts on biodiversity. For critical impacts under the direct operational control of companies, more granular (ideally primary) data on pressures and impacts should be prioritised over modelled estimates.

After using LCAs to identify priority issue areas, other complementary methods can be used to provide more granularity or clarity. For example, if an initial LCA of an organisation's value chain suggests high impacts from agricultural commodities in the upstream supply chain, the next step could be to focus on mapping location-specific supply chain information (e.g., TRASE) and requesting primary data (e.g., on land occupancy and deforestation) from suppliers. This can guide appropriate location-specific mitigation action, such as reducing sourcing from areas on deforestation frontiers. In addition, LCA was designed around the negative impacts of pollutant inventories and is not as compatible with estimating positive biodiversity impacts - a necessary component of Nature Positive strategies (Booth et al., 2024). In these situations, spatially-explicit metrics capable of measuring positive changes in the state of nature are needed to monitor outcomes. It is also important to consider the social consequences of biodiversity impacts, which are place-specific, and strategies built upon environmental LCAs alone could entrench inequalities. In these ways, current LCA frameworks alone are not sufficient to support the entire suite of decisions within biodiversity strategy development and implementation (Crenna et al., 2020). They should be used as part of a broader methodological toolkit for biodiversity strategy design (see Addison et al. 2020).

The absolute values of biodiversity impacts estimated by LCA models should be interpreted cautiously because i) considerable uncertainties are involved, ii) they identify potential but not actual impacts on biodiversity (Barahmand et al. 2022), and iii) estimated footprints are not linked to specific biodiversity taxa, habitats or locations. Although suitable for communicating results, and tracking change over time if the context and methods stay constant, absolute numbers must be accompanied by clear communication of uncertainties. Moreover, if LCAs are to be used to support comparative assertions both within and between companies - a use case for which LCAs have been criticised (Jia et al., 2022) - there must be a robust understanding of uncertainties, and consistency between approaches to ensure embedded uncertainties are equal and therefore comparable.

Until uncertainties in LCAs can be reduced and robustly quantified, it is good practice for organisational targets and strategies to be based around a basket of complementary metrics derived from LCA-based and non-LCA methods, including actions, pressures and primary data on state of nature. Pressure targets could be based on LCA midpoints - which are more tangible to measure and responsive to company action. For example, targets are currently recommended for land use, freshwater pollution, and GHG emission under the Science-based Targets framework (SBTN, 2023). Conversely, goals and targets based solely on endpoints from LCAs would mask high uncertainties, and risk implying mitigation action is fungible across different pressures; which is not the case.

One final key mechanism for ensuring that biodiversity strategies based on LCA footprinting can deliver positive and efficient biodiversity outcomes is to cross-reference and triangulate with other sources of data and well-evidenced recommendations from conservation science. There may be some low-risk mitigation actions that are well-evidenced and very unlikely to have unintended consequences for biodiversity. For example, seeking to reduce and where feasible eliminate conversion of natural habitats. Certain actions may even have positive financial benefits, such as improving resource efficiency or reducing the consumption of commodities that are not critical for business operations (Bull et al. 2022). In practice, lowering consumption may prove unpopular with some stakeholders - but there are clear benefits to exploring biodiversity strategies that adopt avoidance actions to the greatest extent possible: e.g., eliminating unnecessary business travel, reducing consumption of impactful agricultural products etc. Other low-risk actions from a biodiversity perspective include investments in proactive conservation actions, such as increases in philanthropic donations to nature conservation organisations.

Uncertainties are pervasive across the LCA process, leading to high risks associated with their use if these uncertainties are not reduced, understood and navigated. But if appropriately applied alongside other approaches, as we have outlined, LCAs can help inform robust decisions, allowing organisations to develop effective and efficient strategies to reverse biodiversity loss.

Acknowledgements

T.B.W, T.B & I.H were funded by the Leverhulme Trust as part of the Leverhulme Centre for Nature Recovery, University of Oxford. We thank Lucy Walker, Jimmy Jai, Joseph Poore, Patrik Henriksson, Thomas Harwood & Michael Obersteiner for feedback on the concepts and ideas presented in the paper.

Conflict of Interest statement

T.B, T.B.W, A.B, J.B, L.B, E.B, H.B, G.P, L.S & M.S receive income from consultancy services from related to biodiversity footprinting, impact assessment and strategy design for organisations.

Author Contributions

T.B.W. T.B, J.B., & E.J.M.G conceived the study. A workshop and/or conversations between all authors helped refine the approach taken and concepts covered. AB, IH, TBW, TB & SZE developed the worked examples, with analysis conducted by AB, IH, TBW and TB. The original draft was led by TBW & TB, with further input and review from all authors.

References

Addison, P. F. E., Bull, J. W., & Milner-Gulland, E. J. (2019). Using conservation science to advance corporate biodiversity accountability. *Conservation Biology*, *33*(2), 307–318. https://doi.org/10.1111/cobi.13190

Addison, P. F. E., Stephenson, P. J., Bull, J. W., Carbone, G., Burgman, M., Burgass, M. J., Gerber, L. R., Howard, P., McCormick, N., McRae, L., Reuter, K. E., Starkey, M., & Milner-Gulland, E. J. (2020). Bringing sustainability to life: A framework to guide biodiversity indicator development for business performance management. *Business Strategy and the Environment*, bse.2573. https://doi.org/10.1002/bse.2573

Alyaseri, I., & Zhou, J. (2019). Handling uncertainties inherited in life cycle inventory and life cycle impact assessment method for improved life cycle assessment of wastewater sludge treatment. *Heliyon*, *5*(11), e02793. https://doi.org/10.1016/j.heliyon.2019.e02793

Arlidge, W. N. S., Bull, J. W., Addison, P. F. E., Burgass, M. J., Gianuca, D., Gorham, T. M., Jacob, C., Shumway, N., Sinclair, S. P., Watson, J. E. M., Wilcox, C., & Milner-Gulland, E. J. (2018). A global mitigation hierarchy for nature conservation. *BioScience*, *68*(5), 336–347. https://doi.org/10.1093/biosci/biy029

Asselin-Balencon, A., Broekema, R., Teulon, H., Gastaldi, G., Houssier, J., Moutia, A., Rousseau, V., Wermeille, A., Colomb, V., Cornelus, M., Ceccaldi, M., Doucet, M., & Vasselon, H. (2022). *AGRIBALYSE 3: La base de données française d'ICV sur l'Agriculture et l'Alimentation. Methodology for the food products.* (Initial publication Agribalyse 3.0-2020, update 3.1-2022). ADEME.

Azevedo, L. B., Van Zelm, R., Elshout, P. M. F., Hendriks, A. J., Leuven, R. S. E. W., Struijs, J., De Zwart, D., & Huijbregts, M. A. J. (2013). Species richness–phosphorus relationships for lakes and streams worldwide. *Global Ecology and Biogeography*, *22*(12), 1304–1314. https://doi.org/10.1111/geb.12080

Baboulet, O., & Lenzen, M. (2010). Evaluating the environmental performance of a university. *Journal of Cleaner Production*, *18*(12), 1134–1141. https://doi.org/10.1016/j.jclepro.2010.04.006

Bamber, N., Turner, I., Arulnathan, V., Li, Y., Zargar Ershadi, S., Smart, A., & Pelletier, N. (2020). Comparing sources and analysis of uncertainty in consequential and attributional life cycle assessment: Review of current practice and recommendations. *The International Journal of Life Cycle Assessment*, *25*(1), 168–180. https://doi.org/10.1007/s11367-019-01663-1

Barahmand, Z., & Eikeland, M. S. (2022). Life Cycle Assessment under Uncertainty: A Scoping Review. *World*, *3*(3), 692–717. https://doi.org/10.3390/world3030039

Berry, P. M., Fabók, V., Blicharska, M., Bredin, Y. K., Llorente, M. G., Kovács, E., Geamana, N., Stanciu, A., Termansen, M., Jääskeläinen, T., Haslett, J. R., & Harrison, P. A. (2018). Why conserve biodiversity? A multi-national exploration of stakeholders' views on the arguments for biodiversity conservation. *Biodiversity and Conservation*, *27*(7), 1741–1762. https://doi.org/10.1007/s10531-016-1173-z

Booth, H., Milner-Gulland, E. J., McCormick, N., & Starkey, M. (2024). Operationalizing transformative change for business in the context of nature positive. *One Earth*. https://doi.org/10.1016/j.oneear.2024.06.003

Borgelt, J., Dorber, M., Géron, C., Kuipers, K. J. 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

Bracy Knight, K., Seddon, E. S., & Toombs, T. P. (2020). A framework for evaluating biodiversity mitigation metrics. *Ambio*, *49*(6), 1232–1240. https://doi.org/10.1007/s13280-019-01266-y

Brook, B., Sodhi, N., & Bradshaw, C. (2008). Synergies among extinction drivers under global change. *Trends in Ecology & Evolution*, *23*(8), 453–460. https://doi.org/10.1016/j.tree.2008.03.011

Bull, J. W., Taylor, I., Biggs, E., Grub, H. M. J., Yearley, T., Waters, H., & Milner-Gulland, E. J. (2022). Analysis: The biodiversity footprint of the University of Oxford. *Nature*, *604*(7906), 420–424. https://doi.org/10.1038/d41586-022-01034-1

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

Canals, L. M. I., Azapagic, A., Doka, G., Jefferies, D., King, H., Mutel, C., Nemecek, T., Roches, A., Sim, S., Stichnothe, H., Thoma, G., & Williams, A. (2011). Approaches for Addressing Life Cycle Assessment Data Gaps for Bio-based Products. *Journal of Industrial Ecology*, *15*(5), 707–725. https://doi.org/10.1111/j.1530-9290.2011.00369.x

Cazalis, V., Di Marco, M., Butchart, S. H. M., 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

CBD. (2022). *Kunming-Montreal Global Biodiversity Framework* (Version 1). Zenodo. https://doi.org/10.5281/ZENODO.3831673

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., Burivalova, Z., Koh, L. P., & Hellweg, S. (2016). Impact of Forest Management on Species Richness: Global Meta-Analysis and Economic Trade-Offs. *Scientific Reports*, *6*(1), 23954. https://doi.org/10.1038/srep23954

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 & Technology*, *49*(16), 9987–9995. https://doi.org/10.1021/acs.est.5b02507

Cherubini, E., Franco, D., Zanghelini, G. M., & Soares, S. R. (2018). Uncertainty in LCA case study due to allocation approaches and life cycle impact assessment methods. *The International Journal of Life Cycle Assessment*, *23*(10), 2055–2070. https://doi.org/10.1007/s11367-017-1432-6

Cohen, D. J., Ferrell, J. M., & Johnson, N. (2002). What very small numbers mean. *Journal of Experimental Psychology: General*, *131*(3), 424–442. https://doi.org/10.1037/0096-3445.131.3.424

Commission Delegated Regulation (EU) 2023/2772 of 31 July 2023 Supplementing Directive 2013/34/EU of the European Parliament and of the Council as Regards Sustainability Reporting Standards (2023).

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

Damiani, M., Sinkko, T., Caldeira, C., Tosches, D., Robuchon, M., & Sala, S. (2023). Critical review of methods and models for biodiversity impact assessment and their applicability in the LCA context. *Environmental Impact Assessment Review*, *101*, 107134. https://doi.org/10.1016/j.eiar.2023.107134

Dasgupta, P., & Levin, S. (2023). Economic factors underlying biodiversity loss. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *378*(1881), 20220197. https://doi.org/10.1098/rstb.2022.0197

Eyres, A., Ball, T., Dales, M., Swinfield, T., Arnell, A., Baisero, D., Durán, A. P., Green, J., Madhavapeddy, A., & Balmford, A. (2023). *LIFE: A metric for quantitively mapping the impact* *of land-cover change on global extinctions* [Preprint]. Earth and Environmental Sciences. https://doi.org/10.33774/coe-2023-gpn4p-v2

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

Franks, D. M., Brereton, D., & Moran, C. J. (2013). The cumulative dimensions of impact in resource regions. *Resources Policy*, *38*(4), 640–647. https://doi.org/10.1016/j.resourpol.2013.07.002

Goedkoop, M., Rossberg, A. G., & Dumont, H. J. (2022). *Bridging the Gap Between Biodiversity Footprint Metrics and Biodiversity State Indicator Metrics*. PRé Sustainability. https://www.biodiversity-metrics.org/uploads/1/2/7/5/127509512/bridging_the_gap_between_biodiversity_footprint_and_biodiversity_state_indicator_metrics_2e.pdf

Groen, E. A., Heijungs, R., Bokkers, E. A. M., & De Boer, I. J. M. (2014). Methods for uncertainty propagation in life cycle assessment. *Environmental Modelling & Software*, *62*, 316–325. https://doi.org/10.1016/j.envsoft.2014.10.006

Halpern, B. S., Regan, H. M., Possingham, H. P., & McCarthy, M. A. (2006). Accounting for uncertainty in marine reserve design. *Ecology Letters*, *9*(1), 2–11. https://doi.org/10.1111/j.1461-0248.2005.00827.x

Hayes, K. R., Barry, S. C., Hosack, G. R., & Peters, G. W. (2013). Severe uncertainty and info-gap decision theory. *Methods in Ecology and Evolution*, *4*(7), 601–611. https://doi.org/10.1111/2041-210X.12046

Hellweg, S., & Mila i Canals, L. (2014). Emerging approaches, challenges and opportunities in life cycle assessment. *Science*, *344*(6188), 1109–1113. https://doi.org/10.1126/science.1248361

Herrmann, I. T., Hauschild, M. Z., Sohn, M. D., & McKone, T. E. (2014). Confronting Uncertainty in Life Cycle Assessment Used for Decision Support: Developing and Proposing a Taxonomy for LCA Studies. *Journal of Industrial Ecology*, *18*(3), 366–379. https://doi.org/10.1111/jiec.12085

Huijbregts, M. A. J. (1998). Application of uncertainty and variability in LCA. *The International Journal of Life Cycle Assessment*, *3*(5), 273. https://doi.org/10.1007/BF02979835

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. *The International Journal of Life Cycle Assessment*, *22*(2), 138–147. https://doi.org/10.1007/s11367-016-1246-y

Huijbregts, M., Steinmann, Z. J. N., Elshout, P. M. F., Stam, G., Verones, F., Vieira, M. D. M., Hollander, A., Zijp, M., & Van Zelm, R. (2016). *ReCiPe 2016. A harmonized life cycle impact assessment method at midpoint and endpoint level. Report I: Characterization* (RIVM Report 2016-0104; p. 191). National Institute for Public Health and the Environment. https://www.rivm.nl/bibliotheek/rapporten/2016-0104.pdf

Igos, E., Benetto, E., Meyer, R., Baustert, P., & Othoniel, B. (2019). How to treat uncertainties in life cycle assessment studies? *The International Journal of Life Cycle Assessment*, *24*(4), 794–807. https://doi.org/10.1007/s11367-018-1477-1

IPBES. (2019). *Summary for policymakers of the global assessment report on biodiversity and ecosystem services* (summary for policy makers). Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, IPBES. https://doi.org/10.5281/ZENODO.3553579

ISO 14040. (2006). *Environmental management Life cycle assessment Principles and framework, Technical Committee ISO/TC 207, Subcommittee SC 5, Life cycle assessment*. https://www.iso.org/standard/37456.html

Jia, J., Ranger, N., & Chaudhury, A. (2022). Designing for Comparability in GHG Emissions Accounting. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4258460

Kujala, H., Burgman, M. A., & Moilanen, A. (2013). Treatment of uncertainty in conservation under climate change. *Conservation Letters*, *6*(2), 73–85.

Lammerant, J., Driesen, K., Vanderheyden, G., Starkey, M., De Horde, A., Bor, A. M., Kisielewicz, J., & Müller, L. (2021). *Assessment of Biodiversity Measurement Approaches for Businesses and*

Financial Institutions, Update Report 3. EU Business and Biodiversity Platform. https://ec.europa.eu/environment/biodiversity/business/assets/pdf/EU%20B@B%20Platform%20Update%20Report%203_FINAL_1March2021.pdf

Lenzen, M. (2000). Errors in Conventional and Input-Output—Based Life—Cycle Inventories. *Journal of Industrial Ecology*, *4*(4), 127–148. https://doi.org/10.1162/10881980052541981

Lenzen, M. (2002). Differential Convergence of Life-Cycle Inventories toward Upstream Production Layers: Implications for Life-Cycle Assessment. *Journal of Industrial Ecology*, *6*(3–4), 137–160. https://doi.org/10.1162/108819802766269575

Lenzen, M., & Crawford, R. (2009). The Path Exchange Method for Hybrid LCA. *Environmental Science & Technology*, *43*(21), 8251–8256. https://doi.org/10.1021/es902090z

Lloyd, S. M., & Ries, R. (2007). Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment: A Survey of Quantitative Approaches. *Journal of Industrial Ecology*, *11*(1), 161–179. https://doi.org/10.1162/jiec.2007.1136

MacArthur, R., & Wilson, E. (1967). *The theory of island biogeography*. Princeton University Press.

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*, 1–8. https://doi.org/10.1038/s41559-021-01432-0

Martin, P. A., Green, R. E., & Balmford, A. (2019). The biodiversity intactness index may underestimate losses. *Nature Ecology & Evolution*, *3*(6), 862–863. https://doi.org/10.1038/s41559-019-0895-1

Martínez Ramón, V., Bromwich, T., Modernel, P., Poore, J., & Bull, J. W. (in prep). *Similar methods for biodiversity footprinting can suggestqualitatively different strategic priorities: A Dutch dairy multinational companycase study*.

Mekonnen, M. M., & Hoekstra, A. Y. (2011). The green, blue and grey water footprint of crops and derived crop products. *Hydrology and Earth System Sciences*, *15*(5), 1577–1600. https://doi.org/10.5194/hess-15-1577-2011

Mervine, E., Valenta, R., Paterson, J., Mudd, G., Werner, T., & Sonter, L. (2023). *Biomass carbon emissions from nickel mining have significant implications for climate action*. https://doi.org/10.21203/rs.3.rs-2469411/v1

Milner-Gulland, E., & Shea, K. (2017). Embracing uncertainty in applied ecology. *Journal of Applied Ecology*, *54*, 2063–2068.

Newbold, T., Hudson, L. N., Hill, S. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., & others. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50.

Noss, R. F. (1990). Indicators for Monitoring Biodiversity: A Hierarchical Approach. *Conservation Biology*, *4*(4), 355–364. https://doi.org/10.1111/j.1523-1739.1990.tb00309.x

Office for National Statistics. (2022). *Family spending in the UK: April 2021 to March 2022* [Dataset]. https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/bulletins/familyspendingintheuk/april2021tomarch2022

Panwar, R. (2023). Business and biodiversity: Achieving the 2050 vision for biodiversity conservation through transformative business practices. *Biodiversity and Conservation*, *32*(11), 3607–3613. https://doi.org/10.1007/s10531-023-02575-1

Perkins, J., & Suh, S. (2019). Uncertainty Implications of Hybrid Approach in LCA: Precision versus Accuracy. *Environmental Science & Technology*, *53*(7), 3681–3688. https://doi.org/10.1021/acs.est.9b00084

Peura, M., El Geneidy, S., Pokkinen, K., Vainio, V., & Kotiaho, J. S. (2023). Väliraportti: S-ryhmän luontojalanjälki. *JYU Reports*, 1–45. https://doi.org/10.17011/jyureports/2023/20

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

Pilgrim, J. D., Brownlie, S., Ekstrom, J. M. M., Gardner, T. A., von Hase, A., Kate, K. ten, Savy, C. E., Stephens, R. T. T., Temple, H. J., Treweek, J., Ussher, G. T., & Ward, G. (2013). A process for assessing the offsetability of biodiversity impacts. *Conservation Letters*, *6*, 376–384. https://doi.org/10.1111/conl.12002

Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Science*, *360*(6392), 987–992. https://doi.org/10.1126/science.aaq0216

Regan, H. M., Colyvan, M., & Burgman, M. A. (2002). A taxonomy and treatment of uncertainty for ecology and conservation biology. *Ecological Applications*, *12*(2), 618–628. https://doi.org/10.1890/1051-0761(2002)012[0618:ATATOU]2.0.CO;2

Rice, P., O'Brien, D., Shalloo, L., & Holden, N. M. (2017). Evaluation of allocation methods for calculation of carbon footprint of grass-based dairy production. *Journal of Environmental Management*, *202*, 311–319. https://doi.org/10.1016/j.jenvman.2017.06.071

Rounsevell, M. D. A., Harfoot, M., Harrison, P. A., Newbold, T., Gregory, R. D., & Mace, G. M. (2020). A biodiversity target based on species extinctions. *Science*, *368*(6496), 1193–1195. https://doi.org/10.1126/science.aba6592

Sala, S., Amadei, A. M., Beylot, A., & Ardente, F. (2021). The evolution of life cycle assessment in European policies over three decades. *The International Journal of Life Cycle Assessment*, *26*(12), 2295–2314. https://doi.org/10.1007/s11367-021-01893-2

Salafsky, N., Irvine, R., Boshoven, J., Lucas, J., Prior, K., Bisaillon, J., Graham, B., Harper, P., Laurin, A. Y., Lavers, A., Neufeld, L., & Margoluis, R. (2022). A practical approach to assessing existing evidence for specific conservation strategies. *Conservation Science and Practice*, *4*(4). https://doi.org/10.1111/csp2.12654

Sanyé-Mengual, E., Biganzoli, F., Valente, A., Pfister, S., & Sala, S. (2023). What are the main environmental impacts and products contributing to the biodiversity footprint of EU consumption? A comparison of life cycle impact assessment methods and models. *The International Journal of Life Cycle Assessment*, *28*(9), 1194–1210. https://doi.org/10.1007/s11367-023-02169-7

Saxe, S., Guven, G., Pereira, L., Arrigoni, A., Opher, T., Roy, A., Arceo, A., Von Raesfeld, S. S., Duhamel, M., McCabe, B., Panesar, D. K., MacLean, H. L., & Posen, I. D. (2020). Taxonomy of uncertainty in environmental life cycle assessment of infrastructure projects. *Environmental Research Letters*, *15*(8), 083003. https://doi.org/10.1088/1748-9326/ab85f8

SBTN. (2023). *SBTN Technical Guidance Step 1 Assess* (Version 1). Science Based Targets Network. Global Commons Alliance. https://sciencebasedtargetsnetwork.org/wp-content/uploads/2023/05/Technical-Guidance-2023-Step1-Assess-v1.pdf

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

Schipper, A. M., Hilbers, J. P., Meijer, J. R., Antão, L. H., Benítez-López, A., de Jonge, M. M. J., 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. J. (2020). Projecting terrestrial biodiversity intactness with GLOBIO 4. *Global Change Biology*, *26*(2), 760–771. https://doi.org/10.1111/gcb.14848

Scrucca, F., Baldassarri, C., Baldinelli, G., Bonamente, E., Rinaldi, S., Rotili, A., & Barbanera, M. (2020). Uncertainty in LCA: An estimation of practitioner-related effects. *Journal of Cleaner Production*, *268*, 122304. https://doi.org/10.1016/j.jclepro.2020.122304

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.-J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J. H., Theurl, M. C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K.-H., … Tukker, A. (2018). EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional

Input-Output Tables. *Journal of Industrial Ecology*, *22*(3), 502–515. https://doi.org/10.1111/jiec.12715

Steubing, B., De Koning, A., Merciai, S., & Tukker, A. (2022). How do carbon footprints from LCA and EEIOA databases compare? A comparison of ecoinvent and EXIOBASE. *Journal of Industrial Ecology*, *26*(4), 1406–1422. https://doi.org/10.1111/jiec.13271

TNFD. (2023). *Guidance on the identification and assessment of nature related issues: The LEAP approach Version 1.1*. https://tnfd.global/wp-content/uploads/2023/08/Guidance_on_the_identification_and_assessment_of_nature-related_Issues_The_TNFD_LEAP_approach_V1.1_October2023.pdf?v=1698403116

Urban, M. C. (2015). Accelerating extinction risk from climate change. *Science*, *348*(6234), 571–573. https://doi.org/10.1126/science.aaa4984

Urban, M. C., Bocedi, G., Hendry, A. P., Mihoub, J.-B., Pe'er, G., Singer, A., Bridle, J. R., Crozier, L. G., De Meester, L., Godsoe, W., Gonzalez, A., Hellmann, J. J., Holt, R. D., Huth, A., Johst, K., Krug, C. B., Leadley, P. W., Palmer, S. C. F., Pantel, J. H., … Travis, J. M. J. (2016). Improving the forecast for biodiversity under climate change. *Science*, *353*(6304), aad8466. https://doi.org/10.1126/science.aad8466

Verones, F., & Dorber, M. (2023). Biodiversity. In B. R. Bakshi (Ed.), *Engineering and Ecosystems* (pp. 135–165). Springer International Publishing. https://doi.org/10.1007/978-3-031-35692-6_7

Verones, F., Hellweg, S., Antón, A., Azevedo, L. B., Chaudhary, A., Cosme, N., Cucurachi, S., 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. J. (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

Walker, W. E., Harremoës, P., Rotmans, J., Van Der Sluijs, J. P., Van Asselt, M. B. A., Janssen, P., & Krayer Von Krauss, M. P. (2003). Defining Uncertainty: A Conceptual Basis for Uncertainty

Management in Model-Based Decision Support. *Integrated Assessment*, *4*(1), 5–17. https://doi.org/10.1076/iaij.4.1.5.16466

WEF. (2024). *The Global Risks Report 2024 19th Edition*. World Economic Forum. https://www3.weforum.org/docs/WEF_The_Global_Risks_Report_2024.pdf

White, T. B., Mukherjee, N., Petrovan, S. O., & Sutherland, W. J. (2023). Identifying opportunities to deliver effective and efficient outcomes from business-biodiversity action. *Environmental Science & Policy*, *140*, 221–231. https://doi.org/10.1016/j.envsci.2022.12.003

White, T., Bromwich, T., Bang, A., Bennun, L., Bull, J. W., Clark, M., Milner-Gulland, E. J., Prescott, G., Starkey, M., Ermgassen, S. zu, & Booth, H. (2023). *The Nature Positive Journey for Business: A research agenda to enable private sector contributions to the global biodiversity framework.* https://doi.org/10.31219/osf.io/nya52

Wiens, J. A., Stralberg, D., Jongsomjit, D., Howell, C. A., & Snyder, M. A. (2009). Niches, models, and climate change: Assessing the assumptions and uncertainties. *Proceedings of the National Academy of Sciences of the United States of America*, *106 Suppl 2*(Suppl 2), 19729–19736. https://doi.org/10.1073/pnas.0901639106

Zu Ermgassen, S. O. S. E., Howard, M., Bennun, L., Addison, P. F. E., Bull, J. W., Loveridge, R., Pollard, E., & Starkey, M. (2022). Are corporate biodiversity commitments consistent with delivering ‘nature-positive’ outcomes? A review of ‘nature-positive’ definitions, company progress and challenges. *Journal of Cleaner Production*, *379*, 134798. https://doi.org/10.1016/j.jclepro.2022.134798

Supporting Information

Table S1: Expanded typology of uncertainties

LCA Stage	Source	Examples	Nature of Uncertainty							
			Epistemic							
			Structural	Parametric	Variability	Stochasticity	Measurement Error	Information Gap	Linguistic	Human Decision
Organisational Activity Data Inputs	Functional unit representativeness	Units of spend vs quantity vs energy will capture the true extent and magnitude of activities differently.		X						
	Temporal variability	Most data collection for footprints is (at best) collected annually, which may not keep pace with temporal variability of organisational activities.			X					
	Spatial specificity	Knowing the extent of direct operations, or the geographical sourcing of items in the supply chain.						X		
	Technical granularity	Categories can be very specific, or uncertainties can arise from the pooling of activities into broad categories.		X						
	Labelling	Poor data communication or labelling of what activities include.							X	
	Completeness	Some data may be limited, unavailable, or completely inaccessible because employees or suppliers are unwilling or unable to supply information, or because of varying resources and difficulty in accurately quantifying activities, e.g. the flows of products downstream can be particularly challenging.						X		
	Data recording	Incorrect unit conversions or biases towards more comprehensive quantification of some activities over others.					X			

Midpoint Environmental Pressures	Model Boundaries & Structure	Impact representativeness	Not including all impact pathways relevant for measuring a biodiversity impact, e.g. water and land use, but not the impact of invasive species.	X					X		
		Activity representativeness	Some company activities may not be compatible with existing LCA literature or IO economic categories, so cannot be captured in the model.	X					X		
		Temporal variability	As organisations repeat a footprint annually, boundaries may change as organisations change or data or methods improve, which has knock on impacts for results comparison (benchmarking) over time.			X					X
		Functional units	Data may be available in more accurate measures (e.g., quantity) but mechanisms for assessment may only exist less accurate forms (e.g., spend) or there may be a choice to apply consistent methods across activities that means some units have to be converted to be compatible.		X						X
		Scope	Decisions made about where to place boundaries for analysis, i.e., which activities to exclude from the assessment, timescales of impacts, allocation factors etc. These decisions lead to sources of model uncertainty.	X							X
		Spatial variability	Models may not be able to calculate spatially explicit midpoints or endpoints (this may not be binary between non-spatial and spatial, but where spatial specificity may vary substantially)						X		
		Technical granularity	Models may not be able to calculate environmental midpoints, in addition to endpoints, or disaggregate different pressures, which limits interpretation.	X							
	Uncertainties in Conversion Factors	Linear relationships	The use of conversion factors often assumes a linear relationship between activity levels and midpoints. However, this may not always be the case, introducing model uncertainty.	X							
		Underlying data uncertainty	There will be uncertainty in the data underlying the conservation factors (e.g., information reliability).			X	X	X			
		Limited data underlying conversion factors	Data gaps and biases in underlying data.						X		
		Matching	Matching of company data to different activity categories in the LCA dataset.							X	X
		Activity level variation	The relevance of the data when applied to different company activities to estimate midpoints.		X	X					
		Spatial variability	The relevance of the data underlying the conversion when applied to different spatial contexts.		X	X					

		Temporal variability	The relevance of the data underlying the conversion when applied to different temporal contexts.		X	X					
		Process-based or Input-Output based models.	If spend data is used, this can introduce additional uncertainty associated with how spend translates to amounts of activity.		X						
Endpoint Biodiversity Impact	**Choice of Endpoint**	Choice of biodiversity metric	Which biodiversity metric used will influence the output of the model (often due to a combination of the above uncertainties).	X							X
	Underlying datasets	Components of biodiversity & pressures included	Data underlying the biodiversity model - what components of biodiversity are included e.g. genetic, species, ecosystem - and what pressures (if included) are mapped.	X							
		Geographic biases	Biases and measurement errors in the underlying biodiversity dataset towards different geographies.		X	X			X		
		Taxonomic biases	Biases and measurement errors in the underlying dataset towards different taxonomic groups.		X	X			X		
		Measurement error	Data underlying the biodiversity model - error in measurement of data underlying the metric such as the relationship between pressures and extinction risk.		X		X	X			
		Stochasticity in impact	Stochasticity in biodiversity impact (e.g., impacts of predicted population reduction on extinction risk).				X				
	Interpreting outputs	Under specificity in communication	Defining the results of LCA as a 'biodiversity' score without adequate context or explanation leading to uncertainty in interpretation of the output.							X	
		Ambiguity and vagueness in understanding	Confusion as to what the outputs of LCA models regarding biodiversity scores represent.							X	
	Assessing adequacy of outputs	Different assessments of adequacy due to different values placed on biodiversity	Subjective judgements about whether the model parameters are deemed adequate to provide a measure of biodiversity impact (e.g., impact pathways included, activities excluded etc.) due to different values placed upon biodiversity.								X

Worked Example 1: Expanded methods and results

Aim: This example was developed to explore the decision context of an individual company assessing the biodiversity impacts of a single product in order to prioritise actions to address biodiversity impacts. The goal was to highlight how the use of different midpoint and endpoint models can result in both different absolute estimates of biodiversity impact, and variation in how those impacts are distributed across different ingredients and impact pathways.

Methods: For this case study, the biodiversity impact of a hypothetical chocolate cake product was estimated. First a simple assumption was made about the cake inventory (ingredients and activities involved in the baking):

Inventory	Quantity
Butter	100g
Eggs	3 eggs
Chocolate	200g
Flour	100g
Sugar	100g
Process (i.e. baking)	1kWh electricity

Then using four different LCA databases, we estimated the midpoint pressures of these different ingredients (see Figure below). The four LCA databases are detailed below.

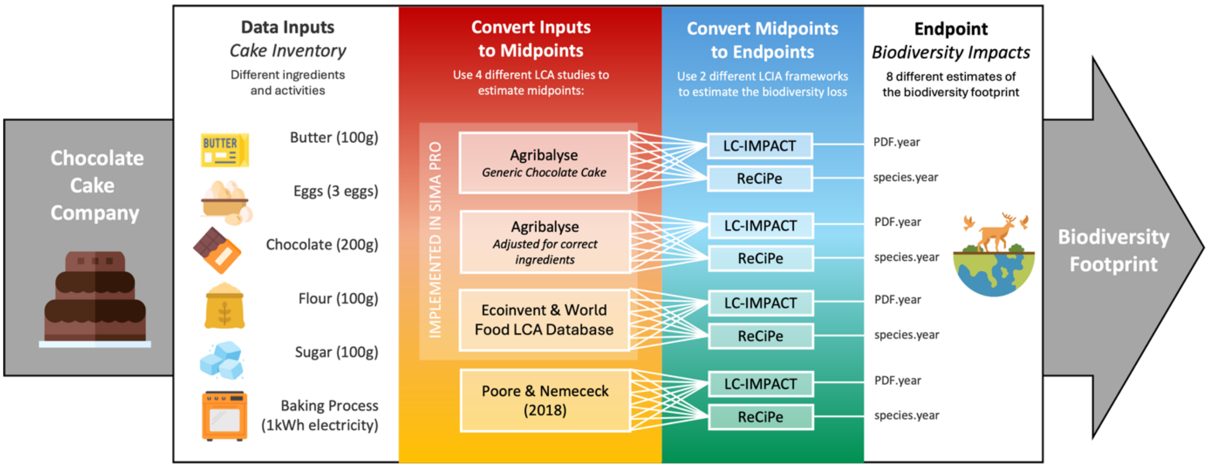
(i) Free “ready to use” Agribalyse generic chocolate cake impact data (Asselin-Balencon et al., 2022);

(ii) Agribalyse data adapted for the specific ingredient quantities of the model cake;

(iii) Access via a paid licence to ecoinvent, one of the world’s leading databases of up-to-date Life Cycle Inventory (LCI) data, and the World Food LCA Database;

(iv) Free data from Poore & Nemecek (2018) which aggregated ~38,000 LCA farm studies, again matching for all cake ingredients.

We then calculated endpoint biodiversity impacts using each of these pressure estimates, using two different LCIA frameworks – LC-IMPACT and ReCiPe. This allowed us to investigate eight different scenarios of biodiversity impact (see Box 1 in the main manuscript).



Variations (i) – (iii) for the midpoint calculations were assessed via the implementation of the LCA databases and LCIA frameworks in software SimaPro 9.6.0.1, whereas the impacts for (iv) were calculated by applying LCA conversion factors manually in Excel. Full details of the specific software versions, inventories, datasets and assumptions can be found in Supplementary Material Dataset 1.

Results and Discussion – The top row plots of Figure 2 (see main manuscript) highlight differences in the total footprint when using different LCA databases, with Agribalyse results estimating the smallest footprint, followed by ecoinvent, and Poore & Nemececk (2018) with the largest. This is due to different epistemic uncertainties, with Poore & Nemececk (2018) aggregating a much larger diversity of geographic locations and production methods. Indeed, the LCA studies underlying Agribalyse and ecoinvent form part of the overall Poore & Nemececk (2018) dataset. Including more countries from a wider range of farms, means Poore & Nemececk (2018) capture more impactful processes and geographies, resulting in larger estimates of potential impacts for each ingredient. It is also notable that compared to differences between LCA methods, there is very little difference between the two

Agribalyse analyses, indicating different LCA database choices have a larger impact on the range on the impact estimates than the slight adjustments made to ingredient quantities.

The top row plots of Figure 2 also highlight that the relative contribution of different environmental pathways is different between the two LCIA models. This difference is due to epistemic uncertainties in these models; land use dominating in ReCiPe, and land use, climate change and water use in LC-IMPACT. This has implications for target setting, where under ReCiPe, organisations might prioritise a land-based target, whereas the LC-IMPACT results could motivate a more diverse portfolio of targets. This would also concretely affect the magnitude of any science-based target for land if these results were used to evidence a biodiversity strategy, e.g. undertaking restoration or offsetting activities proportional to the scale of the footprint attributable to land conversion.

The bottom row plots in Figure 2 highlight that the relative contribution of different ingredients between the different methods is also different between all 8 estimates. Chocolate dominates in most methods, suggesting it may be one of the most impactful ingredients. However, when using Ecoinvent LCAs to estimate mid-point pressures butter is estimated to be as impactful, if not slightly more, impactful than chocolate. This has implications for where an organisation might choose to focus efforts for avoidance and mitigation action, and highlights the unreliability of LCA methods for comparing different activities, services, and goods in the absence of a robust understanding of the uncertainty.

There are many epistemic uncertainties in the different midpoint environmental pathways available in the different methods. For example, in LC-IMPACT the endpoint results for ecotoxicity are in PDF.m3.d, not PDF.year, so are not comparable and were excluded. (Conversion to PDF.year is possible but involves further data manipulation we felt was beyond the scope of most analysts). Indeed, the combination of many different types of uncertainty across this process has resulted in the absolute magnitude of estimated impacts being different for all four underlying LCA databases.

The units on the two plots exemplify the challenge of linguistic uncertainties in communicating LCA biodiversity footprints, with both the PDF and species.year results being very small numbers that are challenging to conceptualise.

In a first iteration of this analysis, the implementation of Agribalyse in combination with LC-IMPACT in the SimaPro LCA software was erroneously generating negative land impacts. This has now been updated in the SimaPro software but highlights the potential for errors in implementation, some of which may not be picked up by LCA practitioners – particularly if results are not obviously different from that expected.

The manual implementation in Excel highlighted many sources of potential uncertainty. For example, the midpoint water impacts of Poore & Nemecek (2018) represent blue water withdrawal, which had to be converted into water consumption using an estimated withdrawal-to-consumption ratio for an agricultural context. Allocation factors had to be used to derive butter impacts from milk, which involves large assumptions and can be implemented in multiple ways (Rice et al., 2017).

Estimates of the impacts of energy use in baking the cake were incorporated in the SimaPro implementation, but not when calculating manually, highlighting uncertainty in choice of activity scope. The impacts of cake packaging, distribution, and end of life are not modelled at all in any methods.

Overall, this case study highlights the epistemic model uncertainty in biodiversity footprinting, with all 8 methodological combinations generating both different absolute biodiversity impact values, and different distribution of impacts across environmental pathways and cake ingredients. This serves to emphasise that LCA-alone cannot be used to justify decisions around target setting. However, agreement across most models that chocolate is responsible for the largest proportion of impacts, most likely via land use and climate change impact pathways, could be used to justify a prioritisation of further investigation into chocolate sourcing, supplementing these results with more spatially-specific biodiversity monitoring and screening in the specific geographies and processes involved.

Worked Example 2: Expanded methods and results

Aim: This example was originally developed to assess the biodiversity impacts of UK household expenditure using IO-based models combined with ReCiPe to calculate the biodiversity impact of households in different income brackets. This highlighted several sources of linguistic and human decision uncertainty in the LCA process that made it extremely challenging to account for all areas of expenditure.

Methods: We first obtained data from the UK's Living Costs and Food Survey (Office for National Statistics, 2022) on average weekly household expenditure on a variety of product and service categories. Data was downloaded for the financial year ending 2022. To estimate the biodiversity impact of UK household expenditure we used EXIOBASE Version 3.8.2 (Stadler et al., 2018) to convert these expenditures to mid-point pressures. End point impacts (species.year) were then calculated using ReCiPe (M. A. J. Huijbregts et al., 2017). To utilise EXIOBASE's environmental impact multipliers, we then attempted to make appropriate matches between each expenditure category in the Living Costs and Food Survey and an EXIOBASE category.

Results and Discussion: In the matching process, certain expenditure categories had clear EXIOBASE matches. For example, household expenditure on the category "fresh fruit" could be clearly matched to the EXIOBASE category "vegetables, fruits and nuts". However, for other expenditure categories, the matching to EXIOBASE presented linguistic and subsequently human decision uncertainty.

Linguistic uncertainty here arises through use of broad terminology, vagueness, and ambiguity in labelling of expenditure data. The survey data provided insufficient detail to determine precisely which products and services are captured within the expenditure category, and therefore which match in EXIOBASE is appropriate. One example is that of expenditure on "Coffee", where broad terminology obscures underlying variation in the products included within this category. Various "coffee" products have different EXIOBASE matches: coffee drinks are reflected by EXIOBASE category "Beverages"; roasted coffee and coffee substitutes match to "Food products", and unroasted coffee matches to

"Crops". Matching this expenditure data to different EXIOBASE categories would lead to very different assessments of biodiversity impact, as is clearly shown in the Figure in Box 2. Similarly, multiple services are aggregated within a single category in expenditure on "Other services and professional fees", each with a distinct EXIOBASE match. The broad terminology used for this category prevents disaggregation. For expenditure on "Petrol, diesel and other motor oils", various fuel types may be included within this expenditure, each matching to different EXIOBASE categories.

Linguistic uncertainty resulting from a lack of specificity or broad terminology subsequently introduces decision-based uncertainty: a subjective decision is required in determining the most appropriate EXIOBASE match. A decision may be made to use a single broad EXIOBASE category as a proxy for the entire expenditure category. For example, expenditure on "Petrol, diesel and other motor oils", could be classified by the broad category of "Non-specific petroleum products". This, however, may fail to capture the true impacts of products included within the expenditure category. Alternatively, the decision may be made to split the expenditure equally between all potential EXIOBASE matches, when the products within a category are known, but absolute expenditure on each is not. This may however lead to overrepresentation of products comprising only a small true proportion of the total expenditure category. For example, the impacts of uncommonly used fuel types may be overrepresented using such an approach for expenditure on "Petrol, diesel and other motor oils". A third decision could be taken to seek a supplementary source of information to estimate the proportional expenditure on each product, such as, by using alternative datasets to estimate average expenditure on petrol compared to diesel.

Uncertainty also arises in certain expenditure categories where there is limited understanding of how the impacts of products or services reflected by the category could be traced down the value chain. Expenditure on "Savings and investments", for example, could conceptually be reflected by various EXIOBASE matches: depending on the products, services, or sectors into which the monetary investments are made. Consequently, the appropriate EXIOBASE match which would accurately reflect impacts of expenditure on “Savings and investments” may vary. This unknown variation and non-specific labelling of categories, leads to difficulty in determining an appropriate matching category, and high levels of uncertainty in endpoint calculations. The same is true of categorisation within the EXIOBASE model. The impact of a ‘saving, investment, pension or mortgage payments’ on biodiversity will be drastically different depending on where that money is invested, in what sectors, and in what locality. But such information is not provided when using generic categories in broad input-output models.

In Box 2, we illustrate the consequences of these uncertainties on biodiversity impact calculations. For “Coffee”, the endpoint biodiversity impact calculated is a factor of 1.3 greater when expenditure is matched entirely to “Food products”, and 1.2 times greater matched to “Beverages” than when this expenditure is matched to “Crops”. Even greater variability in endpoint impacts resulting from linguistic and preference uncertainty is observed for expenditure on “Other services and professional fees”. Endpoints calculated from the average UK household’s expenditure on this category differ by up to a factor of 2.7: the difference when expenditure is classified as “Membership organisation services” compared to “Public administration and defence services”. Most notably, differences in the choices of EXIOBASE match for expenditure category “Petrol, diesel, and other motor oils” result in endpoints differing by up to a factor of 110: the difference resulting from classification of expenditure as “Non specified petroleum products” compared to “Motor gasoline”.