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CRITICAL REVIEW

Prospective macro-level life cycle assessment: a systematic review

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Abstract

Purpose Transitions to sustainable societies require assessments of future environmental impacts at the macro-level. We examined how prospective process-based Life Cycle Assessment (LCA) is used to model environmental impacts at national to global scales. Our research objectives were to (i) provide an overview of modelling approaches in prospective macro-level LCA; (ii) identify common pitfalls and best practices; and (iii) highlight key challenges and suggest priorities for future research.

Method We conducted a systematic literature review. An initial search in Web of Science, complemented by studies reviewed by Bisinella et al. (2021), yielded 925 studies. After screening based on predefined inclusion criteria and adding 33 additional articles through citation tracking, a final set of 86 peer-reviewed articles was analysed. We reviewed these studies with a primary focus on how system scaling, temporal evolution, and temporal distribution were addressed in the inventory analysis phase. In addition, we assessed elements from the other three LCA phases, including research objectives, temporal scope, system boundaries, and the treatment of sensitivity and uncertainty. We also examined terminology use and transparency.

Results and Discussion We classified the reviewed approaches by how system scaling is treated in the foreground system: (i) coupling with Dynamic Stock Models, which captures stock dynamics but overlooks socioeconomic aspects; (ii) coupling with Energy System Models, which provides detailed insights but is limited to the energy sector; (iii) coupling with Integrated Assessment Models, which offers broader socioeconomic coverage but operates at coarse resolution and typically requires collaboration with model developers; and (iv) uncoupled approaches, which allow flexibility but risk oversimplification. Methodological choices in the reviewed literature often appear guided by methods rather than research questions. We identify twelve key pitfalls, including simplified treatments of system scaling, temporal dynamics, and distribution; a narrow climate focus; limited scenario diversity; and weak internal consistency. We also highlight several best practices.

Conclusions and Recommendations Our review reveals a diverse field with inconsistent terminology, assumptions, and modelling practices. To strengthen the field, we recommend improving the representation of the complexity of sustainability transitions; strengthening policy relevance; facilitating transparency and adopting consistent terminology; and developing methodological guidance. Such guidance should clarify which approaches are suited to which types of research questions. Addressing these priorities will improve the robustness of prospective macro-level LCA and advance understanding of sustainability transitions.

Keywords Life cycle assessment · Macro-level LCA · Large-scale environmental impact assessment · Prospective LCA · Dynamic LCA · Systematic literature review

Abbreviations

ABM	Agent Based Modelling
BG	Background
DSM	Dynamic Stock Model
DSM-LCA	Coupling of process-based Life Cycle Assessment with a Dynamic Stock Model
EoL	End-of-Life
ESM	Energy System Model
ESM-LCA	Coupling of process-based Life Cycle

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	Assessment with an Energy System Model
FG	Foreground
GEM	General Equilibrium Model
IAM	Integrated Assessment Model
IAM-LCA	Coupling of process-based Life Cycle Assessment with an Integrated Assessment Model
IEA	International Energy Agency
IO-LCA	Input-Output Life Cycle Assessment
LCA	Process-based Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
PEM	Partial Equilibrium Model
SD	System Dynamics
SSP	Shared Socioeconomic Pathway
TRL	Technology Readiness Level

1 Introduction

Transitions to sustainable societies require informed decisions about which technologies and policies to support today, especially in sectors with long-lived assets, where current investments can lock-in environmental impacts for decades (Geels et al. 2017). Prospective environmental assessments at national, continental, and global scales—hereafter referred to as macro-level—provide a basis for these decisions by anticipating how aggregate environmental impacts may evolve.

Process-based Life Cycle Assessment (LCA) is an established method for such assessments, with three core strengths: (i) a high technological resolution, enabling explicit modelling of technological advancements, technology-specific interventions, and market share changes at the process-level (Hertwich et al. 2015; Wiedenhofer et al. 2024); (ii) a system perspective, covering the full life cycle (Sacchi and Hahn-Menacho 2024); and (iii) the capacity to assess multiple environmental impact categories (Sacchi and Hahn-Menacho 2024). The latter two strengths are important for avoiding problem-shifting (Finnveden et al. 2009).

Conventional LCA, as standardised in ISO14040:2006 (ISO 2006), has three main limitations for prospective macro-level environmental analyses. First, it lacks a time dimension (Guinée et al. 2017), meaning that it disregards the *temporal distribution* of processes, emissions, and effects (Guinée 2002), implicitly assuming that all processes occur simultaneously. This simplification can be problematic, especially for long-lived systems like infrastructure. Second, it neglects *temporal evolution*; that is, changes over time such as technological advancements or structural shifts in supply chains and the broader economy (Müller et al. 2025; Arvesen et al. 2011; Luderer et al. 2019; Hung et al. 2022). Third, it assumes a linear relationship between the functional unit and the scale of the processes providing it (Heijungs 2020; Pizzol et al. 2021). This linear *system scaling* does not capture important aspects, including economies of scale, demand constraints (e.g., market saturation for co-products), and supply limitations (e.g., manufacturing capacities, resource availability, and technology deployment constraints) (Yang and Heijungs 2018, 2019; Pizzol et al. 2021). These constraints become especially important in dynamic transitions where bottlenecks, such as green hydrogen availability, may arise (Hung et al. 2022). Together, these limitations can lead to misleading insights for decision-makers when assessing potential future environmental impacts at the macro-level. Therefore, addressing such questions often requires going beyond conventional LCA and combining it with complementary methods.

Recent advances in prospective LCA—defined here as "LCA that models the product system at a future point in time relative to the time at which the study is conducted" (Arvidsson et al. 2024)—have improved the modelling of temporal evolution. Particularly, the coupling with Integrated Assessment Models (IAM) (Mendoza Beltran et al. 2018; Sacchi et al. 2022) has led to the increased consideration of temporal evolution in LCA studies. While many macro-level studies incorporate prospective elements, the field of prospective LCA has mainly focused on emerging technologies at the micro-level (Thonemann et al. 2020). Meanwhile, calls to broaden LCA's scope (Jeswani et al. 2010; Guinée et al. 2011) have led to an increasing number of studies at the macro-level (Bisinella et al. 2021; Hellweg et al. 2023). Particularly, the energy transition has been the focus of seminal work (e.g., Hertwich et al. 2015).

We propose the following as a first attempt at defining macro-level LCA: *assessment of environmental impacts associated with the life cycle of a system fulfilling a specific function for the demand at the national, continental, or global scale*. We suggest distinguishing two key dimensions: the *type of the functional unit* (ranging from single products to sectors or the entire economy) and *the scale of the functional unit* (national, continental, or global), with only the latter determining macro-level status.

Current prospective macro-level LCAs vary widely in scope, scenario design, modelling of foreground (FG) and background (BG) systems, and terminology. Approaches range from simple parameter adjustments (e.g., future demand) to advanced couplings with dynamic Material Flow Analysis or IAMs. This makes it difficult to compare results and derive robust insights for decision-makers. As Hellweg et al. (2023) point out, standardisation and methodological guidance are needed.

While several reviews address prospective LCA, none focus specifically on macro-level approaches. Some address temporal dynamics in LCA without emphasising the macro-level (Beloin-Saint-Pierre et al. 2020; Lueddeckens et al. 2020; Sohn et al. 2020); others focus on emerging technologies (Buyle et al. 2019; Bergerson et al. 2020; Thonemann et al. 2020; Tsoy et al. 2020; van der Giesen et al. 2020; Erakca et al. 2024); or specific sectors such as metals (Harpprecht et al. 2024). Reviews on the combination of LCA with other types of models focus on the model combination, regardless of the assessment scale and temporal scope (Beaussier et al. 2019; Palazzo et al. 2020; Barkhausen et al. 2023). Other reviews discuss aspects relevant to macro-level prospective LCA, but do not analyse existing approaches (Bisinella et al. 2021; Hellweg et al. 2023; Caiardi et al. 2024; Riondet et al. 2024; Wiedenhofer et al. 2024).

To the best of our knowledge, no review has systematically examined process-based LCAs that are both prospective and macro-level in scope. As a result, the current state of the art remains unclear, including which modelling approaches are available, what key challenges and pitfalls exist, and where future research should focus. To address this gap and support the future development of methodological guidance, our research objectives were to

(i) Provide an overview of modelling approaches in prospective macro-level LCA, focussing on modelling of system scaling (micro- to macro-level), temporal evolution, and temporal distribution;
(ii) Identify common pitfalls and best practices; and
(iii) Highlight key challenges and suggest priorities for future research.

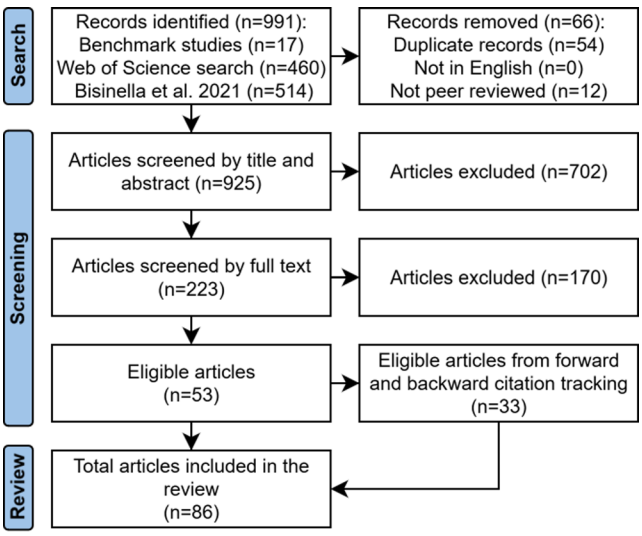

Fig. 1 Summary of the literature selection process, adapted from Page et al. (2021) and based on the recommendations of Siddaway et al. (2019). A complete list of retrieved articles, including reasons for exclusion, is provided in the Supplementary Information

To fulfil the research objectives, we conducted a systematic literature review of prospective macro-level LCAs covering all LCA phases, with particular emphasis on the inventory phase. *Temporal evolution* modelling and *system scaling* guided our literature selection, but we also analysed how *temporal distribution* is addressed within the included studies. Providing detailed methodological guidance for prospective macro-level LCA is beyond the scope of this paper. Instead, we aim to lay the groundwork for future developments in that direction.

We acknowledge the significant progress already made in prospective macro-level LCA. Our intention is not to dismiss these efforts, but to reflect on current practices and encourage dialogue on how the field can advance.

2 Methods

Our review was informed by the methodological guidance of Siddaway et al. (2019) and Zumsteg et al. (2012). A flowchart outlining the literature selection process is shown in Fig. 1.

2.1 Search

The initial literature search was conducted in the *Web of Science Core Collection* using a query developed from 17 benchmark studies identified during an exploratory review (see Supplementary Information). The search string was: '*TS=("life cycle" OR "life-cycle" OR "lifecycle" OR "LCA") AND TS=("prospectiv*") AND TS=("*sector*" OR "*fleet*" OR "nation*" OR "transition*" OR "macro*" OR "at scale" OR "large-scale" OR "large scale" OR "stock*") and English (Languages)*'. Here, *TS* denotes a *Topic Search*, retrieving records where these terms appear in the title, abstract, or author keywords. The search was last updated on July 15, 2025; studies published after this date were excluded.

Due to the lack of standard terminology for prospective macro-level LCA, covering all potential keywords would have resulted in an unmanageable number of studies. Therefore, while we included a broad range of terms related to scale, we adopted a restrictive strategy for the prospective dimension, requiring the root term *"prospectiv*"*. We acknowledge this may have excluded some relevant studies. To mitigate this risk, we additionally: (i) added the 514 studies reviewed by Bisinella et al. (2021), who focused on LCA combined with future scenarios; and (ii) conducted forward and backward citation tracking on included studies using the Web of Science. All identified studies were subject to the selection criteria outlined below.

2.2 Screening

Screening was conducted in two stages, starting with a review of titles and abstracts, followed by a full-text review, as shown in Fig. 1. Studies were included only if they met all of the following criteria:

(1) **Bibliographic requirements**: Peer-reviewed journal articles in English. Letters, books, reports, and conference papers were excluded. No restrictions were placed on the publication year.
(2) **Case study**: Pure method papers without applications (e.g., Ventura 2023) were excluded, but referenced when relevant (e.g., Gibon et al. 2015; Arvesen et al. 2018).
(3) **Life cycle perspective**: Studies had to cover at least two life cycle stages.
(4) **Process-based modelling in FG and BG systems**: We define the FG system as *the set of processes that constitute the object of analysis*, i.e., the focus of the study. The BG system includes *all other processes that provide inputs to the FG system*. Studies based solely on Input-Output Life Cycle Assessment (IO-LCA) for the FG or BG system were excluded. We did not require studies to perform their own inventory modelling.
(5) **Environmental impact assessment**: Studies had to include a characterisation of environmental flows for at least one impact category.
(6) **Macro-level scope**: Studies had to fulfil our above definition of macro-level LCA. However, since functional units were rarely stated explicitly, we based inclusion or exclusion on the scale of the reported results.
(7) **Consideration of temporal evolution**: Studies had to report results for at least one explicit future year, reflecting changes over time in both the FG and the BG system. Changing demand alone was insufficient unless accompanied by changes in how that demand is met over time. For example, studies that changed the material composition of buildings or the composition of the building stock were included, even if the underlying unit processes remained unchanged.

Studies with insufficient documentation (including Supplementary Information) to assess these criteria were excluded. While some relevant studies may have been unintentionally excluded, we believe the range and diversity of works covered provide a comprehensive overview of current approaches in prospective macro-level process-based LCA research.

As shown in Fig. 1, of the 925 articles initially identified, 702 were excluded after title and abstract screening, and another 170 after full-text screening. 33 additional articles were found through citation tracking. Ultimately, 86 publications were reviewed in detail. A complete list of retrieved articles, including reasons for exclusion, is provided in the Supplementary Information.

2.3 Review

We reviewed the included studies with a primary focus on how system scaling, temporal evolution, and temporal distribution were modelled in the inventory analysis phase. In addition, we assessed elements from the other three LCA phases, including research objectives, temporal scope, system boundaries, and the treatment of sensitivity and uncertainty. We also examined terminology use and transparency. We reviewed both the main article and the Supplementary Information, with the exception of model code. An overview of all review variables and their evaluation across the included studies is provided in our Supplementary Information.

3 Overview of modelling approaches

To address the limitations of using process-based LCA for prospective macro-level analyses, particularly the challenge of scaling systems from the typical micro-level scope of LCA to the macro-level, studies often rely on coupling LCA with other types of models. In this paper, we use the term *prospective macro-level LCA* as an umbrella term that encompasses both the LCA component and, where applicable, the coupled model. The intention is not to expand LCA's methodological boundaries beyond those defined in ISO 14040:2006 (ISO 2006), but rather to describe what can be achieved through the combination of LCA's strengths with those of the coupled model.

We classify the reviewed approaches based on how the FG system was scaled to the macro-level, beginning with those that use specific coupled models, followed by approaches that do not involve explicit model coupling. The main groups are Dynamic Stock Models (DSM), Energy System Models (ESM), and IAMs. These groups are not mutually exclusive, and their boundaries may overlap. For example, many IAMs incorporate ESMs and DSMs (Krey et al. 2019), but we treat these as separate approaches. Some studies do not fit neatly into a single category. For example, Hertwich et al. (2015) use pre-defined International Energy Agency (IEA) scenarios as input to a DSM. Since these scenarios are based on the IEA's own ESM, we classify the study as coupling with ESM (ESM–LCA), although classifying it as coupling with DSM (DSM–LCA) would also be possible.

Generally, studies scale results from micro-level LCAs—which we refer to from hereon as *micro-level characterisation results*—rather than scaling within the framework of LCA itself, i.e., the Life Cycle Inventory (LCI). Figure 2 provides a stylised overview of the typical information flows in each modelling approach. Note that by *activity level*, we mean the quantitative extent of a process or system's operation; that is, how much a process is used.

Table 1 presents a more detailed overview of these approaches and their key characteristics, including how they typically model temporal evolution and distribution. By *temporal distribution*, we refer specifically to the timing of LCA processes—that is, whether they are modelled as occurring instantaneously or distributed over time—rather than to the presence of a temporal dimension in the coupled model.

Our focus is on the strengths and weaknesses of these approaches rather than on the specific models themselves. These are based on our observations, the limitations stated by the authors of the reviewed papers, and literature. The following subsections examine each approach in detail. Note that Table 1 and Fig. 1 do not include all identified approaches—those that are rarely applied are discussed separately in subsection 3.5.

We acknowledge that the specific tools and modelling frameworks used in the reviewed studies are relevant for

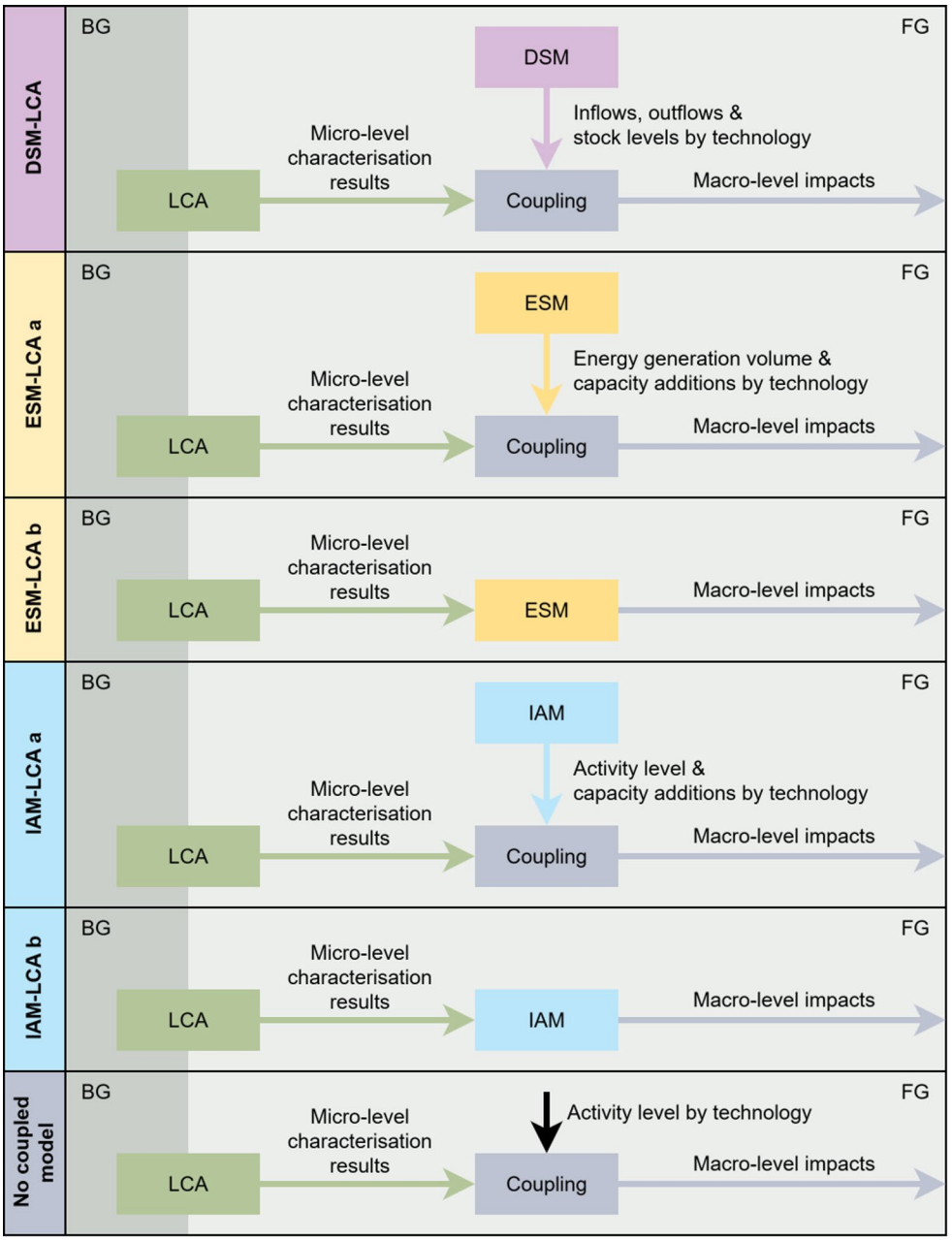

Fig. 2 Stylised Overview of main modelling approaches in prospective macro-level Life Cycle Assessment (LCA), grouped by how the foreground (FG) system was scaled to macro-level: coupling process-based LCA with a Dynamic Stock Model (DSM-LCA), an Energy System Model (ESM-LCA), an Integrated Assessment Model (IAM-LCA), or without a coupled model. Labels 'a' and 'b' indicate whether the combination is applied ex-post (after running the ESM or IAM) or endogenously (with micro-level LCA characterisation results directly embedded). Coupling is illustrated in the FG system; background (BG) system couplings (e.g., via *premise* (Sacchi et al. 2022) are not shown. Note that the characterisation results can be either integrated over time for the whole life cycle or separated by life cycle stage. For ESM- and IAM-LCA approaches, we distinguish two modelling variants; see below for explanation. The diagrams reflect generalised structures; individual studies may differ

Table 1 Overview of main modelling approaches in prospective macro-level Life Cycle Assessment (LCA), grouped by how the foreground system was scaled to macro-level: coupling process-based LCA with a Dynamic Stock Model (DSM-LCA), an Energy System Model (ESM-LCA), an Integrated Assessment Model (IAM-LCA), or without a coupled model. Less common approaches are discussed separately in subsection 3.5

	DSM-LCA	ESM-LCA	IAM-LCA	No explicit model coupling
System scaling	Scaling with inflows, outflows, and stock levels from stock-driven DSMs	Scaling with ESM outputs (capacity additions and energy generation volume) OR incorporated directly into the ESM	Scaling with IAM outputs (activity levels, capacity additions) OR incorporated directly into the IAM	Scaling with demand trajectories, based on extrapolated trends, fixed growth rates, external scenarios, or present-day levels
Temporal evolution	Stock composition changes; selected parameters (e.g., electricity mix)	Typically based on the parameter development of the ESM	Typically based on the parameter development of the IAM	Selected parameters (e.g., electricity mix)
Temporal distribution	Differentiation of life cycle stages and temporal distribution based on inflows, stocks, and outflows	Differentiation of life cycle stages and temporal distribution based on capacity additions and energy generation volumes	Differentiation of life cycle stages and temporal distribution based on capacity additions and activity levels over time	Not consistently considered
Strengths	• Endogenous stock dynamics • Stock–flow consistency and mass balance • Low access barriers • Flexibility in scope and scale	• Detailed representation of energy system dynamics • Captures system constraints • Strong policy link	• Endogenous Representation of technological change and macroeconomic feedbacks • Established scenario framework • Global coverage • Strong policy link	• Low access barriers • Flexible
Weaknesses	• Lacks macroeconomic/ systemic feedbacks • No standardised scenario framework • High data requirements (lifetimes, stocks) • Weak policy link	• Application restricted to the energy system • Mismatches of geographical and technological resolution • High expertise and access barriers	• Application restricted to IAM core systems • Mismatches of geographical and technological resolution • High expertise and access barriers	• No endogenous dynamics or feedbacks • Low comparability
Common applications	Buildings, transport, electricity systems, and materials	Electricity, fuels, hydrogen, batteries, sector coupling	IAM core sectors, like energy or transport	Materials, chemicals, and emerging technologies
Example research questions	How stock dynamics of a system influence its life cycle impacts over time	How the life cycle impacts of future energy systems evolve	How global systems meet climate targets and associated life cycle impacts	How future life cycle impacts change under various assumptions
Number of studies	35	27	6	15

understanding differences in results and methodological choices across approaches. Examining these tools in detail would allow for a more systematic comparison of model capabilities, data structures, and coupling interfaces, but this would require a dedicated review effort that lies beyond the scope of this paper. To support transparency, the Supplementary Information includes a list of the modelling tools used in each study, based on the information provided by the respective authors (note that details such as model versions are often not reported). Only named and publicly known modelling tools are included.

3.1 Dynamic stock models

The first approach combines LCA with DSMs. DSMs, also referred to as Vintage Stock Models, represent stocks of products used longer than one year (Wiedenhofer et al. 2024) and their inflows (additions) and outflows (retirements) over time. DSMs can be stock-driven, with predefined stock trajectories and inflows/outflows derived via lifetime distributions; or inflow-driven, where stocks and outflows follow inflow time series (Deng et al. 2023).

Studies in this group correspond to what Barkhausen et al. (2023) term "environmentally extended Material Flow Analysis". They first use a DSM to project future inflows, stocks, and outflows, which are then combined with micro-level LCA characterisation results for upstream, use, and downstream stages, integrated over time for each stage. For example, Milovanoff et al. (2019), use a dynamic stock model to project future light-duty vehicle production, vehicle stock, and disposal volumes for the U.S. fleet, and then multiply each by micro-level characterisation results for vehicle production, use, and End-of-Life (EoL) disposal. For a given year, the total impact is then calculated by summing all impacts occurring in that year: use-phase impacts from all active cohorts, production impacts from the new cohort, and EoL impacts from stocks retiring that year. However, not all DSM-LCA studies account for temporal distribution: two studies aggregate micro-level results across the considered life cycle stages into a single time point in time before applying them to inflows or stocks (Besseau et al. 2019; Rossi et al. 2024), while another two focus exclusively on upstream impacts (Kalt et al. 2022; Zhong et al. 2021).

Temporal evolution is typically modelled via cohort-specific parameters (e.g., energy efficiency, market shares), BG system parameters (e.g., electricity mix), or global DSM parameters (e.g., lifetimes, recycling rates), often as scenarios. Four studies use *premise* (Alaux et al. 2024, 2025a; Mastrucci et al. 2024; Zhang et al. 2024), a popular approach for modelling of prospective BG systems (Sacchi et al. 2022) that links IAM scenario results to the *ecoinvent* database to generate prospective LCIs "by adjusting technologies' penetration share, efficiency and emission factors for a specific scenario and year" (Šimaitis et al. 2025).

Strengths of the DSM-LCA approach include the inherent ability to model temporal distribution, the granular annual resolution, and the ability to capture system delays from technology diffusion and lock-ins. For example, Milovanoff et al. (2022) demonstrate how climate change mitigation is restrained by vehicle stock turnover despite even under assumptions of aggressive electrification in new vehicle market shares. The DSM-LCA approach supports scenario customisation, is flexible in scale (Ventura 2022), and can be applied to any system with long-lived stocks, whereas ESM-LCA and IAM-LCA are restricted to the sectors represented within their respective models.

Weaknesses include high data demands, particularly lifetimes and stock levels, and reliance on exogenous assumptions for socioeconomic drivers (Wiedenhofer et al. 2024). Unlike IAM-LCA and ESM-LCA, this approach cannot capture macroeconomic feedback and non-linear system behaviour. Few studies model technology diffusion endogenously and representation of policies is often lacking.

Applications focus on transport (18 studies), buildings (8), the electricity system (4), material cycles (4) and consumer goods (1). Research objectives include methodological advances (e.g., Hung et al. 2022) and evaluating strategies like lightweighting (e.g., Milovanoff et al. 2019), EV adoption (e.g., Raugei et al. 2021), and circularity (e.g., Pauliuk et al. 2024b). Many studies (12 of 35) do not cover the full life cycle. Temporal resolution is typically annual (31 of 35 studies). The majority of DSM-LCA studies have a cradle-to-grave scope (23). The remaining are cradle-to-gate including the EoL (5), cradle-to-use (5) and cradle-to-gate (2).

Noteworthy methodological advances include coupling DSMs with discrete choice models (Brand et al. 2013; Mastrucci et al. 2024), which simulate how individual agents make decisions among alternative technologies based on internal preferences and external factors (Brand et al. 2013); improving technological granularity (Alaux et al. 2024); adopting nonlinear technology diffusion models (Sigüenza et al. 2021); and including optimisation (Hung et al. 2022).

Future work should focus on better representing behaviour and policies; exploring approaches to endogenise socioeconomic drivers and dynamics; improving spatial and technological resolution; addressing distributional aspects (Pauliuk 2024); and differentiating drivers of stock levels beyond averages (e.g., urban vs. rural buildings, Zhang et al. 2024).

3.2 Energy system models

The second approach combines LCA with ESMs. As mentioned above, we include studies using pre-defined IEA scenarios, since they are based on the IEA's internal ESM. ESMs model how resource inputs—defined by potentials and cost curves—are used to meet end-use demands through primary (e.g., electricity) or secondary (e.g., heat pumps) conversion technologies, under policy or economic constraints (Blanco et al. 2020). Depending on their goal, they can be used to identify least-cost or least-impact pathways to a desired future state (Weidner et al. 2022). ESMs typically rely on partial equilibrium modelling (Blanco et al. 2020). Inputs include energy resource availability, existing capacities and capacity limitations, (future) demand and demand profiles, technology data, and scenario assumptions like policy targets (Weidner et al. 2022).

Two main approaches for the combination with LCA exist (Blanco et al. 2020): (i) ex-post assessments (20 studies), where LCA is applied after the ESM runs independently (often optimising for cost or direct emissions), and (ii) endogenous inclusion (7 studies), where of micro-level characterisation results are directly embedded in the ESM. These are depicted in Fig. 2 as 'a' and 'b', respectively.

For ex-post assessments, model structures are often similar to DSM-LCA approaches: ESM outputs, i.e., new capacity installations and electricity generation activity levels by technology, are linked to upstream and use-phase micro-level characterisation results, respectively. Two studies combine DSMs with IEA scenario values by using future installed capacity trajectories from the IEA scenarios to drive a vintage stock model, which allocates life cycle impacts of power plants—construction, operation, and decommissioning—to the years they occur (Hertwich et al. 2015; Gibon et al. 2017). EoL is rarely explicitly treated. Some studies allocate EoL impacts to the construction of new capacities as well (Junne et al. 2020), creating temporal mismatches (Arvidsson et al. 2018; Mendoza Beltran et al. 2018).

Temporal evolution is typically inherently modelled by the ESM through improving conversion efficiencies or the emergence of new technologies, which are then harmonised with the LCA data. Six of the studies use prospective BG system data generated by *premise* (Sacchi et al. 2022). Most studies project to 2050, with temporal resolution ranging from yearly to 20-year steps.

Strengths of the approach include detailed energy system representation and non-linear dynamics (e.g., considering merit-order effects); the representation of constraints, such as limited capacities for specific technologies or investment cost; and the inherent inclusion of temporal distribution, at least for new capacity additions and use phase. Compared with DSM-LCA and approaches without a coupled model, ESM-LCA provides a stronger link to policy levers and non-linear system behaviour.

Weaknesses include the energy-sector focus, limiting application beyond it; uncertain mapping of ESM and LCA data due to differences in technological parameters and resolution (Vandepaer and Gibon 2018; Hahn Menacho et al. 2025b); and that many ESMs produce only one optimised future per set of assumptions, limiting their ability to capture disruptive changes or unexpected transitions (Reinert et al. 2021). Furthermore, ESM modelling also requires significant expertise, and model documentation is often lacking (Vandepaer et al. 2020), reducing accessibility and transparency. Compared with the other approaches, ESM-LCA is the most restricted regarding system of analysis.

A key challenge for ESM-LCA is double-counting. ESMs calculate total energy demand, including supply chains. If the micro-level characterisation results include embedded energy, impacts may be overestimated (Volkart et al. 2017; Blanco et al. 2020). National models double-count domestic supply chains; global models all chains unless inventories are adjusted (Volkart et al. 2017). Double-counting also occurs when the micro-level characterisation results are not only applied at the end-use level, for example, accounting for electricity used in both heat pump operation and the generation of that electricity (Blanco et al. 2020). Methods to mitigate double-counting are available (e.g., Volkart et al. 2018; Vandepaer et al. 2020).

Studies focus on the energy systems (18), or specific intermediate goods like hydrogen, ammonia, and batteries. The most common objective is assessing the environmental impacts of future energy systems, often under climate mitigation targets and a focus on the role of specific technologies. The scope of the studies varies, with 6 being cradle-to-gate, 4 cradle-to-use, 16 cradle-to-grave and one focussing on the EoL. Future work should align technological assumptions between ESMs and LCA, enhance transparency, and develop standardised coupling methods.

3.3 Integrated assessment models

The third approach couples LCA with IAMs (IAM-LCA), which integrate models of climate, economy, and society to explore policy questions (Hellweg et al. 2023). We focus on process-based IAMs, which—unlike cost-benefit IAMs—are technology-rich and scenario-driven (Pauliuk et al. 2017). While many IAMs have ESMs at their core, they differ by explicitly modelling the carbon cycle, land-use change, and the global economy (Blanco et al. 2020). IAMs produce long-term projections that align with radiative forcing targets set by Representative Concentration Pathways (van Vuuren et al. 2011) and are situated within broader socio-economic storylines, the Shared Socioeconomic

Pathways (SSPs) (O'Neill et al. 2014; Sacchi et al. 2022). They can take the form of either optimisation models, based on myopic or perfect foresight, or simulation models (Keppo et al. 2021; Pauliuk et al. 2017). IAMs are typically based on general or partial equilibrium frameworks (Keppo et al. 2021). For a concise explanation of how IAMs work and their implications for LCA, see Evans and Hausfather (2018) and Šimaitis et al. (2025).

Five of the six studies reviewed apply ex-post methods (labelled 'a' in Fig. 2), using IAM scenario outputs, such as cement production volumes (Müller et al. 2024), to scale micro-level LCA inventories or characterisation results. Only Pehl et al. (2017) incorporate embodied energy coefficients based on micro-level LCIs into the IAM REMIND using its endogenous emission factors and carbon price assumptions (labelled 'b' in Fig. 2). This approach can, similar to ESM-LCAs, lead to double-counting if not correcting the LCA-based coefficients (Arvesen et al. 2018). It is important to note that while ex-post and endogenous inclusion assessments of ESMs often share similar system boundaries—typically focused on the energy system—endogenous inclusion in IAM-LCA encompasses all sectors represented within the IAM, whereas ex-post assessments in IAM-LCA usually target a single system only (e.g., cement; Müller et al. 2024).

Temporal evolution is captured via IAM market shares and technological parameters (e.g., Dirnaichner et al. 2022; Müller et al. 2024) or based on literature and comparatively simple assumptions (e.g., 100% adoption of a specific technology in a specific year, Cabrera-Jiménez et al. 2025). Two of the studies rely on *premise* (Müller et al. 2024; Cabrera-Jiménez et al. 2025) and two (Pehl et al. 2017; Luderer et al. 2019) on *THEMIS* (Gibon et al. 2015) to model temporal evolution.

IAMs typically operate in time steps of 5–10 years. Three of the six studies include temporal distribution through differentiating construction and operation and mapping them to electricity generation capacity and volume (Pehl et al. 2017; Luderer et al. 2019) or through simply assuming fixed lifetimes afterwards based on the IAM output (Knobloch et al. 2020). The other three studies do not consider temporal distribution.

Strengths of the approach include the global scope; endogenous data on energy and technology development from the IAM, which are based on a large variety of projection strategies and assumptions (Krey et al. 2019); and the inclusion of macroeconomic feedbacks, which are lacking in the other approaches. The alignment with the SSPs is another advantage (Steubing and Koning 2021). Some IAMs also embed regional constraints like land and resource availability (Pehl et al. 2017).

Weaknesses stem from coarse geographical and technological resolution, requiring mapping to LCA data, introducing uncertainty (Sacchi et al. 2022; Šimaitis et al. 2025). Similar to ESM-LCA, the complexity of IAMs and their high entry barriers pose challenges to interpretation and often necessitate collaboration with model developers, particularly when seeking to move beyond predefined model assumptions (Keppo et al. 2021; Wilson et al. 2021). These difficulties are compounded by often incomplete and scattered documentation, which can further hinder transparency and reproducibility (Pauliuk et al. 2017).

There are more than 30 IAMs, representing a wide variety of approaches (Pauliuk et al. 2017), which makes generalisations difficult (de Bortoli et al. 2025). Nevertheless, we want to highlight a few important general criticisms, which include overreliance on negative emission technologies (van Vuuren et al. 2017; Creutzig et al. 2021); underestimation of other technologies like renewables (Creutzig et al. 2017; Way et al. 2022); a weak representation of material cycles (Pauliuk et al. 2017); neglecting actor heterogeneity (Keppo et al. 2021); underrepresenting distributive justice (de Bortoli et al. 2025); and reliance on economic equilibrium frameworks (Keppo et al. 2021), which themselves are subject to a broad set of critiques (see subsection 3.5). Relatedly, IAMs have been criticised for a lack of alternative economic paradigms, potentially excluding viable policy options (Hickel et al. 2021; Proctor 2023; de Bortoli et al. 2025). For a more comprehensive overview of criticisms and corresponding responses from the IAM community, see Keppo et al. (2021). Some of these issues are being actively addressed; for example, through the development of scenarios that avoid the use of negative emissions technologies (Grubler et al. 2018).

Because IAMs represent in detail only those sectors most relevant to climate change (Steubing et al. 2023), IAM-LCA studies are likewise limited to these sectors: electricity (Pehl et al. 2017; Luderer et al. 2019), transport (Knobloch et al. 2020; Dirnaichner et al. 2022; Cabrera-Jiménez et al. 2025), space heating (Knobloch et al. 2020), and cement (Müller et al. 2024). Except for one study (Müller et al. 2024), all apply cradle-to-grave system boundaries. The typical research objective is to evaluate decarbonisation strategies and their trade-offs with other impact categories, which are not represented in IAMs.

3.4 No explicit model coupling

Fifteen studies did not rely on a coupled model for system scaling. Instead, scaling is based on assumed demand trajectories (e.g., Weidner et al. 2023), constant present-day levels (e.g., Adrianto et al. 2023), extrapolation of historical trends (e.g., Kuipers et al. 2018), assumed annual growth rates

(e.g., Bohnes et al. 2022), or scenarios from government-adjacent organisations (e.g., Douziech et al. 2024), industry groups (e.g., Pedneault et al. 2021), or other literature (e.g., Shirmohammadi et al. 2025).

Temporal evolution is generally informed by market shares drawn from the same literature sources or simple scenario assumptions, such as a linear transition to 100% market share (e.g., Zheng and Suh 2019) or regression of historical data (e.g., Kuipers et al. 2018). Technological change is introduced separately via annual improvement rates or adoption curves, often based on expert judgment, roadmaps, or external scenarios. Parameters addressed include the electricity supply mix, the deployment speed of technologies (e.g., Pedneault et al. 2021), energy efficiency, and specific factors like ore grades (e.g., van der Voet et al. 2019). Seven studies use *premise* (Sacchi et al. 2022), with four applying it to both the FG and the BG system (e.g., Weidner et al. 2023). None of the studies in this group accounts for the temporal distribution of processes.

Compared with DSM-LCA, ESM-LCA and IAM-LCA, uncoupled approaches offer the most flexibility and the most simplicity. However, without coupled models, they cannot systematically capture dynamic stock changes, non-linear system behaviours, or temporal distributions. Purely assumption-based scaling can undermine comparability and robustness, and reliance on fixed demand trajectories limits the exploration of diverse futures. While accessible, these approaches risk oversimplification.

Half the studies focus on intermediate goods, like metals (Kuipers et al. 2018; van der Voet et al. 2019; Pedneault et al. 2021; Adrianto et al. 2023), hydrogen (Weidner et al. 2023) or plastics (Zheng and Suh 2019). Consequently, most use a cradle-to-gate scope (7). Temporal resolution varies widely. Research objectives include methodological contributions (e.g., Douziech et al. 2024), assessments of specific technologies (e.g., Adrianto et al. 2023), evaluation of government strategies (e.g., Bohnes et al. 2022), or general impact assessment of the system under analysis (e.g., Horup et al. 2025).

3.5 Less explored modelling approaches

Two modelling approaches appeared rarely and are therefore briefly discussed here.

General Equilibrium Models (GEM) determine "price and quantity jointly in all sectors and regions in the world economy using a solvable system of equations" (Palazzo et al. 2020). Only two studies used GEMs, both in the waste sector (Ljunggren Söderman et al. 2016; Arushanyan et al. 2017). However, GEMs underpin many IAMs (Keppo et al. 2021; Proctor 2023), while Partial Equilibrium Models (PEMs)—which "represent the market for a particular good (or small set of goods) in isolation from the rest of the economy" (Palazzo et al. 2020)—are common in both IAMs and ESMs (Blanco et al. 2020; Keppo et al. 2021). Thus, equilibrium approaches are more prevalent than they initially appear.

Their strengths include modelling prices, substitution, and feedback effects, with strong links to policy instruments (Plevin 2017; Beaussier et al. 2019). Many critiques apply to both, notably their reliance on neoclassical assumptions such as consumer utility maximisation, producer profit maximisation, perfect information, and market clearing (Suh and Yang 2014; Yang and Heijungs 2018; Palazzo et al. 2020; Wiedenhofer et al. 2024). Some criticisms apply more to GEMs than PEMs, particularly their unrealistic assumption of full capacity utilisation (Wiedenhofer et al. 2024). Where stylised production functions are used—more common in GEMs than in PEMs—these typically violate biophysical and thermodynamic consistency (Wiedenhofer et al. 2024).

The limited uptake of GEM in particular may stem from data demands, complexity, and poor fit with LCA's granularity (Earles and Halog 2011; Yang and Heijungs 2018; Beaussier et al. 2019). Given the strong assumptions underpinning equilibrium models, there is a need to diversify the macroeconomic approaches, for instance by incorporating post-Keynesian or stock–flow consistent macroeconomics (Wiebe et al. 2023).

System Dynamics (SD) models simulate system behaviour through stocks, flows, and feedbacks (Moon 2017). They enable the modelling of complex and non-linear system behaviour, are inherently able to account for time and support easy parametrisation (Beaussier et al. 2019; Palazzo et al. 2020; Yi et al. 2023). Despite existing combinations of LCA and SD (McAvoy et al. 2021), we found only one study (Alaux et al. 2025a) using causal loop diagrams to derive scenario parameters and one study (Ginster et al. 2024) building a full SD model, that is very close to a DSM-LCA approach. Complexity, lack of standardisation, as well as high computational and data requirements may hinder uptake (Beaussier et al. 2019; Palazzo et al. 2020).

3.6 Models only used in supporting roles

We expected to find several modelling methods used more frequently, but they mostly appeared only in supporting roles. Below, we briefly outline these approaches, highlight their key features, and discuss possible reasons for their limited use.

Linear Programming Models (LPM) use linear optimisation to represent technology choice under constraints. While many IAMs and ESMs also employ optimisation methods, we focus here specifically on LPMs applied

directly to the mathematical structure of LCA. Five studies use optimisation, two of which combine it with a DSM (Hung et al. 2022; Rossi et al. 2023) and are therefore classified as DSM-LCA. The other three (Zibunas et al. 2022, 2024; Lechtenberg et al. 2024) rely on simple system scaling (fixed or linearly growing demand) and are classified as without explicit model coupling. Technology diffusion is modelled endogenously in the optimisation: the models determine which technologies are adopted based on environmental performance and constraint satisfaction. The main advantage of this approach is the ability to incorporate constraints directly, while its main drawback lies in the high access barriers. The newly developed tool *optimex* (Diepers and Tautorus 2025) may encourage broader uptake.

Agent-Based Models (ABM) simulate interactions between agents and their environment, driving system evolution (Moon 2017). While couplings of LCA and ABM exist, macro-level applications are rare (Beaussier et al. 2019; Wiedenhofer et al. 2024). In our sample, ABM appeared only in supporting roles. ABMs enable more realistic modelling of (non-linear) behaviour, actor heterogeneity and technology diffusion than traditional economic models (Beaussier et al. 2019; Palazzo et al. 2020; Wiedenhofer et al. 2024), but share SD's drawbacks: complexity, a lack of standardisation, and high computational and data demands (Beaussier et al. 2019).

Input-Output LCA (IO-LCA) uses economic input-output tables to trace sectoral transactions within and across regions, enabling quantification of environmental impacts across global supply chains when combined with environmental data (Hagenaars et al. 2025). IO-LCA is relatively easy to implement and is often considered more comprehensive because it captures the whole economy and is not limited by cut-offs in contrast to LCA (Beaussier et al. 2019; Hagenaars et al. 2025). However, fixed prices and static structure limit its reliability to short-term analysis (Beaussier et al. 2019; Le Luu et al. 2024). Furthermore, IO-LCA has a low technological resolution and lacks a representation of use and EoL stages (Hagenaars et al. 2025). In our sample, IO-LCA was only used to extend BG system coverage (e.g., Arvesen et al. 2011), not to scale FG systems. The reason remains unclear to us, considering the increased use of combinations of IO-LCA and process-based LCA in recent years (Hagenaars et al. 2025).

Econometric models identify statistically significant relationships between variables using historical data, often serving as inputs for other models (Wiedenhofer et al. 2024). Beyond their role in IAMs (e.g., Knobloch et al. 2020) and their occasional use to project future stock in stock-driven DSM-LCAs (e.g., Brand et al. 2012), none of the studies in our review applied econometrics as a primary system-scaling framework. Their main strength lies in avoiding the restrictive assumptions characteristic of GEM approaches. However, they are generally constrained to the short term and exhibit strong path dependency (Beaussier et al. 2019; Wiedenhofer et al. 2024).

4 Pitfalls, challenges, and best practices

We identified 12 pitfalls and challenges in the reviewed studies. These are not ranked by priority.

We see the role of LCA here primarily in providing detailed bottom-up environmental data, a supply chain perspective, and impact assessment across multiple categories—either ex-post or endogenously, as outlined in Section 3. The goal is to leverage the strengths of LCA together with those of other models, which are better suited to address broader system dynamics, feasibility, or behavioural responses. As long as the LCI can be consistently updated based on outputs from these specialized models, prospective macro-level LCA can remain as valid as the underlying models while preserving its methodological integrity.

This discussion is therefore not intended as a call to expand LCA's conventional boundaries, but rather as an observation of where combined approaches could be further developed to improve our understanding of potential pathways to sustainable societies.

4.1 System scaling

In all reviewed cases, micro-level characterisation results are calculated first, with system scaling conducted outside the LCA framework. Whether the functional unit maintains a linear relationship with the scale of the processes that provide it (Heijungs 2020; Pizzol et al. 2021) depends on the selected modelling approach.

ESM and IAM frameworks introduce non-linearities in certain aspects; for example, ESMs may model the utilisation of specific energy technologies using merit-order curves. We found only one study explicitly adjusting unit processes based on scale: van der Meide et al. (2022), who include changing ore grades based on production volume. Apart from that, such effects can arise indirectly when parameters from ESMs or IAMs—which often endogenously represent technological learning based on deployment or investment (Keppo et al. 2021)—are incorporated into the modelling of unit processes for micro-level LCA. Other approaches generally preserve linearity and model technological change as a function of time rather than scale. For example, Tang et al. (2023) assume identical efficiency improvements for battery electric vehicles in scenarios with both no uptake and 100% sales share by 2030.

The importance of linking performance to the scale of deployment (or investment) depends on the maturity of the technology (Pizzol et al. 2021). Generally, we recommend this approach rather than relying on identical future assumptions across scenarios It is important to keep in mind that the *ecoinvent* database includes production volumes for certain technologies to construct market processes (Wernet et al. 2016), implying that unit process data are valid for a specific production quantity; though whether they hold at other capacities is uncertain.

Another important challenge for system scaling is that the assumption that the BG system is independent of the FG system no longer holds. Given the scale of the FG system, it must be considered that BG processes may also source from the FG system (Charalambous et al. 2024). A few studies address this (e.g., Hertwich et al. 2015). Charalambous et al. (2024) demonstrate how FG system changes can be propagated through the BG system in *premise* by adjusting BG markets. However, inconsistencies with the original IAM scenario remain, as it does not account for the modelled FG system developments. The significance of FG–BG system inconsistency also depends on the study's scope. ESMs, for example, cover entire electricity or energy systems in the FG system, leaving a small BG. Therefore, a limited error can be assumed. Nevertheless, building on Gibon et al. (2015) and Charalambous et al. (2024) to better integrate FG and BG systems is a key next step.

4.2 Internal consistency

While subsection 4.1 addresses the consistency between system scale and the LCIs of the unit processes, this subsection focuses on three additional potential sources of inconsistency. By internal consistency, we refer not just to the LCA itself, but consistency within the entire model ensemble—within the LCA components, within the coupled models, and between them—although evaluating the internal consistency of individual coupled models is beyond the scope of this work.

First, inconsistencies can arise between the models in the FG system, which are typically coupled one-way: external models inform LCA but not vice versa. Beaussier et al. (2019) highlight the need for high-level coupling—defined as "models that are linked and run together involving variables (…) in closed loops"—when (i) environmental impacts affect system processes or (ii) agents respond to environmental policies. Some ESM-based studies address this by optimising for least environmental impacts based on LCA results (e.g., Vandepaer et al. 2020). Generally, researchers need to be aware that model coupling inherits assumptions and modelling choices from the other model (de Bortoli et al. 2025), posing a potential challenge to consistency.

Second, scenario misalignments are common; e.g., ambitious FG system policies paired with less ambitious BG system scenarios. Aligning the FG and BG system narratives is important for greater internal consistency. When using *premise* (Sacchi et al. 2022), it is important to recognise that it reflects the assumptions of the underlying IAM, which may not always align with FG system scenarios developed using other modelling frameworks, such as ESMs (Weidner et al. 2022).

Third, one more issue we want to highlight is mass balance, a core principle in DSM methods but often violated in other models, such as IAMs (Pauliuk et al. 2017). A systematic assessment was not possible due to limited transparency in many studies. Here, we simply aim to raise awareness that mass balance cannot be assumed—especially when coupling models or representing closed-loop systems—and must be explicitly checked.

4.3 Temporal evolution modelling

Temporal evolution in prospective LCA affects both FG and BG systems, through parameters like technological change (e.g., efficiency, lifetime), system composition (e.g., market shares), and broader configurations (e.g., recycling rates, ore grade degradation) (Vandepaer and Gibon 2018). Outside IAM- or ESM-based studies, technological change of FG processes is typically represented through selective, exogenous updates of a few parameters—typically electricity mixes or efficiencies—based on literature, policy documents, or assumptions. This fragmented approach can create temporal mismatches across subsystems (Arvidsson et al. 2018; Thonemann et al. 2020). Prospective LCI databases like *premise* (Sacchi et al. 2022) help reduce this, but not entirely. While *premise* is the most comprehensive approach, it has so far only integrated IAM variables related to electricity production, steel production, cement production, fuel production and transport (Sacchi et al. 2025), meaning that some temporal mismatches remain. For a recent critique of the use of IAMs for prospective LCI databases, see de Bortoli et al. (2025).

Among the 20 studies that use micro-level characterisation results from existing studies or databases—without their own LCI modelling—19 fail to apply temporal evolution consistently. Often, changes in BG processes are not propagated consistently. For example, Brand et al. (2012) assume a future reduction of the emission intensity of electricity supply, but apply it only to vehicle use, not to upstream or downstream processes.

Apart from not being linked to system scale, technological change is also rarely modelled with the needed complexity. That it is actor-driven and can be environmentally regressive (van Nielen et al. 2025) was not explicitly

considered in any study. Few studies distinguish between emerging (Technology Readiness Level (TRL)<9) and mature (TRL≥9) technologies, despite fundamentally different dynamics: emerging technologies may still undergo major shifts during scale-up, while mature ones evolve incrementally (Buyle et al. 2019). Technological development is seldom modelled explicitly; linear interpolation remains common (e.g., Knobloch et al. 2020). For TRL≥9, van Nielen et al. (2025) propose a structured approach to modelling learning, and guidance on scaling-up emerging technologies is also available (e.g., Thonemann et al. 2020; Tsoy et al. 2020; Erakca et al. 2024).

Technological detail varies widely. Some studies include only a few options—like one drivetrain per vehicle (e.g., Tang et al. 2023)—while others cover a broader range, such as six battery types (Tarabay et al. 2023). Studies that incorporate a wide spectrum of technological variants offer a more comprehensive view of the potential future. Market shares are usually treated as static or scenario-based; few studies model them endogenously, e.g., via discrete choice models (Brand et al. 2012; Mastrucci et al. 2024). Many studies update only market shares (especially electricity) without considering technology development at the process-level.

Overall, we recommend a more systematic modelling of FG systems' evolution. A best practice example is provided by Alaux et al. (2025a), who use the *SIMPL* framework (Langkau et al. 2023) to develop scenarios for the greenhouse gas emissions of the Austrian building stock.

4.4 Temporal distribution modelling

About half of the studies (41) neglect the temporal distribution of processes. The remaining studies (45) differentiate life cycle stages—typically upstream, use, and/or downstream—and link micro-level characterisation results for each to temporally distributed outputs of the respective coupled model, as described in Section 3. It is worth noting that many studies omitting temporal distribution focus exclusively on either production or EoL (21 studies), often because their scope is limited to material-related impacts.

More studies addressed temporal distribution than expected, but none added a temporal dimension at the process-level. While life cycle stage-level differentiation offers a partial solution, resolving the temporal distribution of processes within up- and downstream stages remains an important area of future research (Müller et al. 2025). The tool *bw_timex* (Diepers et al. 2024) shows promise in advancing this approach. Note that considering temporal distributions for all processes in a life cycle—including those in the BG system—would require historical data, as some inflows originate from capital goods built long ago.

We recommend differentiating at least the timing of the upstream, use, and downstream phases in prospective macro-level LCAs while determining on a case-by-case basis whether a differentiation at the process level is needed.

4.5 Inconsistent terminologies

Terminological inconsistencies have long been a challenge in LCA, leading to what has been described as an "alphabet soup" of approaches (Guinée et al. 2018). In macro-level assessments, terms like *large-scale*, *economy-wide*, or *system-wide* are often used ambiguously or interchangeably, without formal definitions. For instance, Hellweg et al. (2023) mention "large-scale LCA analyses (in contrast to product-level LCAs)", but do not clarify their understanding of *large-scale*. To our knowledge, no formal definition exists. To bring clarity, we define macro-level LCA as *assessment of environmental impacts associated with the life cycle of a system fulfilling a specific function for the demand at the national, continental, or global scale*, as shown in the introduction. We employ the term *macro-level LCA*, first used by Dandres et al. (2012) and inspired by economic terminology (micro, meso, macro), mainly to avoid confusion with *upscaling*, which in prospective LCA typically refers to technological maturity (Tsoy et al. 2020).

For temporal aspects, we recommend following the terminology of Müller et al. (2025): *dynamic LCA* for modelling temporal distribution, *prospective LCA* for modelling temporal evolution, and *time-explicit LCA* when both are addressed.

Regarding the micro-level LCA outputs scaled to the macro-level, most studies use the term *emission factor*, *impact factor*, or *LCA coefficient*. We find all three terms potentially confusing. *Impact factor* can easily be mistaken for *characterisation factor*, a distinct concept in LCA. *Emission factor* does not indicate that the values have already been characterised; emissions are typically associated with the LCI. *LCA coefficient*, meanwhile, is vague; a coefficient derived from LCA could refer to almost anything. We use and recommend the term *characterisation result*, which aligns with standard LCA terminology (Guinée 2002).

4.6 Functional units, system boundaries and multifunctionality

Although the functional unit is central to LCA, only 43% of the studies in our sample define it, and just 21% specify it at the macro-level. Examples of macro-level functional units include meeting the European Union's energy demand by 2050 (Blanco et al. 2020), operating the United Kingdom's light-duty vehicle fleet for a year (Raugei et al. 2021), and managing Sweden's annual non-hazardous waste

(Arushanyan et al. 2017). These demonstrate that meaningful functional units can be formulated at the macro-level.

In prospective studies, it is important to account for changing functional units over time. This can be done, for example, by defining different functional units for each scenario and time frame (Moni et al. 2020). Generally, when comparing across time, it is important to account for changes in what the system provides, for example different levels of demand.

With regard to system boundaries, many studies omit parts of the life cycle, especially the EoL. While acceptable depending on objectives, this risks incomplete results and suboptimal decisions. Particularly, the EoL stage for systems with long lifetimes, as many studies evaluate here, can be very important because its EoL lies far in the future, and the respective processes might look very different then (Cucurachi et al. 2023).

Evolving technologies and societal needs can lead to shifts in process and system functions, with important implications in four main respects. First, allocation factors may need to be adapted to future conditions. Second, co-products may become scarce as fossil fuel production decreases, with consequences for resource availability (Månberger 2021; Hahn Menacho et al. 2025a). Third, especially at the macro-level, the handling of co-products becomes increasingly important, for instance due to demand constraints. This aspect has been addressed by two studies (Adrianto et al. 2023; Nabera et al. 2024). Finally, system expansion can be particularly challenging, as additional functions are not necessarily consistent across scenarios. For example, in one scenario agri-photovoltaic may be included, adding an additional function to the system, while in another they may not, leading to a comparison between a system that provides both agricultural products and electricity and one that provides only the former. This issue is not specific to the macro-level but applies to any prospective LCA.

We recommend always reporting the functional unit and any potential changes over time, defining it to allow unbiased comparisons of scenarios and alternatives. Furthermore, while exceptions exist (e.g., cradle-to-gate analyses of future fuels), the full life cycle should generally be included in system boundaries to avoid biased insights.

4.7 Lack of thematic and scenario diversity

The reviewed studies exhibit a narrow thematic focus: 93% cover just four sectors—energy systems (25 studies); transport (26), mainly the transition to electric vehicles; intermediate goods (19), such as aluminium and hydrogen; and buildings (11). This leaves important areas like food, water, sanitation, consumer goods, and waste largely absent, despite their relevance for sustainability transitions. Broadening the thematic scope is important.

Scenario choices also show limited diversity. Many studies rely (33) on IEA scenarios for system scaling or modelling temporal evolution, typically electricity mix projections. While this improves comparability, it risks reinforcing shared assumptions and biases (Schulze et al. 2024), such as underestimating the growth of renewable energy (Creutzig et al. 2017; Way et al. 2022; Lopez et al. 2025).

Regarding the SSP framework (O'Neill et al. 2017), often used via IAMs for system scaling or temporal evolution, as well as sometimes applied directly (e.g., Mastrucci et al. 2024), there is a strong focus on SSP2, the middle-of-the-road scenario. Despite the importance of scenario diversity (Bruhn et al. 2023), the intention of the SSP framework to explore diverse futures (Riahi et al. 2017) and *premise* supporting SSP1 and SSP5 as well (Sacchi et al. 2025), we find only four studies (Pedneault et al. 2021; Kalt et al. 2022; Alaux et al. 2025a; Horup et al. 2025) using other SSPs. For Representative Concentration Pathways (van Vuuren et al. 2011), we find greater diversity. Generally, IAMs often assume convergence towards Western lifestyles with increasing wealth, making modelling of alternative, more imaginative futures difficult (Hickel et al. 2021). This tendency is already embedded in the SSPs, all of which presuppose continued global economic growth (de Bortoli et al. 2025).

Temporal scope also lacks variation: 71% of studies end in 2050, while only six extend beyond 2060. As Schulze et al. (2024) note, this can be problematic for sectors with long-lived assets, where shorter horizons may miss long-term implications due to system inertia or delayed material availability.

To improve future analyses, we recommend focusing on a small set of contrasting, informative scenarios covering a wide range of possible futures. The *SIMPL* approach (Langkau et al. 2023), and its use in Alaux et al. (2025a), demonstrate good practice. Furthermore, with 2050 only 25 years away, longer timeframes should be considered; despite greater uncertainty for longer time horizons (Steubing et al. 2023), especially with regard to disruptive technologies (Sacchi et al. 2022).

4.8 Representing the complexity of sustainability transitions

Sustainability transitions are inherently complex, and no single model captures all relevant dimensions. Understanding each model's scope and limitations is therefore essential. For example, as Wiedenhofer et al. (2024) note, there is often a trade-off between capturing socio-economic complexity and adhering to thermodynamic principles: models

like LCA provide detailed representations of technologies and their interlinkages through energy and mass flows but typically omit inter-sectoral relationships and broader economic feedbacks.

Rather than proposing a comprehensive framework for modelling transitions, we want to highlight aspects addressed or overlooked in prospective macro-level LCA literature. In doing so, we do not suggest that LCA itself should incorporate all these aspects within its methodological boundaries. Instead, we refer to opportunities for improving their representation in approaches that combine LCA with other models.

Cross-sector effects are only captured by a few studies (e.g., Rüdisüli et al. 2022). Whether IAM-LCA studies capture these depends on the coupling: approaches including micro-level characterisation results in the IAM (Pehl et al. 2017) represent all aspects also included in the IAM, whereas ex-post applications (e.g., Müller et al. 2024) capture only those that affect the scaling variables, e.g. demand. The same applies to ESM-LCA studies.

Aspects that we have not found represented explicitly include rebound effects, threshold effects, incumbent power, institutional roles, behaviour, the role of institutions (Hafner et al. 2020), and tipping points (Binder et al. 2025). Actor heterogeneity is only captured in some IAM–LCA studies indirectly through the IAM, and then only to a limited extent, mostly focusing on income inequality (Keppo et al. 2021; de Bortoli et al. 2025). Generally, studies focus on aggregate outcomes, obscuring differences in access, needs, and responsibility.

Prospective macro-level LCA could better represent sustainability transitions by leveraging social science perspectives, such as heterodox economics (Hafner et al. 2020), underused methods like SD or ABM, and new model combinations. Promising research directions include provisioning systems and sufficiency corridors (Pauliuk 2024; Pichler et al. 2025).

Regarding mitigation strategies, Pichler et al. (2025) propose a 2 × 2 framework—supply vs. demand and individual vs. systemic—yielding four perspectives: techno-innovation, industrial transformation, individual decision-making, and embedded lifestyles. They highlight that focusing exclusively on supply or demand leaves critical gaps and clarify that sufficiency measures can also apply to the supply side and efficiency measures to the demand side. Applying the framework to our sample is challenging, as the drivers behind mitigation measures are rarely explicit. We see the framework as valuable for guiding future modelling and stress the importance of clarifying underlying drivers in future studies.

While enhancing the representation of sustainability transitions in current modelling practice is important, it is equally important to keep in mind that modelling complexity has trade-offs, like risking interpretability, and must be purpose-driven (Saltelli et al. 2020; Kaufman and Bataille 2025). Models should be as simple as possible but as complex as necessary for robust decision-making.

4.9 Constraints

Distinguishing constraints from scenario assumptions, parameters, or model structures is often difficult. A detailed discussion and conceptualisation are beyond the scope of this study, and since reviewing each coupled model in detail is not feasible here; we instead highlight only a few important points. While including constraints and assessing feasibility is not part of LCA's conventional methodological boundaries, it is an important consideration for approaches that combine LCA with other models to represent potential future pathways to sustainable societies.

Constraints help assess whether scenarios are not only environmentally beneficial but also feasible. Many studies include constraints, often through coupled models. In particular, ESMs and IAMs introduce constraints related to climate targets, capacities, infrastructure availability, technology-specific deployment, budgets, and many other aspects (e.g., Louis et al. 2018; Luderer et al. 2019; Reinert et al. 2021). DSMs often constrain secondary material availability (e.g., Milovanoff et al. 2019). Optimisation approaches are also able to include constraints well, such as manufacturing capacity (Hung et al. 2022; Lechtenberg et al. 2024). By contrast, studies without model coupling often omit explicit constraints, instead discussing limitations retrospectively, such as comparisons to current production (e.g., Ginster et al. 2024) or resource reserves (e.g., Zhang et al. 2024). While useful for context, this does not improve the feasibility of the modelled scenarios.

Some types of constraints are not explicitly mentioned by any study, such as labour availability or incumbent power (Geels et al. 2017). Only two studies (Adrianto et al. 2023; Nabera et al. 2024) considered constrained co-product market absorption. Another aspect not found explicitly in the literature is competition for production capacities and resources between different systems of analysis (Hung et al. 2022); here, more granular and explicit modelling is needed.

To guide future research, we propose, inspired by Wiedenhofer et al. (2024), four non-exclusive constraint types: (i) physical/ecological (e.g., raw material availability), (ii) social/political (e.g., labour shortages or incumbent interests), (iii) technological (e.g., technology availability or manufacturing capacities), and (iv) economic (e.g., insufficient investment).

Importantly, the temporal dynamics of constraints deserve greater attention (Hung et al. 2022). A resource may

be available in the long term, but short-term bottlenecks—such as mine development (Schulze et al. 2024)—can limit the feasibility of scenarios (Hung et al. 2022). Additionally, geopolitical aspects may gain importance (Post and Le Billon 2025). Explicitly incorporating some of these constraints—both in model formulations and in scenario narratives—can improve realism in prospective macro-level LCA. Life cycle optimisation tools (e.g., Lechtenberg et al. 2024) offer promising means to implement such constraints.

We refrain from providing a general recommendation at this stage, as this topic is highly specific to the goal and scope of each study.

4.10 Narrow focus on climate change impacts

About half of the studies (44) assess climate change only. While crucial, this narrow focus neglects LCA's strength in revealing trade-offs across impact categories. Broadening the scope is essential for future macro-LCAs (Hellweg et al. 2023), as existing research has shown that decarbonisation can lead to large environmental co-benefits and trade-offs (Luderer et al. 2019).

Although a detailed discussion of Life Cycle Impact Assessment (LCIA) in prospective and macro-level LCA is beyond this study, we want to highlight a few important points. First, LCIA typically treats emissions as instantaneous pulses, ignoring temporal dynamics that may be relevant (Cardellini et al. 2018). Second, inconsistencies exist between inventory and impact phases regarding time horizons (Levasseur et al. 2010; Beloin-Saint-Pierre et al. 2020). Third, many models rely on static baseline concentrations, though these may change (Vandepaer and Gibon 2018; Lueddeckens et al. 2020). Using IAMs to project future background concentrations has been proposed but not implemented (Mendoza Beltran et al. 2018). Fourth, emerging technologies may introduce novel emissions not yet covered by LCIA methods, which can result in overlooked impacts and a false sense of certainty (Thonemann et al. 2020; Cucurachi et al. 2023). Existing dynamic LCIA methods are so far focused on climate change (Levasseur et al. 2010; Milovanoff et al. 2022; Ventura 2023; Diepers and Müller 2025). Fifth, prospective LCI databases generated with *premise* are highly uncertain when used to assess impact categories beyond climate change (Sacchi et al. 2022; Bruhn et al. 2023). Finally, no study addressed scale-dependent changes to LCIA methods—an aspect that deserves further attention.

We recommend covering a full set of impact categories to identify trade-offs and to transparently highlight current limitations in impact assessment in prospective macro-level LCA.

4.11 Uncertainty and sensitivity

Uncertainty and sensitivity are widely discussed in LCA but inconsistently defined and applied (Heijungs 2024), including in prospective LCA. For instance, Spielmann et al. (2005) view epistemic uncertainty—arising from limited knowledge of future systems—as central and best addressed through scenarios. In contrast, Langkau et al. (2023) associate it with methodological choices not captured by *future* scenarios. Here, we focus on how uncertainty and sensitivity are treated in the reviewed studies.

Most studies use multiple scenarios, though only some explicitly frame them as addressing uncertainty (e.g., Horup et al. 2025). Dedicated uncertainty analyses using distributions for specific parameters are rare; only five studies apply Monte Carlo simulation (Dirnaichner et al. 2022; Kalt et al. 2022; Tang et al. 2023; Hahn Menacho et al. 2025a; Shirmohammadi et al. 2025). LCIA uncertainty is not considered, except by Sacchi et al. (2023). Challenges include data limitations, especially projecting future uncertainty ranges, and applying uncertainty across coupled models. Given the absence of a 'true' future, we see structured, transparent cornerstone scenarios as the most practical way to address uncertainty (Langkau et al. 2023).

About half of the studies (39) include sensitivity analyses, predominantly using local, one-at-a-time approaches (using the terminology of Heijungs (2024). Changing coupled models (Boyce et al. 2024), LCIA methods (Reinert et al. 2021), accounting scope (Pehl et al. 2017), allocation approach (Dong et al. 2022), foresight horizon (Zibunas et al. 2024), or optimisation targets (Louis et al. 2018) can also be seen as local, one-at-a-time sensitivity analysis. Some studies build scenarios by systematically varying inputs, resembling sensitivity analysis (Ginster et al. 2024; Pauliuk et al. 2024b). Only two studies apply global sensitivity analysis (Alaux et al. 2025b; Hahn Menacho et al. 2025a). The potential advantages of applying global sensitivity analysis more widely warrant closer examination.

We recommend that studies always include sensitivity analyses of key parameters to contextualise the results. Uncertainty analyses should be conducted depending on the availability of data.

4.12 Transparency and reproducibility

Transparent documentation of methods, open-access publication, open-source models, and open data are essential for scientific progress; not only to ensure reproducibility but also to enhance effectiveness by fostering collaboration, enabling critical peer review, improving public trust in research, and upholding ethical standards (Pfenninger et al. 2017; Pauliuk 2020).

In the reviewed studies, transparency is often limited. Unclear objectives, functional units, system boundaries, and modelling choices (e.g., form of interpolation) are common. For instance, 32 studies using the *ecoinvent* database fail to specify the system model applied (Wernet et al. 2016). Model coupling is rarely well-documented. Clear illustrations of model interactions (e.g., Junne et al. 2020) and the FG system, for example through flowcharts, are needed. Scenario variables should be made explicit, ideally summarised in a concise overview as in van der Voet et al. (2019). A clear distinction between model inputs and outputs is equally essential. In addition, data sources and software should be disclosed, including version information where applicable (Steubing et al. 2023). While more challenging for multi-model studies, we recommend aligning with the ISO reporting requirements (ISO 2006), particularly for temporal scope, functional unit, and boundaries.

Most studies (65) share input data, but we did not assess whether shared data is sufficient for reproducibility. Only 23 studies share their models. Müller et al. (2024) provide a good example for sharing data, and Alaux et al. (2024) for a reusable model. We recommend using repositories that support rich metadata, persistent identifiers, clear licensing, version control, and long-term preservation (e.g., Zenodo). For further guidance, see Pauliuk et al. (2024a).

The limited transparency of research objectives also prevents us from providing clear guidance on which tools are best suited for specific questions. Overall, the literature shows little reflection on what is required to achieve a particular research objective or type of decision support and appears largely method-driven. We emphasise that this should be reversed: the research question should always determine the choice of method, not the other way around.

5 Conclusions and recommendations

We reviewed 86 prospective macro-level LCA studies, categorising them into four main (DSM-LCA, ESM-LCA, IAM-LCA, no coupled model) and two less common (coupling GEM and SD) approaches. The approaches vary in focus and complexity. Each brings specific strengths and trade-offs: DSM-LCAs capture stock dynamics but lack coverage of socioeconomic aspects; ESM-LCAs provide detailed insights into energy systems but are also limited to it; IAM-LCAs provide better socioeconomic coverage but operate at a coarse resolution and typically require collaboration with IAM developers; and approaches without a coupled model offer flexibility but risk oversimplification. We also identified common pitfalls, methodological challenges, and best practices. Our review reveals a diverse and growing but fragmented field with inconsistent terminology, assumptions, and modelling practices that limit comparability.

Our review revealed several potential directions for future research. Among these, we highlight four priorities that we consider particularly important for advancing the field:

- **Improve the modelling of sustainability transitions**. Better representation of temporal dynamics—especially for long-lived assets—and the implementation of feedbacks between FG and BG systems are important. Capturing the complexity of sustainability transitions requires advancing existing approaches: drawing on perspectives from the social sciences, such as heterodox economics (Hafner et al. 2020), exploring underused methods like SD and ABM, and experimenting with new model combinations. However, increased complexity must be purpose-driven; models should remain as simple as possible, but as complex as necessary to answer the research question at hand (Saltelli et al. 2020; Kaufman and Bataille 2025). No single model can address all research questions.
- **Strengthen policy relevance.** Stronger links between modelling and policy are needed, particularly in DSM-LCA and uncoupled approaches. Representing distributional aspects, demand-side measures, and behavioural responses will help support more just and effective policy design.
- **Ensure transparency**, **reproducibility and consistent terminology.** Clearly reporting functional units, system boundaries, and data flows between coupled models is crucial. We also urge the field to converge on shared terminology, for which we propose *macro-level LCA*. For the time dimension, we recommend using *prospective LCA* for modelling temporal evolution and *dynamic LCA* for temporal distribution (Müller et al. 2025). Models and data should be, as far as confidentiality considerations allow, openly available. Equally important, research questions and objectives must be clearly stated and should guide the choice of method. Doing so helps avoid unreflective modelling driven primarily by model availability.
- **Develop methodological guidance**. As the scope of LCA expands, so does its complexity, underscoring the need for guidance that maintains modelling freedom while at the same time facilitating transparency, quality, common language, and comparability (Bisinella et al. 2021). Such guidance should clarify which approaches are best suited to which types of research questions. Our review represents an initial step toward this guidance by illustrating how different approaches have been applied

and identifying the systems to which they have been applied.

By addressing the aspects mentioned above, the field of prospective macro-level LCA can improve our modelling and understanding of transitions to sustainable societies.

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Declarations

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