Facilitating dynamic life cycle assessment for climate change mitigation

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Abstract:

Dynamic life cycle assessment (LCA) explicitly takes into account the dynamics of carbon storage and release in the impact assessment of biomass use on climate change, although such approach requires more data and increases the complexity of the calculation. The aim of this work is therefore to assess how the application of dynamic LCA can be facilitated based on: the modelling tool Temporalis, the time dimension of the functional unit, and the contribution of the time dimension to the accuracy of results. Firstly, Temporalis was tested and improved, proving to be an efficient tool for performing dynamic LCA. Secondly, two functional units were compared: 'total number of units produced over the whole lifespan of the plant' (FU1) and '1 unit produced at t_0' (FU2); the results are equivalent when the lifespan of the plant is short compared to the studied time horizon. FU1 should be used for assessing the potential impact of the entire system on climate change relative to climate goals on a calendar-based timeline. Conversely, FU2 should be used for comparing systems that do not share the same temporal distribution of production and for generating inventory data that can be reused as background inventory data in other life cycles. Thirdly, the variation in results induced by the dynamic characterisation of the impact was compared with the variations induced by the uncertainties in the inventory data, which are not always significant. The mathematical properties of the absolute global warming potential were investigated for a time horizon that tends towards infinity, thus generalising previous observations and predicting some of these results derived from simplified temporal information. Further investigation would allow for the development of a method for selecting flows to be distributed over a timescale prior to a full dynamic LCA, using only simplified temporal information.

Keywords:

Dynamic LCA, functional unit, negative emissions, biogenic CO_2, uncertainty, Temporalis

1 INTRODUCTION

The 28th Conference of the Parties held in Dubai reiterated the urgent need for action to limit global warming to 1.5°C (European Council 2023). According to the Intergovernmental Panel on Climate Change (IPCC 2018), limiting global warming to 1.5°C requires the deployment of bioenergy with carbon capture and storage (BECCS) at an average rate ranging from 3 to 7 $GtCO_2$ per year by 2050. BECCS refer to systems that convert biomass into energy and capture the released CO_2 in order to store it permanently outside of the atmosphere. BECCS generate a flow of CO_2 from the atmosphere (capture by photosynthesis during biomass growth) towards a permanent storage outside the atmosphere (CCS). BECCS system generates negative emissions onlyif the beneficial impact of capturing CO_2 from the atmosphere is not offset by greenhouse gas emissions over the entire life cycle of the BECCS system (e.g. including the transport of captured CO2 and its conversion step etc.). The mitigation potential of BECCS needs to be assessed. This is addressed using Life Cycle Assessment (LCA) (14040, 2006; 14044, 2006) in order to take into account all emissions resulting from the consumption of energy (e.g. heat for carbon capture) and chemicals (e.g. solvent for carbon capture). There is ongoing research on how the impact of biomass use on climate change can be taken into account, and on the assessment of negative emissions. Brandão et al. (2019; 2024) compared existing metrics for quantifying the impact on climate change of bioenergy systems. Brander et al. (2021) and Goglio et al. (2020) reviewed the methodological challenges related to the assessment of negative emissions. They identified a key issue in the way the differences in carbon storage and release dynamics are handled.

Dynamic Life Cycle Impact Assessment (LCIA) presents an answer to this question (Brandão et al. 2024; Brander et al. 2021). Dynamic LCIA is defined as "characterisation models of environmental mechanisms that account for the dynamic of ecosphere systems and can therefore use temporal information of dynamic Life Cycle Inventories (LCI)" (Beloin-Saint-Pierre et al. 2020). The original dynamic LCIA method was developed by Levasseur et al. (2010) to characterise the impact on climate change. For an emission of a greenhouse gas at time t and an impact assessed over a time horizon TH, corresponding to the time between t_0 and t_{end}, Levasseur et al. (2010) proposed to calculate the Absolute Global Warming Potential (AGWP) at t_{end} as the integral of the radiative forcing between t and t_{end}. The time horizon is the "relative temporal scope over which environmental impacts are summed up to provide LCA results" (Beloin-Saint-Pierre et al. 2020). Dynamic LCIA on climate change is an active area of research, with new characterization methods (based on GWP (Ventura 2022)) and decision-support indicators (based on Global Temperature Change, GTP (Tiruta-Barna 2021)) that are still being developed. However, Beloin-Saint-Pierre et al. (2020) point out that the execution of a dynamic LCIA requires significant additional effort, with increasing data requirements and the complexity in calculating the LCI. Su et al. (2021) noted a lack of tested tools for calculating both LCI and LCIA. Brandão et al. (2024) rated the ease of application of dynamic LCIA as rather poor (3/5, 1 being really easy to use). Within this context, this work aims at exploring the potential for dynamic LCA (both LCI and LCIA) to be made easier to use.

2 LITERATURE REVIEW

Firstly, temporal differentiation of the LCI, i.e. the distribution of the consumption and production of each process included in a life cycle, on a given time scale, is complex. It is not possible to use conventional LCA software such as Simapro® or Gabi®. The open-source python library Temporalis (Cardellini et al. 2018) is the only currently available tool that can be used for calculating a dynamic LCI and then performing a dynamic LCIA. In the present article, dynamic LCI refers to "LCI that is calculated from supply and value chains where […] temporal differentiation is considered resulting in temporal distributions to describe elementary flows" (Beloin-Saint-Pierre et al. 2020). However, as pointed out by Su et al. (2021) and Beloin-Saint-Pierre et al. (2020), Temporalis still needs to be tested to validate its operability and efficiency. Another challenge lies in the availability of generic dynamic LCIs. Several studies (e.g. (Jury et al. 2022; Zieger et al. 2020)) provide inventory data over the entire lifespan of the system, i.e. for the production of several units of the product or service each year over the entire lifespan of the system. To reuse the data in a different life cycle, it is easier to use an average dynamic LCI, i.e. for the production of one unit of the product or service at time $t_{0,process}$. The definition of a process-relative "time 0" ($t_{0,process}$) enables the creation of a process-relative temporal distribution. The first objective of this study is thus to test Temporalis and propose an algorithm for averaging a dynamic LCI.

Secondly, Su et al. (2021) pointed out that many dynamic LCA studies compare their results to results obtained using static LCA. Static LCA refers to the usual way of performing LCA. Two types of functional units are observed: i) the production of several units of the product or service each year over the entire lifespan of the system (e.g. '100 years of continuous hemp cultivation starting in 2022' in Shen et al. (2022)) and ii) the production of one unit of the product or service at t_0 (e.g. '1 m^3 plywood' in Wang et al. 2022)). Using static LCA, the results obtained using the two types of functional units are equal if the total quantity produced is equal. Would the same observation be made when using the dynamic LCA method? Furthermore, in static LCIA, the potential impact of the system studied on climate change is generally provided for a single time horizon (usually 100 years) which is not calendar based. Using the dynamic LCIA approach, the impact of an emission at time t_e is the product of the mass emitted and a dynamic characterisation factor for a time horizon of $TH - t_e$. TH and t_e are both defined relatively to the same instant noted t_0. t_0 is the link between the inventory timeline and the impact characterisation timeline. t_0 can be equal to 0 (e.g. (Zieger et al. 2020)) or based on a calendar (e.g. (Shen et al. 2022)). There is currently no consensus on how to position the temporal distribution describing the inventory relative to t_0. In the work of Negishi et al. (2019), the first year of production is chosen as equal to t_0. For Zieger et al. (2020), it is rather the year during which the infrastructure was built that is chosen as t_0. Ventura (2022) suggested yet another perspective by defining a total observation duration corresponding to the sum of the duration of the inventory and the time horizon, which is equivalent to choosing the last year of the inventory as t_0. In the present article, the recommendation of Beloin-Saint-Pierre et al. (2020) was followed, i.e. t_0 is equal to the time when the product, service or system is ready to be used. The choice of which event of the life cycle takes place at t_0 is arbitrary. Choosing t_0 as the time at which the functional unit is provided makes it easier to compare results of LCA studies, because the functional unit is the common point between the systems being compared. For example, depending on the system, the temporal scope for the construction of an infrastructure or for biomass growth may differ. Choosing a t_0 other than when the functional unit is provided can lead to a bias in the comparison, simply because the inventory timeline of each compared system is not positioned in the same way in relation to the impact characterisation timeline. However, ambiguity remains when the production occurs over several years. Therefore, the second objective of this paper is to explore, using a case study, the influence of the definition of the functional unit, in order to propose recommendations for facilitating future interpretation and comparison of dynamic LCA studies.

Thirdly, dynamic LCA results are compared to static LCA results for evaluating whether a dynamic LCA is worth performing. For example, in the specific case of a biofuel from perennial crops, Almeida et al. (2015) concluded that dynamic LCA only increased the complexity of the calculations without providing any added value in terms of interpreting the results compared to static LCA. Pigné et al. (2020) added temporal information to a whole background database and only observed significant differences when the datasets included high upstream emissions (due to infrastructure construction). The balance between the complexity of the approach and the addition of precision to the results is thus central for dynamic LCA. Collet et al. (2014) suggested temporal information should only be added to the main contributors of the impact, on condition that their temporal scope is equal to or greater than the temporal resolution of the impact, i.e. one year for climate change. Following this recommendation, the third objective of this work is to explore whether the variation in results induced by dynamic characterisation of the impact on climate change is significant when compared with the variations induced by uncertainties in inventory data.

The final purpose of this article is to investigate the value and feasibility of explicitly including time in environmental assessments of climate mitigation solutions. An illustrative case study (i.e. a shopping bag) is used for fulfilling the three underlying objectives described above, i.e. to test Temporalis, to determine the time dimension of the functional unit and to assess the contribution of the time dimension to the accuracy of results.

3 METHODS

The inventory data used for modelling the case study, the method applied for averaging a dynamic LCI and the method to perform a dynamic LCIA in the impact category ‘climate change’ are presented in section 3.1. Changes made to Temporalis are described in section 3.2. The sensitivity analysis performed on the definition of the functional unit and time horizon is presented in section 3.3. The sensitivity analysis performed to compare dynamic and static LCA is presented in section 3.4.

3.1 Case study, inventory modelling and dynamic LCIA

The production, from biogenic CO_2, of a reusable shopping bag was chosen as a case study for its temporal parameters (duration of biomass growth, lifespan of the plant producing the shopping bag, lifespan of the shopping bag), the availability of inventory data in the literature and the fact that more than 99.9% of the impact on climate change calculated with static LCA is explained by emissions of CO_2, CH_4 and N_2O. The case study is illustrated in Figure 1. Two biomass productions were investigated: miscanthus, a fast dedicated production system and wood residue, a long-term sub-product production system. The biomass was then transformed by alcoholic fermentation into ethanol, electricity and CO_2. The CO_2 is combined with hydrogen to be converted to methanol, then to propylene, and finally produced a polypropylene shopping bag (CO_2 valorisation plant on Figure 1). At the end of life, the shopping bag was incinerated with CCS to allow for the possible generation of negative emissions. The ethanol is burnt to produce energy. Such system boundaries mean that all the carbon can be tracked, from its capture by photosynthesis during biomass growth to its re-emission into the atmosphere or permanent storage. For 1 bag produced, the system also produces around 3 MJ of ethanol and 0.2 MJ of electricity. These three products are produced in the same year. To simplify the expression of the functional units and focus on the dynamics of the system, we will only refer to the quantity of bag produced in the remainder of the article, the production of ethanol and electricity being implicit. All the inventory data were taken from the literature and are provided in the supplementary information (SI) excel file.

A full evaluation of biogenic CO_2 is performed (+1/-1 approach). Flows of biogenic CO_2 captured during the growth of miscanthus or wood residues were included in the inventory with a negative value. The amount of captured CO_2 ($A_{CO2,captured}$ in kg_{CO2}) is linked to the carbon content of the biomass by the following formula:

$$A_{CO2,captured} = m x_C \frac{M_{CO2}}{M_C} \tag{1}$$

With:

- m, (kg): mass of biomass
- x_C (kg_C/kg): carbon content of biomass
- M_{CO2} (kg_{CO2}/mol): molar mass of carbon dioxide
- M_C (kg_C/mol): molar mass of carbon

However, the harvested biomass is only one carbon pool of the biomass production system. Carbon is also stored in the roots and in the soil: from 5 to 15% of global fossil fuel emissions could be offset by soil organic carbon (SOC) sequestration (Goglio et al. 2015). The changes in soil organic carbon (SOC) due to miscanthus production was modelled with the AMG model (Clivot et al. 2019) over the entire lifespan of the plot (15 years), see section 1 of SI_1 for more details. AMG is parametrised for French arable soil and cannot be applied to forest soil. Due to data availability, no SOC variation was included in wood residue production. For wood residue production, the growth of trees was modelled using the Chapman-Richards equation and the parameters from Albers (2019) for the sessile oak (*Quercus petraea*). Sessile oak was chosen in order to achieve the most contrasting result compared to miscanthus. The frequency and amount of thinning were also taken from Albers (2019) (22 thinnings over 200 years). Consumption of energy and materials, such as fertilisers, during miscanthus production was obtained from the work of Jury et al. (2022). Only a diesel consumption for wood residues harvesting is added to the inventory for wood residues production. Calculation details can be found in the SI ‘LCI_from_excel_dyn.ipynb’ (also supplied as an html file that can be opened in a web browser).

Emission and consumption associated with the production of biomass collected in the literature are representative of a production over the entire lifespan of a miscanthus or tree plot. The inventory of miscanthus production described an almost constant production over 15 years. The inventory of wood residues described a production every 5 to 10 years over 190 years, with decreasing amounts. For both miscanthus and wood residues, the temporal distribution of the biomass production was not equal to the temporal distribution of the biomass consumption in the fermentation step. Moreover, the complete details of the system are not fully known. For example, it is not determined whether the biomass originates from the first, second, or subsequent harvest of the studied plot, or even whether the fermentation plant is supplied by a single or multiple plots of biomass. Therefore, the inventory of both miscanthus and wood residues could not be used directly as input in the fermentation step. To overcome this problem, the dynamic LCI for the production of biomass over the entire lifespan of a plot was averaged in order to represent the mean production of one unit of biomass at $t_{0,process}$ according to the algorithm illustrated in Figure 2. Such averaging retains temporal information in the LCI.

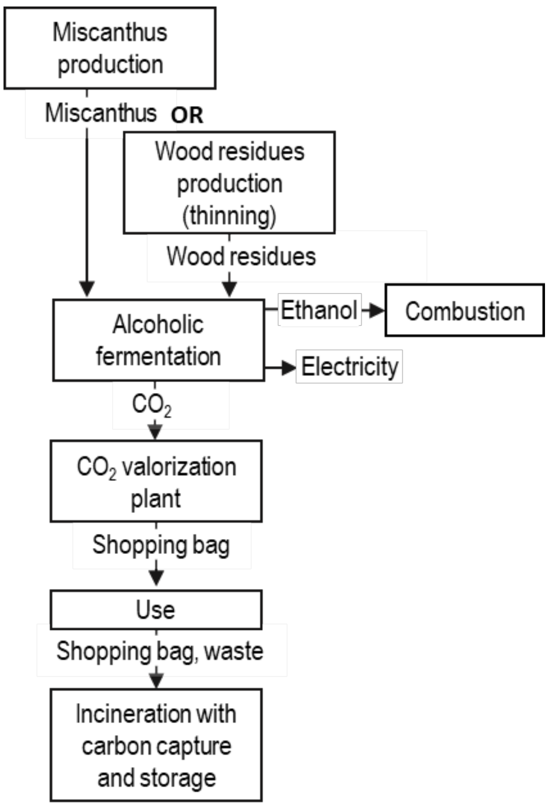

Figure 1: Life cycle steps of the case study

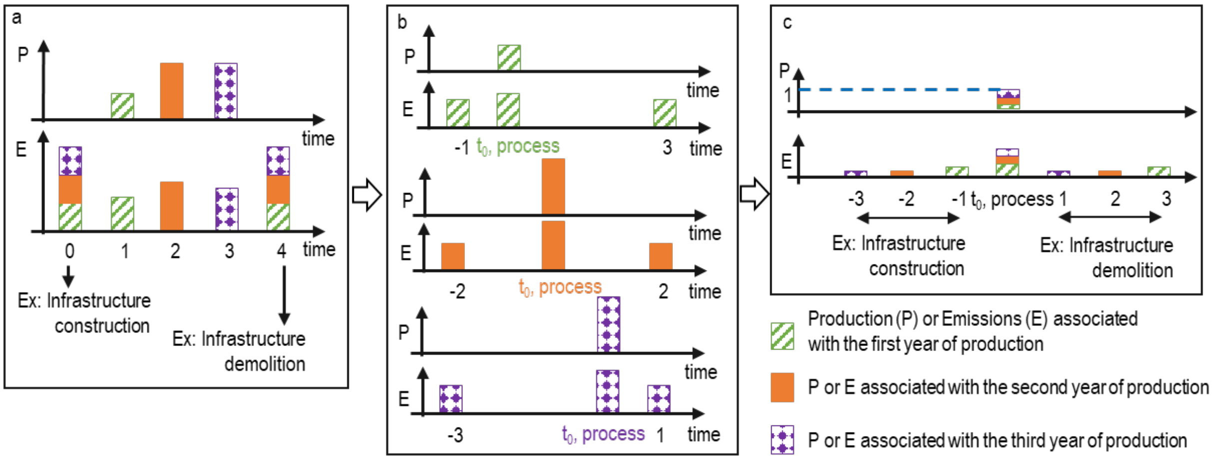

Figure 2: Illustration of the algorithm used for averaging a dynamic LCI by using a fictional system. (a) Dynamic LCI representing the production (P, e.g. in unit, mass, MJ…) over the entire lifespan of the system in chronological order and the associated emissions (E, in mass or volume) of a given pollutant. (b) The inventory is divided into one inventory per year of production. Each year of production is identified by a colour and a pattern. The same colour/pattern code is used to identify the emissions allocated to a given year of production. The emission/capture pulses such as land use change or infrastructure construction are equally divided between the productions cycles. The year of production becomes the $t_{0,\ process}$ of each new inventory. (c) The final averaged inventory representing the mean production at $t_{0,\ process}$ is then the average of the inventory per year of production weighted by the respective production volumes.

The impact on climate change (I) induced by the system is calculated using the following formula, inspired from Levasseur et al. (2010):

$$I(TH) = \sum_{i}\sum_{t_e} m_i(t_e) AGWP_i(TH - t_e) \tag{2}$$

$$I(TH) = \sum_{i}\sum_{t_e} m_i(t_e) \int_{t_e+t_0}^{t_{end}} a_i C_i(t - t_e)dt \ = \sum_{i}\sum_{t_e} m_i(t_e) \int_{t_0}^{t_{end}-t_e} a_i C_i(t)dt \tag{3}$$

With:

- i: greenhouse gas (CO_2, CH_4 or N_2O only)
- $t_{end} - t_0 = TH$: time horizon of the impact assessment (year). If not calendar based, $t_0 = 0$.
- t_e: time of emission or capture of a greenhouse gas (year). t_e values range between $-\infty$ and t_{end}. When $t_e < t_0$, the emission or capture occurs before the time frame of the assessment. The integration time is then greater than TH. Beyond t_{end}, the emissions or captures are cut-off. They do not contribute to the radiative forcing.
- $m_i(t_e)$: mass of greenhouse gas i emitted at time t_e.
- a_i: radiative efficiency of the greenhouse gas i, based on AR5 values (IPCC 2013)($W.m^{-2}.kg^{-1}$).
- $C_i(t)$: decay function of the greenhouse gas i (yr^{-1}).

In the present article, dynamic modelling refers to the calculation of a dynamic LCI and its dynamic LCIA on climate change using Temporalis. Static modelling refers to the use of a LCI without temporal differentiation, i.e. all emissions and consumptions occur at the same time t_0, and to the application of LCIA on climate change for multiple time horizons using Temporalis.

3.2 Motivation for the changes introduced in Temporalis

The calculation of the dynamic inventory from unit processes and the dynamic characterisation on climate change was performed using the version of Temporalis created by Cardellini et al. (2018).

A few changes were made to the original source code. Firstly, as a graph traversal algorithm is used for calculating the dynamic LCI, and as an inventory in LCA can involve thousands of unit processes, a cut-off is applied to halt the graph traversal algorithm and limit the computing time. The balance between accuracy and computation time was well described by Pigné et al. (2020). To help the LCA practitioner to be aware of the magnitude of the impact that is unaccounted for in the calculation, an attribute was added to the dynamic LCA object in Temporalis to store the cumulative impact of all the disregarded processes calculated with $AGWP_{100}$. Secondly, calculation of the dynamic inventory can take up to several hours, depending on the complexity of the system and the performance of the computer. The code was modified to allow for the storage of the calculated dynamic inventory into an excel file in order to perform the characterisation of the inventory at a later date. Lastly, the code used to perform the characterisation of the dynamic inventory was simplified in order to limit numerical integration errors and so future users can more easily understand the calculation process. The analytical formula of the AGWP is directly used, instead of numerical integration, for calculating the radiative forcing induced by an emission (cf. section 5 of SI_1, and the python script 'metrics_SDD' also supplied as an html file that can be opened in a web browser). The emission and capture of atmospheric CO_2 is characterised with the same function as fossil CO_2. The sign provided in the inventory indicates whether it is an emission (positive) or a capture (negative). With this approach, there was also no need to differentiate atmospheric and fossil methane in the characterisation step. The modified source code is available in the SI 'Modified_version_temporalis.zip'.

3.3 Sensitivity analysis on the definition of the functional unit

The production amount of the CO_2 valorisation plant was arbitrarily chosen, i.e. 1000 units per year for 20 years or 400 units per year for 50 years. As explained in the introduction, two functional units could be defined: 'Production of 20000 bags over the entire lifespan of the plant (LP)' (FU_1) or 'Production of 20000 bags at t_0' (FU_2). The dynamic LCI used for modelling FU_1 represented the entire system chronologically, for instance from infrastructure construction to infrastructure demolition of a production plant, as illustrated in Figure 2a. FU_1 could also be written as 'Production of 1000 (or respectively 400) bags each year during 20 (or respectively 50) years". The dynamic LCI used to model FU_2 was averaged as illustrated in Figure 2c. In static LCA, strictly the same results were obtained with both functional units. In a dynamic LCA approach, t_0 was defined as the time when the product, service or system was ready to be used as proposed by Beloin-Saint-Pierre et al. (2020). This definition involved several possibilities for the positioning of the dynamic LCI relative to t_0 in the case of the 'Production of 20000 bags over LP'. t_0 could correspond to any year between the first year of production (noted P_0) and the last year of production (noted P_{end}). To explore the impact of the definition of the functional unit and the position of the dynamic LCI relative to t_0, results were calculated for the two functional units. Furthermore, for the 'Production of 20000 bags over LP' functional unit, the results were calculated for a lifespan of 20 or 50 years and for the two extreme temporal positions of the inventory, i.e. $P_0 = t_0$ or $P_{end} = t_0$. The lifespan of the plant did not affect the results calculated with the 'Production of 20000 bags at t_0' functional unit because, due to lack of inventory data, the infrastructure construction and decommissioning were not included in the inventory.

3.4 SENSITIVITY ANALYSIS: VARIATIONS INDUCED BY DYNAMIC MODELLING VERSUS UNCERTAINTIES IN STATIC ASSESSMENT

To limit the number of varying parameters, the functional unit chosen for performing this sensitivity analysis was the 'Production of 1 bag at t_0'. The only temporal parameter was the lifespan of the bag: either 0 or 20 years. A preliminary sensitivity analysis was performed in static LCA in order to select the key parameters that cause variations in results within the "climate change" impact category.

To identify the main contributors to variations in static results, a parameterized model was built using lca-algebraic. Lca-algebraic (https://github.com/oie-mines-paristech/lca_algebraic) is a Brightway2 package, specific for uncertainty analysis. A few parameters were selected according to the variability observed during data collection and presented in Table 1, except for the range of values for the carbon content of biomass defined as +/-10 % of the default value. Every distribution was assumed to be uniform due to lack of information. 'Energy production' is a Boolean parameter representing the production of heat and hydrogen. Heat and hydrogen are used to produce methanol from CO_2. Heat is also used for capturing CO_2 at the bag EoL. The first alternative of the parameter 'Energy production' corresponds to conventional energy production (EP_{conv}), with heat and hydrogen production modelled by Ecoinvent datasets (Ecoinvent) ('market for heat, from steam, in chemical industry' and 'market for hydrogen, liquid'). For the second alternative, the amount of heat and hydrogen was set to zero to simulate a perfectly decarbonised production (EP_{zero}). Sobol indices were calculated to evaluate the contribution of each parameter uncertainty to the total model variance (Sobol 2001). First-order Sobol indices determined the individual contribution of parameters to the total model variance. Higher-order Sobol indices determined the contribution of the interaction of multiple parameters to the total model variance. The sum of all Sobol indices is 1. The closer the Sobol index to 1, the greater the contribution of the parameter uncertainty to the total variance of the model.

Table 1: Parameters selected to perform a sensitivity analysis in static LCA. SOC: Soil Organic Carbon.

Parameter name	Default	Minimum	Maximum	Unit
Energy production	EP_{conv} or EP_{zero}			unitless
Carbon content miscanthus	0.48	0.43	0.52	$kg_C/kg_{biomass,\ dry\ matter}$
Carbon content wood residues	0.50	0.45	0.54	$kg_C/kg_{biomass,\ dry\ matter}$
SOC miscanthus	0.21	-0.09	0.5	$kg_{CO2}/kg_{miscanthus,\ dry\ matter}$
Stoichiometry fermentation	0.04	0.03	0.04	kg_{CO2} /$MJ_{ethanol}$
Yield fermentation	6	6	10	$MJ_{ethanol}/kg_{biomass,\ dry\ matter}$
CO_2 to methanol	1.45	1.37	1.84	$kg_{CO2}/kg_{methanol}$
Methanol to propylene	2.89	2.8	3.02	$kg_{methanol}/kg_{propylene}$
Heat efficiency CO_2 capture	3.7	2.95	7.52	$GJ/t_{CO2,\ captured}$
Yield CO_2 capture	0.9	0.9	1	$kg_{CO2,\ captured}/kg_{CO2,\ treated}$

4 RESULTS

For the sake of conciseness, the system producing a bag from CO_2 captured from miscanthus fermentation, ethanol and electricity was referred to as "system producing a bag from miscanthus". Similarly, the system producing a bag from CO_2 from the fermentation of wood residues, ethanol and electricity was referred to as "system producing a bag from wood residues". The impacts presented in Figure 3 to 8 are total impacts of the systems, including all the life cycle steps presented in Figure 1.

The resources created to facilitate the use of Temporalis are presented in subsection 4.1. In subsections 4.2 and 4.3, the results of the sensitivity analyses are presented for the production of bags from miscanthus, for their production from wood residues, and finally for the comparison of both systems (miscanthus minus wood residues).

4.1 RESOURCES TO FACILITATE THE USE OF TEMPORALIS

The modified version of Temporalis can be used to carry out a dynamic LCA, as illustrated by the results in the following subsections. All the documents created to carry out this dynamic LCA (jupyter notebooks, excel) are provided in SI. These documents can be used as inspiration to facilitate future dynamic LCA with Temporalis. The script for averaging a dynamic LCI (cf. Figure 2) is available in the SI 'LCI_from_excel_dyn.ipynb'. This SI also offers an example of the construction of unit processes containing temporal information. The SI 'Calculation_inventory.ipynb' shows how to calculate the dynamic inventory and store it in an excel file for future characterisation. The SI 'SA_dynVSstat.ipynb' contains examples of how to visualise contributions by groups of activities and by substances over time. It also contains an example to search for information in the calculated inventory.

4.2 SENSITIVITY ANALYSIS ON THE DEFINITION OF THE FUNCTIONAL UNIT

Beyond a TH value of 50 years, the results of the comparison using FU_1 (miscanthus minus wood residues) lie within a narrow uncertainty range of +/- 5%, when compared with the averaged approach (FU_2) (Figure 3). This comparison is dominated by the cumulative radiative forcing induced by production from wood residues. In particular, the main contributor to its impact is the CO_2 captured by photosynthesis during tree growth. The temporal scope of such capture is at least three times longer (190 years) than the temporal scope of bag production (less than 50 years), as illustrated in Figure 4. This reduces the influence of the definition of the functional unit on the results. According to Figure 5, the dynamic cumulative radiative forcing induced by the production of bags from miscanthus (FU_1) only lies within an uncertainty range of +/- 10 % from the results obtained with the averaged approach (FU_2) for a TH greater than 100 years. Due to the shorter temporal scope of biomass production, this system is more dependent on the definition of the functional unit.

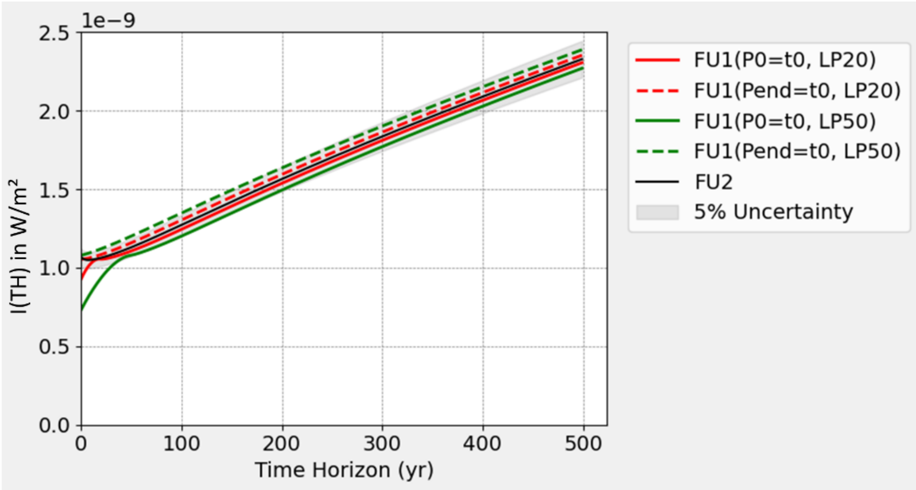

Figure 3: Evolution of the difference between the radiative forcing caused by the production of bags from miscanthus and the production of bags from wood residues (miscanthus minus wood residues). FU_1: 'Production of 20000 bags over LP'. The dynamic inventory is positioned relative to t_0 either with the first year of production equal to t_0 (P_0=t_0) or the last year of production equal to t_0 (P_{end}=t_0). LP: lifespan of the plant. FU_2: 'Production of 20000 bags at t_0'. The +/- 5% of uncertainty is calculated on the results obtained with FU_2.

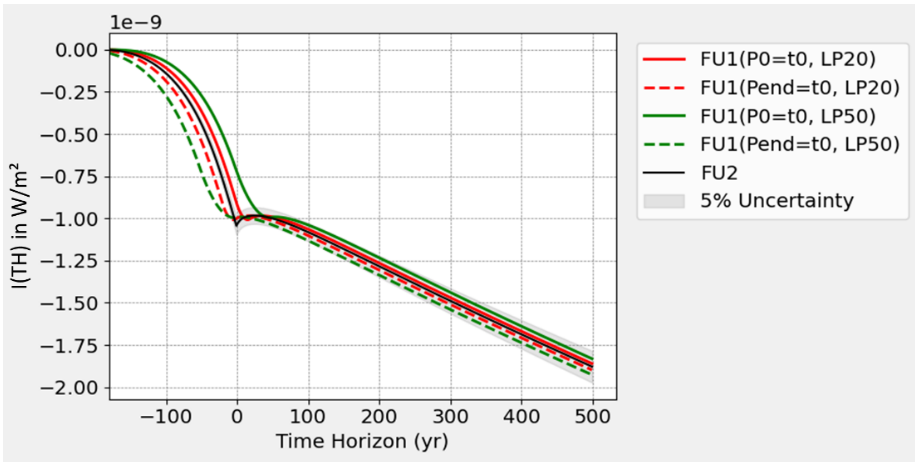

Figure 4: Evolution of the radiative forcing caused by the production of bags from wood residues. FU_1: 'Production of 20000 bags over LP'. The dynamic inventory is positioned relative to t_0 either with the first year of production equal to t_0 (P_0=t_0) or the last year of production equal to t_0 (P_{end}=t_0). LP: lifespan of the plant. FU_2: 'Production of 20000 bags at t_0'. The +/- 5% of uncertainty is calculated on the results obtained with FU_2.

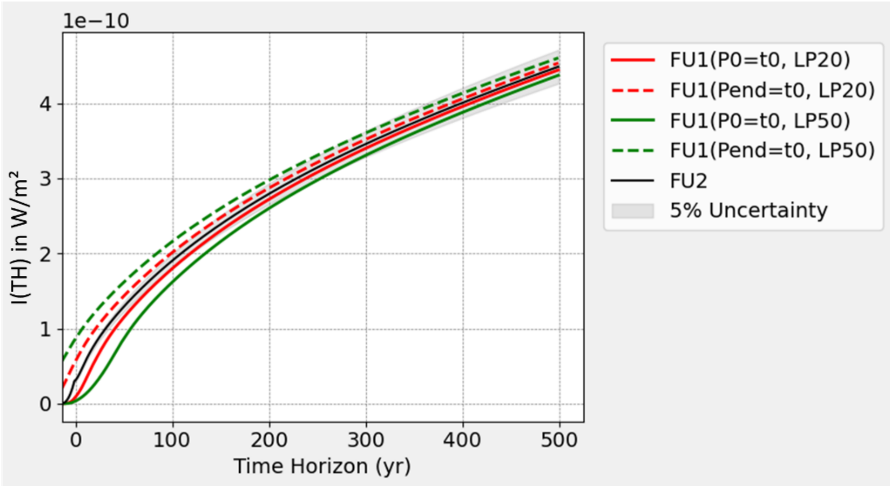

Figure 5: Evolution of the radiative forcing caused by the production of bags from miscanthus. FU_1: 'Production of 20000 bags over LP'. The dynamic inventory is positioned relative to t_0 either with the first year of production equal to t_0 (P_0=t_0) or the last year of production equal to t_0 (P_{end}=t_0). LP: lifespan of the plant. FU_2: 'Production of 20000 bags at t_0'. The +/- 5% of uncertainty is calculated on the results obtained with FU_2.

Figure 3, Figure 4 and Figure 5 share the following aspects:

- For the same time horizon TH, by denoting I_{FU} the impact of the corresponding functional unit:

$$\lim_{TH \to +\infty} \frac{I_{FU1(P_0,TH)} + I_{FU1(P_{end},TH)}}{2} = \lim_{TH \to +\infty} I_{FU2(TH)} \tag{4}$$

when TH tends towards infinity, the impact calculated using FU_2 ('Production of 20000 bags at t_0') is equal to the average of the calculated impact using FU_1 ('Production of 20000 bags over LP') with $P_0 = t_0$ and $P_{end} = t_0$.

- By defining three different time horizons TH_1, TH_2 and TH_3,
-

$$I_{FU1(P_0,TH_1)} = I_{FU1(P_{end},TH_3)} = I_{FU2(TH_2)} \xRightarrow[TH \to +\infty]{} TH_2 = TH_1 - \frac{LP}{2} = TH_3 + \frac{LP}{2} \tag{5}$$

when TH tends to infinity, the impact calculated using FU_2 ('Production of 20000 bags at t_0') is equivalent to the impact calculated using FU_1 ('Production of 20000 bags over LP') with t_0 positioned at the middle of the production time ($\frac{LP}{2}$).

These results derive from the fact that CO_2 emissions were the main contributor to the total impact, and from the choice of two models. Firstly, the production of 1 unit of product was modelled with the same temporal distribution of emissions for both types of functional unit. Secondly, the total production of 20000 units was uniformly distributed over the lifespan of the plant. The graphical observations were mathematically verified using a simple system emitting a total mass of CO_2 uniformly over the lifespan of the system, see SI named 'SI_1.docx'.

4.3 Sensitivity analysis: variations induced by dynamic modelling versus uncertainties in static LCA

In subsection 4.3.1, the results of the sensitivity analysis on static results are presented to select key parameters influencing the calculation of the climate change impact. In subsection 4.3.2, the results of the sensitivity analysis between dynamic and static modelling are presented.

4.3.1 Selection of key parameters contributing to the static impact variation on climate change

The first-order Sobol indices of each parameter are summarized in Table 2. More than 94% of the variance is explained with first-order Sobol indices, so higher-order Sobol indices were not calculated. Table 2 reveals that the variation of 'energy production' explains most of the variation in results for the system producing a bag from wood residues and half of the variation in results for the system producing a bag from miscanthus. The other half is explained by the variation in soil organic carbon change.

Table 2: First-order Sobol indices for each parameter selected to perform an uncertainty analysis. SOC: Soil Organic Carbon.

Parameter name	Miscanthus	Wood residues
Energy production	0.48	0.94
Carbon content miscanthus	0.01	-
Carbon content wood residues	-	0
SOC miscanthus	0.46	-
Stoichiometry fermentation	0	0
Yield fermentation	0.01	0
CO2 to methanol	0.01	0
Methanol to propylene	0	0
Heat efficiency CO_2 capture	0.02	0.02
Yield CO_2 capture	0	0
Sum of the first-order Sobol indices	0.99	0.94

To summarize, in the following subsection, to compare the variation induced by dynamic LCA and the variations induced by uncertainties on inventory data, the impact on climate change was calculated for every combination of parameter values:

- LCI modelling and impact characterisation: static or dynamic,
- LB (lifespan of the bag): 0 or 20 years,
- EP (Energy production): EP_{conv} or EP_{zero},
- SOC changes: high or low.

4.3.2 Sensitivity analysis of dynamic versus static results

The results for wood residues are depicted in Figure 6 and for miscanthus in Figure 7. Figure 8 illustrates the comparison between the two biomass sources.

Two sets of curves stand out in Figure 6. The first set has an impact of 0 W/m² for TH equal to zero. It regroups the results calculated without temporal differentiation in the LCI. The second set has an impact of about 5×10^{-14} W/m² for TH equal to zero. It regroups the results calculated according to a dynamic LCI. At a TH of 100 years, the variation due to the choice between static and dynamic modelling lies around 4×10^{-14} W/m². At $TH = 100\ years$, the variation due to uncertainties in the static inventory data (EP_{conv} versus EP_{zero}) is of the same order of magnitude, about 5×10^{-14} W/m². The variation due to the uncertainties in the static inventory data increases with time due to the cumulative nature of the AGWP. However, the variation due to the choice between static and dynamic modelling remains relatively stable with time. Since CO_2 is the main contributor to the impact, the difference between static and dynamic modelling tends to $a_{CO2} a_0 \sum_{te} m_e t_e$ when TH tends towards infinity, with a_{CO2} the radiative efficiency of CO_2, a_0 the first coefficient of the decay function of CO_2, and m_e the mass of CO_2 emitted at time t_e (demonstration included in the SI named 'SI_1.docx'). Using a simplified emission profile (uniform CO_2 capture over 190 years) the calculated difference between static and dynamic modelling for the system using wood residues is $3\times10^{-}$

^{14} W/m². This is of the same order of magnitude as the asymptotic difference observed in Figure 6 when TH tends towards infinity (static (EP_{conv}) minus dynamic (EP_{conv}) or static (EP_{zero}) minus dynamic (EP_{zero})). The difference between static and dynamic modelling, related to the lifespan of the bag when TH tends towards infinity, is negligible, with values of approximately 5×10^{-16} W/m².

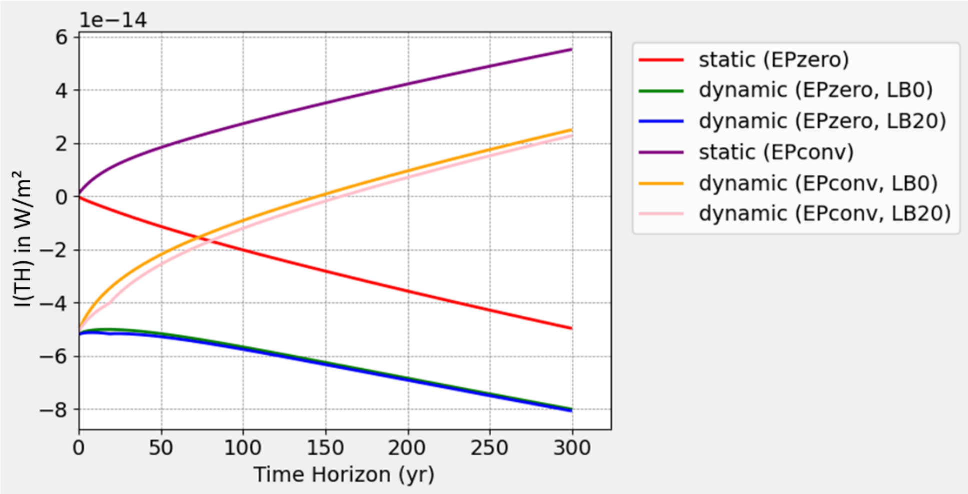

Figure 6: Evolution of the radiative forcing caused by the production at t_0 of one bag from wood residues. EP: energy production, LB: lifespan of the bag.

Four sets of curves stand out in Figure 7. They are directly related to the values of the static parameters: energy production (EP) and SOC changes. The curves calculated with static and dynamic LCIs tend to overlap. The temporal distribution of the mean SOC changes for miscanthus production is symmetrical around t_0. Subsequently, the term $\sum_{te} m_e t_e$ related to SOC changes is equal to zero. When TH tends towards infinity, there is no variation due to the choice between static and dynamic modelling.

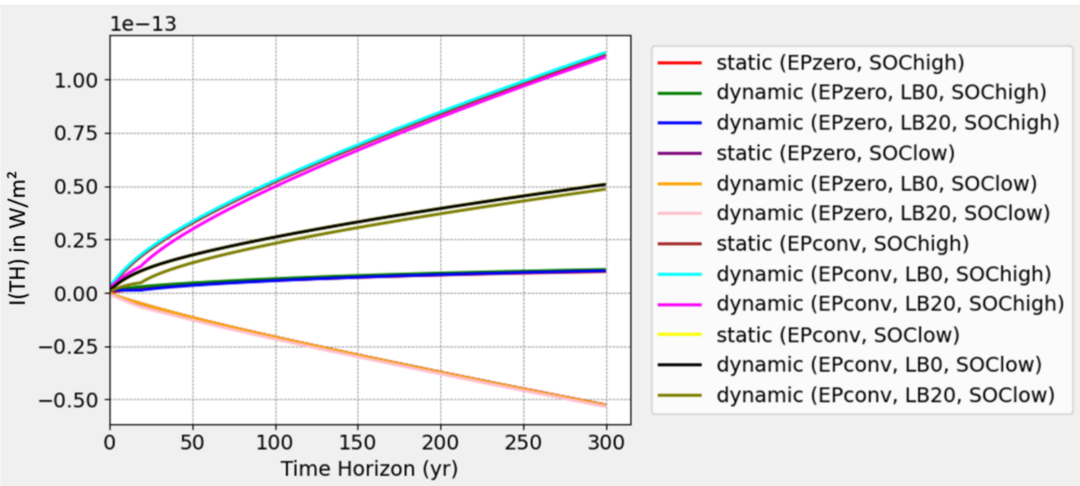

Figure 7: Evolution of the radiative forcing caused by the production of one bag at t_0 from miscanthus. EP: energy production, LB: lifespan of the bag, SOChigh: scenario where miscanthus production leads to a decrease in soil organic carbon stock. SOClow: scenario where miscanthus production leads to an increase in soil organic carbon stock.

The parameter LB, lifespan of the bag, had no influence on the results illustrated in Figure 8. The parameter LB was related to the end of life of the bag, which was identical in both systems, thus causing the same impact variation. The energy production parameter EP was used in the calculation of the LCI of several identical life cycle steps between the compared system (CO_2 transformation into a bag, CO_2 capture after bag incineration), and also in the LCI of the fermentation step. The carbon content of wood residues was different from that of miscanthus, leading to a different yield in CO_2 production during the fermentation step. This explains the small variation due to the parameter EP when comparing both systems. As illustrated in Figure 6 and Figure 7, the variation due to dynamic modelling was strongly dominated by the impact variations in the wood residue system.

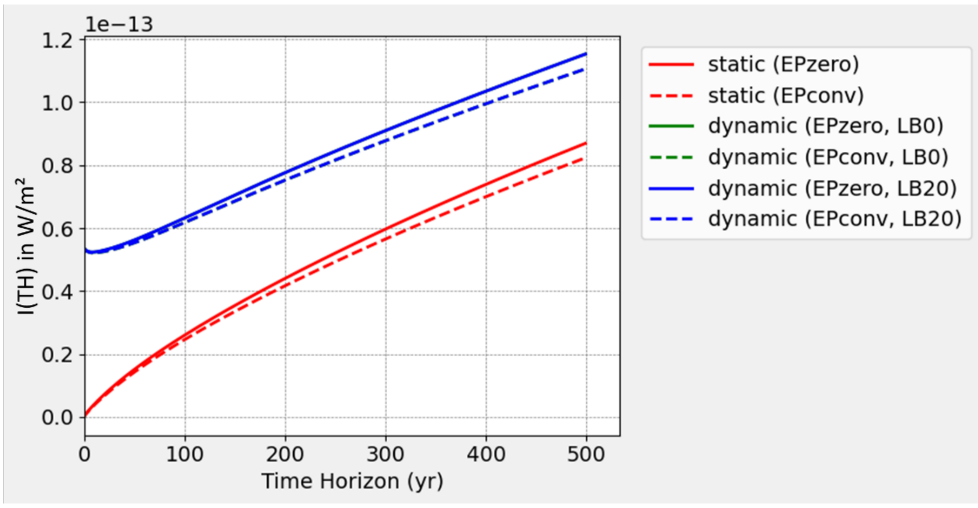

Figure 8: Evolution of the difference between the radiative forcing caused by the production of bags at t_0 from miscanthus and the production of bags at t_0 from wood residues. EP: energy production, LB: lifespan of the bag. The miscanthus production leads to a decrease in SOC stock (SOChigh).

5 DISCUSSION

In section 5.1, the usefulness of Temporalis and prospects for its improvement are discussed. In section 5.2, the results of the sensitivity analyses on the definition of the functional units lead to recommendations for harmonizing their definition, facilitating future interpretation and comparison of dynamic LCA results and studies. In section 5.3, sensitivity analyses on dynamic modelling versus uncertainties on static parameters are discussed according to the method proposed by Collet et al. (2014) for selecting flows where the addition of temporal information is crucial.

5.1 TEMPORALIS – FEEDBACK AND OUTLOOK

It is noteworthy that a promising project to update Temporalis is currently ongoing (https://github.com/brightway-lca/bw_temporalis). Meanwhile, the modified version of Temporalis provided in the SI of this article remains the working tool for dynamic LCA. Nevertheless, there is still room for improvement. Firstly, the modified script could be perfected by allowing for the possibility to take into account in a static way the unit processes that were cut-off. Such an approach is based on the fact that the emissions due to the entire life cycle of the process (calculated with the usual matrix calculation) are emitted the same year as the year of consumption of the process. This would reduce the error in calculation due to the stopping condition of the graph traversal algorithm. Secondly, only AGWP and AGTP using AR5 parameters for CO_2, CH_4 and N_2O without climate-carbon feedback are currently included as characterisation methods in the modified version of Temporalis. The inclusion of additional characterisation formulas would be relevant for performing sensitivity analyses on a given metric. Indeed, the background concentration of CO_2, CH_4, N_2O is steadily rising. The background concentration of CO_2 reached 410 ppm in 2019, leading to an update of the radiative efficiency of CO_2 in the latest IPCC report (IPCC 2021). The decay function of CO_2 has been updated to include climate-carbon feedback effects but remains based on the impulse response function proposed by Joos et al. (2013). Reisinger et al. (2011) and Caldeira and Kasting (1993) demonstrated that an increase in the CO_2 background concentration led to a decrease in the radiative efficiency and an increase in climate-carbon cycle feedback, both effects partially cancelling each other out. The decay function should therefore also be updated so as to avoid underestimating the impact of an emission of CO_2 on climate change.

In dynamic LCIA, the implementation of characterization factors that depend on the evolution of the background concentration of CO_2 would imply the use of a different AGWP formula for each time of emission. The AGWP formula would depend on the initial background concentration of CO_2 and its subsequent prospective evolution. This seems too complex relative to the gain in precision. A more general examination of how to account for the uncertainties of the characterisation factors in LCA seems more useful to address this issue. Thus, for Temporalis, AGWP and AGTP could be proposed with or without climate-carbon feedback, and using AR5 or AR6 parameters in order to perform a sensitivity analysis on the metric used. Lastly, certain indicators can be inferred from metrics such as AGTP. AGTP could be used for calculating indicators such as the amplitude of the temperature change or years of temperature peaks, i.e. as developed by Tiruta-Barna (2021). Script could also be written for computing such indicators from the characterised inventory.

5.2 SENSITIVITY ANALYSIS ON THE DEFINITION OF THE FUNCTIONAL UNIT

The results obtained from the case study allowed for more general recommendations to be formulated. The particularity of the case study is that the same dynamic LCI was used for modelling the production of one unit for both functional units (FU_1 and FU_2). This corresponds to a dynamic LCI that does not involve pulse emissions, such as large infrastructure construction or land use change (cf. the algorithm to create an average dynamic LCI, see Figure 2). For systems sharing this particularity, the results of the comparison obtained with the two functional units are almost equivalent (less than 5% of the difference for TH superior to the lifespan of the plant), as observed in section 4.2.

The following considerations are applicable to all types of systems. The potential impact on climate change of a given system as a whole is evaluated by using the following functional unit: 'production of several units of the product or service each year over the entire lifespan of the system'. Such a functional unit is relevant for evaluating a system relative to specific climate goals. Climate goals are defined for calendar-based time horizons. This resolves the ambiguity identified in the position of the dynamic LCI relative to t_0. For instance, climate neutrality needs to be reached by 2050 in order to limit global warming at 1.5°C (IPCC 2018).

However, the position of the dynamic LCI relative to t_0 ($P_0 = t_0$ or $P_{end} = t_0$) might have an influence when comparing with static results. This depends on the distribution of emissions contributing to the impact. If the majority of emissions occur periodically over the lifespan of the plant (LP), LP is the longest temporal scope included in the LCI. The longer it is, the greater the difference in results depending on the position of the dynamic LCI relative to t_0 ($P_0 = t_0$ or $P_{end} = t_0$). This is illustrated by the case study with miscanthus (Figure 5). For LP=20 years, the results are within the +/-5% window after a time horizon of around 100 years. With LP=50 years, this period increases to about 250 years. However, if LP is not the longest temporal scope, its influence is reduced. This is illustrated by the case study with wood residues: the CO_2 is captured over a much longer temporal scope than LP (190 years as opposed to 20 years or 50 years). Results are within the +/-5% window after a time horizon equal to LP, see Figure 4. In conclusion, if the time horizon were much longer than LP, the chosen position of the dynamic LCI relative to t_0 ($P_0 = t_0$ or $P_{end} = t_0$) would not influence the comparison to static results. If the time horizon were not much longer than

LP and LP were the longest temporal scope included in the LCI, then the position of the dynamic LCI relative to t_0 would influence the comparison to static results and should be clearly stated when communicating the results. $P_{end} = t_0$ is more coherent with the static interpretation of the time horizon. In static LCA, the results represent the potential impact at a given time horizon of delivering the functional unit. The functional unit is entirely delivered only after the last year of production in dynamic LCA.

The 'production of several units of the product or service at t_0' functional unit is relevant to compare systems that do not share the same temporal distribution of production. For example, as explained in section 3.1, the production of miscanthus does not share the same temporal distribution of production as for the production of wood residues. However an LCA practitioner might choose to compare the impact of producing 1 kg of miscanthus with the impact of producing 1 kg of wood residues. Moreover, the inventory data could be reused as background inventory data in another LCA study.

5.3 Sensitivity analysis: variations induced by dynamic modelling versus uncertainties in static LCA

The results indicate that the variations induced by dynamic modelling were significant for wood residue production compared to the variations induced by uncertainties in energy production modelling. However, for miscanthus production, the dynamic modelling variations were not significant when compared with the uncertainty variations in energy production and SOC changes. Based on the Collet et al. (2014) method, the variation in SOC stock was relevant for two reasons. Firstly, the results are sensitive to a variation of the initial value of SOC stock, as demonstrated in Figure 7. Secondly, the variations in SOC stock during miscanthus production were distributed over 30 years, which is more than the identified one year temporal resolution of climate change. Collet et al. (2014) proposed a method applicable to every impact category. The examination of the mathematical formula of each characterisation factor in depth was out of the scope of their study. As demonstrated in section 3.2, information on the magnitude of variations induced by dynamic modelling could be calculated using simplified formulas constructed from the study of the AGWP when TH tends towards infinity. Further investigation on the mathematical properties of AGWP could contribute to improve the method with a focus on climate change.

If the goal of dynamic LCA is to compare systems, it is unnecessary to add temporal information to identical steps for both systems, since this would not change the conclusion of the comparison. With our case study, two productions routes of a reusable shopping bag were compared: from miscanthus or from wood residues. In order not to bias the comparison, the reusable bag utilisation and end-of-life is kept identical between the two systems, i.e. same value of the LB parameter. Another goal could be to determine an optimal lifetime for the reusable bag and thus compare systems with different values of the LB parameter. In this case, to maintain the functional equivalence, additional bag production should be considered, i.e. 1 bag with LB=20 is equivalent to 1 bag with LB=0 produced each year for 20 years.

6 Conclusions

Temporalis proved to be an efficient tool for performing dynamic LCA. Two areas for improvement were identified: to deal with the loss of information due to the cut-off included in the graph-traversal algorithm and to propose more characterisation methods in order to perform a sensitivity analysis.

The 'production of several units of the product or service each year over the entire lifespan of the system' functional unit should be employed for evaluating the potential impact on climate change of the entire system relative to climate goals over a calendar-based timeline. To compare the obtained results to static LCA results, the TH should be defined, beginning with the last year of production. The temporally averaged functional unit ('1 unit produced at t_0') should be employed for comparing systems that do not share the same temporal distribution of production and for building inventory data that could be reused as background inventory data in another LCA study.

It is crucial for an LCA practitioner to be capable of pinpointing the flow which would benefit from being distributed over a timescale, so as to save time for improving a static inventory and performing sensitivity analyses. Further research on the mathematical properties of AGWP would help improve the method proposed by Collet et al. (2014) in order to construct a method for selecting the appropriate flow to be distributed over a timescale prior to a full dynamic LCIA, using only simplified temporal information from a given system.

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