



A joint conceptual and computational structure for dynamic and prospective LCA

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Abstract

Purpose Life cycle assessment (LCA) studies that attempt to anticipate the future impact of product systems are increasingly widespread. However, a lack of clarity remains on what is the accurate terminology to be used in studies with strong focus on the temporal dimension; what are the specific definitions, and what are the underlying computational approaches. This work sets specifically to clarify the differences between “prospective” and “dynamic” elements in LCA studies and focus on representing them with a matrix-based computational structure, attempting to move beyond the ambiguity of existing definitions.

Methods Existing definitions of prospective and dynamic LCA are briefly mapped with special focus on the inventory and impact assessment phases. The classic matrix notation is then expanded to cover all temporal aspects that can be considered in LCA and to propose a classification. Finally, the relation between existing tools that allow prospective and dynamic LCA and the proposed classification is discussed.

Results and discussion A classification of prospective and dynamic LCAs is proposed starting from existing practice and using conventional matrix-based computational structures. Its potential and limitations are discussed in the context of existing approaches and tools, and the associated decision-making processes. The study highlights that trade-offs can arise between comprehensiveness, computational effort, and data requirements. Practitioners are advised to carefully consider the extent to which the inclusion of a temporal dimension in the LCA model can better inform decision-making.

Conclusion The study pragmatically categorizes LCA studies based on computational structures rather than on definitions. The focus is on classifying a model based on its structure rather than based on its name. The classification should facilitate the choice of modelling approach for a knowledge transfer tailored to match the data availability and the needs of decision-makers. Although the matrix-based framework offers clarity, there is nevertheless the research need to move beyond it to cover non-linearity effects, despite computational challenges.

Keywords Anticipatory studies · Temporal resolution · Forecasting · System analysis · Time-specific

1 Introduction

Life cycle assessment (LCA) studies are increasingly focusing on product systems that are either not existing yet at mature scale or that are expected to exist in the future,

for example systems with low technology readiness level (TRL) (Wender et al. 2014; Göswein et al. 2020; Lefebvre et al. 2021). This trend is partly driven by the need to identify early on technological advancements that will enable the green transition, before they are deployed (Arvidsson et al. 2024). The trend is also partly driven by the growing uncertainty on how the global economy will develop and transform to address today's environmental challenges, as such development will inevitably affect the systems under analysis (Nurdiawati et al. 2025). In addition, today's dominant role of LCA as the key methodology for assessing technologies from the environmental perspective has led to performing more and more complex LCA studies over time, also facilitated by advances in LCA software development (Marson et al. 2025; Müller et al. 2025). Representing

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product systems that “stretch” over time requires a LCA modelling approach that can simulate each life cycle stage (e.g., manufacture, use, disposal) and its supply chain at the specific point in time when it takes place and that allows evaluating impacts accordingly.

However, the focus on such temporal dimension of LCA studies is interpreted in different ways in literature, where two terms are predominantly used and sometimes confused without being sharply defined or formalized: “dynamic” LCA and “prospective” LCA (Sohn et al. 2020; Lueddeckens et al. 2020; Lang-Quantzendorff and Beermann 2025). Other terms referring to LCA studies with a clear focus on future time conditions can also be found in literature, commonly considered synonyms of prospective LCA (Heijungs 2024). These include “ex ante LCA” (Cucurachi and Guinée 2018; Jouannais and Pizzol 2022; Arvidsson et al. 2024), “anticipatory LCA” (Wender et al. 2014; Göswein et al. 2020; Lefebvre et al. 2021), “predictive LCA” (Alfaro et al. 2010; Choudhary et al. 2025), “LCA of early-stage technology” (Baaqel et al. 2023), “LCA of emerging technologies” (Bergerson et al. 2020; Moni et al. 2020; Van Der Hulst et al. 2020), and “future-oriented LCA” (Arvidsson et al. 2024).

Additionally, there is a growing number of advanced LCA studies that integrate temporal elements that could be defined both “dynamic” and “prospective”. While some of these studies describe in mathematical terms the computational approach used (Collinge et al. 2013; Di Bari et al. 2024; Lang-Quantzendorff and Beermann 2025; Müller et al. 2025) others only describe it in words (Voglhuber-Slavinsky et al. 2022; Heidak et al. 2025; Abu-Ghaida et al. 2025), making it difficult to compare between approaches. While dynamic and prospective LCA studies have primarily introduced temporal aspects into the life cycle inventory (LCI) phase, recent research introduces them into the life cycle impact assessment (LCIA) phase as well (Lan and Yao 2022; Baustert et al. 2022; Van Den Oever et al. 2024; Sacchi et al. 2025; Barbosa Watanabe and Cherubini 2026) beyond the well-established application to climate change impact category (Levasseur et al. 2010), whilst the inclusion of temporal aspects into the interpretation, normalization and weighting phases remains very limited.

Summing up, there is currently a substantial diversity of LCA studies explicit on the temporal dimension and with a focus on future time, but due to an inconsistent use of terminology (cf. Table 1) and limited reporting of the underlying computational structures, it is difficult to classify and compare them in terms of approach used. A clear and well-established formalization and computational structure exist for the “classic” LCA approach (Heijungs and Suh 2002) and derived ones such as life cycle costing (LCC), as well as for input-output LCA (Heijungs et al. 2013; Nakamura and Nansai 2016). However, what appears to be missing

is a clarification of how the concepts of prospective and dynamic LCA relate to each other, how they differ, and how they can be combined, supported by a univocal computational framework that can cover both dynamic and prospective elements.

In this context the present work intends to facilitate the classification of LCA studies by coherently identifying and defining their dynamic and prospective elements based on a mathematical description. The study does not aim to propose a universal classification but an operational one that can provide practical guidance and insight. The main added value and novelty lies therefore in moving from the use of definitions (that can leave excessive space for interpretation) to the use of a conventional matrix-based mathematical framework (that should allow for univocal interpretation) to explain what is the meaning of “dynamic” and “prospective” in LCA studies, and in the coherent representation and summary of several different approaches using the same theoretical framework. In the following sections, current definitions and approaches to prospective and dynamic LCA are briefly reviewed. Next, a computational structure is progressively derived, by building on the classic theoretical one (Heijungs and Suh 2002) and adapting it using examples from practice. The derived computational structure is intended to show prospective and dynamic elements both individually and together. Furthermore, an attempt is made to frame existing models and tools within the proposed computational structure, to provide guidance for the LCA practitioners on which terminology to use based on the model developed. Approaches and cases where the proposed computational structure does not fit are identified and discussed as well.

2 Current definitions, primarily focusing on the LCI phase

Arvidsson et al. (2018) define prospective LCA as “studies of emerging technologies in early development stages, when there are still opportunities to use environmental guidance for major alterations”. Prospective LCA has later been defined by Arvidsson et al. (2024) as a “LCA that models the product system at a future point in time relative to the time at which the study is conducted”. According to this definition, a prospective LCA therefore covers technology developments over time, with explicit reference to forecasted future scenarios. Collinge et al. (2013) define dynamic LCA as “an approach to LCA which explicitly incorporates dynamic process modeling in the context of temporal and spatial variations in the surrounding industrial and environmental systems” thus encompassing the temporal differentiation not only of the technologies but also of

Table 1 Non-exhaustive summary of existing definitions for dynamic and prospective LCA, in chronological order, including a brief interpretation of how each definition addresses the temporal dimension

Definition of	Original definition	Reference	Temporal dimension in the definition
Dynamic LCA	<i>“In a dynamic LCA, the temporal profiles of emissions are considered so that the LCI result for each emission is a function of time rather than a single number. Once a dynamic inventory is calculated, the LCIA characterization model is solved dynamically, i.e. without using steady-state assumptions, to obtain time-dependent characterization factors that depend on the moment when the pollutant is emitted.”</i>	Levasseur et al. (2010)	Flows of a product system are differentiated over time, and so are characterization factors.
Dynamic LCA	<i>“An approach to LCA which explicitly incorporates dynamic process modeling in the context of temporal and spatial variations in the surrounding industrial and environmental systems”</i>	Collinge et al. (2013)	Differences in temporal occurrence are accounted for in the LCA model.
Prospective LCA	<i>“Studies of emerging technologies in early development stages, when there are still opportunities to use environmental guidance for major alterations”</i>	Arvidsson et al. (2018)	The decision support takes place in the present for a technology that is being developed and will materialize in the future.
Dynamic LCA	<i>“Regardless the level of complexity considered, to take time into account in LCA, the LCI must be dynamic, which means that emissions and resource consumptions are explicitly distributed over time”</i>	Cardellini et al. (2018)	Environmental flows of a product system are differentiated over time.
Dynamic LCA	<i>“LCA studies where relevant dynamic of systems and/or temporal differentiation of flows are explicitly defined and considered”</i>	Beloin-Saint-Pierre et al. (2020)	Flows of a product system are differentiated over time, system changes over time are considered.
Prospective LCA	<i>“The absolute timing of a product provision or decision, leads to a distinction between subtypes of LCA. If this is done in the past, we speak of a retrospective LCA and when done in the future, a prospective LCA”</i>	Schaubroeck et al. (2021)	Reference to a future point in absolute time where the product provision or decision happens.
Prospective LCA	<i>“LCA that models the product system at a future point in time relative to the time at which the study is conducted”</i>	Arvidsson et al. (2024)	Reference to a future point in absolute time where the product system is modelled.
Prospective LCA	<i>“pLCA explicitly references time by modeling the system at a distinct future point [in time]”</i>	Müller et al. (2025)	Reference to a future point in absolute time where the product system is modelled.
Dynamic LCA	<i>“[the inventory] of dLCA [...] is essentially the inventory of a static LCA distributed over time”</i>	Müller et al. (2025)	Inventory flows are differentiated over time.

emissions and extractions of resources across the various activities of a product system.

These definitions address the temporal aspects of the inventory phase from different perspectives, yet with elements of overlap, but most importantly with complementary elements (see Table 1). Some of these areas of overlap have already been addressed in previous research. The notion of dynamic LCA may in fact encompass both dynamics of systems and temporal differentiation, according to a latest review (Beloin-Saint-Pierre et al. 2020), and in this work we primarily focus on the time differentiation of the system (the term “dynamic” in dynamic LCA should thus be intended as “temporally differentiated”). When considering the dynamics of a system in a future time, there can be substantial overlap with prospective LCA, as the latter covers states of the system that change in the future.

From the notion of prospective LCA, the importance of considering subsequent system states that change over time is noticeable as well (Table 1). Earlier definitions of prospective LCA are open to consider dynamic aspects afterwards, with Schaubroeck et al. (2021) mentioning: *“The absolute timing of a product provision or decision, leads*

to a distinction between subtypes of LCA. If this is done in the past, we speak of a retrospective LCA and when done in the future, a prospective LCA”. By pinpointing only product provision as specific reference point, which takes place in the future for prospective LCA, the potential spread of the life cycle over time can be included afterwards. This integration paves the way for a joint consideration of dynamic and prospective LCA. The analysis of these definitions suggests the need to view dynamic and prospective elements together. It also suggests that to capture all time-specific elements of the LCI phase it is important to consider (i) the development of the technological system over time (foreground or background, as per prospective LCA), and (ii) the specific time of generation of the elementary flows over the full period over which the various phases of the analysed system stretch (as per dynamic LCA). The possibility to fully cover these aspects has been demonstrated in recent works although framed in terms of “temporal distribution” and “temporal evolution” (Müller et al. 2025) or “implicit dynamics” as “time series of a set of static inventory databases” and “explicit dynamics” as “temporal distributions of flows” (Lang-Quantzendorff and Beermann 2025). The

various interpretations and operationalization of these temporal aspects in dynamic LCA have also been recently highlighted in Heijungs (2026).

To reach a complete time-specificity of the LCI, with both dynamic and prospective elements, high data requirements are necessary. For example, time explicit production functions might be used to account for the learning curve and development of emerging technologies (Van Der Hulst et al. 2025). The development of the background technological system over time is commonly modelled by considering various forecasted scenarios such as Shared Socio-economic Pathway (SSP) for instance via integrated assessment models (IAM) (e.g., Sacchi et al. (2022), De Souza et al. (2023)). Various other approaches to prospective and dynamic LCI modeling exist as well (Steubing and De Koning 2021; Spreafico et al. 2025), including the use of system dynamics and dynamic material flow analysis (Schaubroeck and Benetto 2024). In short, in current examples of dynamic and prospective LCA, for the LCI phase the focus seems to be on making temporally explicit either the product exchanges in the technosphere or the environmental exchanges between biosphere and technosphere (see also Sajawal Akhtar et al. (2026) and De Jong et al. (2026)).

Table 1 proposes a selection of definitions found in literature and how they address the temporal dimension.

3 Dynamic and prospective elements of the LCIA phase

LCA practice is increasingly focusing on the temporal aspects of the LCIA phase too. In the LCIA phase one converts environmental exchanges into environmental impacts aggregated and grouped across impact categories, which is commonly done using characterization factors (CF). A distinction first needs to be made between dynamic and prospective characterization. Theoretically, dynamic characterization allows to consider the influence of timing and duration of environmental exchanges on their impact and portray the temporal profile of impacts over time. Only some attempts have been made in the latter regard, e.g. on toxicity (Lebailly et al. 2014; Shimako et al. 2017) but mainly for climate change (Tiruta-Barna 2021). Moreover, a temporal differentiation allows considering certain temporal discounting or cutoff, with a derivation of dynamic CF per emission timing. For example, if the time boundary is 100 years, then a CO₂ emission at year 50 would only have a dynamic global warming potential (GWP) CF of 0.58, because only the impact from year 50 to 100 is considered (see the discussion on time frame inconsistencies in Levasseur et al. (2010)). Such cutoffs may be because of ethical implications or practical constraints (Levasseur et

al. 2012), and are arguable from those perspectives. These limitations and their implications have been highlighted in Ventura (2023) which proposes a dynamic GWP CF calculation framework that allows higher consistency across all the time dimensions specific to the impact assessment, such as time horizon of the impact, life cycle duration, and total observation duration (see details in Ventura (2023)).

More relevant from the point of view of accurately reflecting changing background reality, is prospective characterization, and CFs. In the common approach environmental exchanges are assumed to have the same environmental impacts regardless of the extraction or generation timing. For example, 1 L of freshwater extracted today is commonly considered in LCIA to have the same environmental impact of 1 L of freshwater extracted in 20 years from the same water basin. In the same way, 1 kg of methane emitted today is presumed to have the same environmental impact as 1 kg of methane emitted in 20 years. This approach disregards the fact that the background conditions of the receiving environment might be different in the future. For instance, water extraction today might have marginal negative impact on water scarcity on a freshwater basin that is not subject to stress today. However, if the same water basin will reach a stressed condition in the future, then the extraction of water from such basin will exert a higher negative impact (Baustert et al. 2022). Moreover, GHG emission exert their impact solely based on atmosphere physics, but the atmosphere composition at a certain point in the future might differ from the composition of today's atmosphere, meaning that the same emission today and in the future can exert different effects (Reisinger et al. 2011), due to the fact that radiative forcing (the basis of the impact on climate) is a function of the atmospheric state (McAuliffe et al. 2023). Finally, in the case of the emission of pollutants, while their toxicity mechanisms remain constant, their fate factors and effect factors are also state-dependent (Shimako et al. 2017; Fantke et al. 2021). For instance, in terms of fate factors, different meteorological conditions such as stronger winds or a different seawater pH level (both due to climate change) can affect the behavior of molecules leading for instance to different transport pathways. In terms of effect factors, the sensitivity or vulnerability of the receptors (e.g., humans or ecosystems) to the emissions might change over time due to a change in the surrounding environmental conditions – e.g., more acidic or warmer water temperatures, and thus higher baseline stress, can increase the toxic effects of pollutants on aquatic species. Collinge et al. (2013) reports the existence of time-dependent CFs for a few impact categories while the potential for time-dependent CFs for specific flows was also investigated (Cherubini et al. 2011; Bakas et al. 2015; Lueddeckens et al. 2020). Recent advancements in this direction mostly focus on GWP (Lan and Yao 2022;

Sacchi et al. 2025; Barbosa Watanabe and Cherubini 2026), but water-related impact categories (Cosme and Niero 2017; Baustert et al. 2022) and ozone depletion (Van Den Oever et al. 2024) were also investigated.

Besides CFs, the weighting and normalization might be subject to temporal variability too. A dynamic weighting might depend, for instance, on the variation of the age distribution over time (Fearnside 2002) or monetary mechanisms (Su et al. 2017), where the weight varies over time based on shadow prices or specific environmental taxation predictions. On the other hand, a normalization that considers reference factors changing over time based on predicted variations in related background conditions, although conceptualized, is rarely dealt with (Lueddeckens et al. 2020).

While studies reaching a time-resolved LCIA exist, where the impact is calculated and distributed over a certain period and often building on top of time-resolved LCI, prospective LCIA is an emerging research topic. The reason might be that a prospective LCIA requires complex scenarios accounting for the potential change in the broader social and environmental background conditions, to capture the variability of the impact generated by environmental exchanges in different points in time, for relevant impact categories, whereas the LCA field rather focuses on modeling industry and processes.

Overall, LCA studies that consider both prospective and dynamic elements in LCIA are still in their infancy, with recent practical implementations (Abu-Ghaida et al. 2025) and significant steps towards a more robust and comprehensive formalization (Lang-Quantzendorff and Beermann 2025; Müller et al. 2025). In general, the literature shows a tendency towards the development of approaches that are designed for specific environmental exchanges or specific categories only (Baustert et al. 2022; Sacchi et al. 2025).

4 A matrix-based computational structure to jointly account for dynamic and prospective elements

To bring more clarity to the diverse landscape of approaches, this section attempts to formalize different approaches by representing the associated computational structures rather than by providing definitions, and especially focusing on the potential combinations between prospective and dynamic elements of a LCA model. It should be noted that LCA does not necessarily need to be delimited to any strict closed computational structure, not even according to ISO 14040–14044, implying that other computational frameworks can be used as well (Schaubroeck and Benetto 2024). Yet, here the interpretation of dynamic and prospective elements is facilitated by using the most common representation.

This common computational structure of LCA (Heijungs and Suh 2002), focused on matrix inversion, is shown in Eq. (1).

$$\mathbf{h} = \mathbf{QBA}^{-1}\mathbf{f} \quad (1)$$

Where the technology matrix $\mathbf{A} = [a_{mm}]$ is a square $m \times m$ matrix of product exchanges and m is the number of products and also the number of activities in the technosphere. The intervention matrix $\mathbf{B} = [b_{nm}]$ is a $n \times m$ matrix of exchanges between technosphere and biosphere, where n is the number of unique biosphere exchanges. The characterisation matrix $\mathbf{Q} = [q_{cn}]$ is a $c \times n$ matrix of characterisation factors where c is the number of impact categories. The final demand vector $\mathbf{f} = [f_m]$ is a $m \times 1$ vector indicating the final demand or functional unit and the impact vector $\mathbf{h} = [h_c]$ is a $c \times 1$ vector of category totals.

To extend to dynamic and prospective LCA “augmented” versions of these matrices need to be introduced, that consider the time dimension. For this purpose, it is useful to define three specific temporal elements:

- A set $\{t_1, t_2, \dots, t_T\}$ of T time steps t .
- A set $\{y_1, y_2, \dots, y_Y\}$ of Y scenario years y .
- A set $\{s_1, s_2, \dots, s_S\}$ of S scenarios s .

Additionally, an ad hoc subscript notation is here introduced to specify the temporal elements of the different matrices and whether the matrices are augmented. Bold font, non-italic is chosen to signal that the subscript is part of the matrix name and is not a column of the matrix. A bold lowercase subscript is used to distinguish different versions of the same matrix, in particular a version referring to a specific time step, scenario year, or scenario. For example: $\mathbf{A}_{2030}$ is the technology matrix of scenario year 2030 and $\mathbf{A}_y$ is the technology matrix of a scenario year y . Accordingly: $\mathbf{A}_s$ is the technology matrix of a future scenario s and $\mathbf{A}_{\text{SSP5-8.5}}$ is the prospective technology matrix corresponding to the scenario of SSP5 projection under the Representative Concentration Pathways (RCP) 8.5.

A bold uppercase subscript is used to indicate an augmented matrix. For example: $\mathbf{B}_T$ is an intervention matrix that is augmented for T time steps. Matrices with two bold uppercase subscripts are augmented considering multiple temporal elements, for example $\mathbf{B}_{TY}$ is augmented to represent both different time steps and different scenario years.

The use of bold uppercase subscript is meant to distinguish the matrix referring to an individual scenario year or time step (e.g., $\mathbf{B}_y$, and $\mathbf{B}_t$, respectively) from the augmented matrix referring to multiple scenario years or time steps (e.g., $\mathbf{B}_Y$, and $\mathbf{B}_T$, respectively).

In principle, all the terms in the following equations should include a subscript that indicates the scenario under analysis. However, for simplicity this notation is not used. This is a justified choice since there is no interaction between scenarios, in the sense that activities from one scenario do not have exchanges with activities from another scenario, and in the same way prospective characterisation factors (for example those in $Q_{SSP5-8.5}$) are calculated independently for each scenario. Since prospective scenarios are mutually exclusive, each operation is scenario-specific and cross-scenario operations such as $Q_{SSP5-8.5}B_{SSP3-7.0}A_{SSP2-4.5}^{-1}f_{SSP1-1.9}$ are not meaningful. The only meaningful operations are of the kind $Q_{SSP5-8.5}B_{SSP5-8.5}A_{SSP5-8.5}^{-1}f_{SSP5-8.5}$ and make the use of scenario notation redundant.

Given a number T of time steps (e.g. yearly time steps from year 2025 to year 2050), a number Y of scenario years (e.g., a technology system at the years 2030, 2040, and 2050 respectively), and a specific scenario s (e.g. the SSP5-RCP8.5 scenario), one can obtain “dynamic” and “prospective” assessments of increasing complexity. Note that while here the unit [year] is used for both time steps t and scenario years y , any other time unit could be chosen and a different unit could be chosen for each temporal element, if data of adequate resolution is available. Illustrative numerical examples are provided in the Supplementary Information 1 to visualize the use of the equations provided below. The examples consist of a simplified system matching the matrix structures here presented. However, note that the values utilized in the examples are only for illustrative purposes and not supposed to represent any specific process.

4.1 Prospective life cycle assessment

In current applications of prospective LCA that focus on the inventory phase, a different technology matrix A_y is usually obtained that represents the economy at a specific scenario year y . The type and number of activities in A_y might be different from the ones in A and correspondingly B_y is the matrix of environmental exchanges and f_y is the demand vector, while Q is unchanged. The calculation of h_y , the impact at the scenario year y , is obtained as in Eq. (2).

$$h_y = QB_yA_y^{-1}f_y \quad (2)$$

Accordingly, $B_{2030}A_{2030}^{-1}f_{2030}$ represents the life cycle inventory for the scenario year 2030. Note that this mathematical representation is identical to the classic approach (Heijungs and Suh 2002) with the only difference that matrices referring to a specific scenario year y are used. For example, this is conceptually the approach underlying the

widely used python library *premise* for prospective LCA (Sacchi et al. 2022). Note again that the scenario notation s is not included for the reasons explained above. The same simplified notation is applied throughout the rest of the manuscript.

From a theoretical perspective and based on the limited practice observable, extending the prospective approach to the LCIA phase requires to create a LCIA method Q_y according to a specific scenario and scenario year and then using it in combination with a present state inventory as in Eq. (3) or a projected inventory and Eq. (4) respectively.

$$h_y = Q_yBA^{-1}f \quad (3)$$

$$h_y = Q_yB_yA_y^{-1}f_y \quad (4)$$

A recent example of Q_y can be found in Barbosa Watanabe and Cherubini (2026).

4.2 Dynamic life cycle assessment

Following more the definition of dynamic LCA by Collinge et al. (2013), Some studies obtain a dynamic LCA by augmenting B , A and f so that specific time steps become explicit. For example, in the study of the life cycle impact of a building, the operation stage of the building is spread over multiple years and thus a different activity or energy mix might be used for each year, and the end-of-life occurs at a future point in time (Slavkovic and Stephan 2025). This case is described in Eq. (5) and while it might be considered conceptually similar to the case of a prospective LCA, the difference is that these studies do not explicitly define themselves as prospective, nor necessarily use scenario projections, or do not necessarily make the entire product system time-differentiated, but only part of it. Such studies do not assume that the product provision or decision happens in the future. Another difference is that even if activities and their exchanges are time-differentiated, the characterisation factors are commonly not, so Q remains unchanged. In other words, in such a model an emission at a future time has the same impact that an emission at the present time.

$$h_D = QB_DA_D^{-1}f_D \quad (5)$$

Where A_D is an augmented technology matrix that includes one or more activities differentiated for specific time steps t . $A_D = [a_{dd}]$ is a square $d \times d$ matrix of product exchanges. If all activities are differentiated for all time steps, then $d = m \cdot T$. Correspondingly, $B_D = [b_{nd}]$ is the $n \times d$ matrix of exchanges and f_D is a $d \times 1$ demand vector, while Q is unchanged. Examples corresponding to this approach are found in Zimmermann et al. (2014), Roux et al. (2016)

and Asdrubali et al. (2020), where the LCI is dynamic, but the LCIA is not. However, note that the linkage between processes across different time steps might be built in various ways within $\mathbf{A}_D$ – see examples in the Supplementary Information 1. For example, in the case of the final demand vector, reference flow could as well be occurring in one time step (e.g. product delivery or service start) or be split over time steps (e.g. covering full service or functionality duration), or it could be multiple reference flows that are demanded.

Again following the narrow interpretation of dynamic LCA as “time differentiated”, a further common case of a dynamic LCA is when only the intervention and characterization matrices are augmented to include the time steps as in Eq. (6).

$$\mathbf{h}_Q = \mathbf{Q}_Q \mathbf{B}_Q \mathbf{A}^{-1} \mathbf{f} \quad (6)$$

Where $\mathbf{B}_Q = [b_{qm}]$ is an augmented $q \times m$ matrix of exchanges between technosphere and biosphere, where $q = n \cdot T$, and $\mathbf{Q}_Q = [q_{cq}]$ is an augmented $c \times q$ matrix of dynamic characterisation factors. Note that $\mathbf{B}_D$ of Eq. (5) is different from the $\mathbf{B}_Q$ of Eq. (6). The former is augmented only regarding the number of columns (d), the latter is augmented only regarding the number of rows (q). This LCA is “dynamic” in the sense that the intervention and characterisation matrices are explicit regarding the timing of the exchange with the biosphere (e.g. an emission of greenhouse gas at a specific time in the future) and the impact occurring at each different time step, respectively. Relevant cases include landfills (GHG and heavy metals release over time), soil carbon storage and degradation (CO_2 and CH_4 uptake and release over time), forests (carbon uptake and release over time), use of materials that wear out (e.g., coatings, paints, insulation), remediation processes (pollutant uptake over time), and carbonation of cement and bricks (carbon uptake over time). Examples that mathematically can correspond to this approach are found in Levasseur et al. (2010), De Rosa et al. (2017), Cardellini et al. (2018), and Elliot et al. (2024a), among others. However, note that correspondence might not be directly evident from the equations shown in such studies. One could envision a dynamic LCA where all matrices are augmented reflecting all time steps. However, no specific example was found in the literature of such a case described as a dynamic LCA. A computational structure that covers this case is however derived later in the manuscript starting from the prospective LCA angle, the reader is thus referred to Eq. (15).

4.3 Life cycle assessment with combination of dynamic and prospective elements

Studies such as Collinge et al. (2013), Lang-Quantzendorff and Beermann (2025) and Müller et al. (2025) further increase the model complexity by considering a system that develops over multiple scenario years. For example, a system might place the production stage in scenario year y_1 (e.g., 2034), use stage starting in y_2 (e.g., 2035) and end of life in y_3 (e.g., 2038), and have exchanges with the biosphere at multiple time steps, for example the production stage emits greenhouse gases the first year (t_1 e.g., 2034), use stage emits greenhouse gases every year for three consecutive years (t_2, t_3, t_4 , e.g., 2035, 2036, and 2037), while the end of life stage only at the following year (t_5 e.g., 2038). Note the explicit lack of alignment between scenario years and time steps. This is shown to clearly distinguish the temporal coverage of the technology matrix – through scenario years (covering multiple prospective LCAs) – and the temporal coverage of the environmental exchange matrix – through time steps. In the example above three scenario years are considered, one representing the technology matrix that characterizes each phase, but emissions occur across five time steps. Regardless, multiple scenario years can be considered for the various stages.

In this more complex situation, the augmented technology matrix $\mathbf{A}_Y = [a_{dd}]$ is a $d \times d$ matrix of product exchanges and $d = \sum_{y=y_1}^{y_Y} m_y$ where m_y is the number of activities in the technology matrix $\mathbf{A}_y$ in each scenario year y . The corresponding $\mathbf{B}_{TY} = [b_{qd}]$ is an augmented $q \times d$ matrix of biosphere exchanges, where $q = n \cdot T$, and the corresponding $\mathbf{f}_Y$ is an augmented $d \times 1$ demand vector. $\mathbf{Q}_T = [q_{cq}]$ is an augmented $c \times q$ matrix of characterisation factors, similar to $\mathbf{Q}_Q$ of Eq. (6). The calculation is then as in Eq. (7).

$$\mathbf{h}_{TY} = \mathbf{Q}_T \mathbf{B}_{TY} \mathbf{A}_Y^{-1} \mathbf{f}_Y \quad (7)$$

Various considerations can be made on the nature of $\mathbf{A}_Y$ and $\mathbf{B}_{TY}$.

A simple case is where there are no exchanges between activities occurring in different years. For example, the technology matrix for scenario year y_1 does not have exchanges with the technology matrix for scenario year y_2 and vice versa. In this way, in $\mathbf{A}_Y$ the only non-null elements are the diagonal ones, which are the technology matrices $\mathbf{A}_y$ for every y , as shown in Eq. (8).

$$\mathbf{A}_Y = \begin{bmatrix} \mathbf{A}_{y_1} & \mathbf{O} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{A}_{y_2} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \ddots & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{O} & \mathbf{A}_{y_Y} \end{bmatrix} \quad (8)$$

Where $\mathbf{O}$ is the zero matrix (matrix with all elements equal to zero).

Considering an augmented dynamic and prospective intervention matrix $\mathbf{B}_{\mathbf{T}\mathbf{Y}}$ where exchanges between technosphere and biosphere are distinct between activities in different scenario years as in Eqs. (9),

$$\mathbf{B}_{\mathbf{T}\mathbf{Y}} = [\mathbf{B}_{\mathbf{T}\mathbf{Y}_1} \quad \mathbf{B}_{\mathbf{T}\mathbf{Y}_2} \quad \dots \quad \mathbf{B}_{\mathbf{T}\mathbf{Y}_T}] \quad (9)$$

then the calculations simplify, and the total result can be computed as the sum of the impact scores obtained for each scenario year calculated independently, as shown in Eq. (10) (cf. also Collinge et al. (2013) proposing a similar equation).

$$\mathbf{h}_{\mathbf{T}\mathbf{Y}} = \sum_{y=y_1}^{y_Y} \mathbf{Q}_{\mathbf{T}} \mathbf{B}_{\mathbf{T}\mathbf{Y}} \mathbf{A}_y^{-1} \mathbf{f}_y = \sum_{y=y_1}^{y_Y} \mathbf{h}_{\mathbf{T}\mathbf{Y}} \quad (10)$$

This could provide advantages in terms of computational time.

However, it is easy to imagine a technology matrix $\mathbf{A}_{\mathbf{Y}}$ where there are exchanges between scenario years as in Eq. (11).

$$\mathbf{A}_{\mathbf{Y}} = \begin{bmatrix} \mathbf{A}_{y_1} & \mathbf{O} & \mathbf{O} & \mathbf{O} \\ \mathbf{A}_{y_2 \rightarrow y_1} & \mathbf{A}_{y_2} & \mathbf{O} & \mathbf{O} \\ \dots & \dots & \dots & \mathbf{O} \\ \mathbf{A}_{y_Y \rightarrow y_1} & \mathbf{A}_{y_Y \rightarrow y_2} & \dots & \mathbf{A}_{y_Y} \end{bmatrix} \quad (11)$$

Where the notation $\mathbf{A}_{y_2 \rightarrow y_1}$ is used to indicate that there are product exchanges from activities of scenario year y_2 to activities in scenario year y_1 . For example, an activity that, in the future, will require a specific product input. This could be for example a forest plantation where an input of diesel for the chainsaw used to cut a tree is foreseen to be needed in 50 years from now. In this case Eq. (10) is not valid anymore and to calculate the impact score the single, larger, technology matrix is needed in Eq. (7), with $\mathbf{A}_{\mathbf{Y}}$ corresponding to Eq. (11).

An example of $\mathbf{A}_{\mathbf{Y}}$ with each product exchange $a_{i_y j_y}$ explicitly shown within and across the different scenario years is given in Eq. (12) for illustrative purposes.

$$\mathbf{A}_{\mathbf{Y}} = \begin{bmatrix} a_{1y_1 1y_1} & a_{1y_1 2y_1} & \dots & 0 & 0 & 0 & 0 \\ a_{2y_1 1y_1} & a_{2y_1 2y_1} & \dots & 0 & 0 & 0 & 0 \\ \dots & \dots & \dots & 0 & 0 & 0 & 0 \\ a_{(m+1)y_2 1y_1} & a_{(m+1)y_2 2y_1} & \dots & a_{(m+1)y_2 (m+1)y_2} & a_{(m+1)y_2 (m+2)y_2} & \dots & 0 \\ a_{(m+2)y_2 1y_1} & a_{(m+2)y_2 2y_1} & \dots & a_{(m+2)y_2 (m+1)y_2} & a_{(m+2)y_2 (m+2)y_2} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ a_{dy_Y 1y_1} & a_{dy_Y 2y_2} & \dots & a_{dy_Y (m+1)y_2} & a_{dy_Y (m+2)y_2} & \dots & a_{dy_Y dy_Y} \end{bmatrix} \quad (12)$$

Note that in Eq. (11) and Eq. (12) it was chosen to show an upper right diagonal part of the matrix that only contains zero values. A different example of $\mathbf{A}_{\mathbf{Y}}$ can be found in the example illustrated in Müller et al. (2025), displaying

non-zero entries in the upper right part. Section 6.5 further elaborates on this choice.

An explicit example of the structure of the corresponding $\mathbf{B}_{\mathbf{T}\mathbf{Y}}$ is provided in Eq. (13).

$$\mathbf{B}_{\mathbf{T}\mathbf{Y}} = \begin{bmatrix} b_{1,t_1 y_1} & b_{2,t_1 y_1} & \dots & 0 & 0 & 0 & 0 \\ b_{1,t_2 y_1} & b_{2,t_2 y_1} & \dots & b_{1,t_2 y_2} & b_{2,t_2 y_2} & \dots & 0 \\ b_{1,t_3 y_1} & b_{2,t_3 y_1} & \dots & b_{1,t_3 y_2} & b_{2,t_3 y_2} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ b_{1,t_T y_1} & b_{2,t_T y_1} & \dots & b_{1,t_T y_2} & b_{2,t_T y_2} & \dots & b_{d,t_T y_Y} \end{bmatrix} \quad (13)$$

A consideration here is that time steps, and especially the starting time of the analysis, might have priority compared to the scenario years considered. To elaborate on this requires a note on the difference and synchronisation between time steps and scenario years. Exchanges between technosphere and biosphere might be classified based on their time step t of occurrence rather than based on the scenario year y , as these two temporal classifications can be used independently. However, a challenge emerges due to temporal profiles of activities spanning possibly multiple scenario years. One can then either assume that the characteristics of the activity and environmental conditions change (and jump to the next scenario year) or remain with the original scenario year and activity characteristics and spread this over several years. Consider the case of an activity which takes place at a specific scenario year and has emissions stretching across multiple future time steps for a time interval so large that it reaches later scenario years. For example, consider a model with two scenario years ($y_1=2030, y_2=2040$), where a prospective activity generates CO_2 emissions for several consecutive time steps with the first time step corresponding to the first scenario year ($t_1=2030, t_2=2031, t_3=2032, \dots$). Then a 16-years delayed emission for this activity will be $b_{\text{CO}_2, t_{16} y_1} (=b_{\text{CO}_2, 2045 2030})$ and not $b_{\text{CO}_2, t_{16} y_2} (=b_{\text{CO}_2, 2035 2040})$. Similarly, in this model a 16-years delayed emission for a prospective activity happening in scenario year $y_2=2040$ will be $b_{\text{CO}_2, t_{26} y_2} (=b_{\text{CO}_2, 2055 2040})$ as it will happen 26 years after the starting time of the model ($t_1=2030$). A corresponding example of a simplified $\mathbf{B}_{\mathbf{T}\mathbf{Y}}$ matrix is provided in Eq. (14).

One might argue that giving priority to the time step over the scenario year allows for a more realistic model in terms of understanding the hot spots of the system, because it allows to calculate the contribution to the total impact from the activities originating the emissions and not from the scenario years. This might be more useful when supporting decisions concerning a change in the type, amount, and now timing of emissions. This approach also allows using different time steps for the analysis like considering “months” for time steps and “decades” for scenarios years, and enabling for seasonal analysis.

$$\mathbf{B}_{\text{TY}} = \begin{bmatrix} b_{\text{CO}_2, t_1 y_1} & 0 \\ \vdots & \vdots \\ b_{\text{CO}_2, t_{11} y_1} & b_{\text{CO}_2, t_{11} y_2} \\ \vdots & \vdots \\ b_{\text{CO}_2, t_{16} y_1} & b_{\text{CO}_2, t_{16} y_2} \\ \vdots & \vdots \\ 0 & b_{\text{CO}_2, t_{26} y_2} \end{bmatrix} = \begin{bmatrix} b_{\text{CO}_2, 2030 \ 2030} & 0 \\ \vdots & \vdots \\ b_{\text{CO}_2, 2040 \ 2030} & b_{\text{CO}_2, 2040 \ 2040} \\ \vdots & \vdots \\ b_{\text{CO}_2, 2045 \ 2030} & b_{\text{CO}_2, 2045 \ 2040} \\ \vdots & \vdots \\ 0 & b_{\text{CO}_2, 2055 \ 2040} \end{bmatrix} \quad (14)$$

4.4 Combining prospective and dynamic elements by using a single time notation

A final reflection can be made on the difference between time steps t and scenario years y . In practice, the use of two notations for what is essentially the same temporal dimension reflected the fact that several prospective LCA studies usually select a few scenario years (e.g., 2030, 2040, 2050) because of data limitations. It is however not unreasonable to expect that in a near future it will be possible to make very detailed scenarios, on yearly or even monthly basis, or to interpolate between scenarios at any desired time resolution. Therefore, the notation can be simplified by using only the time step t and show the full synchronisation between the timing of product exchanges and environmental exchanges.

In that case, Eq. (7) would change into:

$$\mathbf{h}_{\text{TT}} = \mathbf{Q}_{\text{T}} \mathbf{B}_{\text{TT}} \mathbf{A}_{\text{T}}^{-1} \mathbf{f}_{\text{T}} \quad (15)$$

Where the augmented technology matrix $\mathbf{A}_{\text{T}} = [a_{dd}]$ is a $d \times d$ matrix of product exchanges and $d = \sum_{t=t_1}^{t_T} m_t$ where m_t is the number of activities in the technology matrix $\mathbf{A}_{\text{t}}$ in each time step t , and if all activities are differentiated for all time steps, then $d = m \cdot T$, with a correspondingly augmented $\mathbf{B}_{\text{TT}} = [b_{qd}]$ as $q \times d$ matrix of biosphere exchanges, where $q = n \cdot T$, and augmented $\mathbf{f}_{\text{T}}$ as $d \times 1$ demand vector. With $\mathbf{A}_{\text{T}}$ as in Eq. (16) and $\mathbf{B}_{\text{TT}}$ as in Eq. (17).

$$\mathbf{A}_{\text{T}} = \begin{bmatrix} a_{1t_1 1t_1} & a_{1t_1 2t_1} & \dots & 0 & 0 & 0 & 0 \\ a_{2t_1 1t_1} & a_{2t_1 2t_1} & \dots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{(m+1)t_1 1t_1} & a_{(m+1)t_1 2t_1} & \dots & a_{(m+1)t_2 (m+1)t_2} & a_{(m+1)t_2 (m+2)t_2} & \dots & 0 \\ a_{(m+2)t_1 1t_1} & a_{(m+2)t_1 2t_1} & \dots & a_{(m+2)t_2 (m+1)t_2} & a_{(m+2)t_2 (m+2)t_2} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{dt_T 1t_1} & a_{dt_T 2t_1} & \dots & a_{dt_T (m+1)t_2} & a_{dt_T (m+2)t_2} & \dots & a_{dt_T dt_T} \end{bmatrix} \quad (16)$$

$$\mathbf{B}_{\text{TT}} = \begin{bmatrix} b_{1, t_1 t_1} & b_{2, t_1 t_1} & \dots & 0 & 0 & 0 & 0 \\ b_{1, t_2 t_1} & b_{2, t_2 t_1} & \dots & b_{1, t_2 t_2} & b_{2, t_2 t_2} & \dots & 0 \\ b_{1, t_3 t_1} & b_{2, t_3 t_1} & \dots & b_{1, t_3 t_2} & b_{2, t_3 t_2} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ b_{1, t_T t_1} & b_{2, t_T t_1} & \dots & b_{1, t_T t_2} & b_{2, t_T t_2} & \dots & b_{d, t_T t_T} \end{bmatrix} \quad (17)$$

The notation of Eq. (15) also generalizes the time dimension to cases beyond future scenarios, typical of prospective LCA studies, to represent also scenarios about past conditions as in case of historical LCA (Bruhn et al. 2024). The notation of Eq. (15) also covers the case of a dynamic but not prospective technology matrix (cf. Section 4.2).

It should be noted that using two separate time notations allows to cover cases where the time dimension is expressed in different units, for example seconds for the time steps and decades for the scenarios. The use of two notations was here prioritized as it allowed to separate more clearly prospective and dynamic elements, given that the purpose of this work is facilitating the classification of existing LCA studies and given that in practice the temporal resolution of scenarios is presently lower compared to that of emission profiles.

5 Relations between the proposed computational structures and existing studies, tools, and software

In the following, existing modelling tools and software are compared to the computational structure described in previous sections. The section only proposes a non-exhaustive list of selected examples that were found useful for illustrative purposes.

The *premise* tool described in Sacchi et al. (2022) allows to project the technology matrix $\mathbf{A}$ in the future, generating an augmented version, based on IAMs. This allows to perform prospective LCA as detailed in Sect. 4.1 and Eq. (2).

Asdrubali et al. (2020) considers the changes in the electricity mix over the whole use phase of a building by directly modeling specific mixes for two separate years after the start of the phase and linearly fitting the years between them. However, no dynamic characterization is applied. This approach corresponds to the dynamic LCA shown in Eq. (5). Roux et al. (2016) also applies an approach corresponding to Eq. (5) by focusing on the energy use in a building over one year considering electricity mix variations at two different temporal resolutions. The same approach corresponding to Eq. (5) is applied in Zimmermann et al. (2014) to assess the impact of electric vehicles over their lifetime, with a focus on electricity consumption over the use phase, for which yearly mixes are modeled.

The work by Levasseur et al. (2010) introduces the dynamic approach to LCA with a focus on the development of dynamic characterization factors for GWP ($\mathbf{Q}$ matrix) to be applied to temporally differentiated GHG emission inventory ($\mathbf{B}$ matrix), corresponding to the proposed Eq. (6).

The forest carbon flux model of De Rosa et al. (2017) and the dynamic carbonation model by Elliot et al. (2024a) are respectively older and more recent examples of strictly dynamic LCA tools that do not however include prospective elements. These models fit with the computational structure described by Eq. (6).

Beloin-Saint-Pierre et al. (2014) propose a methodological approach named Enhanced Structural Path Analysis (ESPA) to account for the different timings of the various

processes in a product system. It is based on convolution and allows to obtain time-resolved elementary exchanges ($\mathbf{B}$ matrix). The focus is placed on the temporal aspects of the LCI phase only. Therefore, ESPA can be considered as an example of dynamic LCA as described in Sect. 4.3, getting close to Eq. (6). However, while the discussion clearly highlights this as a necessary step to then extend the time-specificity to the characterization ($\mathbf{Q}$ matrix), the authors limit the discussion to the resolution of the $\mathbf{B}$ matrix.

ESPA is the basis upon which the software-based tool *temporalis* was developed (Cardellini et al. 2018) and integrated into Brightway2 (Mutel 2017). An important difference is that they implemented a best-first strategy for graph traversal instead of a breadth-first one, optimizing the computational requirements. Additionally, *temporalis* does not stop at the $\mathbf{B}$ matrix augmentation, but clearly allows the augmentation of the $\mathbf{Q}$ matrix, reaching a fully dynamic LCA as described in Sect. 4.3 and Eq. (6).

Lang-Quantzendorff and Beermann (2025) introduced *prosperdyn* as a software-based tool that can be integrated into Brightway2 (Mutel 2017) as well. *Prosperdyn* applies *premise* to obtain scenario-based background system matrices for each time step, based on the selected IAM, and also for the years between the steps via interpolation. The foreground system's temporal dynamics is time-resolved too and linked to the corresponding time-resolved background processes. The time-resolution is obtained by distinguishing quasi-simultaneous flows from flows distributed over time. This targeted combination is resolved in a set of " $\mathbf{F}_t$ " matrices representing the foreground part of both technosphere and biosphere flows for each time step t , linked to the respective background flows which are bound to specific year in a prospective scenario (obtained via *premise*). This cuts the computational effort. It also allows a dynamic impact assessment, meaning that it reaches a prospective approach combined with a fully dynamic LCA corresponding in principle to Eq. (7) where $\mathbf{F}_t$ includes the augmented $\mathbf{A}_Y$ matrix in the form similar to Eq. (12) and the $\mathbf{B}_{TY}$ matrix similar to Eq. (13) and including values in the upper right section. However, *prosperdyn* embeds the temporal profile of biosphere exchanges directly in $\mathbf{F}_t$ without utilizing an expanded environmental exchanges matrix (referred to as " $\mathbf{H}$ " in the study).

Another recently introduced tool is *timex* (Müller et al. 2025). It also builds on *premise* to obtain scenario-based background system matrices for each time step, but applies the best-first graph traversal proposed in *temporalis*, and is integrated into Brightway2 to allow the dynamic impact assessment. However, unlike in *temporalis*, in *timex* an absolute timeline of intermediate flows is constructed, rather than that of elementary flows. The computational method based on matrix $\mathbf{A}$ augmentation is clearly shown.

As *prosperdyn*, it reaches a prospective approach combined with a fully dynamic LCA corresponding to Eq. (7) where "temporal markets" generate an $\mathbf{A}^*$ matrix that corresponds to $\mathbf{A}_Y$ in Eq. (11), at least for the foreground exchanges, and a $\mathbf{B}^*$ matrix that corresponds to $\mathbf{B}_{TY}$ in Eq. (13), with values in the upper right section. If the temporal resolution for the scenario years (y) and time steps (t) match, $\mathbf{A}^*$ and $\mathbf{B}^*$ correspond to $\mathbf{A}_T$ and $\mathbf{B}_{TT}$ in Eq. (16) and Eq. (17) which can be combined into Eq. (15).

Sacchi et al. (2025) recently introduced *edges* as a tool extending Brightway2 allowing, among other functionalities, to obtain time-resolved CFs that are based on scenarios that reflect background conditions evolving over time, for certain impact categories. This allows consistency between LCI and LCIA. For instance, this consistency could be based on a certain set of SSP and linked RCP, to reach a prospective LCI as detailed in Sect. 4.2, corresponding to Eq. (3) (e.g., use case 3 in Sacchi et al. (2025)) and Eq. (4). The noteworthy aspect of *edges* appears to be the possibility to select specific exchanges only and thus build the matrices desired for any type of temporal or spatial or even impact-related resolution, thus simplifying the computational structure, which essentially can be reduced to the classic structure of Eq. (1) and then iterated over various types of emissions, without requiring to operate on large technosphere or biosphere matrix.

DyPLCA comprises a framework, model, tool and database for dynamic LCA. It first introduced the use of graph-traversal algorithms to differentiate inventories and elementary flows over time, considering a supply-use model covering different ways of how one process supplies to another, either continuously or in batches (Tiruta-Barna et al. 2016). This tool has some advantageous features. The tool does not rely on convolution, for which clear issues have been pointed out (cf. Section 6 of the supplementary information of the work of Tiruta-Barna et al. (2016)). Additionally, it does not revert back to matrix expansion after graph-based traversal with subsequent matrix inversion but recomputes the amounts linearly when traversing each process. Theoretically such a framework can allow for any non-linear process equation to be used and thus has the potential to overcome limitations associated with matrix inversion, such as restrictions to linearity and single drivers for executing processes (Schaubroeck 2022, 2023; Schaubroeck and Benetto 2024). A full temporal DyPLCA database, originally with temporal parameter values for all ecoinvent 3.2 processes, has been developed and the model has been applied to it leading to the only existing dynamic LCAs that cover the complete background database (Pigné et al. 2020). Limitations include: the need for cut off due to computational requirements and loops across the product systems (Pigné et al. 2020), that both the tool and database

are not open access, and that there are currently no prospective LCA-elements considered in DyPLCA. Since its structure is not based on matrices, it does not explicitly relate with any of the equations in the matrix-based approach, and can be seen as an alternative path forward.

6 Discussion

6.1 Computational structures besides definitions

A set of definitions was here summarized, and a classification proposed, building upon the existing approaches available in literature. However, there might be situations where these definitions do not apply and that cannot be clearly fit into the proposed classification, e.g. DyPLCA. Yet, the focus of this work was placed on the formalization of a matrix-based computational structure, which was considered the best way to clearly and unambiguously distinguish the different kinds of temporal aspects that LCA studies focusing on future can cover, given its common and successful application in the field. The recommendation of this study is therefore to focus on identifying which temporal aspect is being accounted for in the analysed system, thus apply the proper approach, and make this choice and its justification clear to the audience. This pragmatic approach should be used in parallel with the discourse on semantics (Beloin-Saint-Pierre et al. 2020; Di Bari et al. 2024) as it is constructive for the purpose of decision-support to understand how a model works besides discussing how it should be called.

6.2 Relation with uncertainty

The inclusion of different temporal aspects can affect the LCA modelling in terms of input data, normative choices, and mathematical relationships, which are the LCA modelling components that are generally considered in uncertainty analysis (Lloyd and Ries 2007). However, since LCA studies focusing on future are inherently characterized by a higher level of uncertainty (Langkau et al. 2023) compared to LCA studies of existing product systems. This means that the more temporal aspects get covered, the more subject to uncertainty the study gets. However, overlooking temporal aspects leads to uncertainty too, while the use of high quality temporally resolved data to cover a temporal aspect might in some cases reduce the uncertainty compared to the use of low-resolution data.

Consequently, a trade-off arises between having a more sophisticated model that allows reaching a comprehensive coverage of all temporal dimensions and introducing more assumptions and calculations that increase the uncertainty. The alternative is to have a less realistic model that is

however limited to covering the most well-known temporal aspects only. Therefore, practitioners are advised to carefully reflect on this trade-off and identify the appropriate level of modelling sophistication that is helpful for decision making. A qualitative uncertainty analysis might be more readily feasible and already give nuance to this (Huppes and Schaubroeck 2022).

6.3 Reflections on software implementation

The more temporal dimensions are considered, the higher the computational effort becomes. This increase in computational complexity might prevent the diffusion of the approach, as it seems to be the case for highly spatially-resolved LCA approaches (Sacchi et al. 2025), being space the dimensional counterpart of time. The classification we proposed stems from the classic formulation of an LCA computational structure of Eq. (1) that focuses on elementary flows. However, approaches other than the ones structuring data in matrix format as suggested in Eqs. (1–15), and other than performing matrix inversion, might be advantageous in increasing both computational efficiency and modelling flexibility. Sacchi et al. (2025) have demonstrated how the complexity of the time-specific data can be managed and reduced to simpler calculations in existing LCA software. The DyPLCA framework is another example of allowing dynamic LCA while covering the full background system by using graph-traversal, deviating from conventional matrix inversion. Computational requirements and time are though indeed a challenge for the latter, necessitating a cutoff. For example, Pigné et al. (2020) mentioned that 90% coverage would require more than 5 h of computation, and 95% almost nine full days.

In other words, the computational structures proposed in this work are intended to guide and facilitate the understanding of alignment between dynamic and prospective elements of LCA but the development of software and tools for actual computation might take other directions than using matrix inversion. Understanding how the computation should be efficiently implemented in software will then require further research and development, especially building on the existing sets of open software that already allow capturing part of the temporal aspects discussed above (e.g., Brightway (Mutel 2017)) to ensure an easy integration and facilitate the uptake among practitioners.

6.4 Non-linearities introduced with the temporal dimension

The classification here proposed remains within a linear computational framework, intended in the sense that with the operations proposed in Eqs. (2–15) an increase in

demand (f) will correspond to a linear increase in impact (h) (Heijungs 2020). In other words, the impact of 10 units of product will equal ten times the impact of 1 unit of product. However, both dynamic and prospective elements introduce important non-linearities in the assessment, and it has been shown before that the assessment of emerging and scalable technologies does in fact require to consider such non-linearities (Pizzol et al. 2021). Non-linearities can for example be found when comparing technology matrices across scenario years, since these prospective versions of the foreground and background systems are generated using a variety of techniques such as scaling factors, learning curves (Van Der Hulst et al. 2025), and complex external models such as the IAMs, and represent systems that evolve non-linearly over time. In the same way, when making environmental exchanges time-explicit one can account for e.g. different types of emission profiles, including non-linear patterns over time. Yet all these non-linearities are currently addressed “outside” the LCA computational framework and then adapted or fitted to it, rather than being directly embedded into the LCA operations. To achieve a non-linear LCA result another computational framework might be needed, that would bring LCA models towards becoming system dynamic models (Elliot 2022; Elliot and Levasseur 2022; Fernando et al. 2023; Elliot et al. 2024b), thus going beyond linear algebra and into calculus. Non-linearity is for example an opportunity for DyPLCA as discussed in the previous sections.

6.5 Attributional and consequential approaches in relation to the proposed classification

It is appropriate to reflect upon how the temporal dimension of LCA studies focusing on future relates with the two mainstream types of LCA, namely the attributional and consequential approaches. The computational structures here described may apply equally well to both approaches. The reason is that, in matrix-based application, the main difference between attributional and consequential models lies in how the multifunctionality is solved and how the supply mixes are built, which in turn is reflected in how the A matrix is constructed, but does not affect the way computation is carried out: the operations are the same. While most dynamic and prospective studies could be classified as attributional, there are examples of dynamic consequential studies (De Rosa et al. 2018; Schaubroeck et al. 2020) and of prospective consequential studies (Jouannais and Pizzol 2022; Jouannais et al. 2025). These can all be equally well fitted within the classification here proposed. Yet, in practice there might be substantial differences in the way these models are constructed, for example when it comes to making supply mixes in prospective scenarios (Maes et al. 2023).

Another key difference is how the A_Y and B_{TY} matrices might be organized. From a cause-effect perspective typical of consequential studies, consequences of decisions only happen in the future, time only moves forwards, and future activities cannot change past ones. Thus, the upper right diagonal part of A_Y in Eq. (11) (and the explicit example of A_Y in Eq. (12)) might only contain zero values. Accordingly, in the B_{TY} example of Eq. (13) entries $b_{n,ty}$ might be zero for values of $y > t$ as again, from a cause-effect perspective time only moves forwards and future activities will not generate emissions in the past. Instead, from an accounting perspective typical of attributional studies it might be relevant to “back-track” contributions, and one could have matrix elements in the upper right as well as shown in Müller et al. (2025). Related to this, it is worth considering that before the recent surge in “prospective” studies intended as per the definition provided in Sect. 2., the consequential approach was commonly defined as a “prospective” approach and the attributional one as a “retrospective” – although this classification has been criticised (Zamagni et al. 2012; Schaubroeck et al. 2021). The consequential approach used to be defined as “prospective” as it intends to anticipate the future effects of decisions, specifically changes in demand of a product, while the attributional approach used to be defined as a “retrospective” approach as it looks back in time to identify which activities can be attributed the responsibility for the product’s burden. Introducing the time dimension to such a level of detail as what we describe in Eqs. (2–15), however, might blur the meaning of these terms because for example a dynamic prospective attributional model might even have a part of product system into the past due to accounting backtracking (cf. Section 4.4). While it is in practice possible to create technology matrices in consequential or attributional fashion for different scenario years, a deeper reflection is perhaps needed on what is the meaning of anticipating the effects of changes in demand when future conditions are already predicted exogenously in the next scenario year, and what is the meaning of retrospectively allocate burdens from a future point in time that still has to happen. It is beyond the scope of this study to provide a reflection on these aspects, but LCA scholars are here encouraged to discuss them more thoroughly in future research.

7 Conclusions

This study summarized a set of definitions and proposed a classification of dynamic and prospective LCA studies that prioritize the computational distinctions rather than the semantic ones. The study illustrates and discusses the implications of accounting for the temporal aspects in all the

Table 2 Summary of equations representing the approaches that exist according to the two temporal dimensions of dynamic and prospective LCA, all represented using the same matrix based computational structure. The explanations of the notation symbols can be found in the main text

Temporal dimension	Non-prospective	Prospective
<i>Non-dynamic</i>	$\mathbf{h} = \mathbf{QBA}^{-1}\mathbf{f}$	$\mathbf{h}_Y = \mathbf{QB}_Y\mathbf{A}_Y^{-1}\mathbf{f}_Y$ $\mathbf{h}_Y = \mathbf{Q}_Y\mathbf{BA}^{-1}\mathbf{f}$ $\mathbf{h}_Y = \mathbf{Q}_Y\mathbf{B}_Y\mathbf{A}_Y^{-1}\mathbf{f}_Y$
<i>Dynamic</i>	$\mathbf{h}_D = \mathbf{QB}_D\mathbf{A}_D^{-1}\mathbf{f}_D$ $\mathbf{h}_Q = \mathbf{Q}_Q\mathbf{B}_Q\mathbf{A}^{-1}\mathbf{f}$	$\mathbf{h}_{TY} = \mathbf{Q}_T\mathbf{B}_{TY}\mathbf{A}_Y^{-1}\mathbf{f}_Y$ $\mathbf{h}_{TT} = \mathbf{Q}_T\mathbf{B}_{TT}\mathbf{A}_T^{-1}\mathbf{f}_T$

elements of the classic matrix-based calculation approach to provide clear and unambiguous distinctions. The classification is summarized in Table 2 and includes four options depending on which temporal dimension is considered. LCA models can feature either prospective or dynamic elements, or both, and to a different degree of complexity.

The study also frames and discusses current practices in the light of the proposed classification identifying the different levels of comprehensiveness and complexity to inform and guide practitioners. Other existing approaches that do not fit the proposed classification are also discussed. In this regard, matrix calculations have their limitations, and in the long run, switching to other computational structures, e.g. graph-based as done in DyPLCA, could be desirable. Nevertheless, the matrix-based representations offer crucial insights.

While great advancements towards the inclusion of temporal aspects in LCA have been made focusing on the LCI modelling, a higher level of granularity is fundamental for meaningful and coherent prospective assessments. For instance, IAMs still fall short in representing bioeconomy sector – limiting the potential of prospective LCA to fully represent and capture the role of bioeconomy in transitioning towards a lower impact societal status (Steubing et al. 2023). Additionally, more and better inventory data are needed to provide temporal profiles for emissions and resource use of specific activities, as these data remain scarce. The DyPLCA database is a first onset, but lacks validation and is not directly accessible. Further research is needed on the LCIA modelling to support the development of time-resolved characterization factors bound to prospective scenarios. However, the research in this sense should target the impact categories that are most relevant, prioritizing urgency over completeness.

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Declarations

Conflict of interest The authors have no competing interests to declare.

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