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Temporal choices in building LCA: A reporting and diagnostic framework informed by use-phase evidence

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ABSTRACT

Dynamic Life Cycle Assessment (DLCA) is increasingly used to represent time-dependent processes in building assessment. However, the term "dynamic" is used for different forms of temporal modelling, including time-resolved foreground inventories, changing background systems and time-dependent impact characterisation. Studies do not always state clearly which elements vary with time, at what resolution or how they are linked, limiting methodological interpretation and comparison. This study develops a structured framework from a critical methodological review of building use-phase DLCA, with emphasis on non-domestic applications. The review examines temporal treatment across foreground inventories, background systems and Life Cycle Impact Assessment, as well as coupling-rule transparency, timestep justification, data quality and implementation constraints. The synthesis shows that time-varying foreground data are reported more often than temporally differentiated background systems or characterisation methods, while coupling rules and resolution choices remain inconsistently documented. The proposed framework records where and how time is represented and supports assessment of whether those choices are appropriate to the stated goal, scope and time horizon. A worked non-domestic operational-electricity application demonstrates the framework across three configurations combining annual or hourly demand with annual-average or monthly grid carbon-intensity factors. Monthly matching reduced annual operational-electricity Global Warming Potential (GWP) from 812.72 to 754.11 kg CO_2-eq/year, a reduction of 7.21%. These results illustrate the influence of temporal matching within the defined one-year operational-electricity boundary; they do not represent a complete module B6 life-cycle assessment or rank DLCA methods.

1. Introduction

Life Cycle Assessment (LCA) provides a structured framework for evaluating environmental impacts across product and system life cycles (ISO [1]; ISO [2,3]). Conventional LCA generally represents both foreground processes and background systems as temporally invariant [4,5]. This assumption is problematic for long-lived systems, where emissions, technologies, and operating conditions evolve, altering cumulative impacts [6,7].

Dynamic Life Cycle Assessment (DLCA) has been proposed to address this limitation by representing life-cycle inventory exchanges as explicit functions of time, such that time becomes a structural attribute of exchanges rather than contextual information [8,9]. DLCA can also retain emission timing in Life Cycle Impact Assessment (LCIA) through time-dependent characterisation methods [10]. In this paper, operational variability is treated as one possible form of temporal representation. Applications are examined according to the temporal treatment adopted in the foreground inventory, background system, and LCIA, together with the coupling rules that link these elements.

In building use-phase LCA, the term "dynamic" is used to refer to several distinct treatments of time. These include time-varying foreground inventories, changes in background systems, time-dependent impact characterisation, or combinations of these elements [11–14]. These choices differ in scope and temporal resolution and may be reported explicitly against the study goal and scope (ISO [1]; ISO [2]). A time-resolved operational profile alone does not indicate how time is treated in the background system or impact assessment.

The proposed temporal-coupling framework is informed primarily by studies of building use-phase DLCA, with particular emphasis on non-domestic applications. Selected generic building and system-level studies were also included as methodological references. These studies provided clearer treatments of background-system change, time-

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dependent impact characterisation and coupling-rule specification. The study has two objectives. First, it develops a framework for reporting temporal treatment in building LCA and evaluating whether the selected methods are appropriate to the stated goal and scope. The framework is derived mainly from a critical review of building-use-phase DLCA, with support from selected methodological studies. Second, it demonstrates the framework using a controlled non-domestic operational-electricity example. The example shows how temporal assumptions, data sources and coupling rules can be documented and evaluated. It does not test a hierarchy of DLCA methods.

The paper makes four contributions. First, it identifies the principal temporal treatments reported in building use-phase DLCA. Second, it organises these treatments within a module-based reporting matrix. Third, it provides diagnostic checks for temporal resolution, data quality, coupling-rule transparency, implementation constraints and model traceability. Fourth, it demonstrates the framework through a bounded operational-electricity application situated within module B6.

1.1. Framework terminology

Term	Meaning in this study
Dynamic LCA	An LCA in which at least one modelling element is represented explicitly as varying with time.
Temporal treatment	The way time is represented for a modelling element: static, time-varying or scenario-based.
Temporal resolution	The timestep used for a time-varying input, process or characterisation method.
Coupling rule	The stated rule linking time-indexed foreground activity to the corresponding background data and, where applicable, time-dependent characterisation factors.

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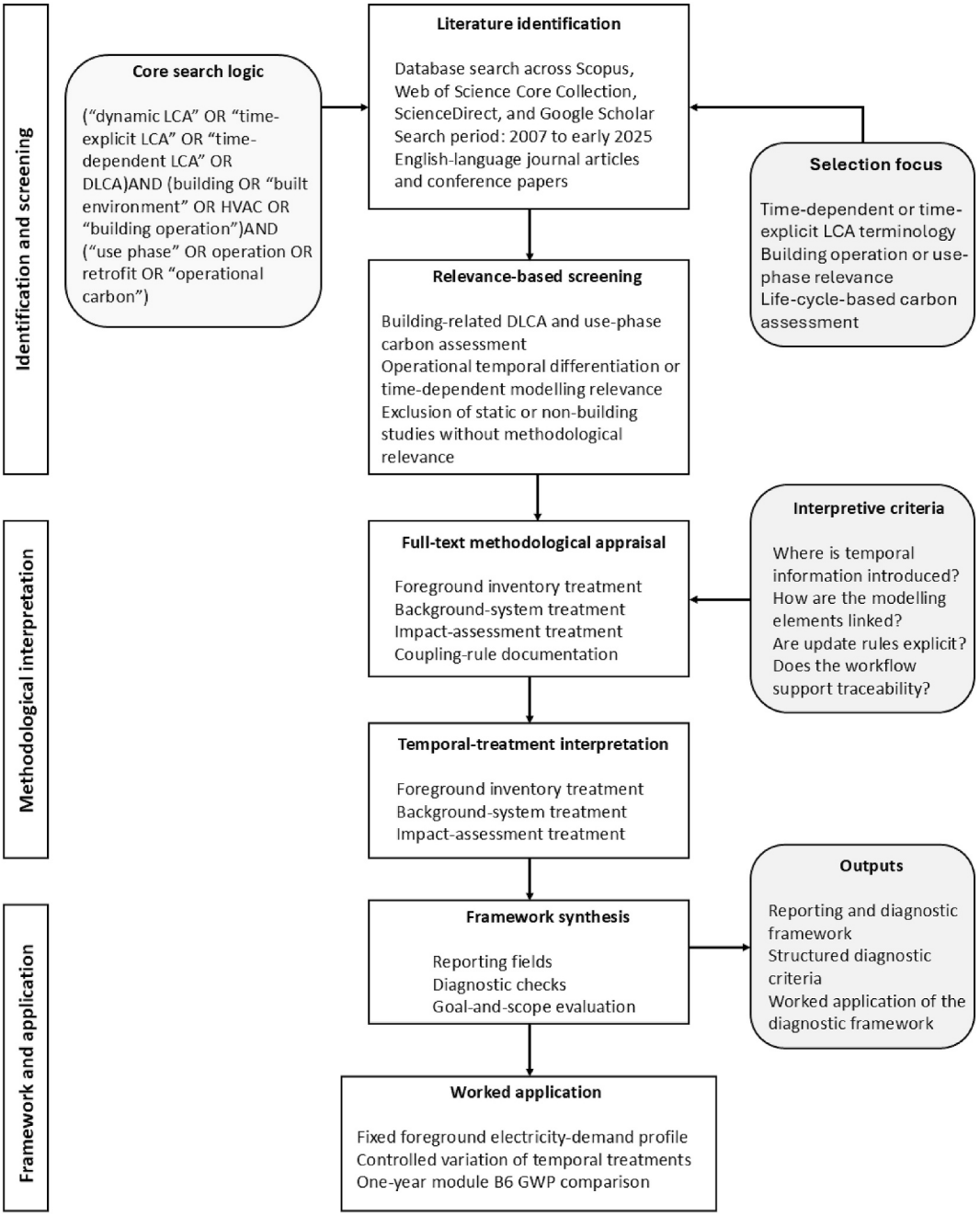


Fig. 1. Literature-identification and framework-derivation workflow.

(*continued*)

Term	Meaning in this study
Time-dependent characterisation factor	A characterisation factor whose value depends on emission timing and the selected impact-assessment horizon.

The framework reports temporal treatment separately from its suitability for the study goal and scope. An assessment may combine static and time-varying elements where appropriate and clearly justified. A greater number of time-varying elements is not treated as evidence of higher methodological quality.

2. Methodology

This study uses a critical methodological review to examine how temporal information is defined and operationalised in building-related DLCA. The review is designed to identify recurring configurations of temporal coupling across heterogeneous methodological literature. Particular attention is given to the points at which temporal assumptions are introduced, transformed, weakened, or lost across the modelling chain.

The review follows a transparent literature-identification and selection process, but remains configuration-oriented rather than meta-analytic. This approach is appropriate because building DLCA studies differ substantially in terminology, boundary definition, temporal resolution, background-system treatment, and LCIA implementation. Fig. 1 summarises the literature identification and framework-derivation workflow.

2.1. Critical review design and analytical scope

The review was designed as a critical methodological synthesis of temporal-coupling practice in building DLCA. It comprised three stages: literature identification, relevance-based screening, and analytical interpretation of modelling structure. The analysis focused on how studies represent foreground temporal resolution, background-system evolution, LCIA temporalisation, and coupling-rule transparency.

The purpose was to derive a methodological comparison framework for a heterogeneous literature, rather than to rank environmental outcomes across studies. The review therefore prioritises interpretive consistency, transparent classification logic, and framework development.

2.2. Research questions

The following research questions guide the review:

- Research question 1: *Which foreground, background and impact-assessment elements are treated as time-varying in building use-phase DLCA?*
- Research question 2: *How are temporal resolution and coupling rules reported and justified?*
- Research question 3: *Which reporting and diagnostic criteria support the alignment of temporal treatments with the stated goal and scope?*

In this review, "dynamic" denotes an explicitly time-varying modelling treatment. Time-series data alone do not establish methodological quality. The analysis records what changes with time, at what resolution and through which coupling rule.

2.3. Literature search strategy

A targeted literature search was conducted to identify studies addressing dynamic, time-dependent or time-explicit LCA relevant to building operation and use-phase carbon assessment. Searches were undertaken in Scopus, Web of Science Core Collection, ScienceDirect and Google Scholar for publications from 2007 to early 2025. The evidence base was subsequently updated through July 2026 using targeted supplementary searches and citation tracking. This approach captures the development of time-explicit LCA methods and their later application to buildings.

The search strategy combined three concept groups: dynamic or time-dependent LCA terminology; building and built-environment descriptors; and use-phase or operational scope. The core Boolean structure was:

("Dynamic Life Cycle Assessment" OR "Dynamic LCA" OR "time-explicit LCA" OR "time-dependent LCA" OR DLCA)

AND (building OR "built environment" OR HVAC OR "building operation").

AND (use-phase OR operation OR retrofit OR "operational carbon").

The search expression was adapted to the syntax and indexing functions of each database. Searches were limited to English-language journal articles and conference papers. Google Scholar was used as a supplementary source to capture interdisciplinary studies and recent publications not consistently indexed elsewhere. Backward and forward citation searches were also undertaken for methodologically central papers.

The search was designed to provide a transparent and sufficiently broad evidence base for critical methodological interpretation of temporal-coupling practice in building DLCA.

2.4. Literature selection and interpretive inclusion logic

Literature selection was undertaken in two stages: title-and-abstract review followed by full-text methodological assessment. The objective was to retain studies relevant to time-dependent LCA of building operation while preserving methodological diversity across DLCA practice.

At the title-and-abstract stage, records were retained where they addressed LCA in buildings or building-related systems and indicated temporal variation, dynamic behaviour, or time-explicit treatment in inventories, energy systems, or impact assessment. Records were excluded where they were clearly unrelated to buildings, operational or use-phase analysis, or life cycle-based environmental assessment. Full texts were then assessed for methodological relevance. Studies were retained where they: examined the use-phase or operational stage of buildings or building-related systems; applied LCA or life cycle-based carbon accounting; introduced temporal differentiation capable of influencing results; and provided enough methodological detail to interpret temporal-coupling structure.

Studies were excluded where they focused solely on embodied impacts, used static LCA without meaningful temporal differentiation, addressed non-building systems without a clear methodological link to building operation, or lacked sufficient methodological detail for interpretation.

The primary focus was non-domestic buildings. However, a limited number of generic building and system-level DLCA studies were retained where they provided formal treatment of background evolution, time-dependent LCIA, or coupling-rule implementation. These studies were used as methodological anchors, not as a shift away from the building-oriented scope. Also, where eligibility was unclear, the full methodological description was examined before a decision was made. This was particularly important where studies used dynamic terminology inconsistently or introduced temporal differentiation without clear downstream propagation.

2.5. Analytical interpretation and methodological synthesis

The literature was interpreted using the analytical fields defined in Table 1. These fields were used to compare how studies specify temporal information at the foreground inventory level, propagate it into background-system evolution, and treat it within LCIA. The purpose was to support methodological interpretation rather than formal coding or

Table 1
Analytical fields for interpreting temporal-coupling structure in building DLCA.

Analytical field (ID)	Description	Allowed values	Decision rule
Foreground temporal resolution (FG_TEMP_RES)	Temporal resolution of operational foreground inventory exchanges	Static / Multi-year / Annual / Monthly / Hourly / Sub-hourly	Time-resolved only if exchanges vary by timestep
Foreground data source (FG_DATA_SRC)	Origin of time-explicit foreground data	Simulation / Measured / Hybrid	Measured only if sensor/m data define exchanges
Background electricity evolution (BG_ELEC)	Treatment of electricity background system over time	Static / Annual or monthly mix / Hourly factor / Prospective scenario	Dynamic only if factors or technology shares vary over time
Background multi-technology evolution (BG_MULTI)	Treatment of non-electricity upstream systems	Static / Partial / Full multi-technology	Full only if multiple upstream systems vary over time
LCIA temporalisation (LCIA_TEMP)	Temporal treatment of characterisation factors	Static CF / Time-dependent CF	Time-dependent only if CFs are indexed to emission timing
Coupling rule documentation (COUPLING_RULE)	Degree to which update logic is reported	None / Partial / Full	Full only if FG → BG → LCIA update logic is explicit
Temporal resolution justification (TEMP_ALIGN)	Justification of timestep selection	Not justified / Partially justified / Fully justified	Fully justified only if timestep matches data quality and system response
Execution feasibility (EXEC_FEAS)	Representation of actuation/control constraints	Not reported / Qualitative / Quantitative	Quantitative only if delay or hysteresis is modelled
Digital infrastructure LCI inclusion (ICT_LCI)	Inclusion of IoT/BMS hardware life-cycle burdens	Included / Excluded	Included only if sensing/control impacts are modelled
Model traceability (MODEL_TRACE)	Reproducibility of modelling workflow	Low / Medium / High	High only if assumptions and logic allow re-implementation

FG = foreground; BG = background; LCIA = life cycle impact assessment; CF = characterisation factor; LCI = life cycle inventory; ICT = information and communication technology; IoT = Internet of Things; BMS = building management system.

statistical synthesis.

Each study was interpreted using an analytical structure comprising analytical fields for foreground temporalisation, background evolution, LCIA temporalisation, coupling-rule documentation, temporal-resolution justification, execution feasibility, digital-infrastructure burden inclusion, and model traceability. Each field was assigned a short identifier and a decision rule, as shown in Table 1.

FG_TEMP_RES, BG_ELEC, BG_MULTI and LCIA_TEMP were used to describe the temporal treatments reported by each study. COUPLING_RULE and MODEL_TRACE were used to assess the completeness of reporting. FG_DATA_SRC, TEMP_ALIGN, EXEC_FEAS and ICT_LCI informed the diagnostic synthesis. Conditional fields were recorded as not applicable where they fell outside the study scope.

The analytical fields were not combined into ranked regimes. The synthesis instead identifies recurring temporal treatments, reporting gaps and diagnostic concerns. The suitability of a study's temporal choices was not inferred where its goal, scope or modelling justification was insufficiently documented.

The methodological synthesis is presented in Section 3, and the resulting framework is developed in Sections 4 and 5.

2.6. Study characterisation and framework derivation

Each study was characterised by the temporal treatment reported for its foreground inventory, background systems and impact assessment. The analysis also recorded the resolution of each time-varying element and the extent to which coupling rules were documented. These characteristics were not combined into ranked categories.

Reporting completeness was examined separately. The analysis considered whether temporal resolution was justified, whether modelling layers were linked transparently and whether relevant data-quality, implementation and reproducibility constraints were reported. Conditional criteria, including actuation delay and digital-infrastructure burdens, were recorded as not applicable where they fell outside the study scope. No judgement about goal-and-scope adequacy was made where the publication provided insufficient information.

3. Methodological state of the art in building DLCA

Section 3 presents the methodological synthesis derived from the reviewed literature. The focus is on recurring temporal-coupling configurations and observable patterns in how building-related DLCA studies represent time-dependent information.

The reviewed literature varies in where and how time is represented. Table 2 presents representative building applications and selected methodological studies. It compares temporal treatment in the foreground inventory, background system and LCIA, along with the rule linking these elements. The configurations are descriptive and do not imply methodological ranking.

Table 2 shows that temporal treatment is distributed unevenly across the modelling chain. In the selected building applications, changing demand is commonly combined with prospective background scenarios and conventional LCIA. Methodological studies more often demonstrate time-explicit inventory propagation and dynamic characterisation. The suitability of each configuration depends on the study goal, scope and supporting evidence.

Fig. 2 summarises the three configurations most evident in the building applications. Methodological studies may also couple emission timing directly to dynamic LCIA while retaining a static background system.

The configurations indicate where temporal treatment is represented across the modelling chain. They do not denote methodological ranking or maturity; their suitability depends on the assessment goal, scope and supporting justification.

3.1. Current practice in building use-phase DLCA

The reviewed literature indicates that temporal differentiation in building use-phase DLCA is introduced most frequently through the foreground inventory. Building energy simulations, monitored data and time-dependent schedules are commonly used to generate annual, hourly or sub-hourly operational profiles [22,23]. These approaches improve representation of changing demand, occupancy and operating conditions, but they do not determine how time is treated elsewhere in the assessment. A time-varying foreground may therefore be combined legitimately with static or coarser background data where that combination is consistent with the assessment goal, scope, data availability and decision context.

The temporal treatment of background systems varies more widely. Some studies incorporate changing electricity mixes, technology pathways or prospective scenarios, whereas others retain annual-average or otherwise time-invariant upstream datasets [24,25]. One study combined annual updates of technological and electricity-related inventory parameters with city-level variation in grid factors, manufacturing

Table 2
Representative temporal treatments and coupling rules in selected building applications and methodological studies.

Study (Author, Year)	Application	Foreground temporalisation	Background evolution	LCIA temporalisation	Coupling rule	Coverage and limitation
[15]	Generic method	Timed emissions	Static	Time-dependent GWP	Emission time → CF	FG + LCIA — static BG
[16]	Generic LCI method	Timed flows	Supply-chain timing	Not applied	Path propagation	FG + BG — LCI only
[17]	Glulam method case	Timed processes	Supply-chain timing	Dynamic CFs	Graph convolution	FG + BG + LCIA — no future change
[7]	Bus-fleet method case	Yearly transition	Prospective databases	Static GWP + dynamic RF	Year → database	FG + BG + LCIA — non-building case
[18]	Building method	Building evolution	Time-varying processes	Dynamic climate/ toxicity	Time-step matching	FG + BG + LCIA — prototype tools
[19]	Office case	Yearly energy	Future electricity mix	Static CFs	Demand → mix by year	FG + BG — single case
[20]	Multi-city buildings	Projected energy	Future grid mix	Static CFs	Scenario-year mapping	FG + BG — scenario dependent
[8]	Campus stock	Annual stock flows	Future electricity/ heat	Static CFs	Year → stock/ energy	FG + BG — stock scale
[21]	Masonry building	Annual demand + replacements	Static	Time-dependent GWP	Emission year → CF	FG + LCIA — static BG

RF = Radiative Forcing.

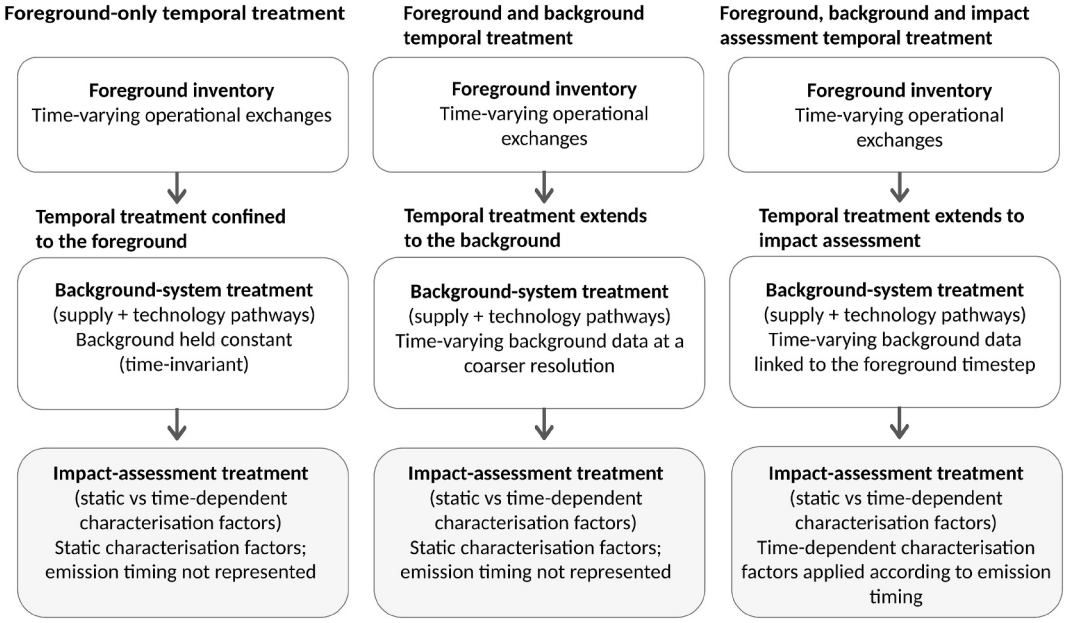


Fig. 2. Recurring temporal-treatment configurations identified in the building DLCA literature.

locations, transport distances, solar irradiance and grid absorption [26]. Static IPCC AR6 GWP100 characterisation factors were retained [27]. This provides a clear example of mixed temporal treatment selected in relation to the study's national, spatio-temporal and decision-oriented scope, rather than as an intermediate stage in a methodological hierarchy.

Such variation is especially relevant to long-lived building operation because reported impacts are sensitive to grid decarbonisation, changes in generation technologies and the spatial and temporal basis of electricity factors. Substantial spatial and temporal variation has been documented in production- and consumption-based electricity carbon footprints across China [28]. For building LCA, this variation means that factor geography, accounting basis and assessment year can affect the operational emissions attributed to a given electricity demand. The methodological concern is therefore not whether every background process varies with time, but whether the selected background treatment is compatible with the foreground activity and sufficiently justified. Where fine-resolution demand profiles are linked to annual, monthly or scenario-based factors, the temporal and spatial mapping must be stated explicitly so that the calculation and its interpretation can be reconstructed.

Time-dependent impact characterisation remains less common than foreground temporalisation or background-system differentiation [13,21,29]. Static characterisation may remain appropriate where emission timing is outside the intended scope, but its use needs to be stated clearly when time-explicit inventories are presented as dynamic. Coupling rules are also reported unevenly, particularly where foreground, background and impact-assessment elements operate at different temporal resolutions. Consequently, studies described as “dynamic” may embody materially different modelling structures. The present review therefore records foreground, background and impact-assessment treatment separately, together with temporal resolution and coupling-rule documentation, rather than assigning studies to hybrid-static, hybrid-dynamic or system-consistent categories.

3.2. Structural mechanisms affecting temporal traceability in building DLCA

Temporal traceability is defined here as the ability to follow time-related data, assumptions and mappings from foreground inventory formation through background-system treatment to impact assessment. This definition draws on time-explicit LCA approaches that distinguish the temporal distribution and evolution of foreground and background processes from the treatment of emission timing in LCIA [30].

Temporal traceability is particularly relevant to building use-phase assessment because long operational periods may coincide with substantial changes in electricity generation technologies and their associated life-cycle emissions [31]. Electricity is therefore an important interface between time-varying building demand and changing background conditions. Building Information Modelling (BIM), spatial zoning, sensing and control are examined below as mechanisms that may structure, preserve or weaken the traceability of temporal information across the modelling chain. Fig. 3 identifies the principal points at which temporal information may be introduced, transformed, aggregated or lost through these workflows.

The following subsections examine how BIM, zoning, sensing and control may strengthen foreground representation while also introducing assumptions, data limitations and feasibility constraints that affect temporal traceability.

3.2.1. Foreground temporalisation through digital building representations

BIM can support foreground development by structuring building data and linking models with energy simulation [32,33]. Where simulation outputs retain timestamps, they can provide time-resolved operational inventory inputs. BIM–LCA workflows commonly transfer quantities or model outputs between tools, with associated interoperability and data-quality constraints [34–36].

BIM-derived information is commonly transferred into LCA workflows as material quantities, product data and operational-energy inputs [37–39]. This can strengthen foreground specification without determining the temporal treatment of background systems or LCIA. The framework therefore records foreground resolution and downstream coupling separately.

Inconsistent data granularity and manual mapping can further limit traceability [40,41]. BIM does not itself establish temporal coupling to background systems or LCIA. The limitation arises when time-resolved foreground profiles are linked to static or coarser downstream elements [29]. Table 3 distinguishes digital support for foreground development from temporal coupling.

These mechanisms support data integration and monitoring, but only one reviewed study links energy simulation to an LCA workflow [43].

3.2.2. Spatial disaggregation in foreground temporalisation

Spatial disaggregation represents building operation through thermal or functional zones with distinct occupancy patterns, schedules, setpoints and service conditions. This structure can reveal temporal variation that is obscured by whole-building aggregation. Multi-zone monitoring studies also show that sensor selection and spatial coverage influence which local conditions are captured [45,46]. These data can support zone-resolved operational profiles for the foreground

Table 3
Digital mechanisms relevant to operational foreground development and traceability.

Study	Digital mechanism	Building-assessment use	Traceability relevance	Temporal-LCA limitation
[42]	Automated LCI matching	Match construction data to LCI datasets	Repeatable data linkage	No temporal treatment
[43]	BIM–energy–LCA integration	Transfer simulated energy demand	Operational foreground input	Downstream timing unspecified
[44]	Performance Ontology	Integrate performance domains	Structured data Relations	LCA application not demonstrated
[45]	Virtual-sensor selection	Optimise sensor combinations	Monitoring coverage	LCA application not demonstrated
[46]	BIM-based sensor placement	Optimise temperature and CO_2 sensing	Multi-zone monitoring	LCA application not demonstrated
[47]	BIM–EPD Integration	Link EPD data to BIM	Material-data traceability	LCA application not demonstrated

EPD = Environmental Product Declaration.

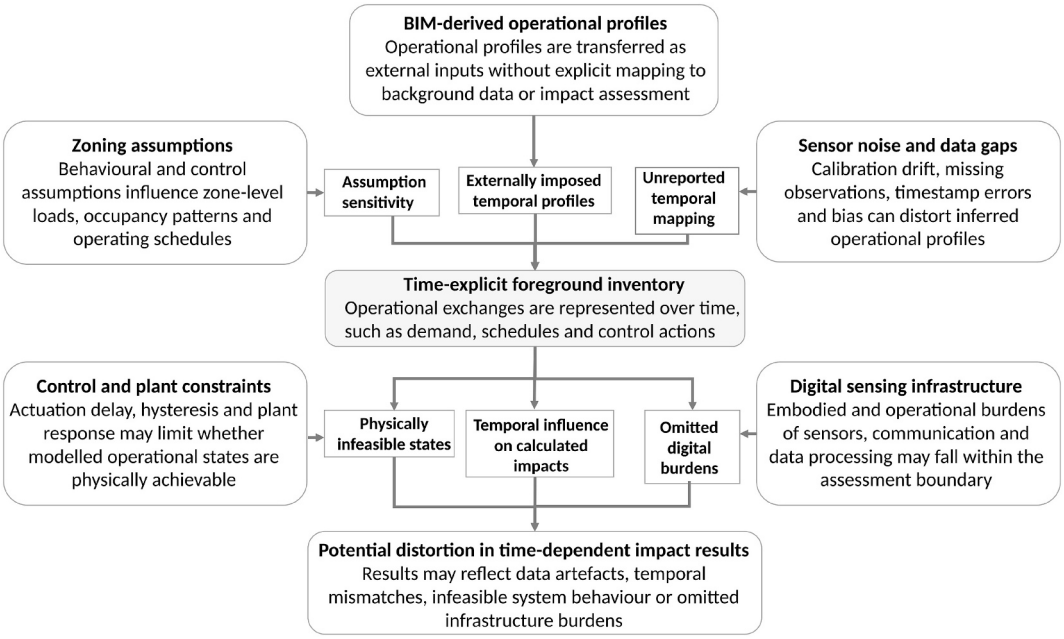


Fig. 3. Conceptual synthesis of temporal distortion pathways identified in current building DLCA research.

inventory.

Greater spatial detail does not necessarily produce a more defensible temporal representation. Zone-level profiles depend on the definition of zone boundaries and the availability of representative operational data. Their interpretation is also affected by sampling intervals, missing observations and the method used to aggregate local profiles. These choices determine which variations are retained and which are averaged within the resulting foreground flows. The spatial unit, time index, data source and aggregation rule therefore require explicit reporting.

Spatial disaggregation remains a foreground inventory operation rather than an additional LCA layer. It defines how local operational states are translated into time-indexed inventory flows. It does not determine the temporal treatment of background systems or impact assessment. The reliability and operational feasibility of these profiles are considered in Section 3.2.3. Their subsequent propagation across the modelling chain is examined in Section 3.3.

3.2.3. Constraints on operational energy tracing in time-explicit DLCA inventories

Indoor sensing and building control influence both measurement quality and operational executability in building DLCA. High-frequency sensor streams are increasingly used to infer time-dependent demand and control actions, including temperature, CO_2 concentration, and occupancy proxies [48]. However, calibration drift, missing values, timestamp misalignment, and context-dependent bias can distort inferred energy profiles if not addressed [49]. These errors may produce inventory trajectories that appear time-structured but partly reflect measurement artefacts, with consequences for time-dependent impact interpretation [50].

Time-explicit inventory states must also be physically achievable by the underlying building systems. Controller sampling, actuation and plant response constrain the realisable timing of HVAC operation [51]. If the inventory timestep is finer than these response characteristics, the model may represent operational states that cannot occur in practice. Temporal resolution therefore requires both reliable measurement and implementation feasibility.

Across the reviewed literature, sensing- and control-derived operational data are not always accompanied by sufficient explanation of data quality, timestep selection, or actuation feasibility. In the proposed framework, these limitations are treated as diagnostic criteria for temporal treatment. Table 4 summarises the evidence base, diagnostic risk and framework use associated with each diagnostic dimension.

3.3. Temporal propagation across the modelling chain

Within the reviewed literature, temporal differentiation is most frequently introduced in the foreground inventory, particularly through time-resolved operational profiles. Its propagation into background systems and life-cycle impact assessment is less consistent. This variation reflects differences in study goals, system boundaries, assessment periods, available evidence and intended decision contexts. Studies concerned with annual reporting or comparative operational performance may therefore retain temporally aggregated background inventories and conventional characterisation factors. By contrast, prospective background scenarios become relevant when technological or energy-system evolution could materially affect results, while time-dependent characterisation is warranted when the timing of emissions and the resulting environmental response are integral to the assessment question [18,24,54,57]. Fig. 4 therefore identifies the interfaces at which temporal information is transferred, matched, transformed, aggregated or omitted across the modelling chain. These configurations do not represent successive levels of methodological advancement; their adequacy depends on their consistency with the stated goal, scope and supporting evidence.

The synthesis identifies three recurring points at which temporal coupling is preserved or weakened:

(i) **Temporal resolution coherence:** Foreground demand and background data require compatible temporal conditions. Climate-dependent building demand can be linked to evolving electricity-mix inventories to preserve this relationship across the modelling chain [58].

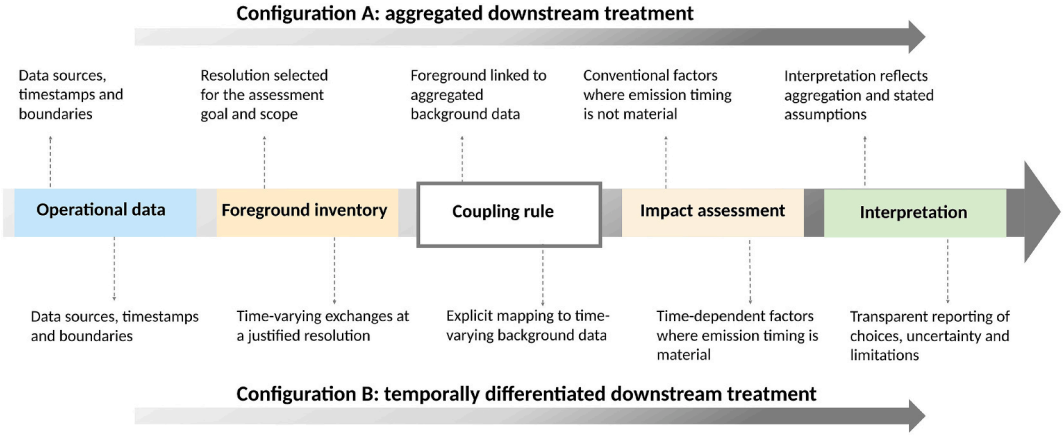
(ii) **Background evolution coherence:** Background-system evolution is less consistently represented than foreground temporalisation. Where electricity-mix evolution is included, reported impact trajectories can differ from those produced under static electricity assumptions, highlighting the sensitivity of operational emissions to background-system change over time [58].

(iii) **Characterisation coherence:** Time-explicit inventories are often interpreted using static characterisation factors. Where time-dependent characterisation is applied, the temporal distribution of climate impacts can differ from static approaches, indicating that inventory temporalisation alone does not preserve the temporal meaning of emissions [7].

Fig. 4 shows that time-resolved foreground data do not, by themselves, determine the temporal treatment of background systems or impact assessment. Temporal coupling is therefore reported as an explicit modelling rule and evaluated against the declared goal and scope, rather than inferred from data resolution.

Table 4
Literature basis and evidential requirements for the diagnostic framework.

Literature basis	Framework dimension	Evidence considered	Risk if unresolved	Framework implication
[52]	Goal-and-scope alignment	Intended use, boundary, modules and assessment period	Temporal treatment is disconnected from the assessment question	Establishes the context for temporal choices
[53]	Temporal-resolution justification	Demand and factor timesteps, aggregation basis and materiality	Unsupported detail or relevant variation omitted	Tests whether the selected resolution is proportionate
([19]; [20])	Foreground–background compatibility	Assessment period, geography, scenario year and accounting basis	Foreground and background represent incompatible conditions	Tests consistency across inventory layers
([15]; [54])	Impact-assessment treatment	LCIA method, emission timing and assessment horizon	Temporal effects are omitted or misinterpreted	Determines whether time-dependent characterisation is warranted
([9]; [30])	Coupling-rule transparency	Time index, mapping, interpolation and aggregation	Temporal propagation cannot be reconstructed	Verifies linkage across modelling layers
([49]; [55])	Data quality and uncertainty	Provenance, coverage, calibration, missing data and uncertainty	Artefacts or model bias are interpreted as temporal variation	Tests the credibility of time-indexed profiles
([51]; [56])	Implementation feasibility	Controller sampling, actuation delays and plant-response constraints	Modelled operational trajectories are unattainable	Tests operational achievability
([17]; [16])	Traceability and reproducibility	Data, parameters, transformations and calculations	Results cannot be independently reconstructed	Supports verification of the calculation chain



Configuration suitability depends on the assessment goal, scope, evidence and decision context.

Fig. 4. Goal and scope-dependent temporal coupling across the building DLCA modelling chain.

4. Reporting and diagnostic framework for temporal treatment in building LCA

The critical review informs a framework for reporting and evaluating temporal treatment in building LCA. The framework separates two tasks. The first records where and how time is represented within the assessment. The second examines whether those modelling choices are adequately justified for the stated goal, scope and evidence. It does not rank studies according to the number of time-varying elements.

The reporting structure is designed for use across the life-cycle modules included within a building LCA. However, the diagnostic evidence developed in this study is derived mainly from building use-phase DLCA. Its wider use therefore supports consistent reporting but does not demonstrate equal empirical validation across all building life-cycle stages.

4.1. Framework derivation and architecture

The framework begins with the study goal, intended use, system boundary and assessment period. These declarations identify the temporal changes relevant to the assessment. Its LCA structure follows ISO 14040 and ISO 14044 (ISO [1,2]). Building-level modules are reported using BS EN 15978 [59] and the information-module conventions of BS EN 15804 [60].

For each included life-cycle module, Table 5 identifies the minimum information required to describe temporal treatment and the corresponding diagnostic check. Detailed assumptions, data sources, calculation procedures and limitations are reported in the study methods and supporting supplementary material.

The fields define a minimum reporting structure rather than a requirement for every modelling element to vary with time. Static, time-varying and scenario-based treatments may be combined where their selection is justified by the study goal and scope. Conditional fields are recorded as not applicable where they do not relate to the assessed system. For example, control delays and plant constraints are relevant when operational responses or load shifting are modelled, but not when the assessment uses a fixed demand profile.

Table 5 defines the information required to report and evaluate temporal treatment. Fig. 5 translates these fields into a four-stage application sequence, beginning with the definition of the assessment and ending with a documented diagnostic conclusion.

The sequence is applied to each life-cycle module included within the assessment boundary. The reporting stage establishes where and how time is represented, while the diagnostic stage examines whether those choices are supported by the study purpose, available evidence and physical system. The resulting conclusion identifies justified treatments, methodological limitations and criteria that are not applicable. The framework therefore supports transparent interpretation without assuming that greater temporal detail necessarily indicates stronger methodological quality.

Table 5
Minimum reporting fields and diagnostic checks for temporal treatment in building LCA.

Field	Datasets, parameters, mappings and calculation files	Diagnostic check
Goal and scope	Intended use, included modules, boundary and assessment period	Are the temporal choices relevant to the stated purpose?
Foreground inventory	Time-varying flows, timestep and data source	Is the resolution supported by the data and system behaviour?
Background system	Dataset, temporal and spatial basis, and historical or prospective basis	Is the background treatment compatible with the foreground activity?
Impact assessment	LCIA method, treatment of emission timing and assessment horizon	Is emission timing treated appropriately?
Coupling rule	Rule linking foreground activity, background data and LCIA	Is the linkage explicit and reproducible?
Data quality	Coverage, aggregation, missing data and uncertainty	Could data limitations affect interpretation?
Implementation feasibility	Relevant control delays and plant constraints	Are the modelled temporal changes physically achievable?
Traceability and reproducibility	Required datasets, parameters and calculation files	Can the workflow be independently reconstructed?
Diagnostic conclusion	Justification, limitations and non-applicable fields	Are the temporal choices defensible within the stated goal and scope?

5. Framework implications and directions for future research

This section discusses the implications of the proposed framework for current building DLCA practice and future methodological development. It focuses on ambiguity in the use of “dynamic”, incomplete downstream temporal propagation, and the need to align measurement quality with execution feasibility. These issues inform the future research priorities outlined at the end of the section.

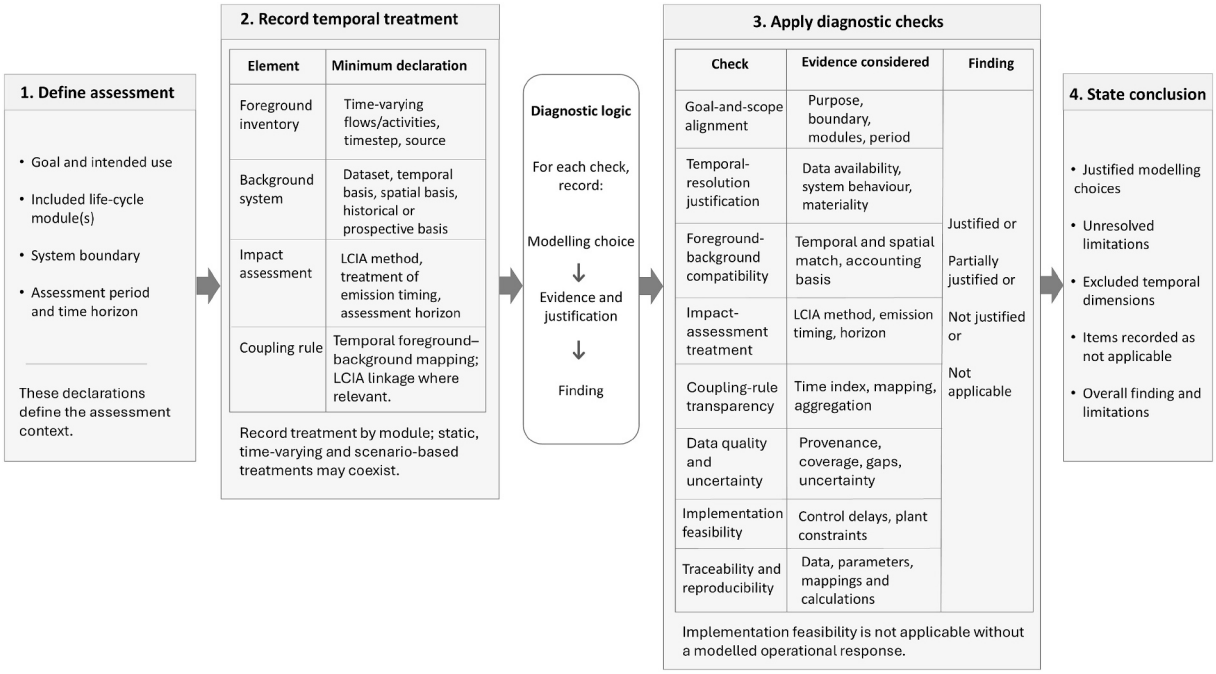


Fig. 5. Application sequence for reporting and evaluating temporal treatment in building LCA.

5.1. *Ambiguity in the operationalisation of "dynamic"*

The term "dynamic" is used inconsistently across the reviewed literature. It may refer to time-labelled scenarios, time-varying foreground inventories, changing background systems, time-dependent impact characterisation or combinations of these treatments. Wider reviews similarly distinguish several temporal dimensions, including inventory resolution, process evolution, characterisation, weighting and assessment horizon [5,12,14,61,62]. Consequently, two studies described as dynamic may differ materially in where time is represented and how temporal information is transferred between modelling elements.

This ambiguity cannot be resolved by treating finer resolution or a greater number of time-varying elements as evidence of methodological quality. An hourly operational profile, for example, may be appropriate for demand–supply matching but unnecessary for an assessment concerned with annual reporting. Similarly, static characterisation may remain defensible where emission timing lies outside the stated assessment question. The framework therefore reports temporal treatment separately for the foreground inventory, background system and impact assessment, together with the resolution and coupling rules applied. Their adequacy is then considered against the study goal, scope, evidence and intended decision context.

5.2. *Downstream temporal treatment and coupling transparency*

The reviewed literature shows that temporal differentiation is often introduced through operational foreground profiles, while background systems are treated at annual, monthly, scenario-based or otherwise aggregated resolutions. This difference is not inherently problematic. Its significance depends on whether the background treatment is appropriate to the assessment's purpose and whether the mapping between foreground activity and background data is clearly stated. Temporally differentiated electricity modelling can materially alter results when consumption varies over time, while prospective background scenarios become relevant when future grid or technology change is part of the assessment question [63,64].

Impact assessment introduces a separate temporal choice. Conventional characterisation factors may be appropriate where the study concerns aggregated potential impacts over a defined reporting horizon. Time-dependent characterisation becomes relevant where emission timing and the subsequent environmental response are integral to interpretation. These alternatives concern different assessment questions rather than successive levels of methodological development [10].

Coupling-rule transparency is therefore central to methodological interpretation. The calculation needs to state how each time-indexed foreground activity is assigned to the relevant background dataset and, where applicable, to a time-dependent characterisation factor. Without this information, the effect of temporal differentiation cannot be reconstructed or separated from assumptions introduced during aggregation. The framework accordingly treats the coupling rule as both a minimum reporting field and a diagnostic criterion.

5.3. *Measurement–execution alignment and temporal traceability*

Time-explicit foreground inventories increasingly draw on monitored energy data, sensor streams, occupancy proxies and control-system outputs. These sources improve the representation of operational variability only when their provenance and quality are controlled. Missing observations, timestamp irregularities and sensor inconsistencies can affect downstream energy analytics [65]. A finer timestep cannot compensate for weak measurement quality and may instead increase apparent precision.

Where the assessment models an operational response, the selected timestep also needs to reflect the behaviour of the physical system. Building controls operate within thermal, technical and communication constraints, including equipment limits, controller sampling intervals, plant response and implementation architecture [51]. Modelled load shifting or short-term control actions may therefore be unsuitable where the assumed response cannot be delivered by the building systems. By contrast, execution feasibility is not applicable when the assessment uses a fixed demand profile and models no intervention.

Smart-control applications may also introduce additional hardware, replacement and infrastructure burdens that fall within the relevant life-cycle boundary [66]. Temporal traceability therefore requires a clear

connection between the data source, inventory timestep, modelled operational response and included system components. The framework records these considerations separately so that their relevance can be judged against the specific goal and scope.

5.4. Directions for future research

Controlled comparative applications can examine one temporal modelling choice while holding the system boundary, demand profile, impact method and remaining assumptions constant. This design distinguishes the effect of temporal resolution from changes caused by factor definition or scenario construction. Relevant comparisons include annual, monthly and hourly electricity factors, regional and national datasets, production- and consumption-based accounting, prospective grid pathways and alternative characterisation horizons. European evidence shows that hourly electricity impacts vary with the accounting basis applied [63]. City-level analysis in China further demonstrates substantial spatial and temporal variation in the carbon footprints of electricity production and consumption [28]. Average, marginal and demand-based operational factors also represent distinct system perspectives and decision questions in building LCA [53]. Their results should not therefore be interpreted as interchangeable estimates. Comparative studies could examine whether these choices alter absolute impacts, scenario rankings, the timing of benefits or the resulting decision. This would provide an empirical basis for selecting temporal and spatial detail according to materiality and intended use. It would also clarify when additional differentiation improves interpretation and when it merely increases data and modelling requirements.

5.5. Temporal-treatment classification and diagnostic evaluation

Fig. 6 consolidates the literature-derived findings against the three research questions. It distinguishes where temporal treatment is represented from the reporting and diagnostic issues that affect its interpretation. The figure does not arrange studies by maturity or prescribe a preferred combination of temporal methods.

Fig. 6 consolidates the review findings into a descriptive, non-hierarchical framework. It distinguishes the temporal treatments applied to the foreground inventory, background system and impact assessment; makes the coupling rule between these elements explicit; and evaluates their adequacy against the assessment goal, scope and available evidence. Its contribution lies not in defining a preferred DLCA configuration, but in enabling different combinations of static, aggregated and time-varying treatments to be reported and interpreted consistently.

Research question 1: Which foreground, background and impact-assessment elements are treated as time-varying in building use-phase DLCA?

Temporal differentiation is reported most frequently in foreground inventories, particularly through monitored or simulated operational profiles. Background systems are treated more variably, using static, temporally aggregated, historical or prospective data. Time-dependent impact characterisation is less frequently represented. Temporal treatment is therefore not a single property of an assessment; different treatments may coexist across the modelling chain.

Research question 2: How are temporal resolution and coupling rules reported and justified?

Foreground resolution is usually stated more clearly than the temporal basis of background data or impact characterisation. Coupling rules are also reported unevenly, particularly where fine-resolution foreground activity is linked to coarser background information. Such differences are not inherently inappropriate, but their alignment, aggregation or scenario-mapping rules need to be explicit and justified in relation to the assessment purpose and evidence base.

Research question 3: Which reporting and diagnostic criteria support the alignment of temporal treatments with the stated goal and scope?

The framework identifies goal and scope, system boundary, included modules, assessment period, data sources and impact-assessment method as the interpretive basis for temporal modelling choices. The corresponding diagnostic criteria address temporal-resolution justification, foreground–background compatibility, coupling-rule transparency, data quality and uncertainty, and implementation feasibility, traceability and reproducibility. These criteria assess whether a temporal configuration is appropriate and traceable; they do not measure methodological maturity.

The framework therefore separates three questions that are often

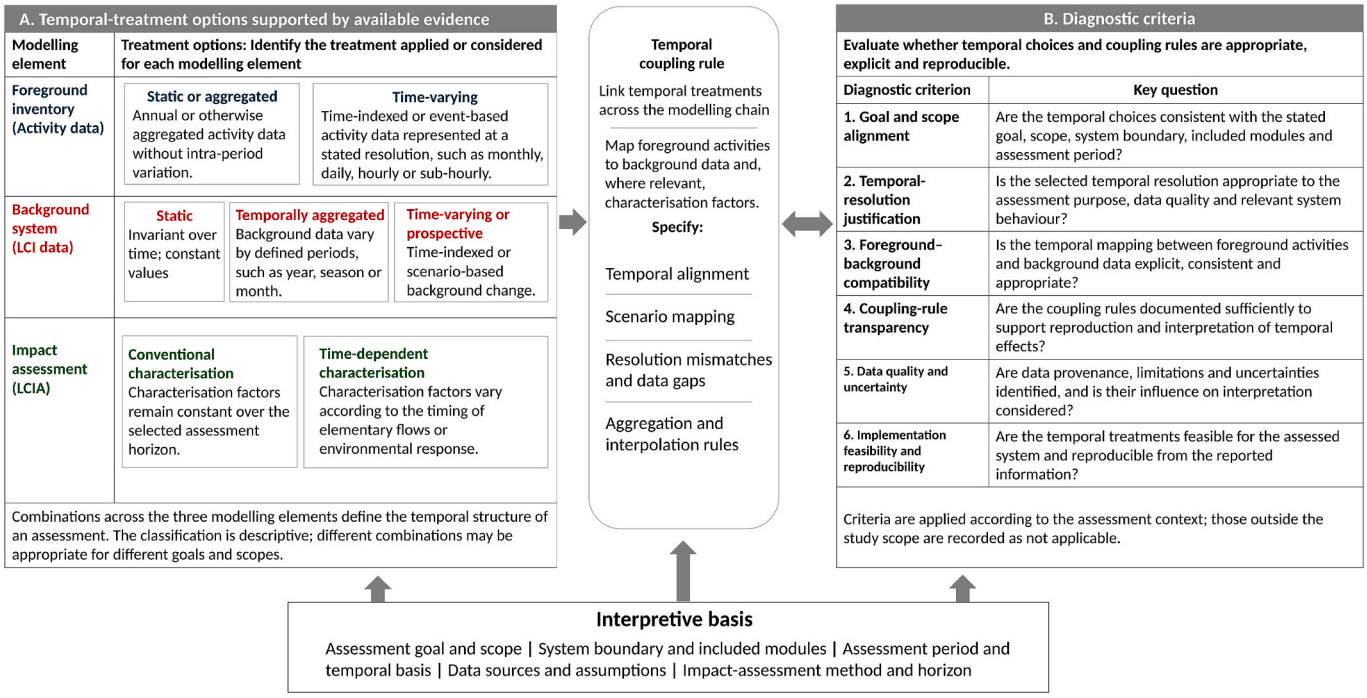


Fig. 6. Classification and diagnostic framework for temporal treatment in building use-phase DLCA.

conflated in DLCA: where time is represented, how temporally differentiated elements are coupled, and whether those choices are justified. Section 6 demonstrates this distinction through a controlled non-domestic operational-electricity application.

6. Worked application of the reporting and diagnostic framework

This section applies the reporting and diagnostic framework to a fixed non-domestic electricity-demand profile. The application examines electricity-related building operation within module B6 over one calendar year and reports operational-electricity GWP. Three configurations vary foreground aggregation and the temporal resolution of pre-characterised operational grid carbon-intensity factors, while the demand profile, annual electricity consumption and assessment boundary remain fixed. The comparison demonstrates how temporal choices, coupling rules, supporting evidence and limitations can be reported transparently. It does not constitute a complete module B6 life-cycle assessment, validate the framework or rank DLCA methods.

6.1. Goal, scope and data sources

The foreground inventory represents the annual electricity demand of a 350 m^2 mechanically ventilated non-domestic social space in the Queen's Building, School of Engineering, Cardiff University, United Kingdom. The profile was derived from a previously calibrated EnergyPlus model [67] and comprises 8760 hourly intervals. Scenario A uses the annual aggregate, whereas Scenarios B and C retain the hourly values. Annual electricity demand is 6406.74 kWh. Natural gas, other operational fuels, embodied impacts, maintenance, replacement and end-of-life processes are excluded.

The hourly profile was mapped sequentially to the 2025 calendar year while preserving its temporal order and annual total. Both factor treatments were derived exclusively from the 2025 observations in the continuously updated National Energy System Operator (NESO) dataset, ensuring that the comparison differed only in the temporal resolution of the electricity factor [68]. For Scenarios A and B, the annual-average factor of 0.126854 kg CO_2/kWh was calculated from all 17,520 half-hourly observations. For Scenario C, the same observations were aggregated into calendar-month means and assigned to the corresponding hourly demand intervals. As the NESO factors represent operational grid carbon intensity rather than cradle-to-grid life-cycle electricity burdens, the results are interpreted as operational-electricity GWP within the stated boundary. Supplementary Material S1 provides the complete demand profile, factor derivation and calculation workflow.

6.2. Modelling configurations and coupling rules

Table 6 defines three configurations that vary foreground resolution and electricity-factor resolution under otherwise fixed assessment conditions. The scenario labels identify modelling choices rather than levels of methodological quality.

Scenario A couples annual demand with the annual-average factor. Scenario B applies the same factor hourly, isolating foreground disaggregation. Scenario C matches hourly demand to calendar-month factors, isolating temporal differentiation of the operational electricity factor. All other assessment conditions remain fixed.

To support reproducibility, the coupling rule specifies each foreground time index, its assigned background factor, any cross-resolution mapping and any aggregation or interpolation applied before impact calculation. Scenario C uses calendar-month matching and sums the 8760 hourly intervals without interpolation or rescaling.

6.3. Diagnostic application

The worked application follows the sequence defined in Fig. 5. Section 6.1 defines the assessment, Section 6.2 reports the temporal treatments and coupling rules, and Table 7 applies the diagnostic checks. Each finding is based on the modelling choice and the evidence available within the application.

Table 7 illustrates the diagnostic function of the framework. Monthly factor resolution is classified as partially justified because aggregation of the half-hourly NESO series removes intramonth variation. If intramonth variation is material to the study goal, the practitioner should test whether the interpretation changes when a higher-resolution factor series is coupled to the demand profile. Implementation feasibility does not apply to this fixed-demand example. In studies of load shifting, the modelling timestep should be compared with actuation delay and plant response. An unresolved mismatch indicates a physically infeasible operational trajectory.

6.4. Numerical interpretation

Scenarios A and B both produce an annual operational-electricity GWP of 812.72 kg CO_2-eq. This equivalence follows from applying the

Table 6
Temporal configurations and operational-electricity GWP results.

Scenario	Foreground inventory	Operational electricity factor	GWP treatment	Change introduced	GWP (kg CO_2-eq yr^{-1})	Change from A
A	Annual demand	2025 annual average	Pre-characterised operational CO_2 intensity; GWP100 = 1	Reference configuration	812.72	0.00%
B	Hourly demand	2025 annual average	Pre-characterised operational CO_2 intensity; GWP100 = 1	Foreground resolution	812.72	0.00%
C	Hourly demand	2025 monthly means	Pre-characterised operational CO_2 intensity; GWP100 = 1	Monthly temporal matching	754.11	−7.21%

The three configurations are calculated as follows:

$$G_A = E_{ann}\overline{CI}_{2025}$$

$$G_B = \sum_{h=1}^{8760} E_h\ \overline{CI}_{2025}$$

$$G_C = \sum_{h=1}^{8760} E_h\ CI_{m(h),2025}$$

where G_a, G_β and G_c are the annual operational-electricity GWP results for Scenarios A, B and C, respectively; E_{ann} is annual electricity demand; E_h is demand during hourly interval h; $\overline{CI}_{2025}$ is the annual-average operational carbon-intensity factor; and $CI_{m(h),2025}$ is the monthly factor assigned to interval h. Annual demand equals the sum of the 8760 hourly values. As the NESO factors report CO_2 intensity, the results are expressed as kg CO_2-eq/year using a GWP100 factor of one for CO_2 [27]

Table 7
Diagnostic evaluation of temporal modelling choices in the operational-electricity application.

Diagnostic check	Evidence and justification	Finding
Goal-and-scope alignment	The three configurations isolate foreground aggregation and electricity-factor resolution within a fixed one-year operational-electricity boundary.	Justified
Temporal-resolution justification	The hourly foreground profile preserves demand variation. Annual and monthly factors provide controlled temporal comparisons, although monthly aggregation excludes intramonth grid variation.	Partially justified
Foreground–background compatibility	Hourly demand is coupled either to a uniform annual factor or to the factor for its corresponding calendar month. The temporal mapping is consistent with each configuration.	Justified
Impact-assessment treatment	The NESO factors are pre-characterised operational CO_2 intensities. Their distinction from cradle-to-grid life-cycle electricity factors is explicitly reflected in the interpretation boundary.	Justified
Coupling-rule transparency	The annual aggregation and calendar-month matching rules are stated mathematically in Section 6.2 and implemented explicitly in Supplementary Material S1.	Justified
Data quality and uncertainty	The demand profile originates from a calibrated EnergyPlus model, and the factors use the complete 2025 NESO series. Uncertainty in the modelled demand and grid-intensity observations is not propagated quantitatively.	Partially justified
Implementation feasibility	The application retains a fixed demand profile and models no load shifting, control intervention or plant response.	Not applicable
Traceability and reproducibility	Supplementary Material S1 provides all 8760 hourly demand values, the complete factor derivation, the coupling rules and the calculation formulas.	Justified

same annual-average factor to an identical annual electricity demand of 6406.74 kWh. Disaggregating the foreground profile into hourly intervals therefore has no effect on the annual result when the downstream factor remains temporally invariant.

Scenario C produces 754.11 kg CO_2-eq/year, representing a reduction of 58.62 kg CO_2-eq/year, or 7.21%, relative to Scenario B. Its demand-weighted operational carbon-intensity factor is 0.117705 kg CO_2/kWh, compared with the annual-average factor of 0.126854 kg CO_2/kWh. The difference arises from the temporal alignment between the hourly demand distribution and the monthly carbon-intensity factors. Fig. 7 decomposes the change across the three configurations.

The decomposition distinguishes the effect of foreground resolution from that of foreground–factor coupling. The unchanged result between Scenarios A and B confirms that hourly disaggregation alone does not affect an annual total when the downstream factor is constant. The reduction in Scenario C is attributable to the case-specific alignment of demand with monthly operational carbon intensities. It should not be interpreted as evidence that monthly factors are universally preferable, because the direction and magnitude of the effect depend on the demand profile, assessment year, geographical coverage and factor definition.

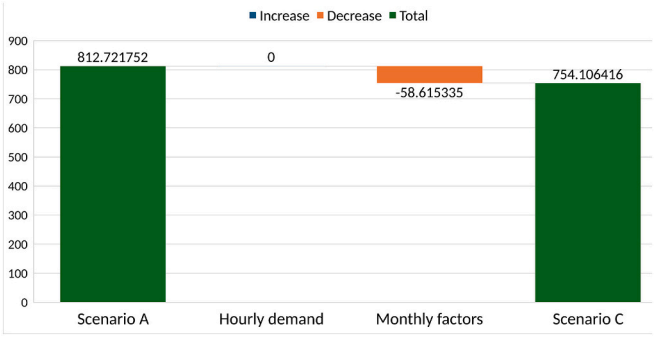


Fig. 7. Decomposition of the change in annual operational-electricity GWP (kg CO_2-eq/year) arising from foreground disaggregation and monthly factor matching.

6.5. *Transferability and limitations*

The worked application is intentionally restricted to one annual electricity-demand profile for a non-domestic space and to operational grid carbon intensity during 2025. It captures hourly demand variation and monthly differences in electricity factors but excludes intramonth and subnational grid variation, interannual change and prospective grid decarbonisation. The factors are average operational grid intensities and do not represent marginal electricity effects or cradle-to-grid life-cycle burdens. The results therefore quantify operational-electricity GWP within the stated boundary rather than complete module B6 or whole-building life-cycle GWP.

The fixed demand profile excludes load shifting, control actions and plant response; implementation feasibility is therefore not applicable. Where operational interventions are modelled, the framework would require evidence that the assumed response is physically achievable and temporally compatible with the building systems. Uncertainty in the calibrated demand profile and carbon-intensity observations is not propagated quantitatively, so the numerical differences should be interpreted as deterministic results for the selected inputs.

The framework is designed for use across building types and does not require a prescribed level of sensing or control complexity. In domestic assessments with limited sensing, foreground inventories may draw on available metering, calibrated simulation or appropriately aggregated data. These inputs are evaluated through the same checks on temporal resolution, provenance, uncertainty and alignment with the declared goal and scope that apply to non-domestic assessments. Control-feasibility criteria apply only when an operational intervention is modelled. The present application is limited to non-domestic operational electricity and GWP. Its practical utility in domestic buildings, other operational flows and additional impact categories therefore remains to be evaluated. Supplementary Material S1 provides the inputs, factor derivation, coupling rules and calculations required to reproduce the application.

7. Conclusion

This study develops a reporting and diagnostic framework for temporal modelling choices in building use-phase DLCA. The framework distinguishes where time is represented from whether the adopted treatment is justified by the assessment goal, scope and available evidence. It considers temporal treatment in the foreground inventory, background system, and impact assessment, as well as temporal resolution, coupling rules, data quality, implementation feasibility, and reproducibility. This structure supports the evaluation of mixed static and time-varying treatments without presenting temporal detail as a hierarchy of methodological quality.

The critical review indicates that temporal variation is most frequently represented in foreground inventories, whereas temporally

differentiated background systems and time-dependent impact characterisation are addressed less consistently. Temporal resolution, coupling rules and operational constraints are also reported unevenly. These differences limit comparison between studies because similar descriptions of "dynamic" assessment may conceal materially different temporal structures. The proposed framework responds by making those structures explicit and relating their justification to the intended decision context.

The worked application demonstrates the framework within a controlled one-year non-domestic operational-electricity boundary. Retaining hourly demand while applying an annual-average factor produced no change in annual operational-electricity GWP. Matching the hourly profile to monthly factors reduced the result from 812.72 to 754.11 kg CO_2-eq/year, equivalent to 7.21%. This difference demonstrates the influence of an explicit foreground–factor coupling rule under the selected demand profile and assessment year. It does not establish the superiority of monthly resolution or constitute a complete module B6 life-cycle result.

The framework may support more transparent and reproducible interpretation of building use-phase DLCA. Future work may examine its application to domestic buildings, other operational flows, longer assessment periods, additional impact categories and further life-cycle modules. Such applications may also test whether the diagnostic fields remain sufficient where temporal inventories, background conditions and characterisation methods differ from those represented in the present case.

CRediT authorship contribution statement

Mohamed Mustafa: Writing – review & editing. **Hassan Alblooshi:** Data curation. **Yacine Rezgui:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2026.118427.

Data availability

Data supporting the worked application are provided in Supplementary Material S1. The source electricity data are publicly available from NESO

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