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CRITICAL REVIEW

Review of weighting methods for life cycle impact assessment under GLAM

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Abstract

Purpose Weighting is the process of assigning relative importance to life cycle inventory results or indicator results across impact categories, using weighting factors based on value choices. It is an optional step within Life Cycle Assessment (LCA) but plays an important role in interpreting and communicating the relative importance of different environmental impacts. As part of the Global LCIA Guidance (GLAM) project under the UN Life Cycle Initiative, a comprehensive review of weighting methods was conducted to better understand which approaches are most appropriate for different applications in LCA.

Methods Members of the GLAM weighting subtask identified and reviewed twenty-seven weighting methods. These methods were grouped into four categories: Multiple Criteria Decision Analysis (MCDA), monetary, data-driven and distance-to-target methods. Classifiers based on inherent features of the weighting methods were applied to support their inclusion or exclusion from further considerations. Each method then was assessed against a set of evaluation criteria defined by the subtask members. A color-code system (green, yellow or red) was applied to indicate the degree to which each method met each criterion to facilitate comparison and communication.

Results and discussion Each method was briefly described with appropriate references, including examples of usage in LCA studies where available. The review results are summarized in a table that highlights the performance of each method against the evaluation criteria. All monetary methods are classified as trade-off rates, whereas there are MCDA methods and data-driven methods that can be either trade-off rates or importance coefficients. All distance-to-target methods are classified as importance coefficients. The ability of each method to incorporate temporal discounting or cultural differentiation varies, depending on the data availability and study design. None of the methods reviewed fully met all evaluation criteria, especially within the scope of the GLAM project. Some criteria (like Scientific validity) are sufficiently met by almost all of these methods.

Conclusions Existing weighting methods based on different approaches have both advantages and limitations. No single method is universally sufficient, and their validity depends on context. This comprehensive overview of available weighting methods provides a valuable starting point for practitioners seeking to identify suitable weighting method for specific LCA applications. To facilitate easy use, a software was also developed based on this review to support the selection of the most appropriate weighting method for LCA studies.

Keywords Weighting · LCIA · MCDA · Monetary methods · Data-driven methods · Distance-to-target · GLAM

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1 Introduction

In Life Cycle Assessment (LCA), impacts are characterized at two levels: midpoints (e.g., climate change, ozone depletion) and endpoints (e.g., human health, ecosystem quality). These potential impacts are quantified in the life cycle impact assessment (LCIA) phase. Weighting is an optional part of LCIA as defined in ISO 14044 (2006), where indicator results are converted using numerical factors based on value choices. ISO/TS 14074 (2022) defines weighting as "converting and possibly aggregating life cycle inventory results or indicator results across impact categories using weighting factors based on value choices". It is important to note that the generation of such a single score depends not only on the weighting step but also on the aggregation procedure adopted (e.g., weighted sum, outranking methods, non-linear functions). Rowley et al. (2012) even state that "the choice of aggregation algorithm has arguably more fundamental implications than the choice of weight elicitation procedures; and all the more so since the very meaning of the weights depends on the aggregation method used." Klöpffer and Grahl (2014) state that weighting is needed if System A is not superior for all impact categories to System B, or similar within the margins of error. Weighting can be helpful for decision-makers when interpreting LCIA results. There can be two primary objectives for weighting (Itsubo 2015): (i) to identify the most important impact categories and, thereafter, the life cycle stages that contribute to these impacts, and (ii) to understand which system performs overall better than the others, usually via a single score.

The important role of weighting in LCA has also been recognised in the Global Guidance on Environmental Life Cycle Impact Assessment Indicators (GLAM) project of the United Nations Environment Programme (UNEP)—Life Cycle Initiative (Life Cycle Initiative 2024). More specifically, it has been part of the GLAM Phase 3 "Creation of a Global Life Cycle Impact Assessment Method", a five-year project that started in March 2020. The aim of this phase of the work was to establish a comprehensive, consistent and global environmental LCIA methodology, building on the recommendations from the first two phases (Frischknecht et al. 2016, 2019 cited in UNEP (2020)). The recommended global LCIA methodology covers four main Areas of Protection (AoPs) to assess the life cycle impacts of products and services on human health, ecosystem quality, natural resources and ecosystem services, including subsequent steps of normalisation and weighting.

Due to the absence of a comprehensive review and assessment of potentially applicable weighting methods in LCA, this paper introduces and applies a set of consensus-based criteria to systematically assess a large set of weighting methods that can be used for different LCA studies. It specifically focuses on discussing how the parameters in each method influence its applicability to a given LCA study. This work is of general interest to the LCA community, but will also help identify weighting methods that could be suitable for the GLAM project.

In the early days of LCA, weighting was called Valuation (Lindfors et al. 1995; Klöpffer and Grahl 2014). Valuation was proposed in 1991 as a component of LCA of its own, but became part of Impact Assessment in the SETAC Code of Practice (SETAC (1993a) in Klöpffer and Grahl 2014), where it has remained since. Lindfors et al. (1995) give examples of three types of methods: "case specific expert-based qualitative", "case specific expert-based quantitative", and "formalised, quantitative". They recommend that users of valuation methods should use several methods for their study; their comments about valuation indicate that this was due to data gaps, political values that may be controversial, and different values in different regions. Baumann and Tillman (2004) describe weighting factors as predominantly based on social sciences and principles that they group as Monetary valuation (costs of environmental damage or goods), Authorised targets (distance-to-target), Authoritative panels, Proxies (a few specific parameters stated as indicative for the whole impact, e.g., energy consumption) and Technology abatement (linked to the possibility of reducing impacts by abatement technology). Soares et al. (2006) describe best available practices in weighting and the principles that specific methods were based on at the time. These are described as "state of the receiving environment" (distance-to-target), "monetary evaluation" (costs of avoidance/prevention/damage related to environmental consequences), and "public opinion" (survey results, panel approach based on MCDA theory). Soares et al. (2006) propose a hybrid approach, which they describe as combining "different weighting parameters (panel approach, criteria judgements, distance-to-target and MCDA)". Another example of a hybrid method is Finnveden et al. (2006). They reviewed existing methods and showed how the methods could be classified in different ways described as i) panel methods, monetization methods, distance-to-target, ii) stated and revealed preferences, and iii) mid-point methods and end-point (or damage) methods. The hybrid method developed by Finnveden et al. (2006) is based on ecotaxes and fees applied to midpoint impact categories. Finkbeiner et al. (2014) describe the three most commonly used weighting methods as the panel method, the distance-to-target method and the monetary method. They recommend applying several methods to case studies as well as supplying the unweighted results.

According to Sala and Cerutti (2018), weighting methods can be classified into five main groups: 1) single item (based on e.g., physical properties), 2) distance-to-target (based on e.g., policy targets or planetary boundaries), 3) panel-based (e.g., based on surveys of experts, citizens, or government panels), 4) monetary valuation (based on monetary estimation from e.g., observed preferences, revealed preferences, stated preferences, budget constraints, abatement cost, damage cost) and 5) meta-models (based on multiple weighting factors from the combination of other weighting sets). The distance-to-target weighting approach was used by Castellani et al. (2016) for Europe, and has been related to the planetary boundaries (e.g., Bjorn et al. 2020) and Sala et al. (2020)). Panel-based methods at midpoint level were used by Lippiat (2007) and Huppes et al. (2006). ReCiPe (Huijbregts et al. 2017), LIME3 (Itsubo et al. 2018) and Ecoindicator99 (EI99, Goedkoop and Spriensma, 2001) used monetary valuation of damage cost to weight impacts at endpoint level. Weights for endpoint-based LCA have also been obtained by Bayazıt Subaşı et al. (2024), who used a discrete choice experiment and a disaggregation method from the Multi-Criteria Decision Analysis (MCDA) family.

Huppes and van Oers (2011) reviewed weighting approaches in LCIA in general, as did Powell et al. (1997). Reviews by Pizzol et al. (2015), Amadei et al. (2021) and Arendt et al. (2020) focused on monetary weighting. Pizzol et al. (2017) is the most recent review that includes several types of weighting methods used in LCA. The review included both normalisation and weighting. A limited number of weighting methods were included in the review (nine in total). The framework for their user survey included questions about robustness, transparency, uncertainty, relevance, validity, calculation, communication, selection, choice (which factors to use) and coverage. It did not include some key features of weighting methods that were deemed important for this current review, such as the meaning of the weights, temporal discounting, absolute or relative assessment, and communicability. Pizzol et al. (2017) found that normalised results and weighting scores are perceived as relevant for decision-making, but further development is needed to improve uncertainty and robustness. They also present a classification of methods that, in addition to the assessment (user survey), they state, allows for the identification of specific advantages and limitations. They recommend that interpretation of results should include referring to the purposes and limitations of the chosen weighting approach(es) and that users should make sure that decision-makers are aware of uncertainties and potential biases introduced by weighting. They recommend weighting of damage (in line with weighting of areas of protection in focus in GLAM) rather than the distance-to-target approach. They suggest that practitioners should prefer panel methods using panels of affected stakeholders, rather than expert panels. If monetary valuation is used, they recommend observed preferences in the form of market prices whenever possible.

While existing literature shows growing interests and efforts to understand the strengths and weaknesses of different weighting methods in LCA, the work presented in this review was developed by a group of LCA experts working specifically on weighting suitable for the GLAM project.

This paper describes the identification of the methods reviewed, and how the review was conducted, including review criteria and classifiers. It provides the results of the review, describing strengths and weaknesses, domains of applicability and implementation requirements. The review also provides links to a method selection tool (The Weighting Methods Selection Software, WEMSS, Cinelli et al. 2023) developed during the GLAM weighting subtask work. This tool uses the developed classifiers, criteria and reviews as a basis for identifying methods suitable for a given study, including the selection of relevant methods that could be applied to calculate weights at the global level suitable for GLAM.

2 Approach

The methodology developed for the review of the weighting methods is presented in Fig. 1. It consists of seven stages. After the formation of the weighting subtask, the weighting methods were identified and grouped into four categories (Stage 1, see Sect. 2.1). In Stage 2, the criteria used to assess the methods were selected, and then they were used to

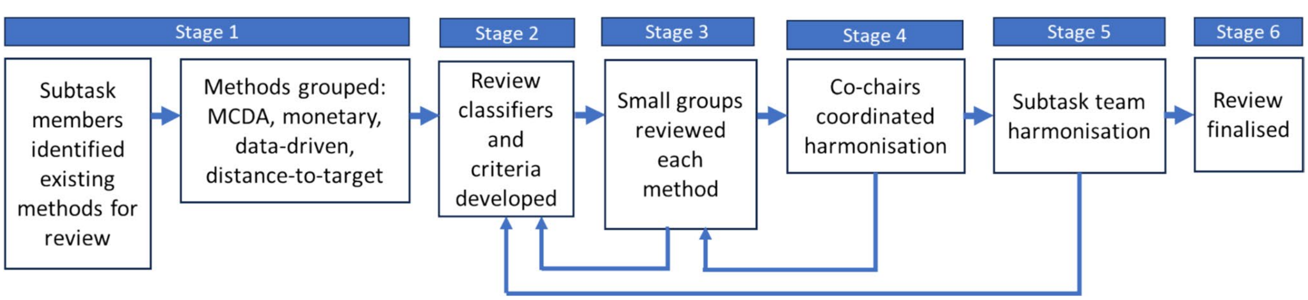

Fig. 1 Weighting subtask review methodology

review the methods by groups of subtask members in Stage 3. This was followed by a harmonisation of the reviews by the co-chairs of the weighting subtask of the GLAM project (Stage 4) and by the whole subtask (Stage 5). After this, the reviews have been finalised in Stage 6.

2.1 Identification of existing methods

The subtask members identified and then reviewed twenty-seven weighting methods that could be suitable for LCA studies, including the GLAM project (Stage 1, Fig. 1). They were selected from existing repositories of weighting methods used for LCA studies (Huppes and van Oers 2011; Powell et al. 1997; Itsubo 2015; Murakami et al. 2018; Pizzol et al. 2015, 2017; Amadei et al. 2021; Arendt et al. 2020; Finnveden et al. 2009; Bjørn et al. 2020; Dias et al. 2019; Prado et al. 2020), as well as from research supporting complex decision-making processes based on multiple criteria and suitable for use in LCA also (Roy and Mousseau 1996, Morton and Fasolo 2009, Choo et al. 1999, Greco et al. 2019, Oliveira et al. 2020).

For this review, four types of weighting methods are distinguished: Multiple Criteria Decision Analysis (MCDA), monetary, data-driven and distance-to-target. MCDA weighting methods are used to define the relative importance of criteria that will then be used to shape a decision recommendation (e.g., ranking via a single score, sorting in preference-ordered categories) for the decision-maker (Seppälä et al. 2001, EPA 2006, Cinelli et al. 2014, see 3.1.1). Monetary valuation is the practice of converting measures of social and biophysical impacts into monetary units (Pizzol et al. 2015, see 3.1.2). Data-driven methods derive the weights from the data that describes the alternatives under assessment, namely its descriptive statistics (e.g., correlation analysis), using no elicited values or any other external information (Greco et al. 2019, see 3.1.3). Distance-to-target methods aim at assessing the distance of an existing system from a desired state (the target, Castellani et al. 2016, see 3.1.4). The authors selected four groups, instead of five like Sala and Cerutti (2018), as they best represented the diversity of typology of approaches used:

Table 1 Method classifiers

Method classifier		Definition
1	Meaning of weights	Distinguishes the meaning of the weights as trade-off rates or importance coefficients
2	Temporal discounting	Ability of the method to weight impacts differently over time
3	Cultural differentiations	Ability of the method to include/account for different cultural backgrounds

– Monetary methods can involve stakeholders and lead to a single measure (in monetary terms)
– MCDA involves stakeholders and keeps the units in their original scale
– Data-driven methods need no stakeholder involvement and are based on the statistical properties of the dataset
– Distance-to-target methods need no stakeholder involvement, and weights are defined according to the distance from a political target

When grouping the methods according to these typologies, this avoids potential overlaps between categories found when more groups are used (e.g. meta models and monetary models can also include panels, as shown in Sala and Cerutti 2018). The authors believed that four groups allowed for a more distinct grouping.

For each of the groups of methods, based on the existing literature, the subtask members reported on their strengths (i.e., common points of popular and scientific advantage), weaknesses (i.e., common points of popular and scientific critique), application (i.e., examples of applications, preferably in relation to LCA), and implementation requirements (i.e., key working axioms and operational conditions that need to be met to apply the method). After this, a set of classifiers (Table 1) and criteria (Table 2) were defined by the subtask group to review each of the identified methods; these are presented in more detail in Sect. 2.2. The classifiers (Table 1) were used to define inherent features of the weighting methods that could help to include or exclude methods from a given application. Each criterion has been used to assess the different individual weighting methods in terms of their capabilities in principle. A qualitative scale for each criterion was developed to aid in distinguishing between the different methods' characteristics (Stage 2, Fig. 1). An iterative process has been developed in which the classifiers and then the criteria were applied. The criteria were then consolidated alongside the method reviews themselves (see the links between stages 2–5 in Fig. 1). The reviews were initially carried out in small groups; each one reviewing a different type of method (Stage 3, Fig. 1). The co-chairs of the working group then assessed the need for harmonisation of reviews between the small groups (Stage 4, Fig. 1). This led to further text adjustments for method reviews to achieve the consolidation and harmonisation required between the small groups. All of the reviews were then presented to the whole task force (approximately 35 members), thus initiating further harmonisation work and revision of the criteria (Stage 5). When the criteria and scale definitions (Table 2) were finalised, these were then applied to complete the reviews.

Table 2 Criteria scale and colour coding* used for reviews

Criteria		Definition			
1	Independence of the set of systems being evaluated	Distinguishes whether the weights are independent or not of the set of systems being evaluated	Weights are independent of the set of alternatives.		The weight values are dependent on the set of alternatives being evaluated.
2	Reproducibility of the weights	Capacity of the method to generate the same weight values regardless of the number of analyses performed	Replicates provide same/similar results when the dataset is the same.	Replicates provide quite similar results	Reproducibility is difficult to achieve.
3	Scientific validity	Assessment of the scientific validity of the published method	Published in peer-reviewed journal or book	Published in peer-reviewed conference proceedings	Not peer-reviewed
4	Method transparency	Level of transparency of method algorithms and value choices	All method algorithms and value choices are explained	Method algorithms and value choices are partly explained	Method algorithms and value choices are not explained

Table 2 (continued)

5	Coverage of GLAM areas of protection (AoP)	Capacity to provide weights for GLAM areas of protection (AoPs)	All GLAM AoPs are covered		Not all GLAM AoPs are covered
6	Uncertainty characterisation	Capacity of the method to address the characterization of uncertainty for the weights	Uncertainties are characterised stochastically	Uncertainties are characterised, but not stochastically	Uncertainties are not characterised
7	Communicability	Easiness of communication of the meaning of the weights to a wide group of stakeholders	The meaning and calculation of the weights are easy to communicate	The meaning or the calculation of the weights is not so easy to communicate	Communication of the meaning and calculation of the weights is difficult.
8	Accounting for differences in utility for the same impact	Capacity of the method to assign different weights to the same impact experienced by individuals living in different social and economic contexts to reflect their loss of utility	The method can assign different weights to the same impact experienced by individuals living in different socio-economic contexts to reflect their loss of utility		The method cannot assign different weights to the same impact experienced by individuals living in different socio-economic contexts to reflect their loss of utility
9	Association with AoP units	Capacity of the method to provide weights that are directly related or relatable to the AoP metrics	Weights are directly relatable to the AoP metrics	Weights are not directly related but can be adapted to the AoP metrics	Weights are not directly related or relatable to the AoP metrics
Criteria 10-16 are related to the implementability of the method					

Table 2 (continued)

10	Geographical resolution	Capacity of the method to differentiate between geographical areas	National differentiation	Continental differentiation	No geographical differentiation
11	Global coverage	Capability of the method to provide global average weights	Global weights can be obtained	Global weights can be calculated from non-global weights	No global weights can be obtained
12	Application demonstrated in case studies	Extent to which the method has already been applied in case studies	Widely used in case studies	Used in just a few case studies	Not used in any case studies
13	Required resources to apply the method	Time, cost and human resources required to apply the method	Little time, cost, and human resources needed	notable time and/ or cost and / or human resources needed	extensive time, cost and human resources needed
14	Required technical and calculation infrastructure	Technical and calculation infrastructure required for the use of the method, such as dedicated software, mathematical models, databases and IT platform	Simple infrastructure	Some simple and some complex infrastructure	Complex infrastructure
15	Representative-ness	Capacity of the method to work with a representative sampling of the affected population	The method can work with a representative sample of the affected population	Indirect sampling of the affected population	No representative sampling of the affected population
16	Bias	Presence (and management) of biases introduced by the method	No known biases	Known biases that can be corrected or accepted	Biases present cannot be corrected or accepted

*colour coding: green stripes, yellow, and red dots indicate full sufficiency, partial sufficiency, no sufficiency for the scope of the GLAM project respectively.

2.2 Review classifiers and criteria

Weighting methods have several attributes (features) that can be used to distinguish among them and to identify those most suitable for their users' needs. These features were selected starting from comparable approaches used for reviews in LCA literature (Pizzol et al. 2015, 2017). They were then extended based on the input received by the weighting subtask members, accounting for the latest development in the area by 2021. This effort led to an overall set of 19 features, divided into three classifiers and 16 criteria. The classifiers (Table 1) were used first, to define the meaning of the weights (whether trade-off rates or importance coefficients), whether they include temporal discounting, and the methods' abilities to include or account for different cultural backgrounds. The criteria were used for the features where preference-ordered levels of performance could be defined, resulting in a qualitative scale for each of them (Table 2).

The method classifier "meaning of the weights" is obtained by asking the question "Are the weights trade-off rates (sometimes called compensation rates, e.g., x units of impact category A are equivalent to y units of impact category B) or importance coefficients (e.g., impact category A weights 80 points and impact category B weights 20 points out of 100 in total)?" (Cinelli et al. 2020; Dias et al. 2015 and Munda and Nardo 2005).

The "Temporal discounting" classification is performed by asking the question "Does the method allow to discount impacts according to the time horizon?" (Yuan et al. 2015).

The question to determine cultural differentiations is "Does the method allow to account for different cultural backgrounds of the affected population?" (Thompson 2002). An example of this could be whether the method allows for the difference in the cultural background of an indigenous population within a country, being different to the cultural background of the rest of the population.

Further to the classifiers above, the set of criteria shown in Table 2 was developed within the weighting subtask, with reference also to further publications (i.e. Cinelli et al. (2020), Dias et al. (2015), Munda (2005), Pizzol et al. (2017)). The criteria relate to the intrinsic and operational characteristics of the methods. The intrinsic ones include, for example, the type of weights that the methods provide (e.g., trade-offs or importance coefficients), as well as the reproducibility of the weights and their uncertainty characterization (e.g., stochastic values). The operational characteristics consider the implementation requirements for the user. Examples of these characteristics are the geographical resolution of the method (e.g., national, continental), the demonstrated use in case studies, and the potential introduction of biases during the application of the method. The colour codes shown in Table 2 were used to grade the methods that were evaluated. A brief description of the criteria shown in Table 2 follows.

"Independence of the set of systems being evaluated" distinguishes whether the weights are independent or not of the set of systems being evaluated, looking at whether there is a dependecy between weights and alternatives under assessment. "Reproducibility of the weights" is used to describe the capacity of the method to generate the same weight values independently from the number of applications of such method. "Scientific validity" grades whether the method has been published in a peer-reviewed journal, conference proceedings or not. "Method transparency" is used to grade whether the underlying algorithms, assumptions and value choices of the method are explained in the reference publications. The next criterion for this review is specific to the GLAM project, and it assesses whether all the GLAM AoPs can be included by the weighting method. "Uncertainty characterisation" addresses the capacity of the method to characterise uncertainties associated with the weights, distinguishing between a stochastic, non-stochastic and no characterisation at all. "Communicability" grades the ease of communication of the meaning of the weights to a wide group of stakeholders. "Accounting for differences in utility for the same impact" focuses on considering whether the method can account for the loss of utility that individuals living in different social and economic contexts experience. "Association with AoP units" is used to grade the capacity of the method to provide weights that are directly related or relatable to the AoP metrics. It distinguishes methods according to their intrinsic link to the measurement units of the AoPs. The rest of the criteria relate to the implementability of the methods reviewed. "Geographical resolution" grades the capacity of the method to differentiate between geographical areas, ranging from national differentiation to no geographical differentiation. "Global coverage" describes whether the method can provide directly global average weights, whether they can be obtained from non-global weights, or whether such weights cannot be obtained with the method. "Application demonstrated in case studies" is considered in order to evaluate the extent to which the method has already been applied in case studies. The criterion "Required resources to apply the method" grades the time, cost and human resources required to apply the method (from limited to extensive). "Required technical and calculation infrastructure" grades whether simple or complex technical and calculation infrastructure is required to use the method. "Representativeness" describes the capacity of the method to work with representative sampling of the affected population. The criterion "Bias" is used to grade the presence (and management) of biases introduced by the method, using the scale of no known bias, known biases that can be corrected or accepted, or whether biases present cannot be corrected or accepted.

3 Results and discussion

Nine MCDA methods, eight monetary methods, six data-driven methods, and four distance-to-target methods were reviewed; see Table 3 for a description of each method, including key references. A summary of the method classifier information from the reviews of the methods is shown in Table 4. A brief overview of each of these types of methods, together with their strengths, weaknesses and implementation requirements, is provided in the next section.

3.1 Strengths, weaknesses, domains of applicability and implementation requirements

3.1.1 MCDA methods

Nine types of MCDA methods were included in the review: precise and imprecise trade-offs, precise and imprecise SWING, precise and imprecise points allocation, precise and imprecise direct rating, ranking, Analytical Hierarchy Process (AHP), Simos and its revisions, disaggregation methods, and Stochastic Multicriteria Acceptability Analysis (SMAA). Except for the last MCDA method presented (SMAA), all methods require a preference elicitation process, e.g., asking questions to decision-makers, stakeholders or experts by means of surveys, focus groups or interviews. These preference elicitation processes may lead to inconsistencies when numerous criteria are involved (e.g., AHP).

Precise and imprecise trade-offs were introduced in the 1970s' in the operational research literature, with key references being Keeney and Wood (1977), Merkhofer and Keeney (1987), Keeney and McDaniels (1999). They provide the relevant representation of trade-off rates accepted by the respondents. They study how much of each criterion is needed to make meaningful trade-offs between criteria. A common point of critique (Roy and Słowiński 2013) is that these methods are cognitively demanding.

Precise and imprecise SWING application examples can be found in Berta et al. (2016) and Vogt Gwerder et al. (2019). The method is easy to apply for up to seven criteria and requires simple calculations to derive the weights. However, it becomes difficult to apply when the number of criteria increases over seven (Miller 1956). This is due to the increasing cognitive load that is placed on the respondent, who must account for more and more information (i.e., criteria) at a time when making their choices (Paas et al. 2003). However, this threshold (i.e., seven) should not be considered a fixed one, as the upper limit of criteria that can be considered depends also on the respondents themselves and the task at hand (e.g., the way the information is provided, the time constraints, Cowan 2015 and Ma et al. 2014).

Precise and imprecise points allocation have been applied, for example, by Ligus (2017). Similarly to the SWING methods, it is easy to apply for up to seven criteria and requires only simple calculations to derive the weights. Compared to direct rating (see below), it is less reliable when testing and re-testing (Bottomley and Doyle 2001).

Precise and imprecise direct rating examples are the OECD's better life index (OECD 2023) and the work of Ruangpan et al. (2021). Their key strengths are that they are easy to apply and require a low cognitive load for respondents. Compared to point allocation, these precise and imprecise direct rating methods are more test–retest reliable, more inter-rater reliable (greater consensus) and more accurate at the individual level (Bottomley and Doyle 2013). Common points of popular and scientific critique are that there is no consideration of the spread of an attribute/criterion (Riabacke et al. 2012) and the restriction to a small set of criteria to avoid respondents' overload.

An example of the application of ranking is Manik et al. (2013). Ranking is easy to apply and requires little cognitive load for respondents. Some points of critique are that decision data is seldom purely ordinal and conversion to cardinal weights is needed for which several approaches exist, leading to different weights for the same ranking (see e.g., Riabacke et al. 2012).

The AHP is a very common method that has been used in many application areas since the 1980s', with examples in Hermann et al. (2007), Bao et al. (2013), and Petrillo et al. (2016). AHP is easy to apply conceptually thanks to its comparative semantic scale (e.g., "X is much more important than Y", Saaty 2016, 2008). However, it becomes demanding to apply when the number of criteria increases over seven, due to the large number of required pairwise comparisons (though some solutions have been proposed to reduce this number, e.g., Abastante et al. 2019). It should also be noted that there is theoretical debate about the methodological soundness of the method (Ishizaka and Labib 2011); it can result in a lot of inconsistencies, possibly leading to the exclusion of those responses with too much inconsistency.

Mutikanga et al. (2011), Govindan et al. (2017) and Kadziński et al. (2018) provide examples of applications of Simos, Revised Simos and SRF (Simos Roy-Figueira). This method is simple to understand. It is well suited to match intuitive notions of criteria importance and, therefore, well-suited to outranking MCDA methods. Some criticism of this method has been that the question of how many times the first level of the ranking is more important than the last level is hard to answer. For this reason, some users prefer

Table 3 Identified weighting methods

Method	Description
MCDA methods	
Precise trade-offs (Keeney and Raiffa 1993)	Based on the comparison of alternatives which perform differently on two criteria (assuming performance for other criteria is fixed). Respondents are asked to indicate if two alternatives are indifferent. If they are not, the respondent indicates the alternative they prefer and then changes one of the values in such a way that would make alternative A as good (or as bad) as alternative B. *Imprecise trade-offs* is an adaptation of precise trade-offs, which allows respondents to assign an interval to the values that would make two alternatives indifferent
Precise and imprecise SWING (Edwards and Barron 1994)	Precise SWING: the change of evaluation of performance on each criterion from one value to a different one (typically from the worst to the best value). A fictitious alternative that performs the worst on all the criteria is considered, the respondent is asked to indicate which criterion they would prefer to improve from its worst value to its best. This swing is assigned 100 points. The respondent is then asked to indicate which criterion of the fictitious alternative would be the second most important one they would like to improve from its worst to its best value. They assign a swing from 0 to 100 to indicate how important that change would be. This continues until all the criteria are ranked in terms of their attractiveness on the 0–100 swing. The points assigned to each criterion are summed and used to normalize each criterion on a 0–100 scale. Imprecise SWING is an adaptation of the SWING method allowing respondents to assign a points interval for the swing for each criterion
Precise and imprecise points allocation (Doyle et al. 1997)	Respondents are asked to distribute a pre-allocated set of points (e.g., 100) to define the importance of each criterion. Imprecise points allocation is an adaptation of the precise points allocation method, allowing respondents to assign a points interval to define the importance of each criterion
Precise and imprecise direct rating (Bottomley and Doyle 2001, Bottomley and Doyle 2013, Zardari, Ahmed et al. 2015, Ruangpan et al. 2021)	Respondents rate each criterion on a fixed scale (e.g. 0–100 or 0–10). Minor variants include first giving the most important criterion a value of 100 or first giving the least important criterion a value of 10, the latter without having an upper bound. The assignment of the points can be either precise (e.g., 10 points for criterion 1) or imprecise (a range of points for the criterion)
Ranking (Riabacke et al. 2012 and Manik et al. 2013)	Criteria are ranked from most to least important, implying imprecise weighting, and the weights are usually derived by applying a mathematical formula, e.g.: rank sum, rank reciprocal, or rank exponent
The Analytical Hierarchy Process (AHP) (Saaty 2008, Saaty 1990, Donegan et al. 1992, Hermann et al. 2007, Bana e Costa and Vansnick 2008, Munda 2005, Ishizaka and Labib 2011, Bao et al. 2013, Petrillo et al. 2016	Criteria are compared on a pairwise comparison basis with a predefined semantic scale (e.g., 1–9). The higher the importance of a criterion with respect to the other, the higher the score. After these comparisons are completed, a matrix is derived based on this set of comparisons (K x K, where K is defined as the set of criteria). The value of the weights is then derived based on the eigenvector of the matrix. The respondent is also provided with a measure of the inconsistency in the given pairwise comparisons
SIMOS/Revised SIMOS/SRF (Simos 1990a, 1990b; Figueira and Roy 2002; Mutikanga et al. 2011; Siskos and Tsotsolas 2015; Danielson and Ekenberg 2017; Govindan et al. 2017; Kadziński et al. 2018)	The respondent is asked to place cards (each representing one criterion) in decreasing order of importance. Ties are allowed for criteria judged to be equally important. The respondent can also place blank cards between other cards in the ranking to indicate a greater difference in importance. Finally, the respondent should indicate how many times the most important (first) criterion (or group of criteria) is relative to the least important (last) ranked criterion (or group of criteria)
Disaggregation methods (Diakoulaki et al. 1999, Dias et al. 2002, Sánchez-Lozano et al. 2014, Chhipi-Shrestha et al. 2018, Matsatsinis et al. 2018	The respondent is asked to provide their judgment about a relatively small number of examples, each one represented by a vector of impact indicator values. The judgment can consist of choice (which vector is preferred), ranking, or classification in predefined categories. Using mathematical programming, the disaggregation approach infers a weighting vector that respects the judgment provided as closely as possible
SMAA (Lahdelma and Salminen 2001; Prado-Lopez et al. 2014; Tervonen 2014; Prado and Heijungs 2018)	Impacts are weighted based on random sampling from a space of weight vectors, usually assuming a uniform distribution (other distributions can be used). The space of weight vectors is typically the unit simplex (vectors of positive weights that add up to 100%), but preferences of decision-makers, experts or other stakeholders can be used to constrain the sampled space
Monetary methods	
Budget constraint (Weidema 2009; Pizzol et al. 2015)	The marginal value of a quality-adjusted life year (QALY) is based on the potential economic production per capita per year. The monetary value for ecosystem damage is derived from the monetary value for a QALY, while the monetary value for resource productivity is measured in terms of the future economic output
Abatement cost (Davidson et al. 2005; Oka 2005; Hendriks et al. 2006; Pizzol et al. 2015)	The cost to reach certain (for example, political) targets; costs can accrue due to emission controls or changing (or replacing) processes (including the machinery). In general, only marginal abatement costs (MACs) are used
Market price (Finnveden 1999; Pizzol et al. 2015; ISO 2019; OECD 2020)	The marginal value of a good is identified on the basis of its market price

Table 3 (continued)

Method	Description
Contingent valuation, CVM (Hanley and Spash 1993, Whitehead and Haab 2013, Freeman III et al. 2014, Johnston et al. 2017, ISO 2019)	Goods (marketed or not) are valued by surveys. Hypothetical markets are created for the respective environmental good; participants are asked how much they would be willing to pay for an increase in the availability of an environmental quality, or how much they would have to be compensated for in order to accept a certain decline in an environmental quality
Conjoint analysis (Itsubo et al. 2004; Itsubo et al. 2012; Murakami et al. 2018)	The utility of individual attributes of marketed and non-marketed goods are valued by surveys. Hypothetical markets for the respective attributes of a good are created; respondents are asked hypothetical questions providing several options with a combination of different conditions of the attributes of the environment (i.e., the AoPs). The respondents are asked which option with a set of attributes is the most preferable, and their utility of each attribute is implicitly quantified through the iterative questions with different options by statistical analysis
Averting behaviour (Dickie 2017; OECD 2018; ISO 2019)	The main premise is the notion that individuals and households can insulate themselves from a non-market bad (as opposed to (non-)market good) by selecting more costly types of behaviour as described in the literature. These behaviours might be more costly in terms of the time requirements they imply, or of the restrictions they impose on what the individual would otherwise wish to do. Alternatively, individuals might be able to avoid exposure to non-market bads via the purchase of a market good. These financial outlays are known as defensive expenditures. The value of each of these purchases represents an implicit price for the non-market good or bad in question
Travel cost (Parsons 2017; OECD 2018; ISO 2019)	Estimation of recreation demand and value recreational uses of the environment, such as fishing, rock climbing, hiking, hunting, boating, etc. Different cost components exist: cost of the journey to the destination in question, including costs related to transport, lodging, food, entertainment, time spent and entrance fees
Hedonic Pricing (Taylor 2017; OECD 2018; ISO 2019)	Variation in product variety gives rise to variations in product prices within each market. The hedonic method relies on market transactions for differentiated goods within the same market (e.g., cars, computers, houses) to determine the implied value or implicit price of characteristics. The hedonic pricing method uses statistical methods to isolate the implicit "price" of each of these characteristics
Data-driven methods	
Criteria Importance Through Intercriteria Correlation, CRITIC (Diakoulaki et al. 1995)	This method considers the standard deviation of each normalized criterion (contrast intensity) and the linear correlation between them (conflict)
Data Envelopment Analysis (DEA) (Charnes et al. 1997; Cherchye et al. 2007; Cooper et al. 2011; Greco et al. 2019)	A mathematical programming approach to assess the relative efficiency of a number of systems. The efficiency score (eco-efficiency or other) involves weighting multiple indicators. The weighting vector for each system under evaluation is chosen to make it compare in the best possible way against its peers. The efficiency score for each system is optimised using the weights as variables to be set. The system is deemed to be efficient if no other systems perform better given the chosen weights vector
Entropy (Hwang and Yoon 1981; Zeleny 1982)	Relies on information theory to measure the amount of useful information that can be obtained. When the evaluated alternatives have a great difference between each other on a particular impact category indicator, the entropy is smaller, meaning that the impact category indicator provides more effective information, and therefore, the weight value corresponding to that indicator should be larger. When the differences are smaller, the entropy is larger, thus the amount of information provided by the indicator is smaller, and its weight value should be correspondingly smaller
Principal Component Analysis (PCA) (European Commission 2008, Gan et al. 2017; Greco et al. 2019)	The decision matrix is transformed into a series of equations (as many as the number of indicators), representing a linear transformation of the original data in such a way that the maximum variance of the original impact category indicators is explained with the first equation, the second-highest variance (which is not explained by the first equation) is explained by the second equation, and so on. The linear combinations of the original indicators are called principal components. The factor loading of the first principal components are rotated to minimize the number of individual variables that have a high loading on the same component. These factors are generally considered the indicators' weights. The largest factor loadings are assigned to the indicators with the largest variation across the dataset, whereas smaller factor loadings are assigned to the indicators with less variation across the dataset
Factor Analysis (FA) (European Commission 2008, Nardo et al. 2008; Gan et al. 2017; Greco et al. 2019)	Contrary to PCA, which is based simply on the linear combination of the data, FA assumes that the data is based on the underlying factors of the model and that the data variance can be decomposed into the variance accounted for by common and unique factors. Each factor is defined as a set of coefficients (so-called loadings), each measuring the correlation between the individual impact category indicators and the latent factor
Regression Analysis (Nardo et al. 2005; Paruolo et al. 2013; Gan et al. 2017)	A statistical method to assess the relationship between a set of independent variables (indicators) and a dependent variable (an outcome measure) based on observation data. E.g., Pearson's correlation ratio (also known as the first-order sensitivity index) is calculated with respect to the composite indicator (the index obtained from the aggregation of the individual indicators). This correlation ratio is a coefficient of nonlinear association and can be considered as an ex-post measure of importance

Table 3 (continued)

Method	Description
Distance-to-target methods	
Carrying capacity (Bjørn and Hauschild 2015; Vargas-Gonzalez et al. 2019)	Carrying capacity estimates from the literature matching existing LCIA midpoint impact indicators are used to develop weighting factors
Planetary boundaries (PB) (Tuomisto et al. 2012; Steffen et al. 2015)	PB estimates from the literature (mainly Rockström et al. 2009 and Steffen et al. 2015) are used to develop weighting factors to applicable impact categories at the midpoint or, potentially, endpoint
EDIP97 (Wenzel et al. 1997; Hauschild and Wenzel 1998; Huppes and van Oers 2011)	The basis for weighting is political environmental targets within each impact category (set as a reduction in society's impact on the environment) and considers only binding targets. The original set of weighting factors was defined for Denmark
Swiss Eco-Scarcity (Frischknecht and Büsser Knöpfel 2013; Ahbe et al. 2017)	Environmental exchanges are evaluated in relation to political targets for Switzerland, and lately extended to other geography, e.g. the EU

to work with a set of multiple compatible weight vectors rather than a single vector that would result from a precise answer to that question. The number of blank cards is usually small in practice, which limits the variety of weight vectors (although, in theory, the limitation does not exist as no limit is placed on the number of blank cards). The differences between the weights can change in an uncontrolled way when the cards are reordered. This can happen because the weights determined differently depend on the number of cards in the subsets of equally ranked cards (Danielson and Ekenberg 2017).

Examples of the use of disaggregation methods can be found in Diakoulaki et al. (1999), Sánchez-Lozano et al. (2014) and Chhipi-Shrestha et al. (2018). The respondents' preferences can be elicited without requiring that they know the aggregation model's details. Its key strength is that the disaggregation strategy can be adapted to any type of multi-criteria aggregation model (value, outranking, rules, Doumpos and Zopounidis 2011). This means that the disaggregation strategy leads to weights whose meaning can be one of trade-off rates or importance coefficients, according to the assumed type of multi-criteria aggregation model. However, the results might depend on the examples assessed, meaning that according to the types of examples used to obtain the judgments, different values of the weights can be obtained for the same type of aggregation model.

SMAA has been used in several application areas, as reported by Tervonen et al. (2009), Prado-Lopez et al. (2014), Vogt Gwerder et al. (2019), and Dias et al. (2022). Its key strength is that there is no need to elicit weights, and the method is able to identify conclusions that hold always, or almost always, considering randomly generated weights. Uncertainty can be characterised stochastically "per response". Furthermore, similarly to disaggregation methods, SMAA also leads to weights that can be trade-off rates or importance coefficients, according to the assumed type of multi-criteria aggregation model (Pelissari et al. 2020). The results depend on the underlying aggregation model and, in the additive model, on the normalisation used. There are no specific key working axioms or operational conditions that need to be met to apply the method if no preferences are provided to be accounted for. In these cases, the sampled weights space is a uniform distribution of all possible weighing vectors. When preferences of decision-makers, experts or other stakeholders are provided (e.g. ranking of the criteria, weight thresholds that cannot be exceeded), they can be used to constrain the sampled space (Dias et al. 2024).

3.1.2 Monetary methods

Eight monetary methods have been evaluated. The budget constraint method (Weidema 2009) builds on Ecoindicator 99 (Goedkoop and Spriensma 2000) values and its AoP indicators (disability-adjusted life years, potentially disappeared fraction of species, and megajoule resource depletion). Budget constraint has been used in Stepwise 2006 (Pizzol et al. 2015). It can be used to assess damage and may also be used at midpoint indicator level. Criticism of the method includes that "budget constraints" implies that environmental impacts are affordable (i.e., having a cost that is not too high). The magnitude of the values linked to biodiversity[1] and resources are contested. There is a need for clarification on whether the method actually does measure willingness to pay (WTP), or whether it is rather an assessment of the "ability to pay". The weights used only work with Quality-Adjusted Life Years (QALYs) for human health, biodiversity-adjusted hectare year[2] for ecosystem quality and "resource productivity" measured as the future economic output in monetary units.

Abatement costs are used in LCA methods, such as MAC (marginal abatement costs), EVR (environmental cost/value ratio) and RVA (resource vulnerability assessment).

[1] Noting that biodiversity assessment and valuation is difficult and comes with a certain degree of uncertainty in general (OECD 2018, Pascual et al. 2023, UNEP-WCMC et al. 2022).

[2] corresponds to 10.000 PDF m^2 year (European Commission 2023).

Table 4 Method classifiers for the methods reviewed

	Method classifier		
	1	2	3
	Meaning of weights	*Temporal discounting*	*Cultural differentiations*
Definition	Distinguishes the meaning of the weights as trade-off rates or importance coefficients	Ability of the method to weight impacts differently over time	Ability of the method to include/account for different cultural backgrounds
MCDA methods			
Method			
Precise and imprecise trade-offs	Trade-offs	It is possible to include temporal discounting in the assessment of the impacts if the respondents are asked to provide their input with respect to their current as well as future preferences (e.g., if participants are asked how they value something now and which value they expect to attach to it in the future). However, it requires a larger effort from the participants, and feasibility depends on the case, e.g. the number of attributes for which they have to assess the importance	The method can account for different cultural backgrounds if people from such backgrounds are part of the pool of respondents. Feasibility depends on the case, e.g. the number of attributes for which they have to assess the importance, as a lower workload for participants makes it more likely that invitees will respond
Precise and imprecise SWING			
Precise and imprecise points allocation	Importance coefficients		
Precise and imprecise direct rating			
Ranking			
AHP			
SIMOS/Revised SIMOS/SRF			
Disaggregation methods	The method works for both interpretations of the weights		
SMAA		Eliciting partial information (e.g., a ranking of the weights) is optional. In cases where preferences are elicited, it is possible to include temporal discounting in the assessment of the impacts, as described above	Eliciting partial information is optional. If preferences are elicited, it is possible to account for different cultural backgrounds if people from such backgrounds are part of the pool of respondents, as described above
Monetary methods*			
Budget constraint	Trade-off rates	Yes, discounting is possible	Good, as it is based on Ecoindicator99
Abatement cost			Low. Nevertheless, if different cultures (e.g. nations) independently set (different or the same) clean-up targets or emission ceilings, there is a possibility to distinguish between cultures
Market Price			Partially, geographically different prices are possible
Contingent valuation			Yes, if surveys are performed globally, different cultural values can be mostly reflected in the method; however, some people might not have practiced trading in these non-marketable goods or perceive that the government should pay for some things, which reduces the validity of the results
Conjoint analysis			
Averting behaviour			The method can be conducted in different cultural contexts and thus can account for different cultural backgrounds
Travel cost			
Hedonic Pricing			

*Note for Cultural Differentiations for Monetary methods: some people would argue that the cultural value of the environment cannot be accounted for, as it is not easily nor meaningfully connectable to a product of nature (Kirchhoff 2012)

Table 4 (continued)

	Method classifier		
	1	2	3
Data-driven methods			
CRITIC	Importance coefficients	The method is sufficiently general and flexible to address this if the temporal data are available	The method is sufficiently general and flexible to address this if cultural background data are available
Data Envelopment Analysis (DEA)	Trade-off rates		
Entropy	Importance coefficients		
Factor Analysis (FA)	Trade-off rates		
Principal Component Analysis (PCA)			
Regression Analysis			
Distance-to-target methods			
Carrying capacity	Importance coefficients	No	No (although the cultural background of the scientists estimating carrying capacities could play a role)
Planetary boundaries			
EDIP97			Yes/No (political target used only). Political targets that may be or not influenced by cultural differences
Swiss Eco-Scarcity			Yes, as far as the cultural background is part of the democratic institutions that determine the critical flows. Method has been applied in Belgium, Sweden, Norway, the Netherlands, Jordan, and Japan

They are mostly used for releases but also as replacement and prevention costs for resources, e.g. for biodiversity and natural resources in EPS2020 (Steen and Rydberg 2020). Abatement costs methods produce values that are easy to understand, such as $/ton reduced CO2 emission. Abatement methods can be used in evaluation of policy targets (Pizzol et al. 2015). Abatement cost is a relevant indicator for financial risks to organisations. Criticisms of the method include a weak relation to environmental impact values; what is valued are costs to avoid environmental aspects that are normally referred to in policy targets (e.g. emission ceilings). It is difficult to allocate control costs or replacement costs to single emissions (e.g. a scrubber may reduce several emissions) or impacts (e.g. NO_x leads to secondary particles, tropospheric ozone formation, acidification and eutrophication; SO_2 and NO_x lead to acidification and secondary particles). There is also a risk of circular reasoning if MACs are used for policymaking (i.e. when MACs are used for both the costs and benefits e.g. in a Cost–Benefit Analysis). If the abatement cost method is used for societal targets in the welfare economic optimum, MAC should be on the same level as the reduction of damage costs, reflecting the best available technology with respect to what is reasonable considering the damage caused (Bachmann 2019).

Market price methods determine monetary values of change in the environment and not the absolute value of the environment. Examples of the market price method in LCAs and beyond are found in European Commission (1999), European Commission (2005), Preiss and Klotz (2007), Ahlroth and Finnveden (2011), Tukker et al. (2013), Wood et al. (2014), Tomaschek (2015), Trucost (2015), Huijbregts et al. (2017), IPCC (2014), de Bruyn et al. (2018), Steen (2019) and Steen and Rydberg (2020). Most of the applications address existing markets, but future market prices may also be estimated. No surveys are needed, unlike for contingent valuation or Discrete Choice Experiments (DCE,[3] sometimes called choice-based conjoint analysis). Market prices are direct and actual expressions of preferences that avoid the uncertainty related to indirect measurements and non-market valuation (like revealed and stated preference methods), because the goods are traded on markets. The market price method is also easy to understand, and statistics are available and easy to check, because they rely on market values that are collected for all kinds of economic purposes. However, market prices do not contain all aspects of total economic value: e.g. valuing human health by forgone income only is debatable from an ethical standpoint (as humans that are unable to or simply do not work would not have any value; Markandya et al. 2019). Market prices can be used to approximate WTP, but usually they will be lower as a consumer surplus remains (Bachmann 2019). There will be uncertainties in WTP, for example, due to fluctuation in market prices (Huppes and van Oers 2011). The market price method is limited by the availability of appropriate market-price data that can be linked directly to the environmental impacts in LCA (Pizzol et al. 2015), which means that it is limited only to goods for which public markets exist, accounts only for use values of goods and

[3] In some parts of the literature, this method, among many others, is classified as conjoint analysis. This paper uses the term DCE to be precise with respect to the method used and the fact that this is firmly grounded in random utility theory (Louivere et al. 2010).

does not cover all environmental goods. The derivation of the production function and the substitutability of environmental quality with capital are challenging and need to be assumed, empirically asked for, or measured. Market prices may need to be adjusted for any market distortions (e.g. taxes, subsidies, externalities).

Both the contingent valuation method (CVM) and DCE are stated preference methods (Johnston et al. 2017). For CVM, a group of respondents are asked hypothetical questions directly about their values for the environmental good. Contingent valuation includes a description of the resource or policy context, a description of the policy or proposed change in resource allocation that will be valued, a payment vehicle, and a payment rule. The CVM has been used for major policy analyses associated with the US Clean Water Act, the US Clean Air Act, and the Natural Resource Damage Assessment associated with the Exxon Valdez oil spill (Freeman III et al. 2014, OECD 2018; Whitehead and Haab 2013; U.S. Environmental Protection Agency 2014). There has been no known use of CVM in LCA so far. Some human health valuations in monetised LCA results are based on stated preference studies in which people are asked how much they are willing to pay to prolong their life, e.g., the study used in the NEEDS project (Desaigues et al. 2006). The following methods rely on this monetisation (Trucost 2015; de Bruyn et al. 2018; De Nocker and Debacker 2018).

CVM and DCE are firmly grounded in welfare economic theory. These stated preference methods can be used for ex-ante studies of a wide range of goods, and to capture other values than use values (i.e. non-use values, which can be existence value, bequest value and altruistic value, which together with use values make the total economic value). Thus, all goods and services can be valued. Additionally, these methods (CVM and DCE) are the only methods that can estimate both use and non-use values jointly or separately (Bachmann 2019; ISO 2019).

An example of DCE application for weighting is the LIME method (Itsubo et al. 2004, 2012). In contrast to contingent valuation, DCE allows the valuation of multiple attributes of one good or service separately. This method models the decision-making process using indirect preference elicitation, e.g., people will decide which car to buy depending on a mix of attributes like price, size, design etc. Decision-making processes, in reality, require implicit weights on multiple attributes, which people usually perform either consciously or unconsciously (OECD 2018).

For both of the stated preference methods, many biases need to be considered and dealt with in the study design (Johnston et al. 2017; OECD 2018). This includes that a hypothetical, credible market has to be created in which the survey participants feel comfortable to take part. The scenario evaluated must be believable and create limited opportunities for free riding. Respondents must believe that their response will be consequential in determining the ultimate implementation of the proposed scenario (Whitehead and Haab 2013). When applied to the assessment of non-marketed goods, some preliminary information needs to be given so that respondents can properly judge the values. For DCE, the maximum number of attributes is in the range of 4–5 (Green and Srinivasan 1990). When there are more attributes to be evaluated, it is hard for the general public to make a consistent decision (Johnston et al. 2017). Respondents should be able to judge the value of each attribute that is given in the questionnaire. When applying this to the assessment of non-marketed goods, some preliminary information needs to be given so that respondents can properly judge the values. For stated preference methods, like for all the survey-based methods, sampling of respondents should be done properly to secure the representativeness of the target population.

Averting behaviour is also known as avoidance, defensive, mitigating, or protective behaviour. ISO (2019) distinguishes three kinds of averting cost methods; in this review, only one of these averting cost methods is described, where costs accrue due to individual averting behaviour. Methods relying on costs decided by public bodies are treated under "abatement costs". Further note that according to ISO (2019), all averting behaviour-related costs may be used for monetary valuation only after spending or a commitment to spending has been made.

According to Steen (2016), the following methods have used prevention methods: the Eco-cost method (Vogtländer et al. 2001) and the projects ExternE (European Commission 1999, European Commission 2005), NEEDS and CASES (Desaigues et al. 2006; Preiss and Klotz 2008; Bachmann and van der Kamp 2014). Although the ExternE/NEEDS/CASES projects have used these kinds of costs, they did not directly apply the monetary values thus derived in LCA. Given that the Eco-cost method relies on "costs [that] are related to measures which have to be taken to make (and recycle) a product", in turn, it is an example of abatement costs (not decided by individuals; see also its classification in Arendt et al. (2020)) rather than for averting costs deliberately borne by individuals. So for now, it appears that this method has not yet been applied in LCA.

A strength of the averting behaviour method is that it is based on observed behaviours of individuals. However, there is only a limited range of environmental impacts that can be valued in this way. Beyond noise annoyance (addressed through noise-reducing windows), Dickie (2017) provides examples, such as:

– human health—morbidity: avoiding water contamination by purchasing bottled water, boiling or purifying

water, reducing air pollution by use of home air cleaners, purifiers, or conditioners, reducing risks of skin cancer by using sunscreen lotion.
– human health—mortality: reduced risk of death by purchasing bicycle helmets.
– building materials: reducing soiling damage from air pollution through household cleaning.
– gardening/agriculture: reducing pest infestation.

Co-benefits need to be considered (e.g. noise-reducing windows will also help make savings in terms of heating/cooling). Further behavioural changes beyond the purchase made need to be considered (e.g., spending less time in the noisy outdoor area). Environmental impacts addressed must be clearly defined (i.e., per unit of environmental aspect). Studies made on general conditions like “air pollution” have low value for LCA use.

Travel cost methods are mostly used for cost–benefit analyses. They could be used for land use in LCA, but no such applications could be identified. The benefit of this type of method is that it is based on observed behaviours by individuals. This method is well-established and suitable for specific local conditions (e.g. a specific scenic site or natural park). However, there is a limited range of environmental impacts that can be valued in this way, i.e. for specific recreational sites. Co-benefits need to be considered (e.g. travelling to several sites or multi-purpose trips). Other limitations or criticisms of this method include how the value of time is measured, accounting for intertemporal substitution and forming a relevant choice set for estimation. Environmental quality must be described in a quantitative way, so implementation of the travel cost method requires there to be sufficient data available to do this.

The hedonic method relies on market transactions for so-called differentiated goods to determine the implied value or implicit price of characteristics. Heterogeneous or differentiated goods are products whose characteristics vary in such a way that there are distinct product varieties even though the product is sold in one market (e.g., cars, computers, houses). The variation in product variety gives rise to variations in product prices within each market. The hedonic pricing method uses statistical methods to isolate the implicit “price” of each of the good’s characteristics. The most common application of hedonic theory in environmental valuation involves housing markets. The choice of housing location and, therefore, neighbourhood amenities (such as scenic views, less air or noise pollution) is observable. The method can also be applied to labour markets, in particular with respect to risks of death.

Hedonic pricing is presently not known to be used in LCA contexts. It is based on observed behaviours of individuals, which is a strength, but there is a limited range of environmental impacts that can be valued in this way. The impacts that can be valued using hedonic pricing are mostly related to environmental amenities that come with different (localised) housing options or risk premia as part of wages. Co-benefits need to be considered (e.g., a house in one place is not only located in a less polluted area but also closer to shopping centres, recreational sites or the workplace). Characteristics vary over space even within the same city. In order to use hedonic pricing, one needs to know environmental characteristics in quantitative terms, as well as the property characteristics.

3.1.3 Data-driven methods

This review covers six data-driven methods: CRITIC, data envelopment analysis (DEA), entropy, principal component analysis (PCA), factor analysis (FA), and regression analysis. Data-driven methods do not need to elicit weights from respondents. The weights are based solely on the systems being compared. This reduces the bias, uncertainty and lack of information that might be associated with subjective judgements. However, these methods reduce the active role of the decision-makers in defining the priorities assigned to the criteria. A common limitation is that the weights depend on the set of alternatives included in the analysis (i.e., removing one of the alternatives changes the weight values). Such methods also depend on the availability and size of the underlying dataset (e.g. at least ten observations). The number of observations should be more than the number of independent variables in general.

CRITIC stands for “Criteria Importance Through Intercriteria Correlation” (Diakoulaki et al. 1995). The method considers the standard deviation of each normalised criterion (contrast intensity) and the linear correlation between them (conflict). Some examples of LCA-related use of CRITIC can be found in Jahan et al. (2012), Chang and Zhu (2020), Piasecki and Kostyrko (2020), Slebi-Acevedo et al. (2020), Wohner et al. (2020), Slebi-Acevedo et al. (2022), Cap et al. (2023), and Lyche Solheim et al. (2023). Apart from the general strengths (and weaknesses) of data-driven methods, CRITIC is also easy to apply by using simple statistics.

When used in the context of composite indicator construction, DEA is called the “Benefit-of-the-Doubt” approach. Applications of DEA can be found in Vázquez-Rowe and Iribarren (2015), Martín-Gamboa et al. (2017), Nascimento et al. (2020), and Vásquez-Ibarra et al. (2020). The method does not return a single vector of weights: each system is evaluated using the vector of weights that maximizes its standing relatively to its peers (i.e., the other alternatives being compared). The method can only be used if the number of systems being compared is relatively large, i.e., at least twice the number of indicators considered, more if possible.

The entropy method relies on the information theory to measure the amount of useful information that can be obtained (Hwang and Yoon 1981; Zeleny 1982). A greater difference between evaluated alternatives on a particular impact category indicator implies a smaller entropy, meaning that the indicator provides more effective information and, therefore, the corresponding weight value should be larger. Examples of the use of the entropy method in LCA are Santos et al. (2019), Yue et al. (2019), Nizamuddin et al. (2021), and Cap et al. (2023). Like CRITIC, the entropy method is easy to apply by using simple statistics.

The principal components analysis (PCA) method is commonly used to develop composite indicators. Examples of the use of PCA can be found in Gan et al. (2017), Greyling and Tregenna (2017), Suarez-Tapia et al. (2017), Tapia et al. (2017). PCA can also assist in selecting subsets of variables for other weighting methods. A key advantage of PCA is its ability to reduce the potential of double counting when indicators are highly correlated. However, this feature may be disadvantageous in cases where correlated indicators (e.g., global warming and photochemical oxidation) should not be assigned lower weights solely due to their correlation.

Factor analysis (FA), a similar multivariate analysis method, is also used to reduce data dimensionality by identifying latent variables that explain the original data. It is often used when there is interest in studying relations among the variables, While PCA is mainly used for data reduction, FA focuses on studying relationships between variables. FA allocates weights to impact category indicators based on the proportion of variance explained by the associated latent factors. Indicators with greater variation across the dataset receive higher factor loadings, while those with less variation are assigned lower loadings. This method is also commonly used to develop composite indicators. Examples of the use of FA are found in Nicoletti et al. (2000), Tapia et al. (2017), and ul Haq and Boz (2020).

Both PCA and FA share advantages, such as reducing double counting in the presence of highly correlated indicators, though (as previously described) this may not always be beneficial. FA has the added advantage of producing more interpretable factors compared to PCA components. They also share disadvantages, such as the sensitivity to outliers and the need for a sufficiently large dataset with indicators exhibiting adequate variability and linear relationships. It is important to follow established guidelines on the alternatives-to-indicators ratio (https://www.oecd.org/en/publications/handbook-on-constructing-composite-indicators_533411815016.html).

There are limited examples of the use of regression analysis methods in LCA; examples of regression analysis use can be found in Porter and Stern (2001), Paruolo et al. (2013), Becker et al. (2017). Porter and Stern (2001) and Becker et al. (2017) are referenced in the EU JRC composition indicator website (European Commission 2023). Key strengths of this method are that one can develop weights for all the indicators simultaneously with associated variabilities, identify the influential indicators, and characterise the overall uncertainty of the output measure with the indicator variables considered. Regression analysis can be applied to linear and nonlinear correlations. It is not invasive, i.e., no changes are made to the composite indicator or to the correlation structure of the indicators. There are some potential issues associated with this method, like multi-collinearity among the independent variables. The high dimensionality of the dataset can potentially be addressed through dimension reduction methods like PCA or through model selection processes based on parsimony. The calculation of the weights may be difficult to communicate to those not versed in statistical methodologies.

3.1.4 Distance-to-target methods

The distance-to-target methods rely on the definition of targeted impact or emission/resource levels, which can be used as benchmark to evaluate the partial significance and magnitude of the assessed impacts. These methods do not involve any expert/stakeholder engagement and are, therefore, generally not resource-intensive, except for the major research efforts that some approaches (like the carrying capacity method) require. However, they depend on the existence and quality of (political) targets. With respect to the carrying capacity method, which has been applied both as weighting and normalisation approach, it is scientifically based, and it is therefore considered less subjective (although there is inevitably an element of subjectivity in estimating carrying capacities (Vea et al. 2020)) and, potentially, more stable over time than many other approaches. Carrying capacity is not straightforwardly applicable to the human health AoP (although this is attempted in Vargas-Gonzales et al. 2019). There are uncertainties in carrying capacity estimations, and choices are needed in the transformation of carrying capacity indicator metrics to LCIA-based indicator metrics (e.g., related to the time frame for climate change). According to some interpretations, carrying capacities can vary over time, for example, if a mitigation pathway aligned with a global target (e.g., an emission scenario consistent with a certain global warming ceiling) is used in the transformation of carrying capacity indicator metrics to LCIA-based indicator metrics. This could be relevant if the LCI contains time information (emissions in later years should be weighted higher than emissions in early years), but this is likely to be difficult to consider in practice.

Rockström et al. (2023) and Richardson et al. (2023) contain the latest planetary boundaries (PB) estimates. An example of the use of PB methods in LCA is farming systems (Tuomisto et al. 2012). PB methods are not applicable to the human health AoP and parts of the other AoPs related to non-renewable resource scarcity. There are uncertainties in PB estimations, and there are choices that must be made in the transformation of PB indicator metrics to LCIA-based indicator metrics (e.g., related to the time frame for climate change). According to some interpretations, PBs can vary over time, for example, if a mitigation pathway aligned with a global target (e.g., an emission scenario consistent with a certain global warming ceiling) is used in the transformation of PB indicator metrics to LCIA-based indicator metrics. This could be relevant if the LCI contains time information (emissions in later years should be weighted higher than emissions in early years), but this is likely to be difficult to take into account in practice.

EDIP methodology is focused on the use of LCA for product development. It is a generic and full-fledged methodology. There are two versions of the EDIP method: EDIP97 and EDIP2003. The later version is a follow-up, not an update; it is a spatially differentiated alternative for some impact categories. Only EDIP97 includes weighting of environmental impacts. Weighting is performed only at the midpoint level (EDIP methodology only has impact indicators at this level). Methodological background and examples of the use of the EDIP methodology can be found in Wenzel et al. (1997), Hauschild and Wenzel (1998), and Alting et al. (1999). In the original methodology, the weighting factors are derived from political targets (in a targeted year) defining substance reductions or impact reductions for each impact category (other types of targets, e.g. non-political, may be envisaged too). Strengths are the political relevance of the results to serve interpretation, i.e., positioning within a political context, and the relative ease to develop and apply the weighting factors, e.g. no need for stakeholder opinions. The weighting factors are representative of, and hence dependent on, a specific time horizon, using specific reference and target years. Another limitation is the possible lack of scientific soundness in the definition of reduction targets, which have been primarily politically defined and, as such, depend greatly on a country's politics and environmental ambitions. The EDIP method has been applied to national and regional (EU) levels, and may have proven difficult to expand globally owing to the lack of global political framework and consensus. Implementation is not difficult, as the method is generic and can be applied to any object of study.

Use of the Eco-scarcity method (Frischknecht and Büsser Knöpfel 2013, Ahbe et al. 2017) is mandatory for all LCAs carried out by or for Swiss government agencies. It is relatively inexpensive to use, as it does not involve any expert/stakeholder engagement. The targets are legitimised as stemming from the policy process. It is transparent and easy to explain and communicate. Limitations of the method are linked to completeness in terms of elementary flows covered; global supply chains require global target setting, i.e., at UNEP level, while the focus so far has been the Swiss (or EU) scale. Policy targets derive from lengthy processes, and accommodate science-based input with stakeholder acceptance, so they can lag behind scientific knowledge. In order to implement the Ecoscarcity method, targets need to be set in a policy process by an authoritative institution to be accepted by the global LCA community.

For distance-to-target methods, it should be noted that some policy targets and interpretations of carrying capacity/planetary boundaries involve target values that become gradually more ambitious over time (e.g., milestones towards a net-zero target for greenhouse gases, GHGs). This time dependency is not straightforward to reflect in weights but may be relevant when LCIs contain time information (elementary flows in later years should then be weighted higher than elementary flows in early years). As this group of methods is based on policy targets, there may be a requirement to understand local languages for access to the information in policy documents. It is also important to note that distance-to-targets methods should require the use of other weighting methods to capture the relative significance across the impact categories. While DtT methods enable the expression of the individual significance of each impact indicator, they do not account for the relative importance of the impact categories between each other. This explains why some of these methods (e.g. carrying capacities, as in Bjørn and Hauschild 2015) have also been advanced as normalisation methods.

3.2 Classification results

The results from classifying the methods are shown in Table 4. The meaning of the weights' classifier is summarised as trade-off rates for the MCDA methods precise and imprecise trade-offs and precise and imprecise SWING. Importance coefficients are provided by the MCDA methods precise and imprecise points allocation, precise and imprecise direct rating, ranking, AHP and Simos/revised Simos/SRF. The other methods assessed that provide importance coefficients are the data-driven methods CRITIC and entropy, and all of the distance-to-target methods (four, carrying capacity, PB, EDIP97 and Swiss Eco-scarcity). Disaggregation methods and SMAA methods provide factors that work as both trade-off rates and importance coefficients. The remaining methods provide trade-off rates; all of the eight monetary methods assessed (budget constraint, abatement cost, market price, contingent valuation, DCE, averting behaviour, travel cost, hedonic pricing) and three of the data-driven methods (DEA, FA, PCA and regression analysis).

The assessment of the classifier temporal discounting found that, with the exception of SMAA, it is possible to include temporal discounting in the assessment of the impacts in the MCDA methods if the respondents are asked to provide their input with respect to their current as well as future preferences (e.g., if participants are asked how they value something now and which value they expect to attach to it in the future). However, it requires a greater effort from the participants, and feasibility depends on the case, e.g., the number of attributes for which they have to assess the importance. For SMAA, eliciting partial information (e.g., a ranking of the weights) is optional. In cases where preferences are elicited, it is possible to include temporal discounting in the assessment of the impacts, as for the other MCDA methods. Temporal discounting is possible for all of the monetary methods. The data-driven methods are sufficiently general and flexible and thus can address temporal discounting if temporal data are available.

For SMAA, eliciting partial information is optional, but all of the MCDA methods can account for different cultural backgrounds if the respondents have such backgrounds. Feasibility depends on the case, e.g. the number of attributes for which they have to assess the importance, as a lower workload for participants makes it more likely that invitees will respond.

All monetary methods can account for some cultural differentiation; however, this might have limited applicability, as it might be in conflict with the cultural values of indigenous peoples (Manero et al. 2022). It needs to be noted, however, that cultural differentiation can mean following cultural theory (e.g. the individualist, hierarchist and egalitarian perspective distinguished by Ecoindicator99 (Goedkoop and Spriensma 2001) to which the budget constraints monetary method relies) or obtaining different weights for different parts of the world or sub-groups within a given area (all other monetary methods). For abatement cost, different cultures would need to independently set clean-up targets or emission ceilings. Such differences would largely be limited to different countries, covered by Criterion 10. For survey-based methods (contingent valuation and DCE), accounting for different cultural backgrounds requires conducting surveys in different parts of the world.

Cultural differentiation for data-driven methods is possible if cultural background data are available. Cultural differentiation is not an inherent attribute of the carrying capacity method, although the cultural background of the scientists estimating carrying capacities could play a role. EDIP97 can differentiate if the political targets used in the method are influenced by cultural differences. Swiss Eco-scarcity has the ability to account for cultural backgrounds as far as the cultural background is part of the democratic institutions that determine the critical flows.

3.3 Criteria results

Table 5 shows an overview of the results of the review using the criteria and colour coding in Table 2 (described in Sect. 2.1). It should be noted that even though some methods have been assessed as not sufficient for the given criterion for the scope of the GLAM project (colour-coded with the red dots) in Table 5, it does not mean that they are unsuitable for other studies.

For some criteria (i.e. Criterion 7 (communicability) and 9 (association with AoP units)), some cells have two colour codes or are half one colour and half white. This is because communicability for the disaggregation methods and SMAA depends on the type of weights being elicited. Both methods score no sufficiency (red dots) for trade-off rates and partial sufficiency (yellow) for importance coefficients. Similarly for association with AoP units, if the weights derived are trade-off rates, both methods score full sufficiency (green, i.e., weights are directly related to the AoP metrics, if the underlying value functions are linear or assumed to be linear); if the weights derived are importance coefficients both disaggregation methods and SMAA score partial sufficiency (yellow), as the weights are not directly related but can be adapted to relate to the AoP metrics.

Criterion 1 (Independence of the sets of systems being evaluated) shows that all of the MCDA, monetary and distance-to-target methods are independent of the set of alternatives. The data-driven methods are, however, all dependent on the set of alternatives being evaluated.

For reproducibility (Criterion 2), the assessment in Table 5 shows that most of the MCDA methods are such that reproducibility is difficult to achieve. The exception is SMAA, for which similar results can be achieved when the dataset is the same. Five of the monetary methods (budget constraint, abatement cost, market price, travel cost and hedonic pricing) have a good reproducibility assessment. However, they will change over time, as the available budget, market prices, travel expenditure and the influence of environmental aspects are changing as well. Averting behaviour is assessed as “replicates provide quite similar results”. Contingent valuation and DCE are monetary methods where reproducibility is difficult to achieve. The reproducibility assessment for all of the data-driven methods and three of the distance-to-target methods (PB, EDIP97 and Swiss Eco-scarcity) is sufficient. Carrying capacity is assessed to “provide quite similar results” by the review team.

Table 5 Methods review summary

Criteria*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MCDA methods																
Precise and imprecise trade-offs																
Precise and imprecise SWING																
Precise and imprecise points allocation																
Precise and imprecise direct rating																
Ranking																

Table 5 (continued)

AHP																
SIMOS / Revised SIMOS / SRF																
Disaggregation methods																
SMAA															N/A**	N/A**
Monetary methods																
Budget constraint																
Abatement cost																
Market price																
Contingent valuation																
Conjoint analysis																
Averting behaviour																
Travel cost																
Hedonic pricing																
Data-driven methods																
CRITIC																
Data Envelopment Analysis (DEA)																

Table 5 (continued)

Entropy																
Factor Analysis (FA)																
Principal Component Analysis (PCA)																
Regression Analysis																
Distance-to-target methods																
Carrying capacity																
Planetary boundaries (PB)																
EDIP97																
Swiss Eco-Scarcity																

*Key to criteria numbers: 1. Independence of the set of systems being evaluated; 2. Reproducibility of the weights; 3. Scientific validity; 4. Method transparency; 5. Coverage of GLAM areas of protection (AoP); 6. Uncertainty characterisation; 7. Communicability; 8. Accounting for differences in utility for the same impact; 9. Association with AoP units; 10. Geographical resolution; 11. Global coverage; 12. Application demonstrated in case studies; 13. Required resources to apply the method; 14. Required technical and calculation infrastructure; 15. Representativeness, 16. Bias.

**N/A: Non-applicable.

Criterion 3 is about scientific validity. All of the MCDA methods are published in a peer-reviewed journal or book. All of the monetary and data-driven methods are published in peer-reviewed journals or books, as are distance-to-target methods, with the exception of EDIP97, which has been published in peer-reviewed conference proceedings.

All of the methods have full transparency for their algorithms and value choices (Criterion 4), except for disaggregation and SMAA (MCDA), budget constraint and averting behaviour (monetary), DEA, FA and PCA (data-driven), whose transparency is assessed as partially sufficient.

Coverage of the GLAM AoPs (Criterion 5) was a specific need for future work towards a global weighting method (Bayazıt et al. 2024). These AoPs can be covered using all of the MCDA methods, five of the monetary methods (budget constraint, abatement cost, market price, contingent valuation and DCE), all of the data-driven methods, but none of the distance-to-target methods.

Uncertainty characterisation (Criterion 6) shows that uncertainties are characterised stochastically for all of the MCDA methods and all of the monetary methods, except budget constraint. Half of the data-driven methods (FA, PCA and regression analysis) have a stochastic characterisation of uncertainties, whereas the other half (CRITIC, DEA and entropy) have no characterisation of uncertainties.

Communicability was assessed as Criterion 7. All of the distance-to-target methods are such that the meaning and calculation of the weights are easy to communicate. This is much more variable for the other groups of methods. Only four of the MCDA methods (precise and imprecise points allocation, precise and imprecise direct rating, ranking and Simos/revised Simos/SRF) were rated as easy to communicate. As far as disaggregation methods and SMAA are concerned, this depends on the type of underlying model chosen. Five of the monetary methods (abatement cost, market price, averting behaviour, travel cost and hedonic pricing) and two of the data-driven methods (CRITIC and entropy) were ranked as easy to communicate.

Criterion 8 concerns the capacity of the method to account for differences in utility for the same impact. All of the MCDA methods can assign different weights to the same impact experienced by individuals living in different socio-economic contexts to reflect their loss of utility. This is the same for all of the monetary methods except for budget constraint. By looking at the global average annual income (Weidema 2009), the budget constraint method cannot (does not intend to) assign different weights to the same impact experienced by individuals living in different socio-economic contexts to reflect their loss of utility. Of the data-driven methods, regression analysis received a partially sufficient grading, whereas the other data-driven methods can account for differences in utility for the same impact. Regarding the distance-to-target methods, only EDIP97 scores full sufficiency on this criterion.

Correspondence with the AoP metrics is assessed for Criterion 9. None of the distance-to-target methods or the market price method (a monetary method) are directly related or relatable to the AoP metrics. All of the data-driven methods are directly relatable to the AoP metrics. Of the remaining monetary methods, only three (budget constraint, contingent valuation and DCE) are assessed as being directly relatable to the AoP metrics. For the MCDA group, only trade-offs, SWING, disaggregation and SMAA can provide weights that are directly related to the AoP metrics. The remaining ones are relatable.

Criteria 10–16 relate to the implementability of the method. For Criterion 10 (geographical resolution), all of the MCDA and data-driven methods have the capacity to have national differentiation. There are six monetary methods that can have national differentiation (abatement cost, market price, contingent valuation, DCE, averting behaviour and travel cost). The methods that have no geographical differentiation are budget constraint (monetary method), carrying capacity and PB (both distance-to-target). However, some would argue that this geographical differentiation is possible with these methods, but it is an implementation decision that this differentiation is not usually done. The other two distance-to-target methods (EDIP97 and Swiss eco-scarcity) are able to have national differentiation.

Global coverage is assessed using Criterion 11. Table 5 shows that global weights can be obtained for all weighting methods with the exception of the distance-to-target methods, where global weights can be calculated from non-global weights.

The extent to which the method has already been applied in case studies is graded for Criterion 12. Most of the methods reviewed have been widely used in case studies. The exceptions to this are precise and imprecise trade-offs, disaggregation methods, averting behaviour, travel cost, hedonic pricing, regression analysis, carrying capacity and PB, which have all been used in just a few case studies.

The methods requiring little time, cost, and human resources to implement (Criterion 13) are all of the data-driven methods, plus SMAA, market price and EDIP97. There are not too many of the methods reviewed that require extensive time, cost and human resources, but the ones that do are precise and imprecise trade-offs, contingent valuation, DCE, averting behaviour, travel cost and hedonic pricing.

All of the distance-to-target methods require only simple infrastructure (Criterion 14), as do six of the MCDA methods (precise and imprecise trade-offs, precise and imprecise SWING, precise and imprecise points allocation, precise and imprecise direct rating, ranking and Simos/revised Simos/SRF), three of the monetary methods (budget constraint, abatement cost and market price), as well as two of the data-driven methods (CRITIC and entropy). The remaining methods require some simple and some complex infrastructure. None of the methods were graded as needing solely complex infrastructure.

The MCDA methods and data-driven methods reviewed for Criterion 15 (representativeness) are all shown in Table 5 as able to work with a representative sampling of

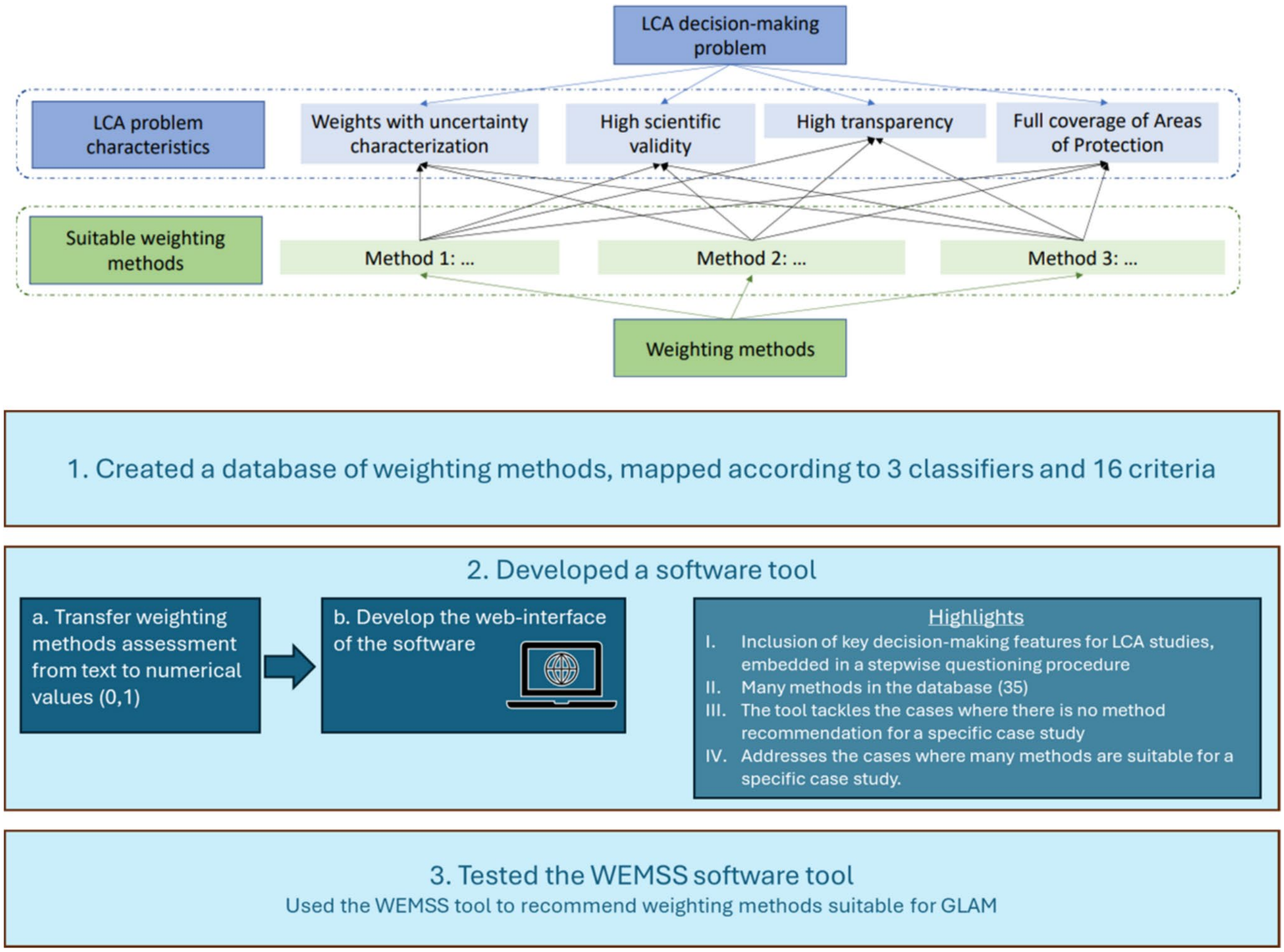

Fig. 2 The decision-making problem and creation of the WEMSS tool, adapted from Cinelli et al. (2023)

the affected population. This was the case for half of the monetary methods (contingent valuation, DCE and hedonic pricing). The other monetary methods use indirect sampling of the affected population, or have another approach of deriving weights such as abatement costs or market prices that do not involve surveys or sampling. For the distance-to-target methods, both carrying capacity and PB were graded as not using representative sampling of the affected population. EDIP97 can work with a representative sample of the affected population and Swiss eco-scarcity can be described by "indirect sampling of the affected population".

Criterion 16 addresses bias. The majority of the methods were assessed as having known biases that can be corrected or accepted. The remaining seven methods (CRITIC, DEA, entropy, regression analysis, carrying capacity, PB and Swiss eco-scarcity) have no known biases.

When considering which methods are appropriate for a study, it is possible to use the methods review summary results shown in Table 5. If the user wants a rapid assessment, then choosing a method with the green colour coding for Criterion 13 (required resources to apply the method) would be a sensible start. If robustness is valued, then methods with a green colour code for Criterion 2 are what the user should look for. If global weights are of interest, as they are for GLAM, then the results for Criterion 11 are important for the user's decision.

4 Method selection tool

The Weighting Methods Selection Software (WEMSS, Cinelli et al. 2023) was developed within the GLAM weighting subtask. The developed criteria and reviews described above, and summarised in Table 5, are the basis for the tool, which guides the user through steps to identify methods that are suitable for a given study. Table 5 is, in essence, the database that has been used to develop the WEMSS, transformed into binary input to be machine-readable.This tool is available (without cost) on the website https://mcda.cs.put.poznan.pl/wemss/index.php.

The tool was created to enable LCA analysts faced with the question: "Which is the most appropriate weighting method for my LCA case study?" The characteristics of the decision-making problem are addressed in the tool in order to select the most appropriate weighting method, or subset of methods, for their specific study. This decision-making problem and the approach to solving it are illustrated in Fig. 2 (Cinelli et al. 2023).

The WEMSS tool provides four main contributions to the GLAM work. Firstly, it allows analysts to learn the sequential and dynamic framework shaped to address complex decision-making problems related to weighting in LCA. This is based upon a decision support approach called decision rules, where the modelling framework uses causal connectors in the form of "If the conjunction of requirements on [selected] features is matched, then the recommended method(s) is(are) [list the method(s)]". Secondly, it comprises the widest (N=35) available database of weighting methods assessed according to the set of 16 criteria described in this paper. Thirdly, it also suggests weighting methods for those case studies for which the analysts' requirements (i.e., desired features) are not fully satisfied. Finally, even when the description of the decision-making problem is not complete, WEMSS offers a strategy to narrow down the list of suitable weighting methods, using the most selective questions.

The application of WEMSS was demonstrated using the UNEP GLAM project as a main case study. This consisted of the identification of the weighting methods suitable for calculating a set of global weights, which LCA practitioners can use by default when they do not wish to compute or use other weights. The agreed constraints (and answers in the WEMSS) for the selection of the weighting methods for the UNEP GLAM project included:

1. Weights should not be dependent on the set of alternatives being assessed. They should be applicable to any type of system under evaluation;
2. The methods generating the weights should have been peer-reviewed and hence recognized by the scientific community;
3. The methods should be transparent enough to be approachable and understandable by practitioners. This implies that they should not be perceived as 'black boxes' by the users of the methods;
4. The methods should be capable of characterizing the variability of the weights according to different preferences. This means that weights in the form of at least ranges should be prioritized;
5. The weights should be directly connected to the metrics used for the different AoPs. This requirement is connected to the foreseen use of these weights, which is an additive aggregation model;
6. The weighting methods should provide weights that are applicable on a global scale. This constraint is related to the need of having weights that are usable to account for the impacts on a global scale, without geographical differentiation.

Screenshots of the WEMSS results for the UNEP GLAM project are shown in the supplementary information section of this paper. This exercise led to a list of ten suitable methods. The ten suitable methods identified for use in developing the UNEP GLAM weighting method were: budget constraint, conjoint analysis, contingent valuation, disaggregation methods, imprecise swing, imprecise trade-offs, precise swing, precise trade-offs and SMAA (both with and without stakeholder preferences). Two of these methods (conjoint analysis in the form of a discrete choice experiment and an MCDA disaggregation method) were then used to develop weighting factors presented in Bayazıt Subaşı et al. (2024).

5 Concluding remarks

For many of the methods described, it is necessary to develop surveys in order to elicit relevant respondents' views. For all the methods that rely on such surveys, time, effort and crucial involvement of social scientists and cultural anthropologists are important in order to inform how these surveys are designed and how to interact with the surveyed population. This aspect is relevant for Criterion 13. The methods that are survey-based are considered to have a higher chance of being representative of the opinions of the relevant population, and thus to be truly representative, the methods used will be resource-intensive (i.e., requiring significant time, funding and technical resources).

It should be noted for monetary methods that scientists from different disciplines express their ethical concerns regarding the monetisation of environmental goods, as it suggests exchangeability of natural and financial capital (Spash 2009; Wolff and Gsell 2018). While acknowledging ethical concerns in general, environmental economists argue that mainly the unit-of-account function of money is used here and not its trading function (Calow 2015; OECD 2019).

Inclusion of temporal discounting in the assessment of the impacts in the MCDA methods (where respondents are asked to provide their input with respect to their current as well as future preferences) becomes increasingly less credible when projecting further into the future, as people today cannot fully understand or anticipate the conditions and challenges future generations will face, which are influenced by numerous unpredictable factors.

While there had been unambiguous support for the criteria defined in Stage 2 prior to the reviews, some members of the task force expressed concerns about the way in which some of them were interpreted and used afterwards. Notably the Criterion 5 “Coverage of GLAM areas of protection” (i.e. Capacity to provide weights for GLAM areas of protection (AoPs)) was not merely descriptive in what a given method was capable of but was used to disqualify all weighting methods that could not cover all AoPs. Especially regarding the monetary valuation methods, it is common practice in the welfare economic literature to use different valuation (weighting) methods for different endpoints (de Bruyn et al. 2018, OECD 2018, ISO 2019, European Commission 1999, European Commission 2005). As a result, using combinations of methods, i.e. using the best-placed method for a given AoP, was not considered an option. However, the evaluation of no sufficiency in Criterion 5 for the methods is only applicable for the definition of the AoPs in the GLAM project, which doesn’t mean the sufficiency of those methods in the context of application to other LCIA methods. Moreover, this is also valid in the cases of other criteria.

The criterion of representativeness was applied to all methods, though it is less relevant for non-survey-based approaches. The epistemic paradigms that underlie the respective methods should be further investigated in future work. For example, threshold values for pollutants from distance-to-target methods rely on political systems and thus representation, while planetary boundaries stem from natural sciences and ecology, and survey-based weights rely on public opinion. This reflects differing paradigms, not differing quality. Moreover, representation of affected populations for survey-based weights and those relying on political systems is limited, because it cannot incorporate future generations, who will be most affected by climate change and biodiversity loss, making them inherently unrepresentative of those that are most affected.

Sustainability frameworks extend beyond LCA and the three GLAM AoPs. Other examples are doughnut economics (Raworth 2017), which integrates planetary boundaries and human needs. LCA can help measure technologies’ contributions to such frameworks. However, approaches that trade off human health against ecosystem health conflict with both doughnut economics and the planetary and one health frameworks (Correia et al. 2021), which view ecological and human health as complementary constraints rather than competing goals. This can lead to the view that weighting sets that measure the contribution to fulfil human needs and remain within planetary boundaries would be more easily attainable by weighting at the midpoint level combined with a distance-to-target approach than with endpoint modelling and weighting AoPs against each other.

Finally, the longevity of weighting methods is a concern that could not be addressed in this review. Many weights are over 10 years old, despite societal, economic, and ecological changes, raising questions about their continued validity.

The review presented in this paper laid the foundations for the creation of the WEMSS, which is an easy-to-use software for recommending weighting methods for LCA studies. The WEMSS was developed as part of the UNEP GLAM project, and it was used to identify suitable methods that could be used in this project. Search constraints for the GLAM project included the independence of the weights from the set of alternatives being considered, the scientific recognition and understandability of the methods, the capability of characterising weights variability, the relation to the AoPs metrics, as well as the applicability on a global scale. These requirements led to the identification of 10 candidate methods for the UNEP GLAM project, namely budget constraint, conjoint analysis, contingent valuation, disaggregation methods, imprecise swing, imprecise trade-offs, precise swing, precise trade-offs and SMAA (both with and without stakeholder preferences). Thus, several methods can be used for developing weighting factors suitable for use by GLAM.

6 Outlook

This review provides an evaluation summary of twenty-seven weighting methods as part of the Life Cycle Initiative on developing a global LCIA method (Phase 3). The developed criteria and reviews can be used to develop guidelines for choosing weighting methods for different LCA applications. Even though some methods have been assessed as not sufficient for the given criterion for the scope of the GLAM project, it does not mean that they are poor weighting methods, only that they are less suitable for the GLAM project.

This paper provides the reader with a good overview of the available methods for weighting. It is a useful starting point for practitioners who want to get a global overview of the available methods and to understand whether they are suitable for their specific LCA study. Use of more than one weighting method is good practice in sensitivity analysis, so this paper can be helpful to find other methods that are different, but also valid for the given study. This research also opens up avenues for developing tools that can streamline the selection of weighting methods for LCA.

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Data availability The data generated in this study is of a qualitative nature. This article contains all the references to publications consulted for this review. All data available from this review is included in this article.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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