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Review

Life cycle assessment applied to bio-based platform molecules: Critical review of methodological practices

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ABSTRACT

Bio-based platform molecules are chemicals identified as key agents in the development of circular bioeconomy. Their penetration into the current market would sustain the shift of a chemical industry mainly based on the use of petrochemical feedstock to the use of resources of biological origin. Bio-based platform chemicals have received much attention during the last decades, and thus, there is plenty of literature focused on their production throughout a plethora of different technologies. Nevertheless, most of these procedures lack of maturity and are subject to constraints. Thus, the way to ensure improved environmental sustainability is through the application of tools such as life cycle assessment (LCA). Although the integration of LCA is increasingly common during the design phase of these processes, the diverse modeling options can lead to very unlike results. Converging practices around consensus methodologies would lead to more reliable and comparable results. The purpose of this review is to identify the critical points of divergence that hinder this comparison and try to reconcile them towards the best options within biomass-derived platform chemicals specific context. The performed meta-analysis revealed the existence of three key aspects to be considered in the comparison of LCA studies: cradle-to-gate scope (mostly intermediate chemicals), prospective analysis (technologies under development), and multifunctional processes (biorefineries with several valuable outputs). Regarding the scope, reconciling the temporal scope of the studies with the correct allocation of biogenic carbon fluxes is the aspect that requires a deeper discussion. Evaluating novel technologies (characterized by industrial data scarcity) require careful scaling of the systems, as well as rigorous calculations of the uncertainty of results. Concerning multifunctionality, modelling many flows and their interactions is the most challenging task. Within this context, the consequential perspective seems a more correct approach to capture all the elements of these novel and complex systems, although the lack of data can make it unfeasible in numerous cases. Finally, a limited comparison is performed based on the key aspects previously identified. Thus, broader conclusions are inferred for the most promising routes to produce three bio-based platforms among the selected as a case study: lactic acid (chemo-catalytic transformation of swine manure), succinic acid (fermentative pathways using lignocellulosic biomass), and ethylene (wood gasification).

1. Introduction

Fossil resources are one of the principal drivers of the global economy. Both energy and bulk commodities derived from petroleum are indivisible from our current way of life. Still, an already settled conscience of the damages inflicted by its unbridled consumption is forcing a paradigm shift. The environmental concerns resulting from their extraction and use, the depletion of fossil resources, the energy independence, and the climate change effects are perceived as especially urgent.

The solution necessarily involves the transition to renewable and sustainable carbon sources. In this context, biomass is one of the most abundant and promising feedstocks available. Only in the territory of EU27, 348 Mt of dry forestry biomass are produced annually, according to the JRC (Avitabile et al., 2020). Lignocellulose is the prevalent structure form of biomass in nature, and thus harnessing lignocellulosic biomass has received much attention in the last decades, as its use would enable a new and potentially profitable industrial and economic context. In 2016 the total bioeconomy turnover reached 2.3 trillion euros in Europe (Piotrowski et al., 2016). Moreover, 803 biorefineries were operating in 2018, 507 of which produced bio-based chemicals (Parisi,

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Nomenclature

AA	Adipic Acid
AAC	Aquatic Acidification
AC	Acidification
ADP	Abiotic Depletion Potential
AE	Aquatic Ecotoxicity
ALO	Agricultural Land Occupation
CED	Cumulative Energy Demand;
CExD	Cumulative Exergy Demand;
EP	Eutrophication Potential
ET	Ecotoxicity
ETN	Ethylene
FDCA	2,5-Furandicarboxylic acid
FDP	Fossil Depletion Potential
FESP	Fossil Energy Saving Potential
FUR	Furfural
FWEP	Freshwater Eutrophication
FWET	Freshwater Ecotoxicity
GWP	Global Warming Potential
HMF	5-Hydroxymethyl furfural
HT	Human Toxicity
HTc	Human Toxicity (cancer effects)
HTnc	Human Toxicity (non-cancer effects)
iLUC	Indirect Land Use Changes
IR	Ionizing Radiation
JRC	Joint Research Centre
LA	Lactic Acid
LO	Land Occupation
LU	Land Use
LUC	Land Use Change
LvA	Levulinic Acid
MDP	Metal Depletion Potential
MEP	Marine Eutrophication Potential
MET	Marine Ecotoxicity
NRCED	Non-Renewable Cumulative Energy Demand;
NREU	Non-Renewable Energy Use
OD	Ozone Depletion
PED	Primary Energy Demand;
PM	Particulate Matter
POCP	Photochemical Ozone Creation Potential
POF	Photochemical Oxidants Formation
RE	Respiratory Effects
SA	Succinic Acid
TA	Terrestrial Acidification
TE	Terrestrial Ecotoxicity
TEP	Terrestrial Eutrophication Potential
TEU	Total Energy Use
TRL	Technology Readiness Level
ULO	Urban Land Occupation
WU	Water Use

2018), involving most of them the production of platform chemicals. Bio-based platform chemicals are a set of compounds identified as key intermediates for biorefineries development. Although this constitutes a promising scenario, incumbent technologies are hampered by intrinsic difficulties such as the decentralized collection of raw materials or the fluctuations in their quantity and quality (Hassan et al., 2019).

In this sense, life cycle assessment (LCA) is a fundamental tool to identify hotspots and ensure environmental improvements of the new bioresources-based processes as compared to their conventional fossil-based counterparts. As a measure of its importance, the environmental performance of novel bioprocesses has been extensively reviewed (Yates and Barlow, 2013; Kajaste, 2014; Hottle et al., 2017; Fiorentino et al., 2017; Kakadellis and Harris, 2020; Ryan and Yaseneva, 2021; Escobar and Laibach, 2021). Even though the number of LCAs published on biomass-derived chemicals has rapidly grown, comparison between them is still limited due to the heterogeneous methodological choices applied. This is also acknowledged in the case of bio-based plastics by other authors (Spierling et al., 2018; Walker and Rothman, 2020), who greatly discussed how LCA is applied to this particular field. Additionally, Montazeri et al. (2016) analyzed the conclusions of 86 life cycle case studies on the main priority biochemicals to compare their impact on energy and greenhouse gas emissions, although most normative choices were disregarded.

Assessing the sustainability of a process without considering other externalities related to cost analysis and social impacts is an incomplete approach. A rigorous analysis of the sustainability of a system should include these aspects. However, the number of published studies following this holistic approach is very limited. Therefore, this paper focuses only on the environmental side and the methodology applied to its assessment.

The present work aims to cover three objectives. In a first step, an evaluation of how LCA is customarily applied to biomass-derived chemicals is presented. This first target aims at finding the main discrepancies between analogous studies (Section 3.1). Next, the major findings in this stage are critically examined to derive recommendations based on consensus practices which might help to mitigate methodological divergences (Section 3.2). Finally, conflicting parameters for LCAs comparison are identified, and a limited evaluation of the reviewed processes is performed (Section 3.3). In short, the main purpose of this work is to determine the key methodological choices that restrict the comparison between studies and try to find a common ground around the best practices identified to converge underpinning decisions as much as possible.

2. Methodology

2.1. Literature review

Literature searching was conducted following a methodological procedure to ensure completeness and appropriateness of the retrieved data. Two databases were employed, namely Scopus and Google Scholar. In both cases, the same arrays of terms were defined, which are summarized in Table 1. The first column corresponds to the name of the molecule of interest. Various names were used for each of the selected chemicals to avoid loss of information (e.g., adipic acid AND hexanedioic acid). The second column comprises the terms used as browsing keywords for biomass derived molecules (e.g., biobased, biomass-

Table 1
Terms used for literature search. The Boolean function OR was introduced for items in the same columns, while function AND was introduced to separate items in different columns.

Col-1 (NAME)	Col-2 (TOPIC)	Col-3 (FIELD)
Molecule	Bio-	Assessment Life Cycle
Molecule Synonym 1		Environment- Eco-
Molecule Synonym 2		Sustainab- Green Footprint

All considered, 64 publications were deemed for the analysis. The selection of the molecules evaluated is justified in the following section.

derived, etc.), which is the topic of interest. The third block includes keywords referring to LCA and similar studies. No time limit was defined, and only scientific peer-reviewed publications were considered, excluding book chapters and other sources of information.

2.2. Selection of bio-based platform chemicals

The choice of the evaluated molecules was performed as described hereafter. First, a broad screening was carried out based on the report on global trends for bio-based building blocks published by Nova-Institute (Skoczinski et al., 2021), from which the original bio-based platform chemicals list has been extracted (including up to 29 molecules). From this list, only molecules receiving the highest attraction from research community were considered for further analysis. The selection is based on two criteria, namely the number of publications in which the bio-derived chemical is mentioned and the expected industrial relevance for each one of them. For the first condition, the Col-1 and Col-2 arrays in Table 1 were used. That contributed to distinguishing between oft-cited (e.g.: lactic acid, 3241 documents) and scarcely cited (e.g.: caprolactam, 49 documents) molecules. The latter were then excluded from the analysis. The number of citing documents for each selected molecule is shown in Fig. 1. For the second requirement, the criteria discussed by Bozell and Petersen in (Bozell and Petersen, 2010) were considered (9 criteria for evaluating bio-based product opportunities). Thus, only the most relevant bio-based platform molecules were evaluated, as the data used in these studies is expected to be more accurate due to larger availability. A third cut-off criterion was applied to the remaining molecules in the list, introducing the terms in Col-3 of Table 1 to exclude molecules with a low number of published LCA studies, since its inclusion would not add any statistically significant information to the review. This is the case of sugar alcohols (i.e., xylitol and sorbitol), with four (Dávila et al., 2016; Dasgupta et al., 2021; Shaji et al., 2022; Rendra et al., 2019) and three (Akmalina, 2019; Moreno et al., 2020; Kapanji et al., 2021) documents published respectively, to the best of our knowledge, a too low number to establish proper comparison between works. Similarly, only three indexed studies of 5-hydroxymethylfurfural (HMF) are found. Conversely, HMF was included in the analysis due to its similarities with the rest of the examined furanic compounds (i.e., furfural, and 2,5-furandicarboxylic acid (FDCA)). For instance, references (Schöppe et al., 2020) and (Bello et al., 2018) jointly evaluate the production of HMF with furfural and FDCA respectively. Contrastingly, ethanol is excluded from the analysis, since the profuse number of studies about its production would constitute a separate work itself. Furthermore, five review papers about environmental considerations in the production of bioethanol are already available in existing literature (von Blottnitz and Curran, 2007; Singh et al., 2010; Borrion et al., 2012; Morales et al., 2015a; Gerbrandt et al., 2016), so its consideration might be redundant.

All considered, eight molecules were chosen for the analysis. These include four acids: lactic, succinic, levulinic, and adipic acid; three furanics: furfural, 5-hydroxymethylfurfural, and 2,5-furandicarboxylic acid; and ethylene.

The timeframe of the studies included in this paper spans from 2010 to the present. Before this period, the number of studies related to the life cycle analysis of these molecules is not significant. In addition, the literature search for the construction of this meta-analysis was carried out during the first half of 2022.

2.3. Technological context

The state-of-the-art regarding the production technologies available for the selected chemicals, as above mentioned, is briefly reviewed to provide some context to the LCA meta-analysis.

2.3.1. Furfural (FUR)

Furfural is an aldehyde formed by a furan ring substituted with a formyl group (Fig. S1). It is extensively used in many applications of different industries such as oil refining, plastics, pharmaceutical, and additives, among others (Mamman et al., 2008), although its main use is the production of cyclic compounds like furfuryl alcohol (Hoydonckx et al., 2007; Mariscal et al., 2016). Typically, furfural is produced by acid hydrolysis of pentosan-rich lignocellulosic feedstock. C5 sugars (xylose and others) are released from hemicellulose-containing feedstock through acid hydrolysis and subsequently dehydrated to produce furfural. Purification processes consist of the neutralization of the resulting mixture, and its distillation if high concentration is required (Dashtban et al., 2012). Furfural industrial production dates to 1922, when Quaker-Oats Company started to produce it from agricultural wastes such as oat husks. Nowadays, most of the worldwide furfural production is concentrated in China via the Huaxia process (Tin, 2005).

2.3.2. 5-Hydroxymethylfurfural (HMF)

Similar to furfural, 5-hydroxymethyl furfural is composed of a furan ring with a formyl group in position 2 and a hydroxymethyl substituent in position 5 (Fig. S1). HMF is used in the food industry as a biomarker as well as a flavoring agent for food products. Production of HMF is conducted through triple dehydration of the C6 sugar fraction contained in the lignocellulosic raw biomass (Saeman, 1945). Alternatively, other

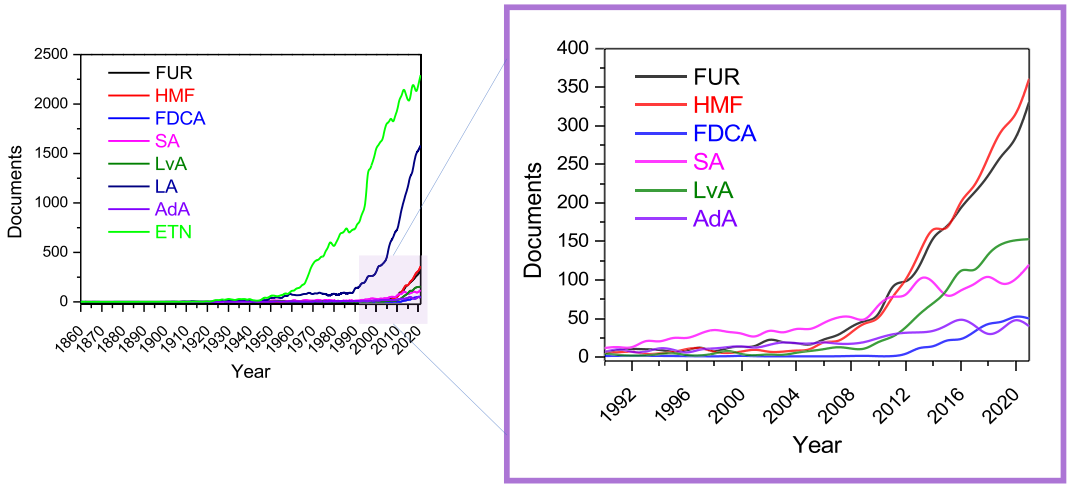

Fig. 1. Temporal series of the number of publications of the selected molecules. FUR: Furfural | HMF: 5-Hydroxymethyl furfural | FDCA: Furan dicarboxylic acid | SA: Succinic Acid | LevA: Levulinic Acid | AA: Adipic Acid | LA: Lactic Acid | ETN: Ethylene.

reaction pathways have been proposed, conducting to HMF from polysaccharides and sugar acids (van Putten et al., 2013).

From an academic perspective, FUR and HMF have received great attention over the last 15 years (Fig. 1). This has resulted in notorious advances in its synthesis, as summarized in extensive reviews published about novel production routes using heterogeneous catalysts (Agirrezabal-Telleria et al., 2014), ionic liquids (Zakrzewska et al., 2011), or enzymes (Wang et al., 2018). Currently, large-scale HMF production is still limited. The first industrial plant (AVA Biochem AG) begun its operation in 2013, with a production capacity of 20 tons·year^{-1}. To the best of our knowledge, no new plants have been reported ever since.

2.3.3. Furan dicarboxylic acid (FDCA)

FDCA is a furanic compound consisting of two carboxylic acid groups attached to a central furan ring (Fig. S1). It is considered as a direct substitute of terephthalic acid in the production of polyesters and other polymers such as polyethylene terephthalate. It can be produced from certain carbohydrates but at present synthesis from HMF is used, achieving high yields towards the target product with minor sides formation. In 2011, Avantium was the first company to build a FDCA pilot plant in Geleen, the Netherlands. Avantium has fully proven its technology to produce FDCA and the company now plans to open the world's first commercial FDCA plant, which is scheduled to be completed by the end of 2023 and operational by 2024 (de Jong et al., 2022).

2.3.4. Succinic acid (SA)

Succinic acid or butanedioic acid is a dicarboxylic acid (Fig. S1) naturally present in a variety of plant and animal tissues as well as microorganisms. It is a precursor to some polyesters and a component of some alkyl resins, or for producing 1,4-Butanediol (BDO). Nowadays most of the commercially produced succinic acid is obtained through chemical synthesis pathways. Common industrial routes include hydrogenation of maleic acid, oxidation of 1,4-butanediol, and carbonylation of ethylene glycol. Succinic acid market in 2013 comprised a world demand of about 710 ktons, with a net value of $115.2 million (Salma et al., 2021). The growing succinic acid market is stimulating the commercialization of bio-based succinic acid, and many companies, such as Reverdia, Myriant, Succinity and BioAmber, have already made the leap of alternative fermentation processes for succinic acid production to the stage of industrialization (Li et al., 2017). However, most of these plants, due to the lack of competitiveness in a context of cheap crude, have already closed or are under hibernation.

2.3.5. Levulinic acid (LvA)

Levulinic acid is a C5 chemical, also called γ-ketovaleric acid or 4-oxopentanoic acid, classified within the group of short chain fatty acids (Fig. S1). It is a versatile green chemical because of its high reactivity and functionality, and thus, it has been used as precursor to biofuel additives like ethyl levulinate. LvA has received much attention from researchers over the last 15 years (see Fig. 1), since its use as starting material in the synthesis of a wide variety of important chemicals, such as γ-valerolactone (GVL), and diphenolic acid, as well as several alkyl valerates and ketones, among others. Its synthesis is carried out from hexoses (glucose, fructose) or starch in an acid medium under high pressure and temperature conditions. Regarding LvA commercial production, Quaker-Oats developed in 1953 the first continuous process for its synthesis. However, due to the multiple challenges to face, including catalyst selection and effective product recovery (Schmidt et al., 2017) the commercial production of this chemical was delayed until 2015, when GFBiochemicals starting it by using lignocellulose as raw material.

2.3.6. Adipic acid (AA)

Adipic acid or hexanedioic acid (Fig. S1) is a dicarboxylic acid derivative from hexane. It is the most important dicarboxylic acid industrially produced with an overall estimated production of about 2.5 billion kilograms per year with a market value of almost USD 6 billion, growing at a compound annual growth rate of 3–5%. Its most widespread application is as a precursor for the production of nylon, but it also finds uses in the production of plasticizers and polyurethanes, and as additive in food and pharma industries. Current production routes rely on petrochemical precursors, the most common starting from benzene (Polen et al., 2013). Biobased production of adipic acid is currently under development (Beardslee and Picataggio, 2012).

2.3.7. Lactic acid (LA)

Lactic acid is an alpha-hydroxy acid (AHA) (Fig. S1) bearing a high functionality in a 3-carbon backbone, making it a highly versatile molecule. It is present in most of living organisms and thus its natural occurrence is the highest among the products in this list. Lactic acid is used as a synthetic intermediate in organic synthesis such as in the production of alkyl lactates, lactide, poly (lactic acid), and acrylic acid, among many others. The lactic acid is commercially produced through carbohydrate fermentation routes (Komesu et al., 2017). However, lactic acid has a high affinity for water and tends to oligomerize at high temperatures. For this reason, purifying lactic acid turns out to be one of the most important stages of the production process. It is possible to find several biomasses that make the process valuable and environmentally advantageous (Juodeikiene et al., 2015).

2.3.8. Ethylene (ETN)

Ethylene is the shortest hydrocarbon olefin, widely used in the chemical industry (Fig. S1). Its production currently exceeds 150 million tons (230 million tons by 2030), and it is mostly based on steam cracking of larger hydrocarbons. In the last decade, several alternative, both biochemical and thermochemical, technologies have been proposed to produce ethylene from lignocellulosic biomass. For instance, first-generation bioethanol to ethylene is a well-established pathway in which ethanol is fermented from starch (e.g., corn or wheat) or sugar (e.g., cassava or sugarcane) feedstocks, and then subsequently dehydrated to ethylene (Restrepo-Flórez and Maravelias, 2021).

3. Results and discussion

3.1. LCA meta-analysis

The LCA meta-analysis has been performed through six critical aspects: the definition of the initial conditions (i.e., system boundaries and functional unit definition), the perspective followed (attributional or consequential), data gathering and management (i.e., inventory construction, data quality, and uncertainty), multifunctionality handling, impact assessment, and carbon flow considerations.

3.1.1. Definition of initial conditions

The basis for any comparison between two LCA studies is the function(s) it provides, and the reference flow chosen as the basis for calculations. The aim of biorefineries is to deliver several valuable outputs from a single (and complex) input (Ubando et al., 2020). In this context, the selection of these parameters is already challenging. Looking at the studies within this review, reference flows are more or less comparable depending on the considered molecule. For instance, all ethylene (ETN) LCAs are based on the mass of ETN produced, while only three out of nine furfural (FUR) studies consider FUR output as the reference flow. Succinic (19 LCAs) and lactic (16 LCAs) acids receive great attention, and consequently almost 90% of the studies use these two molecules as the only output to define the reference flow.

It is noteworthy that the difference between reference flow and functional unit is not always clear, and in many cases, the last is omitted. That can imply errors when determining the conditions required to fulfill the function(s) provided by the system. In this sense, the attributional or consequential perspective followed, as well as the method used to solve the multifunctionality, play a decisive role, as discussed later.

As for the system boundaries, 86% of the studies reported a cradle-to-gate scope (Fig. 2). That is coherent considering that the reviewed molecules are intermediate products that can follow multiple downstream pathways. Furthermore, most of these molecules are drop-in chemicals, so that effects occurring after the factory gate can be considered to be the same to those observed for analogue molecules obtained from non-biomass resources (Miller and Keoleian, 2015; Yao and Masanet, 2018). However, the scarcity of data could be slightly alleviated by including information related to well-stablished technologies for petrochemical counterparts production, as it would serve as a benchmark reference. Additionally, carbon fate has a profound effect on the results, so that including end-of-life (EoL) scenarios could provide further insights about product system behavior (Adom and Dunn, 2017; Adom et al., 2014; Hertwich et al., 2015).

Cradle-to-grave boundaries are covered most notably in the case of succinic (21%) and lactic acids (19%). That is in line with the state-of-the-art regarding the technologies to produce the main commodities derived from them: polybutylene succinate (PBS) (Platnieks et al., 2021) and poly (lactic acid) (PLA) (Jem and Tan, 2020).

3.1.2. Attributional and consequential perspective

The attributional approach (ALCA) is the most common way to perform LCA studies on bio-based platform molecules (Fig. 3). This type of analysis assesses the proportional share of the global impacts attributable to the function (product) under study and it is based on average data. As opposed to that, the consequential approach (CLCA) focuses on the changes implied by the use of the analyzed function (e.g., the production of bio-based FDCA would entail a decrease in the demand of fossil-based terephthalic acid), and thus it requires the use of marginal data. Extensive discussion about ALCA and CLCA perspectives can be found elsewhere (Venkatachalam et al., 2018; Ekvall, 2020).

It is noteworthy that most of ALCA studies are unspecified (i.e., authors do not mention they are following the attributional approach). In fact, more than 80% of the case studies do not provide that information, probably because this seems to be the default approach. In contrast, despite CLCA is less frequent, this type of analysis is indicated in the vast majority of the cases when used. There might be different reasons for explaining the difference. In the first place, attributional LCA is easier to conduct: the availability of average data, the more intuitive analysis, and avoiding the need for competing processes data, makes it reachable to a wider number of practitioners. On the contrary, dealing with external processes in the consequential approach also involves expanding the boundaries to consider the implications related to the functions provided by the system. That itself is a complex task and it is frequently confused with partitioning the impacts by substitution, typical of the attributional perspective. In addition, the interpretation of the results is more straightforward in the case of the attributional approach. This facilitates the analysis and communication of the environmental implications of the system under study to third parties (stakeholders, researchers, public opinion, etc.). Finally, since ALCA is the prevalent way of analysis, related publications have a broader context to rely on when following this approach. Bearing all that in mind, it is foreseeable that most practitioners prefer the attributional analysis, both for simplicity (more reported) and because it requires a shallower knowledge of the methodology and product system (mostly unspecified), and therefore is less time-consuming.

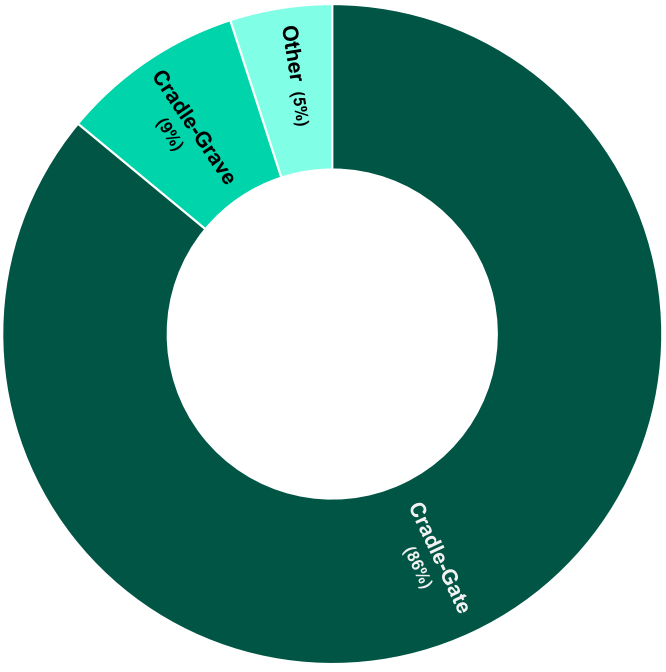

Fig. 2. System boundaries reported in the analyzed LCA studies. The category "Other" include "gate-to-gate", and "gate-to-grave" scopes, as defined by the authors.

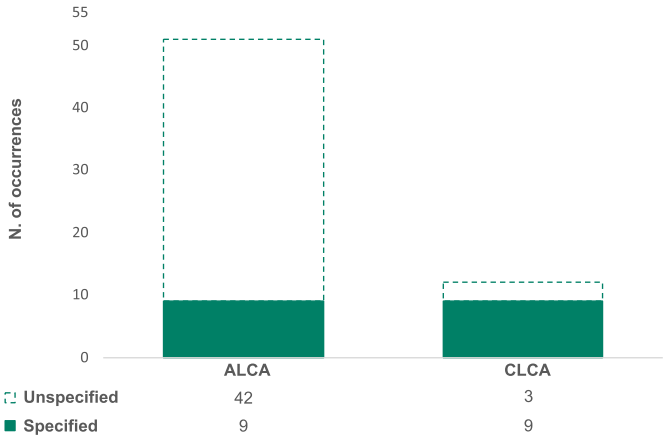

Fig. 3. LCAs with attributional (ALCA) and consequential (CLCA) focus. Filled portion of the bar represent the studies that specify the perspective followed, while hollow portion of the bar indicate the studies that do not mention it. In the second case, authors of this review deduced the followed approach.

The extra knowledge required to account for the interrelated processes within the analysis, aiming to expand the function of the product system, seems to restrict the application of CLCA to the more mature technologies. Thus, from the total twelve consequential analysis reported, six allude to lactic acid and four to succinic acid (see Table 2).

3.1.3. Multifunctionality handling

The concept of multifunctionality refers to the ability of a system to simultaneously produce several products within a time frame. In these cases, assigning all the environmental loads only to the reference product would lead to distorted results, as they would not reflect the totality of the consequences of the process under study. For this reason, there are different strategies for correctly distributing these impacts. The most common are: avoidance of allocation (by subdivision, substitution or expansion of the system), allocation based on physical relationships such as mass, or allocation based on non-physical relationships such as economic value.

Multifunctionality is expected to be solved mostly by allocation of the impacts between the different by-products. Indeed, allocation based on the economic value of system outputs is the most common method within the analyzed studies (21 occurrences). Fig. 4 depicts the aggregation of methodologies in three levels following the recommendations of the ISO 14044:2006 (ISO 14044, 2006) and the International Life Cycle Data system Handbook (ILCD) (European Commission, 2010). Thus, level one (LV-1) considers studies in which impact allocation is

Table 2
Complete list of reviewed studies.

Ref.	Definition			Data Collection	Multioutput Handling		LCIA [c]		Uncertainty		
	System Boundaries	Reference Flow	Perspective [a]	Primary Foreground Data [b]	Credits for by-products	Method	Method	Impact Focus	Parametric	Scenario	Data Quality
Morales et al. (2015b)	Cradle-Gate	1 Kg LA	CLCA	X	X	SE	CED | IPCC | EI-99 [e]	Midpoint| Endpoint		X	
Daful et al. (2016)	Cradle-Gate	1Ton LA	*ALCA*		X	*SB*|EA	ReCiPe (H)	Midpoint	X	X	
Adom and Dunn (2017)	Cradle-Gate| Cradle-Grave	1 Kg LA	*ALCA*				GREET	Midpoint	X	X	
Parajuli et al. (2017)	Cradle-Gate	1 MJ ethanol + 1 Kg LA	ALCA|CLCA		X	SE|EA	EDP | ReCiPe (H)	Midpoint	X	X	
Gezae Daful and Görgens (2017)	Cradle-Gate	1Ton LA	*ALCA*		X	*SB*|EA	ReCiPe (H)	Midpoint		X	
Mandegari et al. (2017)	Cradle-Gate	1Ton LA	ALCA		X	EA	CML	Midpoint		X	
Helmes et al. (2018)	Cradle-Gate	1 Kg LA + co-products	*CLCA*	X	X	SE,SD	ReCiPe (H)	Midpoint| Endpoint	X	X	
Awiszus et al. (2019)	Cradle-Gate	1 kW h electricity	*ALCA*	X	X	SB|EA	IPCC | ReCiPe (H)	Midpoint		X	
Ögmundarson et al. (2020)	Cradle-Grave	1 Kg LA	*CLCA*		X	SE	ReCiPe (H) | SWB	Midpoint| Endpoint	X	X	X
Khoshnevisan et al. (2020)	Cradle-Gate	1Ton biopulp	CLCA	X	X	SE	Impact 2002+	Endpoint	X	X	
Fei et al. (2020)	Cradle-Gate	1 Kg LA	ALCA				TRACI	Midpoint			
Pachón et al. (2020)	Cradle-Gate	1 Kg LA	*ALCA*		X	EA	ReCiPe (H)	Midpoint	X	X	
Albizzati et al. (2021)	Cradle-Grave	1 Kg LA	CLCA	X	X	SE	ILCD	Midpoint	X	X	
Lee et al. (2021)	Cradle-Gate	1 Kg LA | 1 Kg waste	*ALCA*		X	SB	IPCC	Midpoint	X	X	
Munagala et al. (2021)	Cradle-Gate	1 Kg LA	*ALCA*	X	X	EA	ReCiPe (H)	Midpoint| Endpoint	X	X	
Li et al. (2021)	Gate-Gate	1 Kg LA	*ALCA*				GREET	Midpoint	X	X	
Cok et al. (2014)	Cradle-Gate	1 Kg SA	*ALCA*	X	X	SB|MA| EA	CED | IPCC	Midpoint	X	X	
Adom et al. (2014)	Gate-Grave	1 Kg SA	*ALCA*				GREET	Midpoint	X	X	
Gnansounou and Kenthorai Raman (2016)	Cradle-Gate	1 Kg biodiesel	*ALCA*	X	X	*SB*	ReCiPe (E) | GDVP[f]	Midpoint		X	
Morales et al. (2016)	Cradle-Gate	1 Kg SA	*ALCA*				CED | IPCC | EI-99	Midpoint| Endpoint		X	
Moussa et al. (2016)	Cradle-Gate	1 Kg SA	*ALCA*	X	X	*SB*	IPCC	Midpoint		X	
Zucaro et al. (2017)	Cradle-Gate	1 Kg SA	*ALCA*	X			CED | IPCC	Midpoint		X	
González-García et al. (2018)	Cradle-Gate	1 Kg SA	ALCA				CED | CML	Midpoint		X	
Cai et al. (2018)	Cradle-Gate	1Ton SA |1 MJ| 1 year	*ALCA*	X	X	SB|MA| CE,EA	GREET	Midpoint	X	X	
Brunklaus et al. (2018)	Cradle-Gate	1Ton SA | 1Ton food waste	*ALCA*		X	MA	Unspecified	Midpoint	X	X	
Foulet et al. (2019)	Cradle-Gate	1000Ton SA	*ALCA*	X	X	EA	CML	Midpoint	X	X	
Nieder-Heitmann et al. (2019)	Cradle-Gate| Cradle-Grave	1 Kg SA| 1 Kg bioproduct| 1 kW h	ALCA		X	MA|EA	CML | IPCC | WSI | Impact 2002+	Midpoint| Endpoint	X	X	
Hafyan et al. (2020)	Cradle-Gate	1 Kg SA	*ALCA*				IPCC	Midpoint			
Gadkari et al. (2021)	Cradle-Gate	1 Kg SA	*ALCA*		X	MA	CED | IPCC	Midpoint		X	
Stylianou et al. (2021)	Gate-Gate	1 Kg SA	*ALCA*	X			CML	Midpoint			
Shaji et al. (2021)	Cradle-Gate	1 Kg SA	*ALCA*	X	X	EA	ReCiPe (H)	Midpoint			
Dickson et al. (2021)	Cradle-Gate	1 Kg SA	CLCA		X	SE	CML	Midpoint			
Bello et al. (2022)	Cradle-Gate	1 Kg SA	ALCA|CLCA	X	X	SE|MA| EA	ReCiPe (H)	Midpoint	X	X	
Khoo et al. (2015)	Cradle-Gate	1 Kg 2-MeTHF [d]	*ALCA*				CML | IPCC | KWTIS [g]	Midpoint		X	
González-García et al. (2016)	Cradle-Gate	100 Kg wood chips | 1€ LvA	ALCA	X	X	Other	ReCiPe (H)	Midpoint		X	
Sadhukhan and Martinez-Hernandez (2017)	Gate-Grave	1Ton municipal solid waste	CLCA		X	SE	CML | Impact 2002+	Midpoint			

(*continued on next page*)

Table 2 (*continued*)

Ref.	Definition			Data Collection	Multioutput Handling		LCIA [c]		Uncertainty		
	System Boundaries	Reference Flow	Perspective [a]	Primary Foreground Data [b]	Credits for by-products	Method	Method	Impact Focus	Parametric	Scenario	Data Quality
Isoni et al. (2018)	Cradle-Gate	1 Year	*ALCA*				Unspecified	Midpoint		X	
Khoo et al. (2019)	Cradle-Gate	1000KTon LvA	*ALCA*				CML | IPCC | KWTIS [g]	Midpoint		X	
Kapanji et al. (2021)	Cradle-Gate	1 Kg LvA	ALCA		X	EA	CML | AWARE | EI-99	Midpoint	X	X	
Hong et al. (2015)	Cradle-Gate	1 Kg furfuryl alcohol	*ALCA*		X	MA	ReCiPe (H)	Midpoint	X		
Raman and Gnansounou (2015)	Cradle-Gate	1 Km (Well to Wheel)	*ALCA*				ReCiPe (E)	Midpoint	X	X	
Aristizábal-Marulanda et al. (2020)	Cradle-Gate	1 Kg product	*ALCA*	X			ReCiPe (H)	Midpoint		X	
Schöppe et al. (2020)	Cradle-Gate	1 Kg FF	*ALCA*				Unspecified	Midpoint			
Putra et al. (2021)	Cradle-Gate	1 Kg dissolving pulp	CLCA	X	X	SE	CML	Midpoint	X	X	
Thompson et al. (2021)	Gate-Gate	1Ton FF	*ALCA*	X			CML	Midpoint	X	X	
Lam et al. (2018)	Cradle-Gate	1 Kg food waste	*ALCA*	X			ReCiPe (H)	Midpoint| Endpoint		X	
Bello et al. (2018)	Cradle-Gate	1 Kg FDCA/h	*ALCA*		X	EA	ReCiPe (H)	Midpoint		X	
Isola et al. (2017)	Cradle-Grave	1 g biopolymer	*ALCA*	X			ReCiPe (H)	Midpoint	X	X	
García et al. (2018)	Cradle-Gate	1 Kg biopolymer binder	ALCA	X	X	EA,EnA	CED | GGP | ReCiPe (H)	Midpoint	X		
Bello et al. (2020)	Cradle-Gate	1 Kg FDCA/h	*ALCA*		X	EA	ReCiPe (H)	Midpoint	X	X	
Kim et al. (2020)	Cradle-Gate	1 Kg FDCA	*ALCA*	X			ReCiPe (H)	Midpoint			
Hong et al. (2014)	Cradle-Gate	1Ton ETN	*ALCA*		X	MA	ReCiPe (H) | Impact 2002+	Midpoint| Endpoint	X	X	
Liptow et al. (2015)	Cradle-Gate| Cradle-Grave	50KTon ETN	ALCA		X	EA	Unspecified	Midpoint		X	
Yang et al. (2018)	Cradle-Gate	1 Kg ETN	*ALCA*		X	EA	Unspecified	Midpoint			
Alonso-Fariñas et al. (2018)	Cradle-Gate	1Ton ETN	ALCA		X	SB | EA, EnA	CML	Midpoint		X	
Zhao et al. (2018)	Cradle-Gate	1Ton ETN	*ALCA*		X	MA	Unspecified	Midpoint			
Somoza-Tornos et al. (2020)	Cradle-Gate	1 Kg ETN | 1 Kg waste polyethylene	CLCA		X	SE	ReCiPe (H)	Midpoint| Endpoint			
Akmalina and Pawitra (2020)	Cradle-Gate	1 Kg ETN	*ALCA*				CML	Midpoint			
van Duuren et al. (2011)	Cradle-Gate	1Ton AdA	*ALCA*	X			Unspecified	Midpoint			
Aryapratama and Janssen (2017)	Cradle-Gate	1 Kg AdA	ALCA	X	X	EA	CED | CML	Midpoint	X	X	
Corona et al. (2018)	Cradle-Gate	1 Kg AdA	CLCA	X	X	SE	IPCC | TRACI	Midpoint	X	X	
Duuren et al. (2020)	Cradle-Gate	1Ton AdA	*ALCA*	X			CED | IPCC	Midpoint			
Choe et al. (2021a)	Cradle-Gate	1 Kg biofuel	*ALCA*		X	MA	ReCiPe (H)	Midpoint	X		
Choe et al. (2021b)	Cradle-Gate	1 Kg ethanol	*ALCA*		X	MA	ReCiPe (H)	Midpoint	X		

[a] Concepts in italics represent information adapted to the definitions used within this work (rather than specified by the authors).
[b] Data obtained from simulations based on literature data have been considered as a secondary source.
[c] The information on indicators has been excluded from the table for reasons of simplicity, as it is too long and redundant.
[d] 2-Methyltetrahydrofuran.
[e] Ecoindicator-99.
[f] As described in Gnansounou et al. (2009).
[g] As described in Khoo et al. (2015)

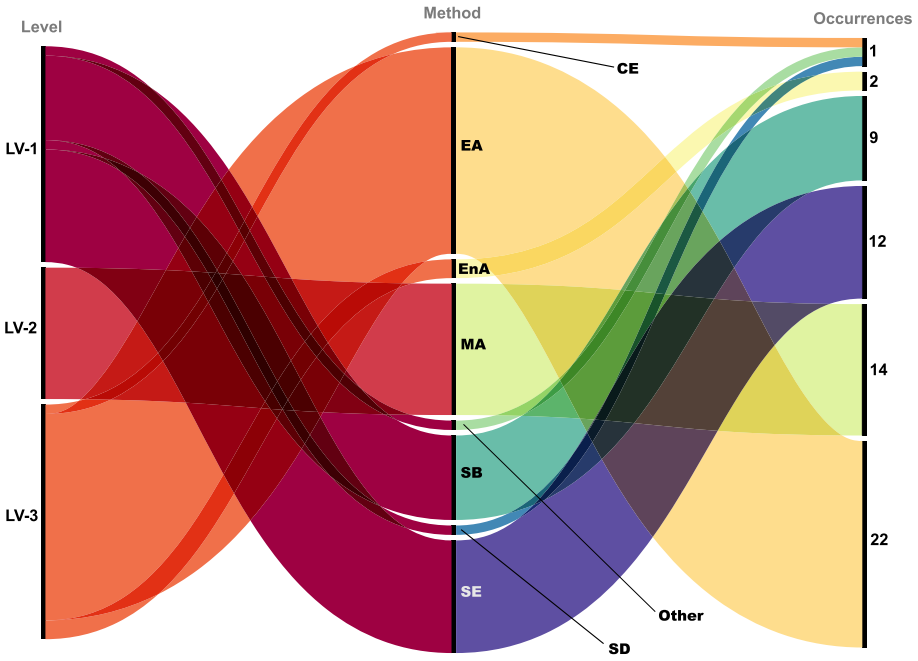

Fig. 4. Method used for multifunctionality handling. Level classification: LV-1: avoid allocation; LV-2: allocation based on physical relations; LV-3: allocation based on non-physical relations. Method classification: LV-1 (SB: Substitution | SE: System expansion | SD: Subdivision | Other); LV-2 (MA: Mass allocation); LV-3 (EA: Economic allocation | EnA: Energy allocation | CE: Carbon efficiency allocation).

avoided, level two (LV-2) includes approaches which allocate impacts based on physical relations, and level three (LV-3) comprises those works allocating the impacts based on non-physical relationships. That considered, it is possible to discern two overall findings. First, multifunctionality is addressed in a very heterogeneous way, and the only practice that garners more consensus than the others seems to be the economic allocation. Second, the recommended hierarchy for solving these systems does not match the real practice, being LV-3 methods approaches the most reported.

One plausible cause for this trend might be the intelligibility of the results. Allocating the impacts among the different by-products relying on practical parameters (i.e., mass or economic value) is more intuitive than considering external systems to subtract their effects or subdivide a process attending to complex interactions. As an example, differences between substitution and system expansion are usually fuzzy, and the first is frequently reported as the expansion of the system boundaries. To account for this, we used the definition provided by Heijungs et al. in (Heijungs et al., 2021), where authors claim that more efforts in the differentiation between these two concepts should have been included in the second amendment (2020) of the ISO 14044:2006 (International Organization for Standarization, 2020). Accordingly, expansion is considered when system boundaries are actually broadened to provide an integrated function containing the different products yielded. Conversely, substitution implies the isolation of the functional unit, deducting the burdens avoided by the co-generated products. Results in Fig. 4 and Table 3 are shown adapted to this definition, aiming to homogenize the analysis.

Mass allocation is less reported than economic allocation, and it is relegated to steadier systems (e.g., cultivation and harvesting in the case of agricultural raw materials) to consider upstream effects. Although economic value is regarded by some authors as a more reliable way to account for predictable trends in an economic-driven context (Mandegari et al., 2017), fluctuations in the value chain might introduce significant errors. Therefore, this type of allocation should not be applied unless justified. Nevertheless, accurately ascribing the effects of both the economic and physical systems is virtually impossible in attributional modeling, unless mass and revenue balances are proportional (Weidema et al., 2018), thus favoring the avoidance of the allocation.

Table 3
Method used for multifunctionality handling.

Molecule	LV-1				LV-2	LV-3		
	SE	SB	SD	Other	MA	EA	EnA	CE
LA	6	4	1			8		
SA	4	4			6	6		1
LvA	1			1	3	1		
AdA	1	1			3	2		1
FAL	1				2	2		
HMF						1		
FDCA						3	1	
ETN	1	1			2	3	1	

Level classification: LV-1: avoid allocation; LV-2: allocation based on physical relations; LV-3: allocation based on non-physical relations. Method classification: LV-1 (SB: Substitution | SE: System expansion | SD: Subdivision | Other); LV-2 (MA: Mass allocation); LV-3 (EA: Economic allocation | EnA: Energy allocation | CE: Carbon efficiency allocation).

Results in Table 3 list data previously depicted in Fig. 4, but itemized by molecule. The sum of all studies following each method is superior to the total in this review. The reason is that some authors provide more than one method for solving multifunctionality, both for considering different process stages (Morales et al., 2015b) (e.g.: upstream and downstream) or for evaluating the influence of this decision on the results (Cai et al., 2018; Bello et al., 2022). Also, some of the reviewed LCAs provide information about more than one product, so they are considered in this analysis in more than one molecule. This double counting is subtracted in Fig. 4 for analysis purposes.

Additionally, LV-1 methods require deeper knowledge of the product system. That is noticed again in the case of lactic (11 occurrences) and succinic (8 occurrences) acids.

3.1.4. Data collection, quality, and uncertainty

Uncertainty is a critical aspect when approaching an LCA study. There are various sources of uncertainty (Heijungs and

HuijbregtsOsnabrük, 2004; Bojacá and Schrevens, 2010), although one of the most widely accepted classifications is that defined by Huijbregts et al. (2003), which differentiates three sources: parametric, scenario and model. The first refers to the low representativeness or absence of data, the second is related to normative choices, and the third to the characterization methodology employed.

In the case of the studies included in this review, although a good number of them evaluated the parametric uncertainty, most cases approached uncertainty through scenario analysis. Thus, we focus on the methods to deal with these specific sources of variability, leaving aside model uncertainties. Reporting parametric uncertainty is not as straightforward as scenario building and comparison. Therefore, several methods have been developed. According to Mahmood et al. (2022), some valid approaches are the pedigree matrix, sensitivity analyses, and sampling, analytical, and statistical methods. All these approaches are shown in Fig. 5, except for statistical methods since none were found.

A brief introduction to these methodologies is given below to facilitate the discussion. Concerning parametric uncertainty, two factors are relevant to its study. First, a variability is assigned to inputs and then it is propagated through all calculations to evaluate its effect on the outputs. Assuming that most of the uncertainty comes from the stochastic nature of the system, the most common approach is to assign a probabilistic distribution of the initial parameters. For this purpose, the pedigree matrix (Weidema and Wesnæs, 1996) defines five qualitative indicators (i.e., reliability, completeness, and temporal, technological and geographical representativeness) which are assigned a value that is used to generate a lognormal distribution. A simplified approach, also widely used, is to assign an arbitrary normal, uniform, or triangular distribution based on scientific evidence or expert judgment. That is the basis for analytical models, while sampling models involve defining specific functions based on individual measurements of each input parameter. Alternatively, local sensitivity analyses allow determining which parameters lead to larger deviations in the results if they are modified. These are also known as perturbation analyses and are conventionally used for the identification of critical parameters (i.e., those that would explain most of the parametric uncertainty). These analyses are also often used *per se* to provide model sensitivity ranges. That is similar to scenario studies, where outputs are compared when varying inputs or methodological decisions (e.g., type of allocation, functional unit, etc.).

Looking at Fig. 5, one consideration is necessary. Most of the investigated studies refer to methodologies for uncertainty propagation, rather than the definition of uncertainty on the input parameters. Bearing this in mind, and the classification defined by Mahmood et al. (2022), models for uncertainty propagation such as Monte Carlo or Latin Hypercube are considered sampling methods, while some others such as the use of Taylor series, are classified as analytical methods.

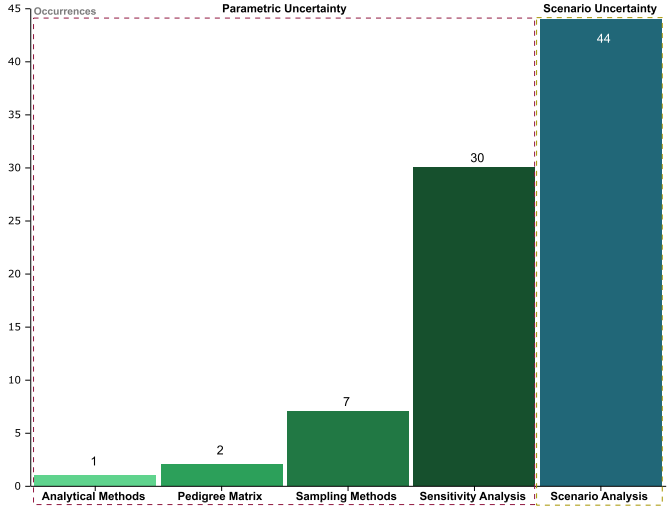

Fig. 5. Methods used for the evaluation of parametric (red-dotted box) and scenario (yellow-dotted box) uncertainty. The methods for assessing parametric uncertainty are further divided into the pedigree matrix, sensitivity analysis, and analytical and sampling methods. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

The difference between the use of sensitivity and scenario analysis and the rest of the methodologies is notorious, as evidenced in Fig. 5. The reason underlying this difference is clear: these formulas are more straightforward and their interpretation is simpler. Additionally, in the case of scenario analysis, its more frequent use can be related to its usefulness for purposes beyond the study of uncertainty, such as the comparison of different operating configurations or the location of a production plant. In a context marked by the low maturity of the considered technologies, this type of analysis is clarifying as it provides a range of possible outcomes. On the other hand, perturbation analyses reliably identify the parameters whose uncertainty may lead to results that are farther from reality. Thus, they should be accompanied by the study of parametric errors in a greater number of cases than those shown in Fig. 5. For this purpose, the most repeated methodology is the propagation of uncertainty by Monte Carlo analysis. Six of the seven cases of sampling methods in Fig. 5 refer to this approach, while the remaining one is a Latin Hypercube analysis (Li et al., 2021). On the other hand, the only manuscript using an analytical method refers to an evaluation using the Taylor series (Hong et al., 2014). All this is in line with the tools integrated into the most common LCA software, which frequently include modules for scenarios, sensitivity and Monte Carlo analyses.

Finally, it is noteworthy the scarce number of studies reporting the use of the pedigree matrix, only two, despite its implementation is easier than other methods when using widespread LCA utilities such as the SimaPro software and the Ecoinvent database, both of which are the most reported tools. Moreover, this contrasts with previous studies, as Thonemann et al. (2020) identified the utilization of the pedigree matrix as the most extended method to assess data quality. Possibly the number could be higher, although this information was not always provided. Furthermore, from these two studies, only one of them reports data on quality indicators (Ögmundarson et al., 2020). Overall, data quality receives little attention, and this is the only study that provides quantitative information. Again, in a context dominated by low TRL, data quality can be very influential over the results (Guo and Murphy, 2012; Wender et al., 2014; Piccinno et al., 2016; Bicalho et al., 2017). Most of the data reported for the foreground system is supported by secondary data (Fig. S2). The main source of information is literature (including patents, book chapters, etc.), often in combination with the up-scale simulation of these secondary inputs. On the other hand, primary data usually rely on experimental work, although some pilot and industrial scale data are available for succinic acid processes (Cok et al., 2014; Zucaro et al., 2017). In this context, the inclusion of data quality indicators might help to compensate for the lack of primary sources. In this regard, the method proposed by the European Commission (Directorate-General for Environment, 2021) also makes use of temporal, geographical, and technology representativeness, as well as precision, to evaluate data quality and would perfectly meet this purpose.

3.1.5. Life cycle impact assessment

The life cycle impact assessment (LCIA) phase is subjected to multiple methodological divergences regarding the calculus method applied, the impact categories considered, and the indicators used for their quantification. In order to ascertain which are the most widespread options for LCIA in this complex analysis context, we have first outlook LCIA methods and stablished relationships with the reported categories and indicators. For the sake of clarity, categories are aggregated considering the framework adapted from the ILCD Handbook (Fig. S3). This classification is performed to facilitate the comparison between works by overseeing the differences in the naming of some categories. As an example of the purpose of this analysis, consider indicators called

"water consumption", "water depletion" and "water use". These are redefined as a single indicator called water use (WU) and collected within the Resource Depletion (RD) category shown in the right column of Fig. S3. In this categorization, endpoint categories and areas of protection (AoPs) are disregarded. This simplification is accepted given that 98.5% of the reviewed studies consider the impact attribution based on a midpoint focus, while only 17% (i.e., 11 articles) provide further endpoint values.

Attending to the results in Fig. 6, the hierarchist perspective of the ReCiPe model (Huijbregts et al., 2016) is the most used method to translate the results at the inventory level to actual impacts. The broad consensus around this model might arise from its long trajectory and the diversity of actors involved on its development, including academia, the private sector, and the public administration. That enables covering a great number of topics, and thus, some categories are studied almost exclusively with the ReCiPe (H), such as it is the case for the land use (LU). The CML 2001, developed by the Institute of Environmental Sciences of Leiden University (Guinée and Lindeijer, 2002), is the second most reported LCIA model. Other relevant models include Impact 2002+ (Jolliet et al., 2003), and TRACI (Bare, 2014).

The climate change category is not only the one most reported by the authors, but also the one with the greatest division of models for its calculation. As depicted in Fig. 7, at least eleven methodologies are identified for the calculation of the global warming potential (GWP, main indicator for climate change effects). In addition to the previous ones, the method developed by the Intergovernmental Panel on Climate Change (IPCC) has a prominent use in the estimate of the climate change, and most of the considered works rely on the fifth assessment report (AR5) published by the Panel (Meyer et al., 2014), given the time range of the reviewed studies. Even though, since then (2013), a refinement report for the estimate of greenhouse gas inventories was launched in 2019 (Calvo Buendía et al., 2019), and the contribution of working group I (WG1) of the sixth report is available since 2021 (Arias et al., 2021). This method is based on the concepts thoroughly provided by the WG1 in chapter 8 of the AR5. Given the large scientific authority of this publication, other models follow an almost identical approach to define critical aspects such as the impact pathway, the considered substances, or the characterization factors. In this way, all of them lead to closer results when calculating the GPW indicator as compared to other

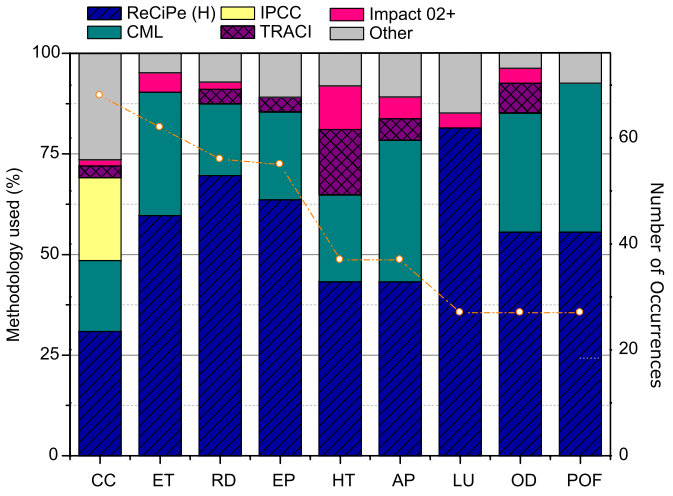

Fig. 6. LCIA methodologies reported for the most common impact categories. Bars filling color indicate the methodology used (%, left axis), while the orange dashed line represents the number of occurrences of each impact category (right axis). Categories displayed are CC: Climate Change; ET: Ecotoxicity; RD: Resources Depletion; EP: Eutrophication; HT: Human Toxicity; AP: Acidification Potential; LU: Land Use; OD: Ozone Depletion; POF: Photochemical Oxidants Formation. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

impact categories. The time horizon is a more intricate question. Further discussion considering these features within the reported LCIA models across the board would enrich the conclusions, but the version of the methodology is not usually reported, so that essential details are unavailable.

Regarding the frequency in the use of indicators, for some of them scarce references have been found (e.g., cancer and non-cancer effects, ionizing radiation, or particulate matter formation), and some are moderately reported (e.g., fossil depletion potential, freshwater ecotoxicity, or human toxicity). Within this point, it is remarkable that despite agricultural or forestry biomass being the raw materials for many bio-platform chemicals, indicators related to biodiversity or soil quality are barely reported. In the case of biodiversity, this is probably due to the lack of available methods for considering the main drivers of biodiversity cost (Teixeira et al., 2016; Damiani et al., 2022). On his part, soil indicators are usually related to land occupation and/or land transformation but not specifically to the determination of properties affecting its quality. Only GWP is thoroughly investigated, being considered in 93% of the studies. Furthermore, up to 10% of the published works rely solely upon this indicator (carbon footprint studies). This is a consequence of several coincidental factors. In the first place, scientific community is steeply devoted to understanding, alleviating, adapting, and communicating the climate change effects. Therefore, the physical basis and its implications are better understood, allowing for an accurate definition of the cause-and-effect chain. As a result, the amount of available and specific data is larger as compared to other categories and indicators (e.g., regionalized data, disaggregated inventories, etc.). Besides, as in the case of the ALCA vs CLCA section, a larger number of preceding studies including GWP as impact category are accessible, which might encourage new practitioners to undertake similar approaches. Finally, climate change is no longer a scientific-only concern but a socially relevant motif. As such, it is perceived as a crucial aspect above others.

Still, underlying any conclusions on one indicator might entail unfair outcomes as well as biased conclusions. In line with that, if the Environmental Footprint is considered as a reference, the communication of sixteen midpoint indicators is recommended. However, almost half of the reviewed studies reported four or fewer indicators ($\leq$25%) to substantiate their findings. Furthermore, their inclusion or exclusion is rarely justified.

3.1.6. *Carbon fate*

Among the particularities on the inclusion of climate change impacts in LCA works applied to biogenic products, time horizon considerations, biogenic carbon accounting (BCA), and the effects of direct and indirect land-use changes (dLUC and iLUC) have been the focus of extensive debate. Fig. 8 provides an overall picture of the application of these features in the considered publications. Regarding the relation between time horizon and biogenic carbon, two scenarios are defined: carbon neutral (CN) and carbon storage (CS) scenario. Carbon neutral scenario assumes a lifespan for the evaluated product shorter than the time horizon envisaged for the study, so that carbon absorbed during biomass growth is released into the atmosphere within the temporal boundaries of the analysis. On the other hand, assumption for carbon storage scenario is just the opposite. Consequently, carbon remains absorbed in the product and it is deducted from the emissions inventory.

Most authors do not specify how biogenic emissions are handled in the considered studies, as evidenced in Fig. 8. Thus, it is expected that the most probable situation in all these cases is that a neutral scenario is considered. That can be presumed since the deduction of biogenic emissions, if practiced, is foreseeable to be communicated within the methodology of the study. According to Wiloso et al. (2016), although many studies assume a neutral scenario, this might conduct to misleading results, since many particularities, such as the form of the emissions or the soil carbon stocks are disregarded. In the same sense, Liu et al. (2017) demonstrated that neutral scenario is limited on its

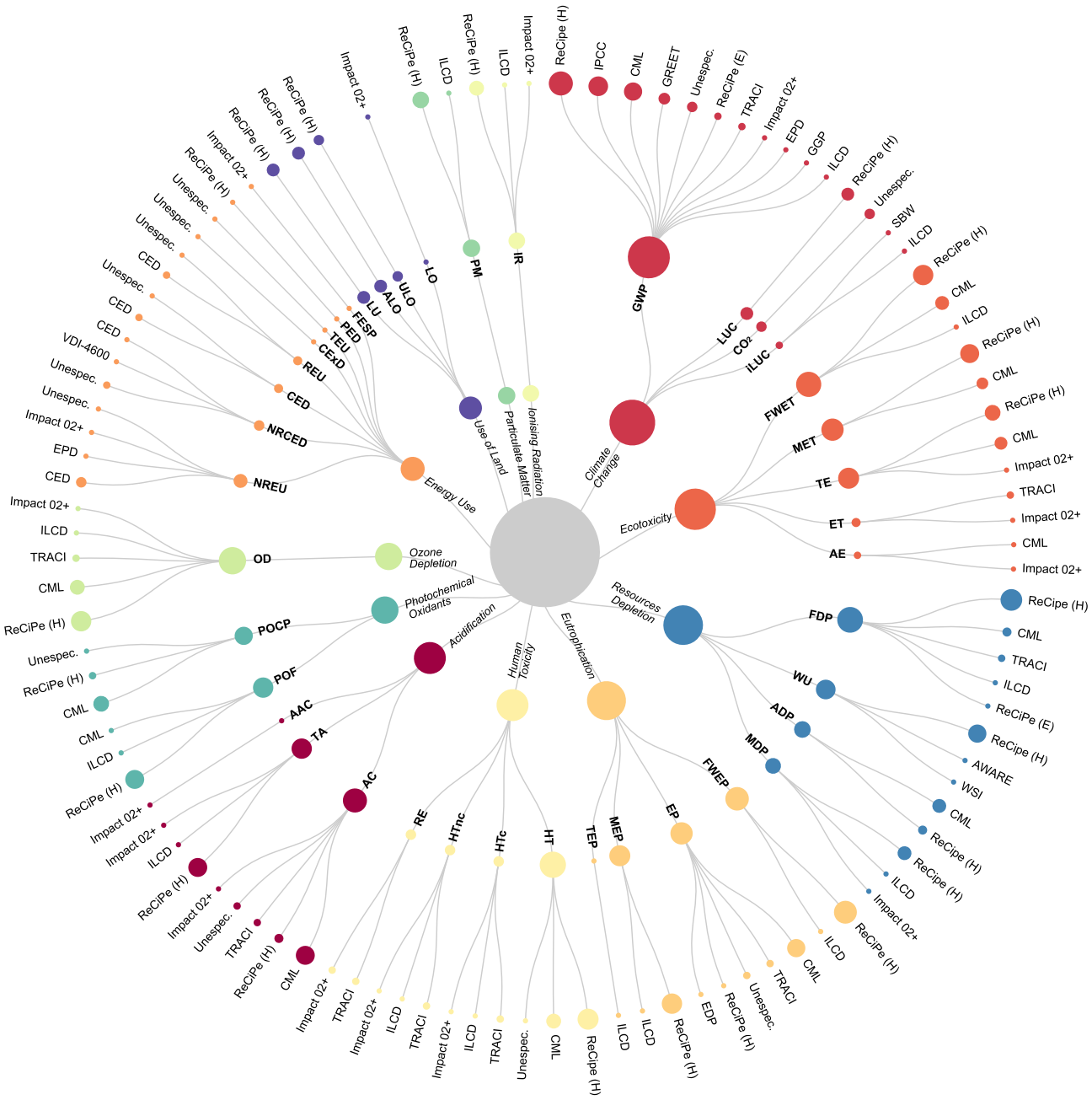

Fig. 7. Information is described from internal circumference outwards. First circumference: Environmental categories. Second circumference: indicators reported to quantify the environmental categories. Third circumference: LCIA methods to assign values to the indicators. Size of the colored circles relates to the number of occurrences. For clarity, abbreviations in the figure are compiled in the abbreviations section.

predictions due to complex interactions, such as the required time for crop rotation (or biomass growth rate) as compared to the product lifespan. The sensitivity regarding the time considered for CO_2 uptake during biomass growth is also ratified by Garcia et al. in (Garcia et al., 2020) by analyzing the implications of five existing allocation methods at the EoL stage and six BCA protocols in a multi-output wood-based cascade system. Also, long time lags between carbon uptake and emission are identified by Liptow et al. (2018) as a determining factor that can disfavor routes based on slow-growing biomass.

A different approach to solve temporary issues in the accounting of carbon flows is the application of a dynamic assessment (Levasseur et al., 2013). The dynamic GWP consideration is based on the integration of the results from the variation over time of both the inventory inputs and the characterization factors. In this way, it tries to overcome the temporal inconsistencies resulting from the conventional analysis. In this sense, in 2010 Levasseur et al. (2010) proposed a dynamic expression of the GWP indicator. That definition has been recently updated by Ventura (2022) to overcome the weaknesses derived from the difference in the definition of the time horizon of the impact and the time during which this impact is observed. Temporal reconciliation of these two parameters ensures that all flows are considered for quantification during the analysis. Although this approach helps to alleviate the drawbacks of a single point, steady state assessment, no dynamic assessments were found within the reviewed LCAs, probably because the difficulties on its application.

Carbon release behavior is more easily appreciated in cradle-to-grave studies since the evaluation of different EoL options would yield a range of results. In the case of the platform molecules, as shown in Fig. 2,

Fig. 8. Counting carbon fluxes depending on the defined scenario (inner circumference), the scope of the study (intermediate circumference), and consideration of dLUC and iLUC (outer circumference).

cradle-to-gate boundaries are dominant. To solve that particularity in which the time frame needs to be set in a less tangible way, Pawelzik et al. (2013), evaluated different protocols for carbon counting by comparing both scopes. Most fair results were achieved using the European Commission's Lead Market Initiative protocol (European Commission, 2009), which advocates for biogenic carbon deduction in cradle-to-gate studies.

The assumptions necessary for the application of any methodology require an in-depth knowledge of both the protocol to be used and the process itself. As an example, in (Albizzati et al., 2021) Albizzati et al. provide a detailed discussion before allocating different factors to account for short- and long-term biogenic CO_2. Similarly, Liptow et al. separately reported biogenic CO_2 considering the peculiarities of their system (Liptow et al., 2015). Conversely, up to 34 studies did not specify the scenario assumed for biogenic CO_2 flows nor the effects regarding land use changes. The impact that this last aspect can have on the results makes it indispensable for robust conclusions, as suggested by Tonini et al. (2016). The consideration of the effects derived from direct and indirect land use changes can turn around the conclusions in comparative studies concerning bio- and fossil-based routes, which is a critical aspect when novel bio-based transformation technologies are being evaluated. Moreover, this analysis can be decisive when comparing different raw materials. For example, the implications of using primary resources (crops) versus secondary resources (residues) are worth comparing. In the first case, utilization of dedicated crops usually implies further land use to compensate for their original use, thus inducing indirect changes. In the case of using residues, there are different possible scenarios to be considered, depending on their present use. If these are currently used e.g. for animal feed manufacture or soil amendments, again the reduced availability of these resources will lead to additional production (thus generating an indirect land use change). However, if their current use is non-productive (e.g. stubble burning), a previously non-existent waste valorization will occur, which is expected to have distinctly positive consequences.

3.2. Discussion and recommendations

Establishing a framework to normalize the application of LCA to these context-specific cases is out of the scope of this review since the lack of flexibility might incur in a desultory analysis. Instead, we try to compare consensus methodologies with actual practice, aiming to narrow the gap within a plausible margin. In other words, we try to converge methodological decisions around models that better represent this specific reality, making easier a broader comparison between studies.

To do so, we have looked for common features in the selected works. Thus, three aspects are found to be ubiquitous among the reviewed assessments: cradle-to-gate scope (platform molecules), low TRL technologies (biomass-based novel developments), and multioutput systems (technologies based on biorefinery schemes). Insights on these three different aspects of the evaluated LCA studies are following disclosed.

3.2.1. Scope of the studies

As for the scope of the analyses, one of the main limitations in this regard, is the exclusion of use and end-of-life phases. Nevertheless, one fundamental objective of novel processes is to overcome the lack of

environmental sustainability of conventional refinery technologies. Bearing that in mind, downstream effects could be disregarded since drop-in chemicals would lead to identical impacts. However, there is one key aspect that cannot be overlooked: the accounting of carbon flows. This is a pivotal difference between bio and conventional products, and thus it should be addressed critically. In this sense, recommendation derived by Pawelzik et al. in (Pawelzik et al., 2013) seems the most accurate choice up-to-date. This recommendation proposes considering the deduction of biogenic emissions in cradle-to-gate studies where the product lifespan does not exceed the time frame of the study, as described in the European Commission's Lead Market Initiative protocol (European Commission, 2009).

Also concerning the topic of carbon flows accounting, although not usually considered, emissions arising from land-use changes are also a determining factor. How to address this issue is an ongoing debate, since its application is subject to uncertainty (Wicke et al., 2012; Daioglou et al., 2020). Even so, not considering the effects of land use change would lead to biased results. Biophysical (or deterministic) models generate more consensus. Among existing models, the framework developed by Schmidt et al. (2015) has a prominent unifying character since its applicable to all regions in the world, considers intensification, and fits both from an attributional and consequential perspective. In any case, this is an evolving issue and therefore it would be wrong to fix a single way of approaching it. Therefore, the main recommendation at this point must be to avoid ignoring both direct and indirect effects derived from changes in land use, as well as to provide the greatest possible transparency and justification when communicating the results.

3.2.2. Low TRL technologies

Regarding the maturity of the technology, the studies included within the scope of this review present a generalized prospective nature. Many authors have previously made efforts to build models adapted to this context (Wender et al., 2014; Thonemann et al., 2020; Hetherington et al., 2014; Cucurachi et al., 2018; Moni et al., 2020; Bergerson et al., 2020). Prospective LCA studies are characterized by their application to technologies with low technological maturity, and much of their inputs are based on projections. Therefore, this type of analysis requires a great effort to ensure data quality and to reduce and correctly communicate uncertainty. Nevertheless, the effort is well deserved, as the conclusions of prospective LCA are very useful for process design based on life cycle thinking, and thus, its use is becoming a general practice in recent years.

The key aspects identified in these works are well reflected in (Thonemann et al., 2020) by structuring the main challenges of prospective analysis in three blocks: comparability, data, and uncertainty. In this review we have focused on how to address uncertainty and data handling. In this context, scarcity of data and the complexities of up-scaling experimental results are two of the major sources of uncertainty. This can be partially overcome by coupling LCA studies with process design, for generating scenarios and the iterative optimization of the new technological developments from an environmental perspective (Azapagic and Clift, 1999; Pieragostini et al., 2012; Steimel et al., 2013; Guillen-Gosalbez et al., 2008; Guillén-Gosálbez et al., 2019; Su et al., 2021). Although this serves to alleviate the unpredictability of scaling-up, only the measurement of data quality and uncertainty can improve the robustness of the analysis. The assessment of data quality can help improving two things both decision-making and interstudy comparison. On the one hand, it provides an idea of the extent to which a study enables decision-making based on its results. If the quality of the data is acceptable, this decision will be more endorsed than if it is not, whereas if this parameter is unknown, the decision will be taken "blindly". On the other hand, it provides a more appropriate framework for inter-study comparison. In this way, a comparison between studies with good data quality will be more justified. Among the existing methodologies for data quality assessment, that described within the Environmental Footprint standard (Directorate-General for Environment, 2021) is intuitive, easy to implement, and comprehensive. We therefore suggest its application, although we emphasize that the most important thing is the calculation of this factor regardless of the model.

As seen in section 3.1.4, most studies include scenario analysis, and approximately 40% of them include sensitivity analysis, while the remaining assessments of parametric and model uncertainty are largely ignored. In this context, the analysis of different scenarios, taking into account different projections and giving flexibility to the models, is very positive and is in line with sound practice. Some critical aspects to be evaluated in this type of analysis might be the electricity and heat mix, the geographical scope, or the raw materials considered. On the other hand, parametric uncertainty is underrepresented. Although sensitivity analyses are of great interest, in our opinion it is a step that should be completed with the uncertainty analysis of the critical parameters to get solid conclusions for decision-making. To this end, the simplest way is by using the most consolidated tools in practice. Thus, the calculation of the uncertainty of the input parameters can be easily performed through the pedigree matrix (Weidema and Wesnæs, 1996), or the assignment of probabilistic distributions based on analytical methods (assumption of normal, uniform or triangular distributions according to expert criteria). For the propagation of this uncertainty throughout the calculations, Monte Carlo analysis generates reliable dispersions, and its application is straightforward since it is integrated into the main LCA software. On this basis, if we look at the approaches proposed by Mahmood et al. (2022), our recommendation would be, in a context so subject to variability, to follow the intermediate (Monte Carlo sampling + local sensitivity analysis) or advanced (advanced sampling + global sensitivity analysis) approaches, while studying different scenarios for parameters more subject to fluctuations.

3.2.3. Multifunctionality of the systems

Multifunctionality consideration is highly variable in the selected investigations. This is not only expected but beneficial since homogeneity in the criteria may work against the general interest. We have therefore attempted to define an appropriate hierarchy to guide decision-making rather than to unify the possible models. On the one hand, consequential analysis can cover a wider scope while avoiding problems in defining system boundaries. The latter is key in a projected environment, where a large number of elements are only assumptions. However, the low availability of marginal data makes it less applicable. In addition, basing the analysis on potential consequences may imply taking responsibility for actions outside the system. This would be an obstacle when communicating with stakeholders, although it is in any case preferable to circumvent impacts. On the other hand, attributional analysis is much more widespread and easier to apply. Also, the wide availability of data can often make it return more accurate results (at least for the time being). In this sense, in our view, a plausible scheme for resolving the multifunctionality of these processes could be the following.

i. At the top of the hierarchy the approach from the consequential perspective should be considered.
ii. If the scarcity of data made it unfeasible or unrepresentative, the system would be represented following an attributional approach applying the substitution methodology where necessary.
iii. If none of these models is suitable, a subdivision of the system as much as possible, and the application of a distribution of impacts based on mass ratios, as recommended by the standard (i.e., prioritizing physical relationships over others), should be favored.

This sequence conforms, in our view, to what is described in ISO 14044, although it goes a little further in the hierarchy to suit this particular context.

3.2.4. Other aspects

As for the impact calculation methodology, it is beyond the scope of

this study to propose any of them for the evaluation of the data. This is because it is not intended to restrict the flexibility of the practice, and certain methodologies are more adapted to some specific contexts. This is the case of TRACI in the United States or LIME (Life-cycle Impact assessment Method based on Endpoint modelling) in Japan (Itsubo and Inaba, 2003). However, we do intend to identify the key aspects that allow us to expand the comparative framework at this point. First, the characterization factors may vary significantly within the same model depending on whether global or regionalized data are considered. This has a decisive influence on the results, so it is important to specify this information in detail, which is not always the case. If two studies provide regionalized data in two different locations, the results may be comparable because they provide accurate data from two different locations. However, if the provided data are unspecific, the comparison is restricted because the level at which they are described is unknown. On the other hand, in terms of the used methodology or the provided (midpoint) indicators, although we defend flexibility, we do consider it interesting to include data calculated based on standardized models beyond those used for the analysis. In other words, although a detailed review of the results is made concerning a specific model and indicators, it would be beneficial to include the results obtained when analyzing the inventory with consensus methodologies such as the Environmental Footprint. If all the indicators recommended by this standard are also included, it provides an extra point of support to sustain the comparison with other studies.

Finally, it is noteworthy that this comparison is only possible if two studies refer to an identical functional unit and the reference flow of both is in the same units. This fact cannot be modified as it must support the objective of each study in the most appropriate way. However, as seen in Section 3.1, most LCAs refer to a reference flux based on the mass of the main product at the outlet of the system. Considering this trend, this would not be an obstacle in most cases.

3.3. LCA comparison

As previous sections explained, the LCA methodology has been applied for the evaluation of several bio-based platform molecules but using quite different assumptions. In this way, different scopes and perspectives, impact allocation methods, data sources and quality, environmental impacts indicators, etc., have been utilized when performing these assessments making it difficult a direct comparison among the different studies and their results. In any case, there are few studies with sufficiently close approximations to allow comparison. Among the studied chemicals, only three presented a high enough number of analyses with similar methodologies: ethylene (3 articles), lactic acid (2 articles) and succinic acid (3 articles). Connecting outcomes of methodologically comparable LCAs could show up trends in the strengths and weaknesses of these novel technologies from an environmental point of view, guiding the development of the biobased industry towards the most environmentally sustainable pathways. In this regard, the following section offers an extended discussion of the conclusions of different studies identified as comparable. The key criteria identified to enable the comparison between different studies are as follows.

- First, that they consider the indicator on GWP since it is present in most analyses and the different methodologies for its calculation are more similar than in other cases.
- That they use the same reference flow as a basis for calculation.
- That they consider the same scope.
- That they follow the same analysis perspective, either attributional or consequential.
- That they use the same methodology for the assignment of impacts among the different functions provided by the system.
- Finally, that they consider the same scenario for the consideration of carbon fate, either storage or neutrality. It is also taken into account whether and how the effects of land use change are evaluated or not.

Thus, the possibility of comparing two studies in the case of lactic acid, three studies on succinic acid, and another three on ethylene was determined. The main conclusions are given below.

3.3.1. Bio-based lactic acid (LA)

The works published by Adom et al. (Adom and Dunn, 2017) and Lee et al. (2021) both consider different fermentation pathways for LA production. Interestingly, several raw materials were evaluated in these investigations, providing a screening of the environmental profile of different production routes for farming bioindustries.

Specifically, Adom et al. compared two different scenarios: conventional fermentation pathway starting from sugar obtained in a corn mill and neutralizing the mineral acid used in the carbohydrate hydrolysis step with $CaCO_3$ (leading to $CaSO_4$ as the main waste of the process) and an emerging technology, based on acid-resistant microorganisms that metabolize sugars coming from hydrolysed corn stover. In the case of Lee et al. LA is produced from four types of wastes: wastewater sludge, food waste, swine manure, and FOG (fat, oil, and grease) inhibiting the methanogenesis step of the conventional anaerobic digestion process to promote LA formation, which is separated from the fermentation broth by electrodeionization. Despite the uncertainty associated with the analysis of non-commercial technologies (due to the numerous hypotheses assumed), some interesting conclusions can be extracted by comparing these two LCA studies.

- Direct CO_2 emissions coming from the LA manufacturing process are mainly related to energy consumption, which is ascribed to the fermentation and product purification steps. This fact points to an important drawback of the fermentative pathways: the very low concentration of the culture broths. Within this context, chemocatalytic routes, that allow operation with much higher concentrated streams, emerge as interesting alternatives to be considered within an efficient biorefinery scheme (Morales et al., 2015b; Awiszus et al., 2019).
- The selected feedstock for LA production has a critical effect on the environmental profile of the process, not only because of technical issues related to its transformation into LA, but also because of the way in which the carbon balance is calculated to obtain the GWP indicator. Thus, when crops are used as carbohydrate source (corn or corn stover, are the most usual options), CO_2 uptake during feedstock growth is generally deducted from the emissions of the inventory, resulting in a carbon storage scenario (see section 3.1). This is the case of the work of Adom et al. leading to net CO_2 emissions of 0.65 kg CO_2/kg LA, using corn stover as raw material, and 1.4 kg CO_2/kg LA if starting from corn flour. On the other hand, if wastes are selected as feedstock, the LA production process involves an alternative to conventional treatment methods applied to the starting raw materials, otherwise residues, avoiding the impacts associated with them. If authors subtract these impacts for LCA calculations, as Lee et al. did, a significant reduction of the environmental burdens is achieved. Accordingly, the production of LA from wastes presents, for all the four considered cases, negative net CO_2 emissions (-1.4 kg CO_2/kg LA for water sludge, -3.3 kg CO_2/kg LA for food waste, -4.2 kg CO_2/kg LA for swine manure, and -3.7 kg CO_2/kg LA for FOG). Obviously, these deductions are hugely conditioned by the presumably avoided waste management practices. Bearing in mind that more restrictive practices are expected for waste management due to new legislation frameworks (European Parliament European Council, 2018), the environmental credits associated with the use of organic residues as raw materials will be considerably lower, promoting the development of new production pathways with low emissions (since residual raw material could not be further considered a sink of environmental impacts).

3.3.2. Bio-based succinic acid (SA)

LCA reported by Morales et al. (2016), Nieder-Heitmann et al.

(2019), and Foulet et al. (2019) on the production of succinic acid were developed according to the comparable methodological and technical assumptions listed above, using the IPCC methodology for GWP, and describing fermentative pathways. The two first works describe similar biorefinery configurations evaluating the manufacture of bio-based SA, and other side products, from different lignocellulosic biomasses (sugar beet, sugarcane bagasse, wood wastes, etc.). According to their findings, some interesting conclusions can be inferred.

- As for the SA production, CO_2 emissions are mainly attributed to the energy requirements of fermentation and, especially to the purification steps required to get commercial grade SA. Since fermentative processes involve very low sugar concentration in the aqueous solutions of the biological reactors, achieving highly pure SA for further applications (i.e., as monomer) avoiding huge consumption of energy arises as one of the key challenges of these biorefinery schemes. In this context, different SA purification methods are explored by the authors without existing consensus on the best technology to be used yet. Thus, Morales et al. (2016) reported reactive extraction as the preferred downstream alternative from an environmental point of view. This technology is based on contacting the fermentation broth with an organic solution of trioctylamine in octanol, aiming to extract the succinic acid from the aqueous phase. Since other acids (such as acetic acid, pyruvic acid, etc.) can be also present, an additional purification step is usually required for high purity grade (either through distillation or re-extraction). Anyway, if the organic solution is properly recovered and reused, results indicated this purification method could become a competitive route. However, Nieder-Heitmann et al. (2019) concluded that a combination of ion-exchange columns, nano-filtration and evaporation steps for SA purification leads to better environmental performance than reactive extraction. Therefore, more data about purification methods of bio-based SA are necessary for addressing efficient biorefinery designs. These efficient designs will have to consider not only the SA purity required for commercia applications, but also the starting raw material, since it widely influences the biological reactors operating conditions as well as the required downstream purification steps.
- To achieve economic and environmentally competitive biorefinery schemes, as compared to their fossil counterparts, mass and energy integration of different units and sections of the plant is compulsory. In this sense, biorefinery schemes that allow for producing several valuable chemicals (integral utilization of the starting biomass) as well as the application of the energy integration tools, could be useful alternatives to consider during the biorefinery conceptualization.

Finally, the work of Foulet et al. (2019) was focused on obtaining SA through bioelectrosynthesis. This technology is based on stimulating microbial activity (in an electrolytic cell) to promote the degradation of organic molecules, leading to the production of bio-based chemicals. Despite this alternative being an emerging technology with low TRL, the reported LCA reveals some outcomes in agreement with the above investigations. First, the correct integration of the bioelectrosynthesis step with other biorefinery stages (such as biomass hydrolysis or anaerobic digestion) to maximize mass and energy use within the plant leads to better environmental performance of the process. Besides, when the electricity consumption is relevant (as it occurs within the electrolytic cell), the electricity mix included in LCA calculations has a critical influence on the environmental impacts caused by the system. In this sense, the selection of the electricity mix should be properly justified and sensibility studies about the effects of changing the mix are highly recommended.

3.3.3. Bio-based ethylene (ETN)

Ethylene production from biomass has been considered in three LCA investigations showing quite similar approaches (close enough to compare their conclusions) (Liptow et al., 2015; Alonso-Fariñas et al., 2018; Akmalina and Pawitra, 2020). Interestingly, after evaluating different scenarios and technologies to produce biomass-derived ethylene, wood gasification emerges as a more environmentally friendly alternative in comparison with both biomass fermentation routes, via bioethanol dehydration, and conventional chemical transformations, based on cracking fossil feedstock. All the analyzed gasification schemes, including different transformation pathways and several side products, led to less than 1 kg CO_2/kg ETN, regardless the selected allocation method. On the contrary, fermentation and catalytic cracking routes were assessed to emit higher greenhouse amounts (from 1.1 to more than 2 depending on the selected technology and raw material). Accordingly, the main weaknesses of the fermentative pathways are energy requirements of the biological reactors (as in the case of LA and SA), a huge amount of consumed biomass (involving significant impacts in farming stages), and high emissions associated with the enzyme production. Fossil-based processes to produce ethylene showed greater contribution to GWP category than biomass-derived technologies, mostly due to the type of released CO_2. LCA assumed in these cases a neutral scenario for carbon, i.e., emissions of biogenic carbon are not considered (which is in agreement with the recommendation of Pawelzik et al. (2013)). Since within biomass-derived technologies biogenic carbon implies an important fraction of the released CO_2, the GWP category is clearly reduced as compared to fossil feedstock utilization. This advantage of biomass raw materials for carbon balance calculations should be properly detailed during the LCA development to achieve realistic and fair comparisons with systems using fossil feedstocks, as it is the case of the evaluated works (Liptow et al., 2015; Alonso-Fariñas et al., 2018; Akmalina and Pawitra, 2020).

4. Conclusions and perspectives

The objective of this review is to orient methodological decision-making towards the same direction, adapted to the context of biomass derived chemicals. In this way, the aim is both to adequately represent this particular reality and to increase comparability between studies.

Through the meta-analysis of the selected LCA studies, three broadly prevalent aspects were identified: cradle-to-gate scope (intermediate products), prospective analysis (technologies under development), and multifunctional processes (biorefineries). Although the practice of LCA must remain flexible, having references to guide methodological decisions toward a more accurate representation of this context is undoubtedly beneficial. In the case of bioproducts, we find certain bottlenecks around the three aspects mentioned above that make it difficult to choose the most appropriate assessment practices. Some general conclusions about these three aspects are detailed below, although all the detailed information can be found in section 3.2.

- Regarding the scope of the studies, reconciling the temporal scope of the study with the correct allocation of biogenic carbon fluxes is the aspect that requires the most discussion. The application of methodologies such as those proposed in this work, or the analysis of scenarios to fill this gap, are essential for the consistency of the results. Also, the inclusion of indicators related to changes in land use will lead to more reliable conclusions once they are consolidated in standard practice.
- Concerning the multifunctionality of processes, the degree of complexity of inputs and outputs is not restricted to the manufacturing stage, but also affects the value and supply chains of the process. Modelling this large number of flows and interactions fairly is a challenging task. The consequential perspective seems a more correct approach to capture all elements of this intricate system, although the scarcity of marginal data currently available in databases makes it unfeasible in many cases. It is to be hoped that over time, if efforts are devoted to it, the amount of such information

will become more accessible. In our opinion, this would lead to a substantial improvement in the representation of multifunctional systems.

- Likewise, the technologies that are now being discussed as future developments will materialize. At that time, the availability of reliable primary data will increase, allowing for more accurate analyses. Until then, careful scaling of system inputs and outputs, as well as the communication of the uncertainty of the results, is the only reality to which we can adhere.

With this in mind, future work should be directed towards increasing rigor and producing more accurate and transparent data. It is necessary not only to give a faithful approximation of reality but to provide information on how representative a model is. In addition, the number of environmental categories and mechanisms included in the studies should not disregard any information that could lead to burden shifting. This implies the development of indicators still in the pipeline, such as effects on biodiversity. The area of bioproducts is particularly sensitive to this indicator due to the significant changes in land use. Therefore, it is of great interest advancing in the definition of criteria and the formulation of representative characterization factors. A major research effort is therefore required in this regard. Similarly, progress in integrating the other pillars of sustainability is essential. While cost analysis (LCC) has a high degree of maturity, the evaluation of social indicators is currently undergoing strong development. There must be a common effort by the community of LCA practitioners to implement these methodologies. All recommendations in this paper apply only to the depicted context and should be framed under the umbrella of higher standards. Methodologies such as the Environmental Footprint provide a skeleton from which further actions can be subscribed.

The conclusions envisioned in this review are valid from a scientific perspective. However, the application of these conclusions in the practical realm of LCA, including Product Category Rules and Environmental Product Declarations, requires a distinct approach. It is important to acknowledge that we are addressing intermediate products, and thus, standardizing phases like defining system boundaries may be arduous and even counterproductive when use and end-of-life stages are not considered. Nevertheless, the work here presented has the potential to guide the creation of future guidelines for final product development.

We must not lose sight of the fact that decisions based on LCA can guide the technological drift of the future and tip the balance toward these or other processes. It is therefore essential to start from common schemes adapted to each context, obviously without detriment to the necessary flexibility in practice. This will make it possible to collect and reproduce a larger portion of reality, and to generate more comparable conclusions that will allow us to find the most appropriate solutions to advance toward sustainability in a circular bioeconomy context.

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Data availability

No data was used for the research described in the article.

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Basic structure of Figs. 4, 7 and 8 were prepared using the open source RAWGraphs tool for data visualization (Mauri et al., 2017).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.137513.

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