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Temporalis, a generic method and tool for dynamic Life Cycle Assessment

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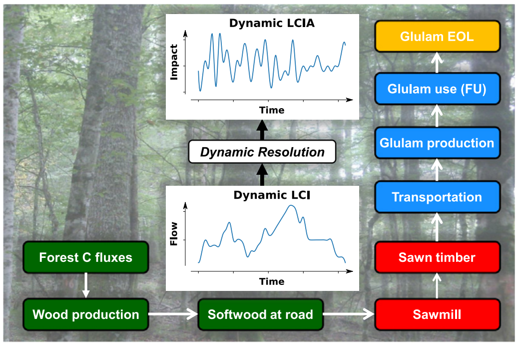
HIGHLIGHTS

- Temporalis allows performing dynamic Life Cycle Assessment (LCA).
- The method makes use of graph traversal and convolution to solve the LCA.
- It is compatible with existing commercial LCI databases.
- Developed as open Source framework
- The importance of using dynamic LCA is shown.

GRAPHICAL ABSTRACT



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ABSTRACT

The limitations of the static nature of Life Cycle Assessment (LCA) are well known. To overcome the loss of temporal information due to the aggregation of flows in the Life Cycle Inventory (LCI), several dynamic LCA methodologies have been proposed. In this paper we present a new generic and operational methodology for dynamic LCA that allows for the introduction of temporal information in both in the inventory and the Life Cycle Impact Assessment (LCIA) phases. The method makes use of graph traversal and convolution to calculate the temporally differentiated inventory, and makes it possible to use several types of dynamic impact assessment. We describe our method and apply it to a cradle-to-grave dynamic LCA of a glued laminated timber (glulam) product. We also test the sensitivity of the global warming results to temporal explicit LCI data. There is a considerable difference in outcome between the static and dynamic approaches. We have implemented our framework in the free and open source software Temporalis that is fully operational and can be used with existing LCA databases.

1. Introduction

Life Cycle Assessment (LCA) is a well-established method to estimate the potential environmental impacts of services and products throughout their entire life cycle. One of the shortcomings of LCA practice is the lack of consideration of the temporal and spatial variation of

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flows and emissions (Huijbregts, 1998). Already in the early days of LCA Finnveden and Nielsen (1999) stressed the importance of considering the long term emissions from landfills. The lack of temporal considerations is still considered an unresolved problem and an important limitation for the accuracy and representativeness of LCA (McManus and Taylor, 2015; Reap et al., 2008). Methodologies to include time and space in LCA have been proposed (Mutel and Hellweg, 2009; Beloin-Saint-Pierre et al., 2014, 2017; Tiruta-Barna et al., 2016; Yang and Heijungs, 2016), but it is still difficult to easily perform dynamic and spatialized LCA for practitioners. This is also due to the lack of accessible and transparent (possibly open source) software. Since "LCA is primarily a steady-state tool" (Udo de Haes, 2006) the conventional approach sums all the emissions for a given pollutant into a single value in the Life Cycle Inventory (LCI), regardless of its time of occurrence. Subsequently, the impacts of the aggregated environmental interventions are characterized during the Life Cycle Impact Assessment (LCIA), irrespective of their timing.

Time can be considered at the level of: (i) the Functional Unit (FU), by giving it a temporal dimension (e.g. one year of energy use); (ii) the LCI, by explicitly considering the temporal relationship between flows; (iii) the LCIA, by using dynamic characterization factors (dCF) or characterization functions (CFun) in place of characterization factors (CF) and (iv) the weighting of impacts, for example by discounting them (Collet et al., 2014; Hellweg et al., 2003). 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. In their seminal book on the computational aspects of LCA, Heijungs and Suh (2002) already discussed a theoretical extension of the matrix-based method to include both spatial and temporal differentiation of the inventory. But already at that time the authors warned the reader that, despite the solid theoretical base, the method's operationalization posed problems. This is due to the huge amount of temporal data required and its high computational demand. In the first studies talking about dynamic LCA (dLCA) (Pehnt, 2006; Kendall et al., 2009; Zhai and Williams, 2010) time was not explicitly considered. In these works the temporal changes in the processes studied were implicitly considered and eventually both emissions and impacts were still aggregated following the traditional LCA approach.

To be dynamic a LCI must be able to locate and differentiate activities and flows in time. This ability to consider and compute temporal characteristics in LCIs, to the best of our knowledge, has been presented in three methodological proposals. In Collinge et al. (2013) the traditional approach based on matrix inversion (Heijungs and Suh, 2002) is used and improved with the inclusion of temporal information. Although it is possible with this method to consider time for each dataset in the LCI, it shows the important operational limitations already recognized from Heijungs and Suh (2002). Beloin-Saint-Pierre et al. (2014) developed the enhanced structure path assessment (ESPA), which extends on structural path analysis, a widely known technique in input-output analysis. It makes use of power series expansion to solve the dynamic inventory, and the matrix inversion is replaced with a product of convolution of the discrete distribution functions. The ESPA has recently been further integrated with the possibility to consider time also at the level of LCIA by applying time-dependent characterization factors (Beloin-Saint-Pierre et al., 2017). The major drawback of this approach is that it is still insufficiently documented and, to date, it has not been made operational and thus not available for the LCA community. A final approach consists in a direct traversal of the supply chain graph, as done by Tiruta-Barna et al. (2016). They recently introduced a very promising method for dynamic LCI that has been developed as a prototype web application. It is based on a process flow network structure and makes use of a graph search algorithm to build the temporal model. Despite the promises of this methodology, it is still a proof of concept that needs to face the implementation challenges of a desktop application. For example, the need for a reduced utilization of memory and computational resources in comparison to a server application. Moreover, it is not coupled to a LCIA framework and it is not clear if the method can deal with datasets without temporal information, raising doubts over its integration potential with existing LCA databases. Regarding the treatment of the LCI as a graph, it is worth mentioning that this approach poses a key methodological challenge due to the cyclic nature of the supply chain graphs. Loops can be encountered, and a cutoff function must be applied to halt potentially infinite loops in supply chain traversal.

Available temporal information can be absolute (e.g. May 25, 1978) and relative (e.g. two weeks ago) in time. While for most impact assessment methods it is necessary to know the absolute calendar date of the emissions (Beloin-Saint-Pierre et al., 2014), both relative and absolute distributions can be encountered in the inventory. This is essentially dependent on how the data are collected during the LCI construction and there are no specific indications to use one or the other. The work of Collinge et al. (2013) is based on absolute temporal data while Beloin-Saint-Pierre et al. (2014) and Tiruta-Barna et al. (2016) use relative temporal information. Ideally both types of temporal information can be handled by a dynamic LCA framework.

The timing of emission is also relevant in impact assessment (IA). In conventional LCIA methods, emissions are integrated over the life cycle, hence they are treated as a pulse rather than a temporally distributed flux. But the moment when the emissions occur can affect the impact. An example is those impact categories influenced by the background concentrations of the pollutants, like aquatic eutrophication (Udo de Haes et al., 2002) and acidification (Potting et al., 1998). Noise impact on human health (Cucurachi et al., 2012), photochemical smog production (Shah and Ries, 2009) and water scarcity (Kounina et al., 2013) are other examples of time-dependent environmental responses. Timing of emissions is also relevant when their impact assessment is performed on a finite time horizon (TH). The typical example of a time horizon-dependent CF is the Global Warming Potential (GWP). This metric, in fact, is very sensitive to the time horizon considered, and the impacts are directly related to its length (IPCC, 2013). In the non-dynamic approach it is implicitly assumed that all the life cycle emissions occur at year 0 and remain in the environment for the entire TH. Levasseur et al. (2010) applied time-dependent CFs to temporally differentiated LCI, overcoming the inconsistencies due to the application of a static approach in the IA.

Numerous authors have demonstrated how neglecting time consideration in LCIA can lead to mis-estimation of impacts (Almeida et al., 2015; Kendall, 2012; Lebailly et al., 2014; Levasseur et al., 2012; Levasseur et al., 2010; Levasseur et al., 2013; Pinsonnault et al., 2014). The limits of the non-dynamic approach are further amplified when biogenic carbon and long life cycles are studied (Jørgensen and Hauschild, 2013). To address the issue of emissions timing in LCA Kendall (2012) also proposed the use of the Time Adjusted Warming Potential (TAWP), a static, time-corrected GWP metric that weights the global warming impact on the basis of the timing of the emissions.

While the systematic introduction of temporal dynamics would increase the representativeness of the LCA results, the process needs to be confronted with the increase in complexity of the LCA modelling and the lack of temporal parameters in LCI databases. In addition, the collection of temporally differentiated data can be a long and costly task, and it should be undertaken only for those datasets that are more sensitive to time. Pinsonnault et al. (2014) demonstrated that temporally differentiated information, on first approximation, are not needed for every process, and their use can be restricted to the ones more sensitive to time. Collet et al. (2014) also introduced a method to identify the specific flows requiring such a temporal differentiation. The method uses a stepwise approach to assess the sensibility of the results to the temporal variability of environmental and product flows. Despite the limitations due to the upfront choice of the LCIA method, this method can represent an important instrument to help in understanding where temporal explicit data are needed and further efforts are necessary during data collection. The possibility to deal also with datasets without temporal parameters is a necessary feature of a dLCA framework.

In short, despite the substantial work done on developing dynamic LCA in the past ten years, no methods have been defined and implemented to provide (i) efficient resolution of temporally differentiated life cycle inventories (LCI); (ii) handling of both absolute and relative temporal distributions, as well as exchanges with databases that have no temporal information; (iii) dynamic characterization of emissions, including both distribution over time and characterization as a function of time; (iv) correct temporal accounting of biogenic carbon (i.e. no carbon neutrality assumption); (v) implementation in accessible and open source computer code. In this paper, we present a novel numerical computational approach to dynamic LCA which meets all our criteria. We implemented our approach in the open source Temporalis software library, built on top of the Brightway2 LCA framework (Mutel, 2017). In this paper we will present the methodology, validate it with a virtual example, and introduce its software implementation. We will use Temporalis to calculate the cradle-to-grave climate impact of 1 m^3 of glued laminated timber (glulam) and show how, by explicitly considering the temporal information, the LCA results diverge from the conventional steady state approach.

2. Methods

We first introduce the computational framework and the way temporal information is stored. We then explain the functioning of the implemented best-first graph traversal used to solve the dynamic inventory problem, validating it with a virtual example. Finally, the dynamic impact assessment and software implementation are explained. To ensure the necessary transparency and reproducibility of the study requested by several scholars (Frischknecht, 2004; Pauliuk et al., 2015), all the analysis have been performed using Jupyter notebook (Shen, 2014) and have been uploaded on a public GitHub repository (Ram, 2013) with its web-link reported in the Supporting Information (SI).

2.1. Framework

The solution to the dynamic inventory problem in our method is rooted in the traditional matrix-based approach for LCI computation proposed by Heijungs and Suh (2002):

$$\overrightarrow{s} = A^{-1}\overrightarrow{s}; G = B\widehat{\overrightarrow{s}} \tag{1}$$

where → is used for vector notation and ^ denotes diagonalization.

In the technosphere matrix A, each element $a_{i,p}$ represents the flows from the products i to the processes p; in the biosphere matrix B each element $b_{j,p}$ represents the biosphere flow j due to the processes p and $\overrightarrow{f}$ is the demand vector (i.e. the Functional Unit FU). Here A and B are time invariant (i.e. do not change over time) and have the implicit assumption that the system is assessed over a temporal interval of adequate duration to account for all the relevant flows. The scaling vector $\overrightarrow{s}$ and the inventory matrix G represent, respectively, the amount of each process p needed to satisfy the FU demand and resulting environmental interventions j due to the process p. But while in the case of a static LCI, for each process p, we are interested in all its j environmental interventions $G_{j,p}$, in the case of a dynamic analysis we also need to know their time t. The solution to the dynamic inventory problem is thus to find all the environmental interventions $G_{j,p}(t)$ for the FU assessed. Technosphere and biosphere matrices are also adjacency matrices of weighted directed graph (Valiente, 2002), where the nodes are processes and edges are exchanges. The rows i and j represent the source (i.e. exchange flow from) and the columns p the destination of each edge in case of $a_{i,p}$ (i.e. exchange flow to) or the process p responsible of the exchange with the environment in the case of $b_{j,p}$. The weight is represented by the value in the cell $a_{i,p}$ and $b_{j,p}$ (i.e. the exchange amount of i and j respectively flowing to process p and to the environment) (Kuczenski, 2015). These edges are dynamic, meaning that the flows occur over a time interval. In non-dynamic LCI, edges are statically represented, and flows $a_{i,p}$ and $b_{j,p}$ represent the integral over time of the flows and are represented by a single value (total flow over the operating interval). But these edges can also be represented by a temporal distribution, which explicitly represents the temporal distribution of flows over time. We introduce two further variables to represent the temporal flows of the dynamic edges, the product-process Temporal Distribution (TD_{ip} hereafter) and the biosphere-process Temporal Distribution (TD_{jp} hereafter). These two TD represent the flow (y-axis) per unit of time (x-axis) of the product i and the biosphere element j respectively, due to the process p over the operating time of the exchange (Eq. (2)), in analogy with Section 3.1 in Beloin-Saint-Pierre et al. (2014).

$$a_{i,p} = \int_{-\infty}^{+\infty} TD_{ip}(t)dt; \;\; b_{j,p} = \int_{-\infty}^{+\infty} TD_{jp}(t)dt \tag{2}$$

Often the available temporal data in the LCI, and consequently the temporal distributions of the edges, are relative to each unit process. The advantage of using process-relative differentiation is that two relative temporal distributions can be convolved to propagate temporal information. The product of convolution (indicated with ∗) is a mathematical operation that, applied to two distributions, produce a third one which results in the integral of the product of the previous two, where one is reversed and shifted along the other. Convolution can be used in LCI networks to propagate in time the temporal information and determine the amount of each flow and when they occur (first case in Eq. (S1)). For the details on the application of convolution the reader is invited to consult Beloin-Saint-Pierre et al. (2014) and Maier et al. (2017) where the operator and its application to temporal distributions' propagation in life cycle analysis is explained in detail. Edges which occur at a precise point in time, such as a pulse emission, can be represented by the Dirac delta function. While such a function may seem strange upon first glance, it can be easily convolved with more normal temporal distributions (Raju, 1982). Finally, edges with inputs or emissions which occur at a fixed time (i.e. with absolute temporal distribution) do not need to be convolved - these absolute temporal distributions are instead simply scaled by the amount of the edge (second case in Eq. (S1)). In the software implementation these TDs are stored as discretized arrays and represented by two one-dimensional numpy arrays of the same length: TD(i) and TD(t). The former represents the y-axis values and reports the amount of the exchanges in double precision float (numpy data-type: float64), the latter is corresponding to the x-axis value and stores the time of the exchanges in datetime (numpy data-type: datetime64). TD(t) can use any temporal resolution below 1 s, which is the highest resolution in current software implementation, and the software automatically converts the user-defined TD(t) into seconds to make all the temporal information uniform (e.g. 1 year is converted to 31,556,952 s). Both TDip and TDbp are optional, and when not reported the exchanges are automatically modelled as a one-time pulse (Dirac) with the implicit assumption that the emission happens the same year of the downstream consuming exchange and not spread over time. It is up to the user to make sure that, when this is not the case, the correct TD for the exchanges is entered in the database. TDs can be both result of a function (e.g. modelling) and TD (t) can be also non-continuous. This approach enables the treatment of the three situations reported in the introduction and, if available, temporal distributions of different time-scales and time-steps. To solve the inventory problem another temporal information is also necessary, namely a calendar date representing the start time t0 of the FU. This other parameter is necessary to propagate in time the flows when reported in relative time as explained in the SI. To solve the dynamic inventory problem the matrix-based approach is used to represent the network of flows between processes and biosphere flows and a graph traversal is used to explore all the important processes of the network and solve the inventory dynamically.

2.2. The best-first graph traversal

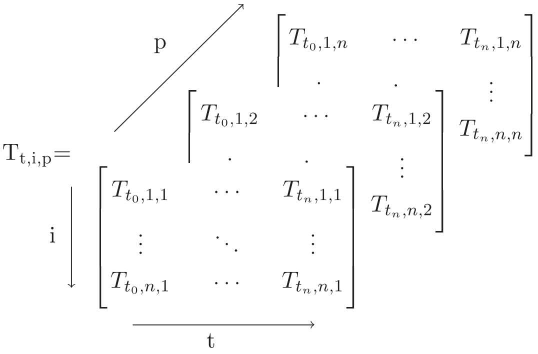
Graph traversal algorithms are used to explore the nodes of a network and are classified based on the order in which each node in the graph is visited. A well-known method is the breadth-first search strategy, used by ESPA (Beloin-Saint-Pierre et al., 2014). Despite its short running time, this method has high memory requirements, mainly when big databases are traversed, making its application limited for simple desktop utilization (Marvuglia et al., 2013). Another quite widespread traversal algorithm is the depth-first search strategy used also by Tiruta-Barna et al. (2016). It has lower memory requirements but a longer running time (Marvuglia et al., 2013). Here we propose to traverse the supply chain to solve the LCI dynamically based on a LCA informed best-first search strategy (Zhang and Korf, 1993). Starting from the FU, the order in which each exchange $\mathrm{a_{i,p}}$ (i.e. the node) in the technosphere matrix A is traversed is based on its relative contribution to the LCA score of the FU (see Temporalis algorithm in SI for details). This means that the nodes with the highest impact relatively to the impact of the FU are evaluated first. The traversal continues through the supply chain until either the impact of the traversed node is below the LCA cutoff criterion, represented by the potential relative impact of the exchange to the FU assessed (by default, 0.1%), or until the maximum number of traversal steps has been reached (by default, 10,000). Calculating the relative LCA score can be tricky for dynamic impact assessment functions, as our general-purpose methodology should allow such functions to have arbitrary complexity. The approach we have chosen to handle such functions is to evaluate them over the entire time period of interest and use a conservative worst-case strategy when solving the dynamic LCI with the traversal algorithm. An incorrect use of the CF at this stage might lead to the exclusion of important flows, but if an input is not important (in the sense of contributing to the total LCA score) applying even the highest possible characterization factors, then we can safely exclude it. Three different cases can be encountered depending on the nature of the IA used, for which the worst-case CF used to solve the dynamic LCI changes accordingly (Eq. (3)).

$$worse-case\,CF = \begin{cases} CF & \text{if CF static} \\ \max(\{CF(t) : t = 0, \dots, TH\}), & \text{if CF dynamic} \\ \displaystyle\int_0^{TH} CF(t)dt, & \text{if CF extended} \end{cases} \quad (3)$$

The simplest is when a static CF is used. In this case the CF consists of a value that is time-independent (e.g. GWP) and the CF values are used as they are (first case in Eq. (3)). In the other two situations the impact assessment used is time-dependent. For those impacts that are subject to seasonal variations, like photochemical oxidation, the highest possible value of the dCF is used (second case in Eq. (3)). By doing so we are sure that, if the impact for a certain process is below our cutoff, even with the highest possible CF, it is not prematurely excluded. The last case is when a CFun is used, namely when the impact of the flow emitted is distributed over time. When calculating the Radiative Forcing (RF), for instance, the impact is spread over time for a length that is function of the decay rate of the flow emitted. The most impacting situation is when the emissions occur at year 0. Consequently, the integral over the TH of the analysis is taken in the worst-case approach for all the environmental interventions (third case in Eq. (3)). Depending on the characteristic of the IA method, the use of the worst-case strategy ensures that all potentially important flows are not prematurely excluded during the resolution of the dynamic inventory problem. The CF to use during the traversal must be decided by the user before starting the calculations based on the CF that will be used in the IA phase following the worst-case approach of Eq. (3). For example, if the goal is to estimate the climate impact using RF, the dynamic LCI must be resolved using as worst-case CF the third case in Eq. (3). The algorithm is CF-specific, meaning that when other impact categories are required to be assessed, the dynamic LCI must be resolved against the new worst-case CF. Failing to do so can produce incorrect results since each process can have a different relative importance depending on the evaluated impact category.

A methodological problem arising from the treatment of the technosphere matrix as a graph is its cyclic nature. The presence of loops, in fact, makes the traversal infinite without any stop condition. Other dynamic LCA methods that apply graph traversal use a temporal cutoff as stop condition, interrupting the iterations when exchanges occur outside a certain time window (Tiruta-Barna et al., 2016). In our case, when loops occur, they continue to be traversed until the impact of the node falls below the LCA cutoff value or the loop is repeated a certain amount of times. By default, this loop cutoff (Lco) is set to 10 iterations but can be modified according to practitioner needs (the higher the number, the higher the precision at the expense of running time). After an exchange is looped Lco times, the same approach used for static databases is applied (first case in Eq. (S1)). This approach avoids infinite loops; the resulting introduction of imprecision in can be reduced by increasing the Lco value.

For each node evaluated during the traversal, both process and elementary flow are calculated, temporally propagated, and all the resulting environmental interventions $g_{j,p}(t)$ are added to a timeline $T_{t,i,p}$, a three dimensional array containing all the $g_{j,p}(t)$ flows of the studied FU. In $T_{t,i,p}$ the dimension i corresponds to a specific elementary flow (e.g. kg of CO_2), the dimension t to the calendar date of that emission and the last dimension p to the process responsible of the emission, as presented in Eq. (4).



(4)

The resulting timeline contains the time of occurrence of all environmental interventions meeting the requirements of a dynamic LCI, as given by Levasseur et al. (2010). To this timeline it is easy to apply both static and dynamic characterization factor, as well as characterization functions, as we show in the next section.

2.3. Dynamic impact assessment

Dynamic impact assessment methods that spread impact over time, such as dynamic GWP, can be easily implemented in our proposed framework. Each characterization factor would behave the same as an edge in the supply chain graph - it would have a relative temporal distribution that could be convolved with inventory distributions.

The inclusion of dynamic impact assessment functions, which produce characterization factors or temporal characterization distributions, can also be included in our method. Indeed, such functions can even take discretized temporal distributions as inputs, treating each pair of (emission amount, time) as a separate flow to be characterized.

With the timeline populated, it is possible to calculate impact for the chosen IA method both for the whole system or separately by processes and/or flows. When the whole system is assessed, the timeline $T_{t,i,p}$ is reduced by one dimension to $T'_{t,i}$ in order to reduce subsequent IA calculations time (Eq. (5)).

$$T'_{t,i} = \sum\nolimits_{p \in p} T_{t,i,p} \tag{5}$$

At this stage it is easy to calculate the environmental impact over time of the studied FU (h_t) or by environmental interventions ($h_{t,i}$). Thanks to the nature of the timeline, which retains also information about the process responsible for each environmental intervention ($T_{t,i}$ $\forall$ p:$T_{t,i,p}$), it is also possible to calculate environmental impact by the process p over time simply by looping over each $T_{t,i}$. Practically, when using a static CF, the environmental interventions are multiplied by the CF and the data are grouped based on time t. We simply take our two dimensional array $F_{t,i}$ ($F_{t,i} = T'_{t,i}$ or $T_{t,i}$ $\forall$ p:$T_{t,i,p}$) and the q_i vector with the CFs for each environmental interventions i and apply Eq. (6).

$$h_{t,i} = \sum\nolimits_{i \in i} F_{t,i} q_i; h_t = \sum\nolimits_{i \in i} h_{t,i} \tag{6}$$

When a dCF or a CFun is used Eq. (7) is applied.

$$h_{t,i} = \sum\nolimits_{i \in i} \sum\nolimits_{t \in t} F_{t,i} q_{t,i}; h_t = \sum\nolimits_{i \in i} h_{t,i} \tag{7}$$

2.4. Software implementation

We have implemented our methodology in a free and open source software package called Temporalis. One of the limitations of the previous approaches for dLCA is that they are still experimental and not yet operationalized into a readily usable tool. In our case, the software has been implemented as part of the open source framework for Life Cycle Assessment Brightway2 (Mutel, 2017). It is well known that opening up software and algorithms increases transparency, a feature that LCA still lacks as already stressed several times in recent years (Finnveden et al., 2009; Frischknecht, 2004; Pauliuk et al., 2015). An increased level of openness of LCA algorithm and software development can help to get constructive feedback from other users with the final result of obtaining also better software and, broadly speaking, LCA analysis. Brightway2 is fully compatible with many existing commercial LCI databases like, among others, Ecoinvent (Wernet et al., 2016), Agrybalise (Colomb et al., 2015), the World Food LCA Database (Lansche et al., 2013) and FORWAST (Villeneuve et al., 2009). As part of the software library, we wrote a custom convolution function that does not require a fixed and continuous temporal resolution. Furthermore, dynamic IA methods for climate impacts based on the 2013 Intergovernmental Panel on Climate Change (IPCC) methodology (IPCC, 2013) are already included. They allow calculating GWP and Global Temperature Potential (GTP) dynamically, and overcome the temporal inconsistency due to the use of static IA. To explicitly account for the temporal discrepancy of biogenic carbon fluxes due to their delayed re-sequestration after emission, also the methodology of Cherubini et al. (2011, 2012) has been implemented (see Section 2.6 and SI for further explanation).

All the variables needed for the use of the methodology are summarized in Table 1. In the SI, we give links to the source code repository, documentation, and the explanation of the algorithm used to solve the inventory dynamically.

Table 1
Parameters needed to perform a dynamic LCA using the software Temporalis.

Variable	Description	Mandatory (M) or optional (O)
TD_{ip}	Temporal distribution (absolute in time or relative to the consuming process) of technosphere exchange of the process j	O
TD_{jp}	Temporal distribution (absolute in time or relative to the consuming process) of biosphere exchange of the process j	O
t0	Starting date of the analysis	M
Worst case CF	Characterization factor used during the traversal	M
LCA cutoff	Cutoff below which the process nodes are excluded during the traversal	M (in the software set by default to 0.01 of FU score)
Maximum calculation number	Maximum number of iteration of the graph traversal	M (in the software set by default to 10,000)
Lco	Maximum number of iterations in a loop	M (in the software set by default to 10)

2.5. Virtual example

Here we illustrate and validate the functioning of the Temporalis tool using a simple fictitious example. Fig. 1 presents a system of six unit processes, involving a loop between process 2 and 6, and two processes (1 and 3) without temporal information (i.e. static). Three biosphere flows are considered and a fictitious CF that is equal to 1 for all the flows is used as worst case CF. The FU for this example is one unit of the product 4 and t0 is set equal to 01.01.2017. In Table 2 all the exchange amounts with their relative TD used in this example are given (for the sake of clarity a 1 year resolution has been used both in the codes and in the figure). Fig. 2 shows the dynamic environmental interventions for each individual process $g_{j,p}(t)$ for the analyzed FU. The results are validated by comparing the static and dynamic cumulative environmental interventions and products' supply (Table 2). As can be seen the dynamic approach gives almost the same outcome as a conventional static LCA. There is a slight difference in the results due to the nature of the best-first traversal methodology. This difference is in the order of magnitude of the LCA cutoff chosen and can be reduced by simply lowering the cutoff, at the expense of computation time.

2.6. Application in a case study

The very long life cycles involved in the forestry-wood sector systems make them an exemplary field to illustrate the developed framework. An additional complication of impact assessment in this sector is due to the temporal discrepancy between the emissions of biogenic CO_2 and their capture through forest regrowth. We thus performed a cradle-to-grave dLCA for a reference flow of one m^3 of glulam. Biosphere and technosphere exchanges were modelled using own data for the foreground system and Ecoinvent 2.2 and 3.2 for the background. The choice of using both Ecoinvent databases is not casual. With this we want to show (i) that the framework can be efficiently applied to big commercial databases (Ecoinvent 3.2, consists of about 12,900 datasets) and (ii) how it is possible to temporalize also data coming from databases conceived in a static way, like Ecoinvent 2.2. In Fig. 3 a representation of the dynamic system is given. The detailed system graph of the inventory can be found in the Github repository, together with the Jupyter notebook with the commented codes showing the step-by-step procedure followed to create the dataset.

Raw wood production in the forest has been modelled based on the Ecoinvent 3.2 unit process “softwood forestry, mixed species, sustainable forest management”. This dataset represents the sustainable forest management practices related to the production of 1 m^3 of softwood under bark over a rotation length of 130 years. It includes site preparation (assuming natural regeneration) and all processes related to forest management (i.e. clearing, tending, pruning, thinnings and harvesting operations). We made this unit process dynamic by adding temporal parameters to the silvicultural management practices and temporally explicit biogenic carbon fluxes due to forest regrowth based on the information reported in the unit process description from Ecoinvent. For the management practices, the original exchanges in the Ecoinvent dataset were made dynamic by equally spreading their inputs over 9 thinnings and a final harvest. It was assumed that each of these 10

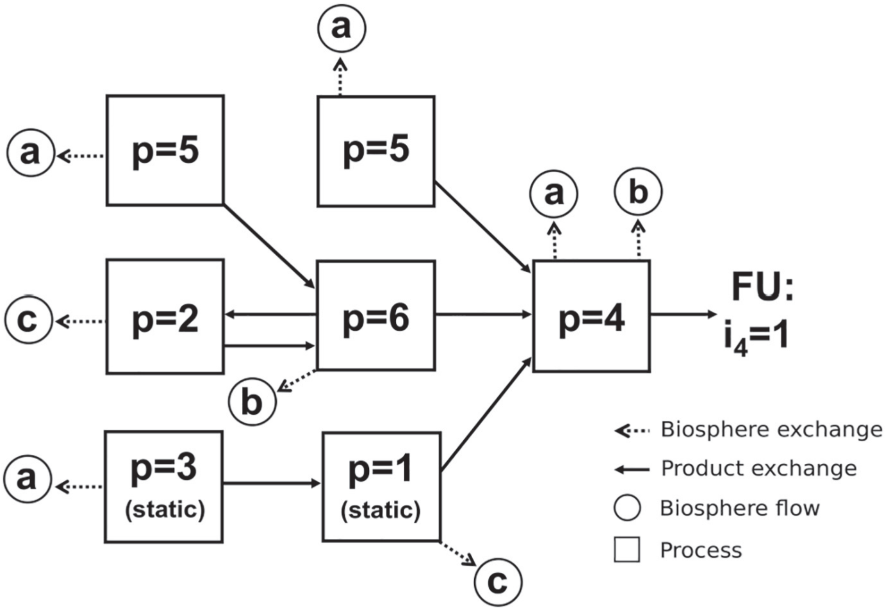


Fig. 1. Schematic representation of the virtual example modelled. Functional Unit is equal to 1 unit of product 4. Processes 1 and 3 are static (i.e. without temporal distributions).

interventions had the same intensity and occurred every 10 years starting from year 40. For what forest regrowth is concerned, we applied the methodology proposed by Cherubini et al. (2011) to model its atmospheric CO_2 re-sequestration rate. The rate of biomass re-growth has been modelled as a normal (Gaussian) distribution with mean (μ) equal to half of the rotation length and the variance (σ) that is assumed to be half of the mean (Eq. (8)).

$$g(t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(t-\mu)^2/2\sigma^2} \tag{8}$$

Table 2
Parameters used in the virtual example and validation of the results.

Inventory exchanges

Technosphere exchange (from-to)	TD(t) (years, relative to the consuming process)	TD(i)	$a_{i,p}$
3 to 1	Static	Static	0.4
6 to 2	[−3, −1]	[0.2, 0.2]	0.4
1 to 4	[−1, 0]	[0.2, 0.4]	0.6
5 to 4	[−2, 0]	[0.4, 0.2]	0.6
6 to 4	[−1, 0]	[0.14, 0.16]	0.3
2 to 6	[−5, −4]	[0.2, 0.3]	0.5
5 to 6	[−1, 0, 1]	[0.04, 0.06, 0.1]	0.2

Biosphere exchange	TD(t) (years, relative to the consuming process)	TD(i)	$b_{j,p}$
c to 1	Static	Static	7.5
c to 2	[−5, −4, −1, 0]	[1, 1.5, 1.7, 0.8]	5
a to 3	Static	Static	4
a to 4	[−2, −1, 0, 1]	[1.5, 0.5, 0.4, 0.6]	
b to 4	[−1, 1]	[1, 1]	2
a to 5	[−10, −9, −8, −7, −6, −5, −4, −3, −2, −1]	[1, 1, 1, 1, 1, 1, 1, 1, 1, 1]	10
b to 6	[−2, −1, 0, 1]	[1, 1, 1, 1]	4

Balance check

Process	Static ($\vec{s}$)	Dynamic	Difference (%)
1	0.6000	0.6000	0.0000
2	0.1875	0.1875	−0.0053
3	0.2400	0.2400	0.0000
4	1.0000	1.0000	0.0000
5	0.6750	0.6750	−0.0030
6	0.3750	0.3750	0.0000

Flow	Static ($\vec{g}$)	Dynamic	Difference (%)
a	10.7100	10.7098	−0.0022
b	3.5000	3.5000	−0.0006
c	5.4375	5.4374	−0.0011

Inventory exchanges: biosphere and technosphere flows exchanges (from-to); TD(i) amount and TD(t) time (in years, relative to the consuming process) of relative temporal distribution; $a_{i,p}$, $b_{j,p}$: technosphere and biosphere flows. Balance check: validation of the results obtained comparing the cumulative product supply and the environmental interventions $g_{j,p}(t)$ of the dynamic results respectively with the scaling $\vec{s}$ and the inventory $\vec{g}$ vectors.

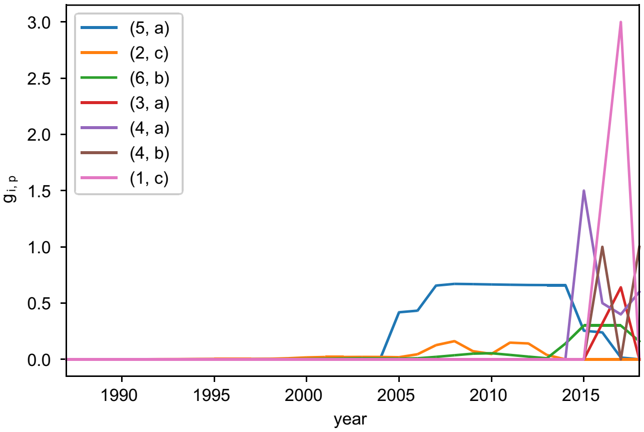


Fig. 2. Temporally defined environmental interventions $g_{j,p}(t)$ for the virtual example i.e. environmental interventions (letter) for each individual processes (number) over time.

We modelled a two years gap between forest harvesting and first transformation into sawnwood, and another two years between first and second transformation to glulam.

The life cycle of the glulam has been modelled in accordance to the Environmental Product Declaration (EPD) standard EN 15804 (CEN, 2012). The life cycle inventories of both first and second transformation have been modelled mostly based on Ecoinvent 2.2. In accordance with the aforementioned standard in both stages economic allocation was applied. Also steel fittings are included in the modelling of the glulam production. At the end-of-life the glulam beam was assumed to be partially recycled, partially landfilled and partially used for energy recovery according to the figures reported in Mantau et al. (2010). Following the EPD standard, system expansion is applied in this stage and substituted impacts for recycling and energy recovery are included in the calculation. It was assumed that the electricity and heat recovered substitute respectively the current European electricity and heat production grid. The part that is recycled is assumed to replace the production of wood panels from virgin wood. For the glulam, a service life λ of 50 years has been considered and the discarding rate has been estimated using a gamma distribution, as already suggested by Marland et al. (2010). This distribution has been parameterized with $a = k / 2$ and $b = 2$, where k is a positive integer corresponding to the year of maximum oxidation (i.e. mean lifetime of the product λ) as proposed by Cherubini et al. (2012). This parametrization of the gamma

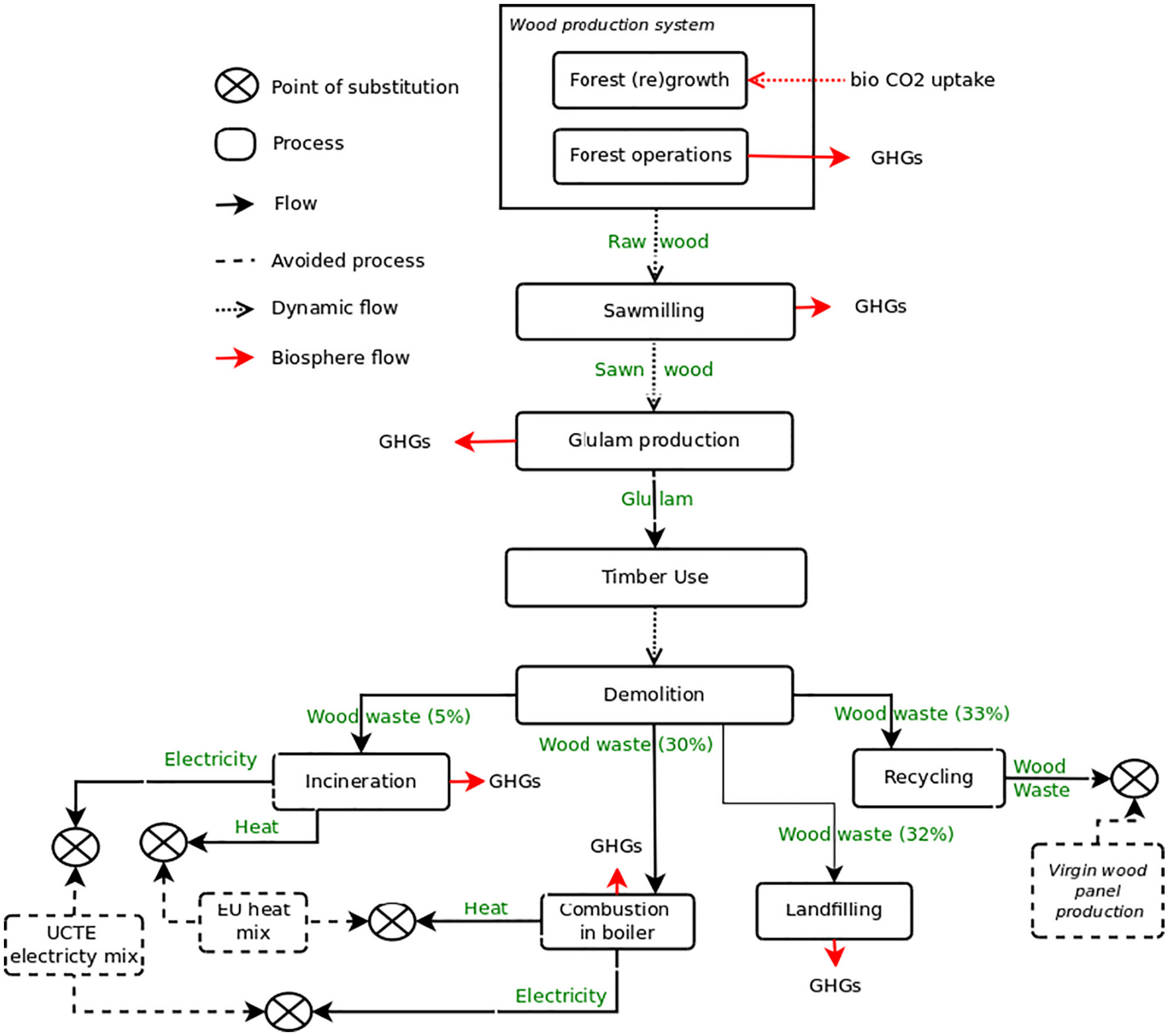


Fig. 3. The product flow diagram of the Glulam use as modelled in the case study.

distribution is equivalent to a Chi-squared distribution with k degrees of freedom (Eq. (9)).

$$\chi^2(t;k) = \frac{(1/2)^{k/2}}{\Gamma(k/2)} x^{k/2-1} e^{-t/2} \tag{9}$$

where $t =$ time and $\Gamma(k / 2)$ is the gamma function in Eq. (10).

$$\Gamma(k/2) = \int_0^{-\infty} t^{k/2-1} e^{-x} dx \tag{10}$$

We solved the LCI statically and dynamically with t0 as the year of production of glulam (01.01.2017) and calculated for both the cumulative climate impact. As IA method we used the (static) CFs for GWP published by IPCC and implemented in Ecoinvent (Bourgault, 2015) and compared them with the dynamic GWP result, which accounts also for the climate impact of forest biogenic CO_2 emissions and removals (see Cherubini et al., 2012; Cherubini et al., 2011).

3. Results

Fig. 4 shows the cumulative climate impact for the case study over a time horizon TH of 20, 100 and 500 years using both static and dynamic LCA.

First, we compared the results obtained using static (sLCI) and dynamic LCI (dLCI) for a static GWP over 20 (Fig. 4a), 100 (Fig. 4b) and 500 years TH (Fig. 4c). It can be seen that the closer t0 to the end of TH, the greater is the discrepancy between the two results. This is due to the fact that when using a static LCI all the environmental interventions are characterized regardless the timing of their occurrence, while using the dynamic LCI only the environmental interventions occurring within the TH are considered. The results over the complete TH, in fact, are equivalent between the two approaches, provided that all the environmental interventions are within this time window (as in the case of Fig. 4c). In the results, the negligible difference between dynamic and static approach (~0.01%), is explained by the approximated results yielded by the graph traversal and explained above.

Next, we compared these results with the cumulative climate impacts obtained using a fully-fledged dLCA (i.e. both LCI and LCIA dynamic) over a time horizon of 500 years (Fig. 4d). In this case the results revealed are quite surprising and the difference between a conventional and a fully dynamic approach with a correct accounting of forest biogenic CO_2 fluxes are substantial. The estimated impacts are lower in the static approach with a relative difference of 226%, 406% and 42% over 20, 100 and 500 years TH respectively. Even assuming the carbon neutrality of forests (i.e. without accounting biogenic carbon) the relative difference between the two results is important (274%, 151% and 29% over 20, 100 and 500 years TH respectively). Also when comparing these dynamic results (Fig. 4d) with those using dynamic LCI and static LCIA (Fig. 4c) it can be seen that the temporal evolution of impacts is sensibly different and the climate impact due to forest regrowth plays an important role bringing the system to a higher impact for the first 145 years and then lower. Notable is the fact that while a fully static approach always gives negative values (thus a positive, mitigating, climate impact due to glulam use), a fully dynamic analysis shows positive effects only 145 years after t0.

Next, we assessed the sensitivity of our results to the temporal parameters used evaluating the same system but with varying rotation lengths of 50, 130 and 200 years and product lifetimes of 1, 50 and 150 years (Fig. 5). The results change quite substantially depending on these temporal parameters. For all three TH considered the shorter the rotation length the lower is the impact. Inversely, the longer the lifetime of glulam, the higher are the climate benefits of postponing biogenic carbon emissions. For the same system the GWP impact for a TH of 20 years can range from −71 kg CO_2eq (Fig. 5b) to 443 kg CO_2eq (Fig. 5g), from −901 kg CO_2eq (Fig. 5c) to 667 kg CO_2eq (Fig. 5g) for a TH of 100 years and from −546 kg CO_2eq (Fig. 5c) to −120 kg CO_2eq

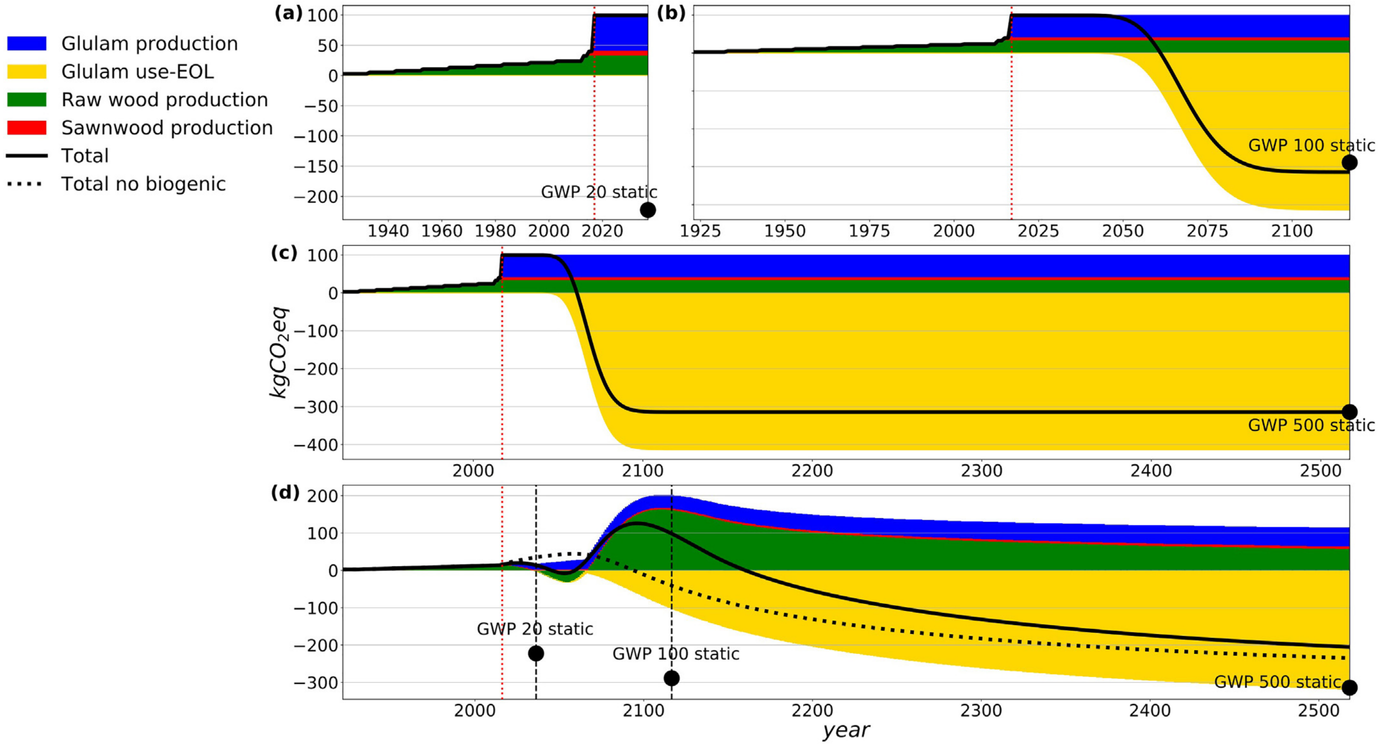


Fig. 4. Cumulative climate impact of the cradle-to-grave dLCA of 1 m^3 of glulam calculated over a time horizon of 20 (a), 100 (b) and 500 (c) years using static GWP and over 500 years using dynamic GWP (d). Vertical red dotted read line represents t0 (2017). The temporal evolution of the impact is shown for each of the main four phases and for the total (black line). Black dotted line shows the total results without accounting for biogenic carbon (i.e. assuming carbon neutrality) and black dots indicate the results of the static LCA (i.e. both LCI and CF static) using different time horizons for GWP (20, 100 and 500 years). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

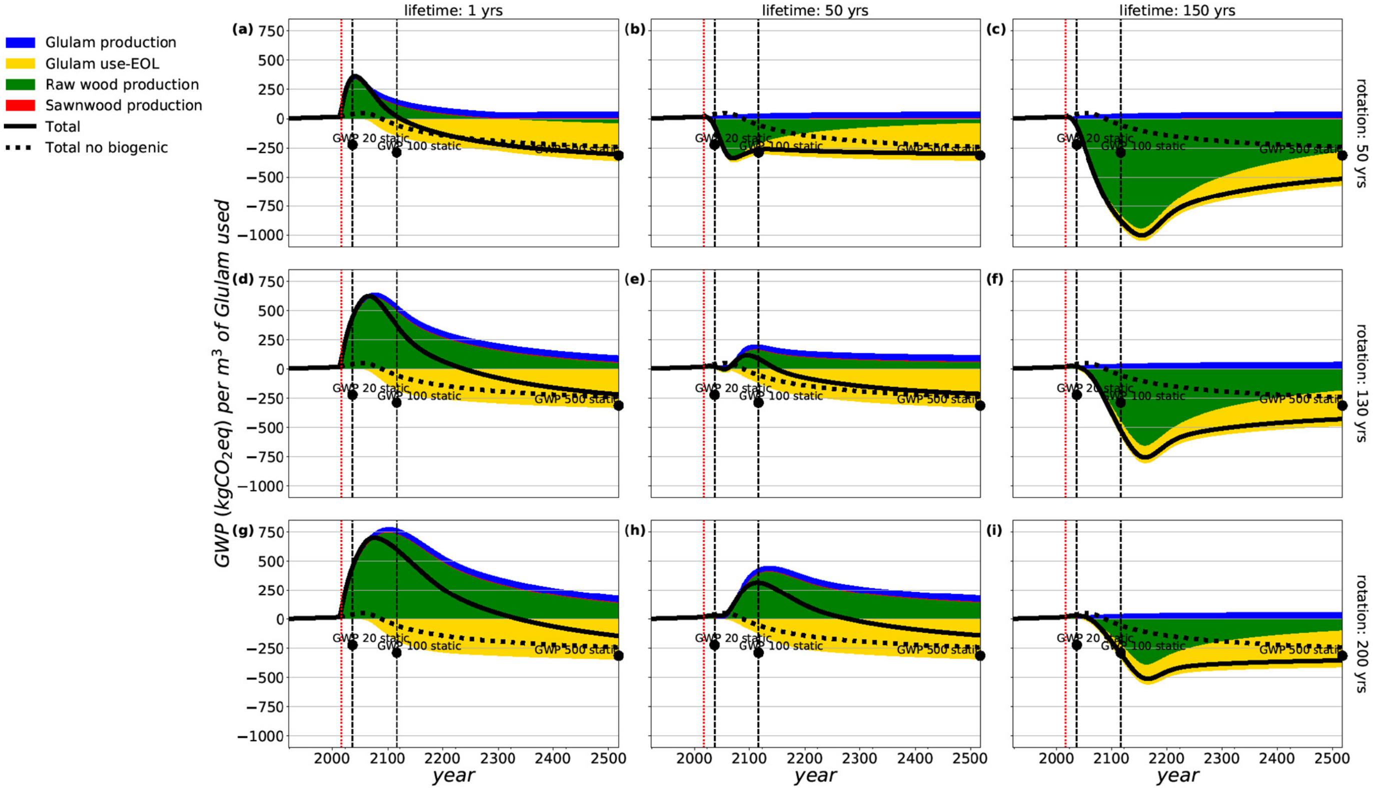


Fig. 5. Sensitivity analysis of the cumulative climate impact of the cradle-to-grave dLCA of 1 m^3 of glulam to rotation length and glulam lifetime over a time horizon of 500 years. Rotation length in the forest of 50 (a, b, c) 130 (d, e, f) and 200 (g, h, i) years and lifetime of glulam use of 1 (a, d, g) 50 (b, e, h) and 200 (c, f, i) years are considered. Vertical red dotted read line represents t0 (2017). The temporal evolution of the impact is shown for each of the main four phases and for the total (black line). Black dotted line shows the total results without accounting for biogenic carbon (i.e. assuming carbon neutrality) and black dots indicate the results of the static LCA (i.e. both LCI and CF static) using different time horizons for GWP (20, 100 and 500 years). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(Fig. 5h) for a TH of 500 years based on the rotation length and the lifetime of the product studied.

4. Discussion

The methodology reported in this paper goes a step further compared to what has been already done in the field of dynamic LCA. It allows for the accounting of time at all the levels outlined in the introduction and is fully flexible for what the temporal information is concerned. This flexibility makes it possible to easily and efficiently use the methodology and the Temporalis software with already existing databases that traditionally lack temporal information. In our case study, for example, the dynamic LCI is solved in about 16 s and the dynamic LCIA in approximately 34 s on a regular laptop (Intel® Core™ i7-6820HQ CPU 2.70 GHz, 8 GB RAM), with a maximum usage of memory of less than 350 MB.

Data availability is and will continue to be a major limitation for the application of dynamic LCA. The ability of Temporalis to combine both static and dynamic inventory data is therefore remarkable. While already operational, Temporalis and its underlying methodology can still be further refined and improved. For example, the dynamic LCIA implementation could be improved, creating a more robust framework based on an improved version of the one developed by Beloin-Saint-Pierre et al. (2017). They proposed the use of the Hadamard product between a two-dimensional matrix G' representing the biosphere flow emissions (row) and the time of their emission (column) with the matrix H containing specific time-dependent CF (column) for each biosphere flow (row). An improved version of this approach could be implemented using a three-dimensional matrix for the G' with the inclusion of a third dimension for the process responsible of each emission to allow for a better interpretation of the results compared to Beloin-Saint-Pierre et al. (2017).

The importance of using dynamic analysis and accounting properly for biogenic carbon is confirmed by the case study results. The alleged positive climate effects due to glulam use (Sathre and O'Connor, 2010), when studied dynamically, is only seen with a certain delay (from 9 to 352 years in our glulam case-study) that depends on the temporal characteristics of the system, essentially rotation length and product lifetime. This aspect is of tremendous practical importance for wood products when their sequestration and substitution effect is estimated. In fact, while in static analysis the (potential) climate substitution effect of wood product use is always found, a temporal explicit approach reveals that this phenomenon is very much influenced by the way the analysis is performed. From our results it can be seen that, first, the positive effects are often over-estimated, and even more importantly, that, when seen, they take place only with a delay that is depending on the temporal characteristics of the studied life cycle. Most studies, ours included, are forward-looking, assessing forest carbon regrowth (Helin et al., 2013) and thus analyzing the forest carbon dynamics from the moment of harvesting onwards. However, some authors suggest taking a backward looking in which the past carbon fluxes due to the forest growth (and not re-growth) is considered (Sedjo, 2011). While it is outside the scope of the paper to discuss which is the most correct assumption, the backward approach would reduce the time needed from the system to start exerting its substitution effect. As both approaches are discussed in the literature, the importance of an adaptable and efficient dynamic LCA tool is reinforced.

The results of this case study confirm how dynamic LCA is particularly relevant when analyzing long life cycles and, in assessing climate impacts, when also the dynamics of biogenic carbon are accounted for (i.e. without assuming any carbon neutrality).

Further progress towards more accurate LCA analysis will certainly be obtained by coupling temporally and spatially resolved analysis. The idea is to come to a full spatio-temporal framework easily applicable with the computational structure of LCA software and databases in use nowadays. Being based on the traditional matrix-based approach, our dynamic methodology could be easily combined with location data, provided that the regionalized LCA methodology used fits into matrix math structure. Our next step is to work towards this spatio-temporally defined LCA approach including uncertainty, coupling our method with the matrix-based regionalized framework proposed by Mutel and Hellweg (2009) and already developed in Brightway2.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.07.044.

References

Almeida, J., Degerickx, J., Achten, W.M.J., Muys, B., 2015. Greenhouse gas emission timing in life cycle assessment and the global warming potential of perennial energy crops. Carbon Manage. 6:185–195. https://doi.org/10.1080/17583004.2015.1109179.

Beloin-Saint-Pierre, D., Heijungs, R., Blanc, I., 2014. The ESPA (Enhanced Structural Path Analysis) method: a solution to an implementation challenge for dynamic life cycle assessment studies. Int. J. Life Cycle Assess. 19:861–871. https://doi.org/10.1007/s11367-014-0710-9.

Beloin-Saint-Pierre, D., Levasseur, A., Margni, M., Blanc, I., 2017. Implementing a dynamic life cycle assessment methodology with a case study on domestic hot water production. J. Ind. Ecol. 21:1128–1138. https://doi.org/10.1111/jiec.12499.

Bourgault, G., 2015. Implementation of IPCC impact assessment method 2007 and 2013 to ecoinvent database 3.2.

CEN, 2012. 15804: Sustainability of construction works-Environmental product declarations-Core rules for the product category of construction products. European Committee for Standarization Brussels.

Cherubini, F., Peters, G.P., Berntsen, T., Strømman, A.H., Hertwich, E., 2011. CO2 emissions from biomass combustion for bioenergy: atmospheric decay and contribution to global warming. GCB Bioenergy 3:413–426. https://doi.org/10.1111/j.1757-1707.2011.01102.x.

Cherubini, F., Guest, G., Strømman, A.H., 2012. Application of probability distributions to the modeling of biogenic CO2 fluxes in life cycle assessment. GCB Bioenergy 4: 784–798. https://doi.org/10.1111/j.1757-1707.2011.01156.x.

Collet, P., Lardon, L., Steyer, J.-P., Hélias, A., 2014. How to take time into account in the inventory step: a selective introduction based on sensitivity analysis. Int. J. Life Cycle Assess. 19:320–330. https://doi.org/10.1007/s11367-013-0636-7.

Collinge, W.O., Landis, A.E., Jones, A.K., Schaefer, L.A., Bilec, M.M., 2013. Dynamic life cycle assessment: framework and application to an institutional building. Int. J. Life Cycle Assess. 18:538–552. https://doi.org/10.1007/s11367-012-0528-2.

Colomb, V., Amar, S.A., Mens, C.B., Gac, A., Gaillard, G., Koch, P., Mousset, J., Salou, T., Tailleur, A., Hays, M., 2015. AGRIBALYSE, the French LCI Database for agricultural products: high quality data for producers and environmental labelling. Oilseeds Fats Crops Lipids 22 (DOI:).

Cucurachi, S., Heijungs, R., Ohlau, K., 2012. Towards a general framework for including noise impacts in LCA. Int. J. Life Cycle Assess. 17:471–487. https://doi.org/10.1007/s11367-011-0377-4.

Finnveden, G., Nielsen, P.G., 1999. Long-term emissions from landfills should not be disregarded. Int. J. Life Cycle Assess. 4, 125.

Finnveden, G., Hauschild, M.Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., Koehler, A., Pennington, D., Suh, S., 2009. Recent developments in Life Cycle Assessment. J. Environ. Manag. 91:1–21. https://doi.org/10.1016/j.jenvman.2009.06.018.

Frischknecht, R., 2004. Transparency in LCA - a heretical request? Int. J. Life Cycle Assess. 9:211–213. https://doi.org/10.1007/BF02978595.

Heijungs, R., Suh, S., 2002. The Computational Structure of Life Cycle Assessment. Springer.

Helin, T., Sokka, L., Soimakallio, S., Pingoud, K., Pajula, T., 2013. Approaches for inclusion of forest carbon cycle in life cycle assessment – a review. GCB Bioenergy 5:475–486. https://doi.org/10.1111/gcbb.12016.

Hellweg, S., Hofstetter, T.B., Hungerbuhler, K., 2003. Discounting and the environment should current impacts be weighted differently than impacts harming future generations? Int. J. Life Cycle Assess. 8:8. https://doi.org/10.1007/BF02978744.

Huijbregts, M.A.J., 1998. Application of uncertainty and variability in LCA. Int. J. Life Cycle Assess. 3:273–280. https://doi.org/10.1007/bf02979835.

IPCC Climate Change, 2013. The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (2013).

Jørgensen, S.V., Hauschild, M.Z., 2013. Need for relevant timescales when crediting temporary carbon storage. Int. J. Life Cycle Assess. 18:747–754. https://doi.org/10.1007/s11367-012-0527-3.

Kendall, A., 2012. Time-adjusted global warming potentials for LCA and carbon footprints. Int. J. Life Cycle Assess. 17:1042–1049. https://doi.org/10.1007/s11367-012-0436-5.

Kendall, A., Chang, B., Sharpe, B., 2009. Accounting for time-dependent effects in biofuel life cycle greenhouse gas emissions calculations. Environ. Sci. Technol. 43: 7142–7147. https://doi.org/10.1021/es900529u.

Kounina, A., Margni, M., Bayart, J.-B., Boulay, A.-M., Berger, M., Bulle, C., Frischknecht, R., Koehler, A., Canals, L.M.i., Motoshita, M., Núñez, M., Peters, G., Pfister, S., Ridoutt, B., Zelm, R.v., Verones, F., Humbert, S., 2013. Review of methods addressing freshwater use in life cycle inventory and impact assessment. Int. J. Life Cycle Assess. 18: 707–721. https://doi.org/10.1007/s11367-012-0519-3.

Kuczenski, B., 2015. Partial ordering of life cycle inventory databases. Int. J. Life Cycle Assess. 20:1673–1683. https://doi.org/10.1007/s11367-015-0972-x.

Lansche, J., Gaillard, G., Nemecek, T., Mouron, P., Peano, L., Bengoa, X., Humbert, S., Loerincik, Y., 2013. The world food LCA database project: Towards more accurate food datasets. 6th International Conference on Life Cycle Management—LCM.

Lebailly, F., Levasseur, A., Samson, R., Deschênes, L., 2014. Development of a dynamic LCA approach for the freshwater ecotoxicity impact of metals and application to a case study regarding zinc fertilization. Int. J. Life Cycle Assess. 19:1745–1754. https://doi.org/10.1007/s11367-014-0779-1.

Levasseur, A., Lesage, P., Margni, M., Deschênes, L., Samson, R., 2010. Considering time in LCA: dynamic LCA and its application to global warming impact assessments. Environ. Sci. Technol. 44:3169–3174. https://doi.org/10.1021/es9030003.

Levasseur, A., Brandão, M., Lesage, P., Margni, M., Pennington, D., Clift, R., Samson, R., 2012. Valuing temporary carbon storage. Nat. Clim. Chang. 2:6–8. https://doi.org/10.1038/nclimate1335.

Levasseur, A., Lesage, P., Margni, M., Samson, R., 2013. Biogenic carbon and temporary storage addressed with dynamic life cycle assessment. J. Ind. Ecol. 17:117–128. https://doi.org/10.1111/j.1530-9290.2012.00503.x.

Maier, M., Mueller, M., Yan, X., 2017. Introducing a localised spatio-temporal LCI method with wheat production as exploratory case study. J. Clean. Prod. 140:492–501. https://doi.org/10.1016/j.jclepro.2016.07.160.

Mantau, U., Saal, U., Prins, K., Steierer, F., Lindner, M., Verkerk, H., Eggers, J., Leek, N., Oldenburger, J., Asikainen, A., et al., 2010. Real potential for changes in growth and use of EU forests. EUwood. Final report.

Marland, E.S., Stellar, K., Marland, G.H., 2010. A distributed approach to accounting for carbon in wood products. Mitig. Adapt. Strateg. Glob. Chang. 15:71–91. https://doi.org/10.1007/s11027-009-9205-6.

Marvuglia, A., Benetto, E., Rios, G., Rugani, B., 2013. SCALE: Software for CALculating Emergy based on life cycle inventories. Ecol. Model. 248:80–91. https://doi.org/10.1016/j.ecolmodel.2012.09.013.

McManus, M.C., Taylor, C.M., 2015. The changing nature of life cycle assessment. Biomass Bioenergy 82:13–26. https://doi.org/10.1016/j.biombioe.2015.04.024.

Mutel, C., 2017. Brightway: an open source framework for Life Cycle Assessment. J. Open Source Softw. 2. https://doi.org/10.21105/joss.00236.

Mutel, C.L., Hellweg, S., 2009. Regionalized life cycle assessment: computational methodology and application to inventory databases. Environ. Sci. Technol. 43:5797–5803. https://doi.org/10.1021/es803002j.

Pauliuk, S., Majeau-Bettez, G., Mutel, C.L., Steubing, B., Stadler, K., 2015. Lifting industrial ecology modeling to a new level of quality and transparency: a call for more transparent publications and a collaborative open source software framework. J. Ind. Ecol. 19: 937–949. https://doi.org/10.1111/jiec.12316.

Pehnt, M., 2006. Dynamic life cycle assessment (LCA) of renewable energy technologies. Renew. Energy 31:55–71. https://doi.org/10.1016/j.renene.2005.03.002.

Pinsonnault, A., Lesage, P., Levasseur, A., Samson, R., 2014. Temporal differentiation of background systems in LCA: relevance of adding temporal information in LCI databases. Int. J. Life Cycle Assess. 19:1843–1853. https://doi.org/10.1007/s11367-014-0783-5.

Potting, J., Schöpp, W., Blok, K., Hauschild, M., 1998. Site-dependent life-cycle impact assessment of acidification. J. Ind. Ecol. 2:63–87. https://doi.org/10.1162/jiec.1998.2.2.63.

Raju, C.K., 1982. Products and compositions with the Dirac delta function. J. Phys. A Math. Gen. 15:381. https://doi.org/10.1088/0305-4470/15/2/011.

Ram, K., 2013. Git can facilitate greater reproducibility and increased transparency in science. Source Code Biol. Med. 8:7. https://doi.org/10.1186/1751-0473-8-7.

Reap, J., Roman, F., Duncan, S., Bras, B., 2008. A survey of unresolved problems in life cycle assessment. Int. J. Life Cycle Assess. 13:374–388. https://doi.org/10.1007/s11367-008-0009-9.

Sathre, R., O'Connor, J., 2010. Meta-analysis of greenhouse gas displacement factors of wood product substitution. Environ. Sci. Pol. 13:104–114. https://doi.org/10.1016/j.envsci.2009.12.005.

Sedjo, R.A., 2011. Carbon Neutrality and Bioenergy: A Zero-sum Game? Resources for the Future (DOI:)

Shah, V.P., Ries, R.J., 2009. A characterization model with spatial and temporal resolution for life cycle impact assessment of photochemical precursors in the United States. Int. J. Life Cycle Assess. 14:313–327. https://doi.org/10.1007/s11367-009-0084-6.

Shen, H., 2014. Interactive notebooks: sharing the code. Nat. News 515:151. https://doi.org/10.1038/515151a.

Tiruta-Barna, L., Pigné, Y., Navarrete Gutiérrez, T., Benetto, E., 2016. Framework and computational tool for the consideration of time dependency in Life Cycle Inventory: proof of concept. J. Clean. Prod. 116:198–206. https://doi.org/10.1016/j.jclepro.2015.12.049.

Udo de Haes, H., 2006. How to approach land use in LCIA or, how to avoid the Cinderella effect? Int. J. Life Cycle Assess. 11:219–221. https://doi.org/10.1065/lca2006.07.257.

Udo de Haes, H.A., Finnveden, G., Goedkoop, M., Hauschild, M., Hertwich, E.G., Hofstetter, P., Jolliet, O., Klopffer, W., Krewitt, W., Lindeijer, E., Muller-Wenk, R., Olsen, S.I., Pennington, D.W., Potting, J., Steen, B., 2002. Life-cycle Impact Assessment: Striving Towards Best Practice. SETAC.

Valiente, G., 2002. Algorithms on Trees and Graphs. S. B., Heidelberg.

Villeneuve, J., Vaxelaire, S., Lemiere, B., Weidema, B., Schmidt, J., Daxbeck, H., Brandt, B., Buschmann, H., 2009. The FORWAST project: design of future waste policies for a cleaner Europe. Abstracts WASCON, pp. 3–5 (DOI:).

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B., 2016. The ecoinvent database version 3 (part I): overview and methodology. Int. J. Life Cycle Assess. 21:1218–1230. https://doi.org/10.1007/s11367-016-1087-8.

Yang, Y., Heijungs, R., 2016. A generalized computational structure for regional life-cycle assessment. Int. J. Life Cycle Assess. 22:213–221. https://doi.org/10.1007/s11367-016-1155-0.

Zhai, P., Williams, E.D., 2010. Dynamic hybrid life cycle assessment of energy and carbon of multicrystalline silicon photovoltaic systems. Environ. Sci. Technol. 44:7950–7955. https://doi.org/10.1021/es1026695.

Zhang, W., Korf, R.E., 1993. Depth-first vs. best-first search: new results. Proceedings of the Eleventh National Conference on Artificial Intelligence. AAAI Press, Washington, D.C., pp. 769–775.