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Chris Mutel

Temporal life cycle assessment:

Critical review and a simplified approach

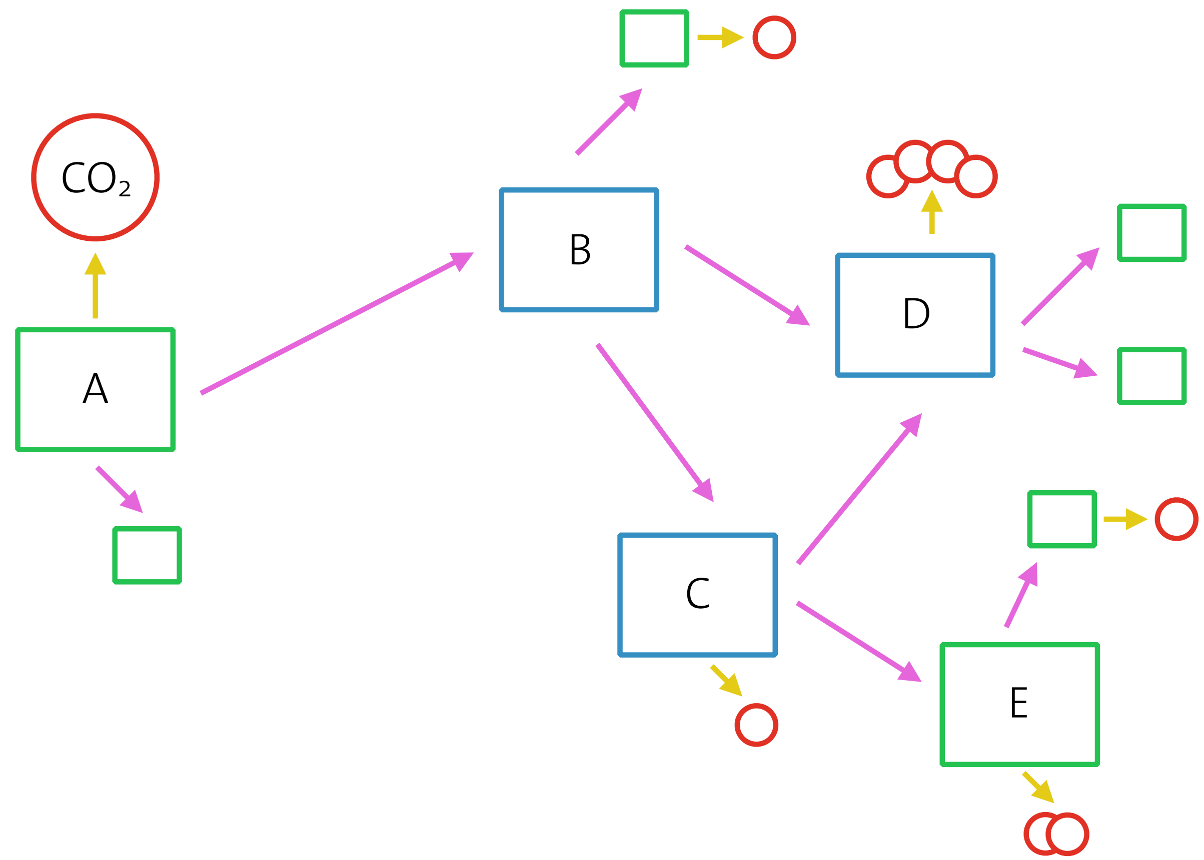
Wait, what is happening now?

1. Links in supply chain graph are distributed through time
2. Assess effects of emissions throughout time
3. Total impact of emissions varies as a function of time emitted

Temporal LCA can mean at least three different things, and we will explore all three.

All cites available at the Mendeley group for dynamic LCA: https://www.mendeley.com/groups/4995001/dynamic-lca/

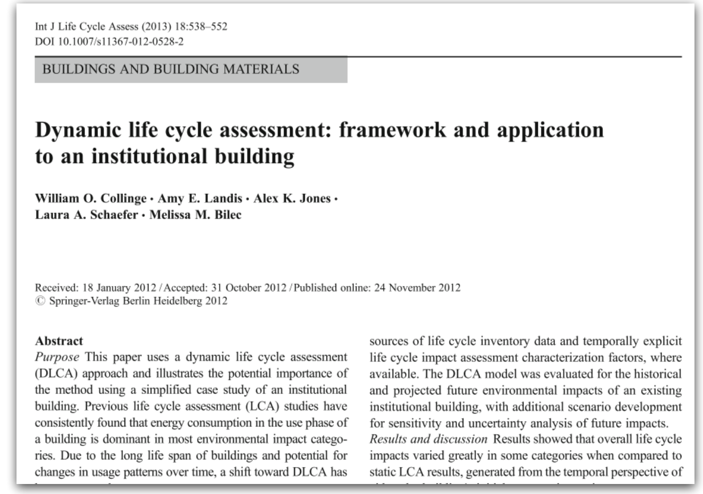
Meaning 1: Supply chain links spread over time



First, we can locate our processes and exchanges in time.

Meaning 1: Supply chain links spread over time

Locate processes absolutely in time


Int J Life Cycle Assess (2013) 18:538–552
DOI 10.1007/s11367-012-0528-2

BUILDINGS AND BUILDING MATERIALS

Dynamic life cycle assessment: framework and application to an institutional building

William O. Collinge · Amy E. Landis · Alex K. Jones · Laura A. Schaefer · Melissa M. Bilec

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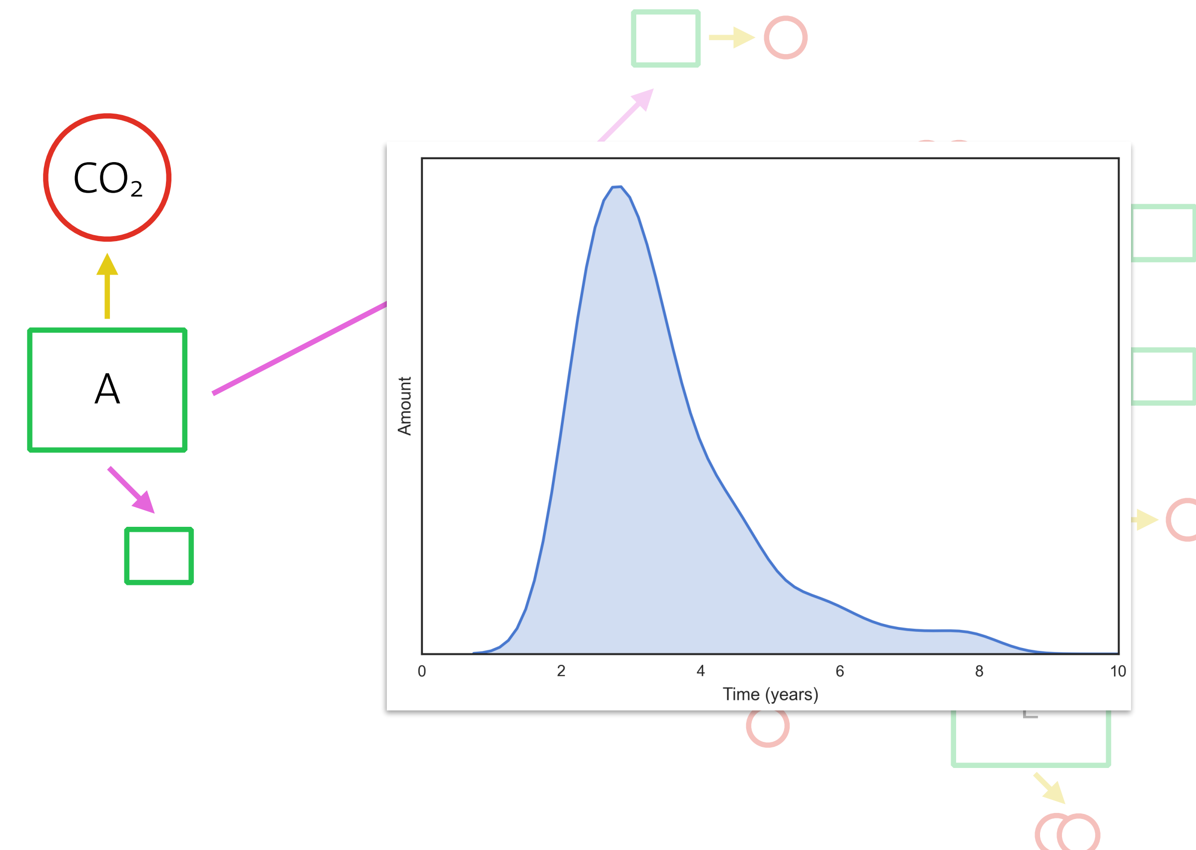
Abstract
Purpose This paper uses a dynamic life cycle assessment (DLCA) approach and illustrates the potential importance of the method using a simplified case study of an institutional building. Previous life cycle assessment (LCA) studies have consistently found that energy consumption in the use phase of a building is dominant in most environmental impact categories. Due to the long life span of buildings and potential for changes in usage patterns over time, a shift toward DLCA has

sources of life cycle inventory data and temporally explicit life cycle impact assessment characterization factors, where available. The DLCA model was evaluated for the historical and projected future environmental impacts of an existing institutional building, with additional scenario development for sensitivity and uncertainty analysis of future impacts.
Results and discussion Results showed that overall life cycle impacts varied greatly in some categories when compared to static LCA results, generated from the temporal perspective of

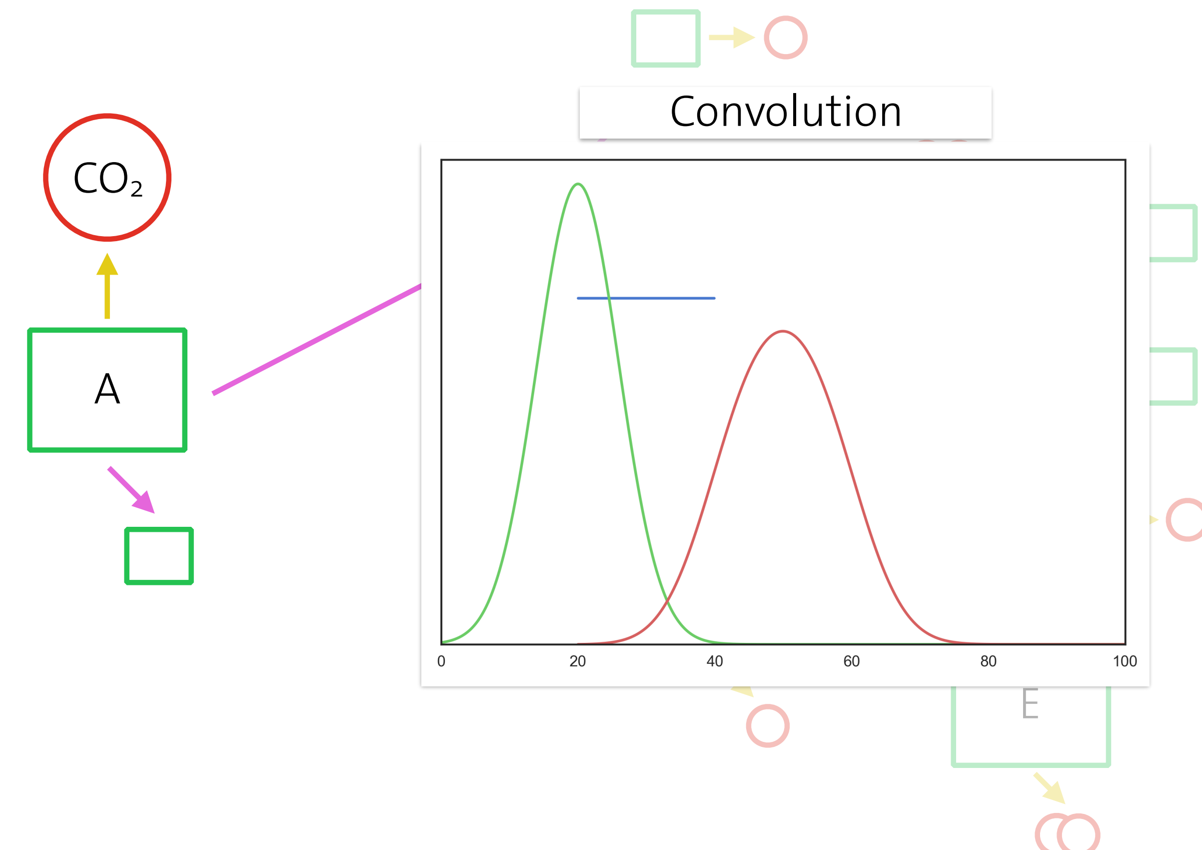
Collinge showed how each process could occur at an absolute time. It is then easy to plot the life cycle of our functional unit in time. However, most of the time we want relative times, i.e. an input or emission occurs before or after a process occurs.

Meaning 1: Supply chain links spread over time



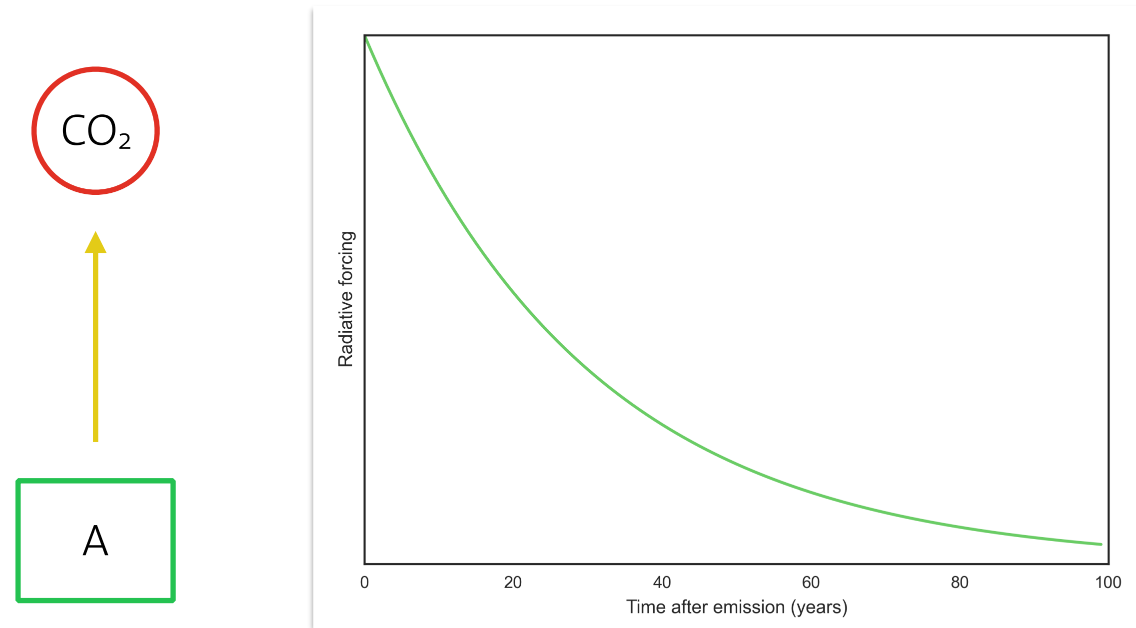
We can distribute exchanges and biosphere flows in time using our standard statistical toolkit: distribution functions, either analytical or discretised into arrays.

Meaning 1: Supply chain links spread over time



Combining two different temporal exchanges is easy, though it sounds complicated: we call it “convolution”. The graph shows the convolution of the green and blue temporal distributions to produce the red distribution.

Meaning 2: Spread emissions effects over time

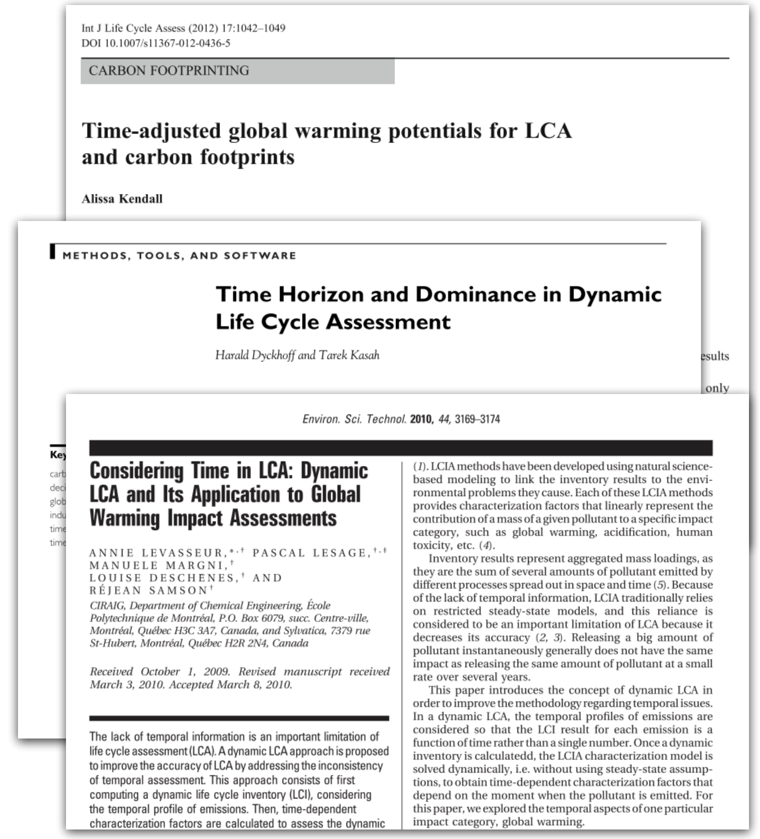


A second meaning of temporal LCA is to spread our characterisation factor over time. The most prominent example is radiative forcing for greenhouse gases, which is a function of atmospheric lifetime, but also the atmospheric mixing time and other physical processes.

Meaning 2: Spread emissions effects over time

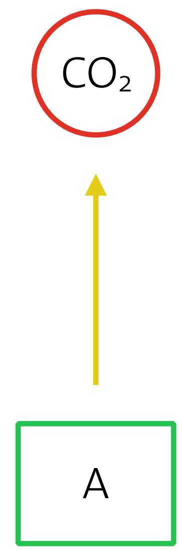
Methodology is simple

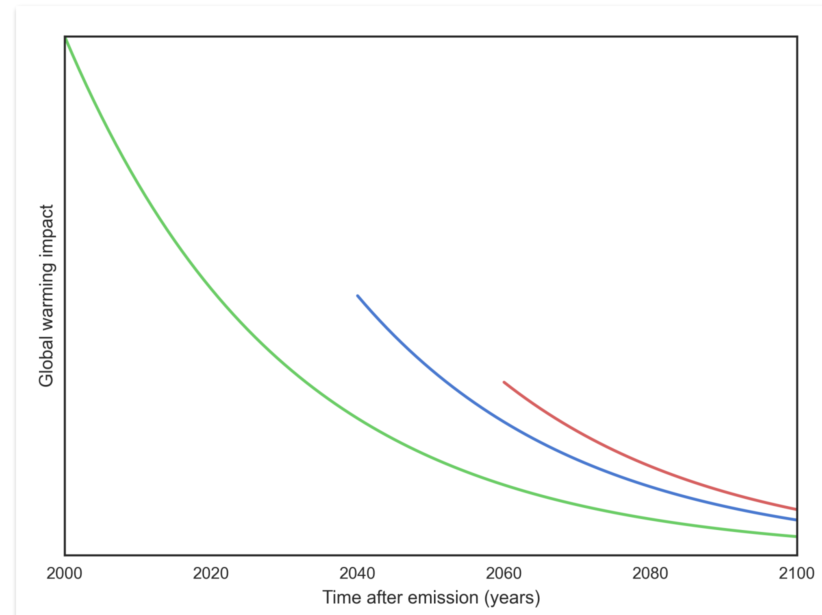
Models taken from the subject areas



This meaning has a lot of literature, especially concerned with criticising existing indicators such as “IPCC 100”, and proposing new single-value indicators. In my opinion, we would be better served to move away from a single number and show the integration of our different characterised flows over time.

Meaning 3: CFs are f(year emitted)





A third meaning is changing the **total** CF depending on time of emission. Most CFs are marginal, which means that they depend on a certain background level of exposure, which can change over time. Although it adds complexity, we sometimes want to be able to include this dynamic interaction, as things like climate urgency are real considerations for policy makers.

Meaning 3: CFs are f(year emitted)

Methodology is simple

Models taken from the subject areas

Int J Life Cycle Assess (2014) 19:919–930
DOI 10.1007/s11367-013-0693-y

NON-TOXIC IMPACT CATEGORIES ASSOCIATED WITH EMISSIONS TO AIR, WATER, SOIL

Assessment of urgent impacts of greenhouse gas emissions—the climate tipping potential (CTP)

Susanne V. Jørgensen · Michael Z. Hauschild · Per H. Nielsen

nature climate change

LETTERS

PUBLISHED ONLINE: 25 APRIL 2014 | DOI: 10.1038/NCLIMATE2204

Climate impacts of energy technologies depend on emissions timing

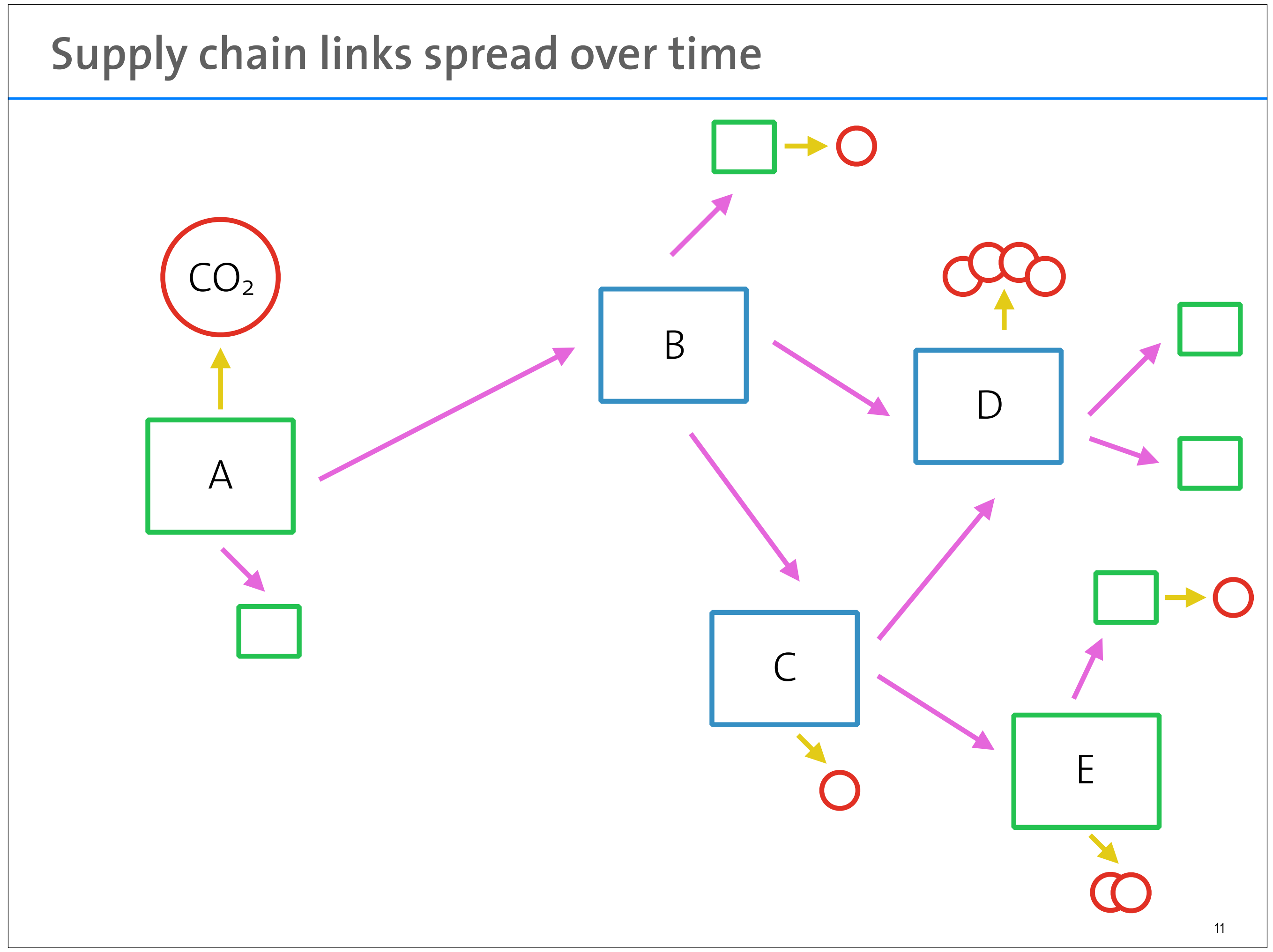
Morgan R. Edwards[1] and Jessika E. Trancik[1,2*]

Energy technologies emit greenhouse gases with differing radiative efficiencies and atmospheric lifetimes[1-3]. Standard practice for evaluating technologies, which uses the global warming potential (GWP) to compare the integrated radiative forcing of emitted gases over a fixed time horizon[4], does not acknowledge the importance of a changing background climate relative to climate change mitigation targets[5,6]. Here we demonstrate that the GWP misvalues the impact of CH_4-emitting technologies as mid-century approaches, and we propose a new class of metrics to evaluate technologies based on their time of use. The instantaneous climate impact (ICI) compares gases in an expected radiative forcing stabilization year, and the cumulative climate impact (CCI) compares their time-integrated radiative forcing up to a stabilization year. Using these dynamic metrics, we quantify the climate impacts of technologies and show that high-CH_4-emitting energy sources become less advantageous over time. The impact of natural gas for transportation, with CH_4 leakage, exceeds that of gasoline within 1–2 decades for a commonly cited 3 W m^{-2} stabilization target. The impact of algae biodiesel overtakes that of corn ethanol within 2–3 decades, where algae co-products are used to produce biogas and corn co-products

their climate impacts on a single scale. For technology evaluation, equivalency metrics must be forward-looking and robust to inherent uncertainties about the future climate scenario, to inform the advanced commitment needed to develop new technologies and infrastructure. Determining an appropriate metric for this application is becoming increasingly urgent as we consider major public and private investments in technologies with significant CH_4 emissions, including natural gas[1,19–22].

Although many equivalency metrics have been proposed, previous research has not emphasized testing their performance against intended climate goals to determine a principled treatment of time in metric formulations. Here we propose a new class of dynamic metrics that, unlike the static GWP(τ), are designed to avoid an overshoot of an intended radiative forcing stabilization level. We develop a method to test the performance of these and other metrics against this climate change mitigation goal. The new metrics differ from other dynamic metrics[16–18] in that they do not require detailed information about the emissions scenario for achieving the mitigation goal. Climate targets are commonly formulated around a stabilization level[23], which can be reached by a number of emissions scenarios. The proposed metrics are designed to evaluate technologies in this context.

There has been some recent literature on climate urgency and metrics for life cycle assessment.



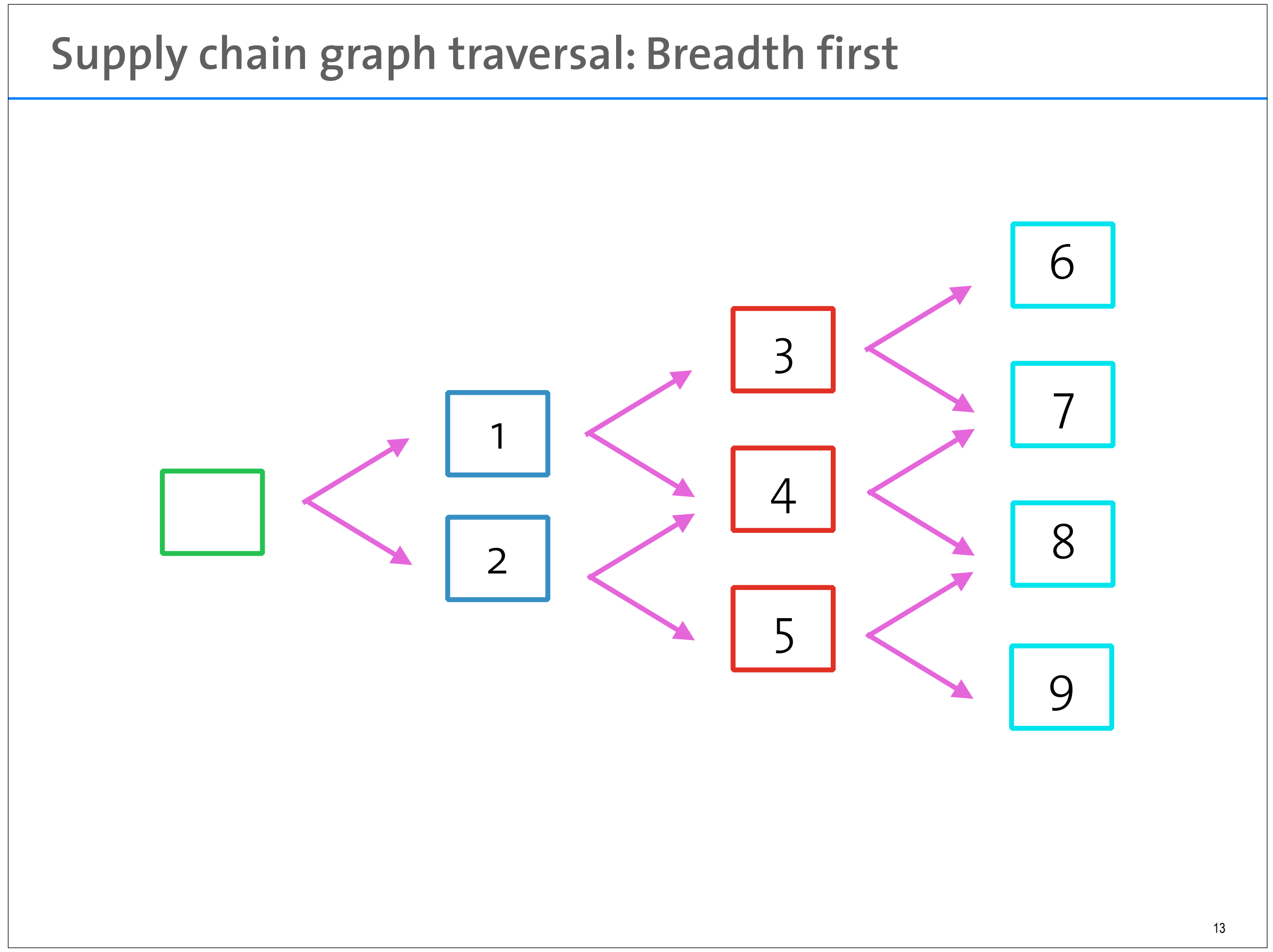
The methodology for meanings 2 & 3 are relatively straightforward, but meaning 1 - temporal exchanges - requires a new approach. Building a linear set of equations doesn't work; we need to propagate the relative temporal shifts as we traverse the supply chain.

Enhanced Structural Path Approach

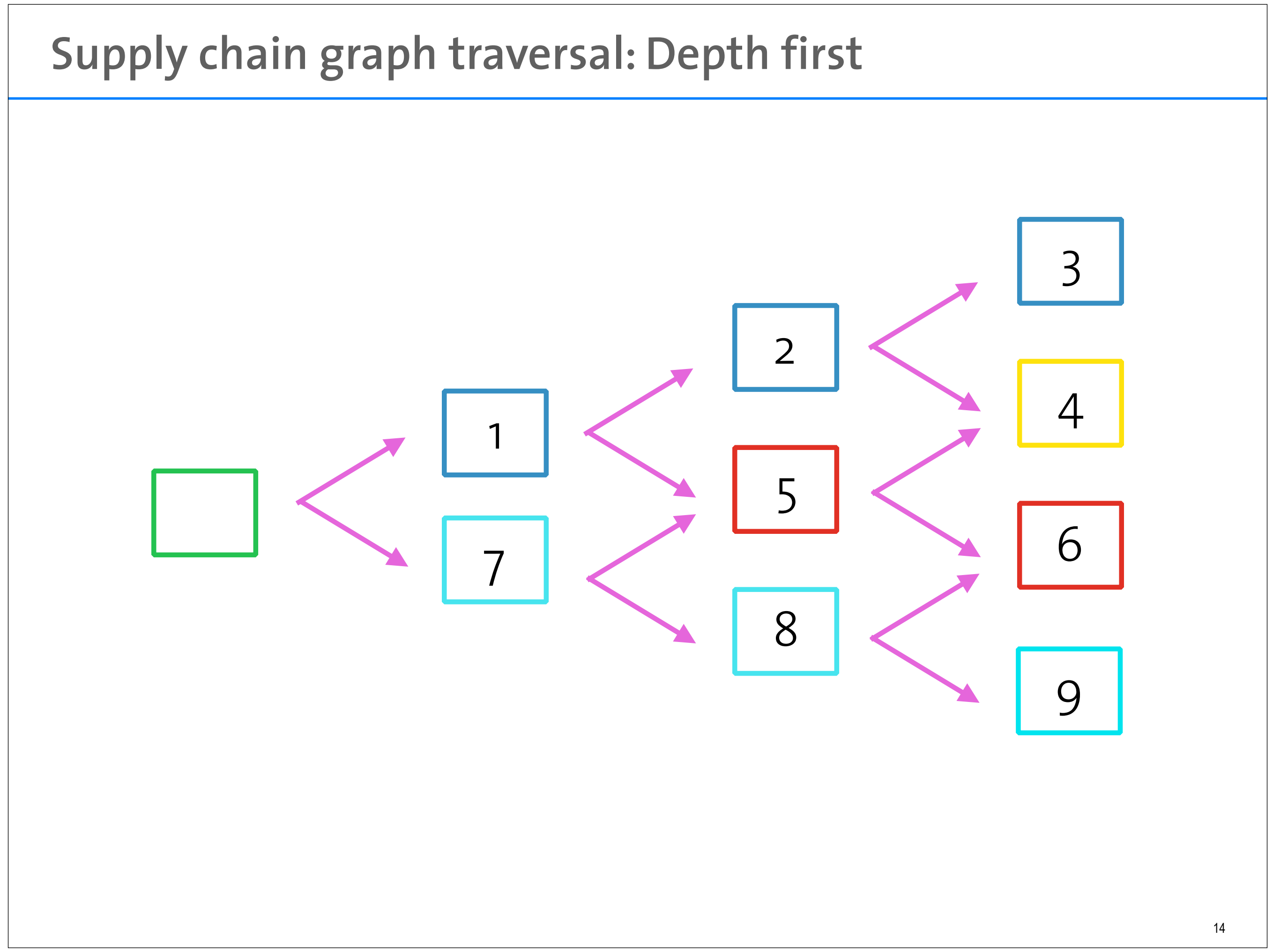
$$\vec{o} = \mathbf{E} \cdot \left(\mathbf{I} + \mathbf{T} + \mathbf{T}^2 + \mathbf{T}^3 + \cdots + \mathbf{T}^j + \cdots + \mathbf{T}^n \right) \cdot \vec{r}$$

- Each series step is one level deeper in supply chain
  - One additional temporal convolution
    - Not actually matrix math
- Barna (manuscript)
  - Graph traversal algorithm instead of matrix formulation
  - Detailed process model

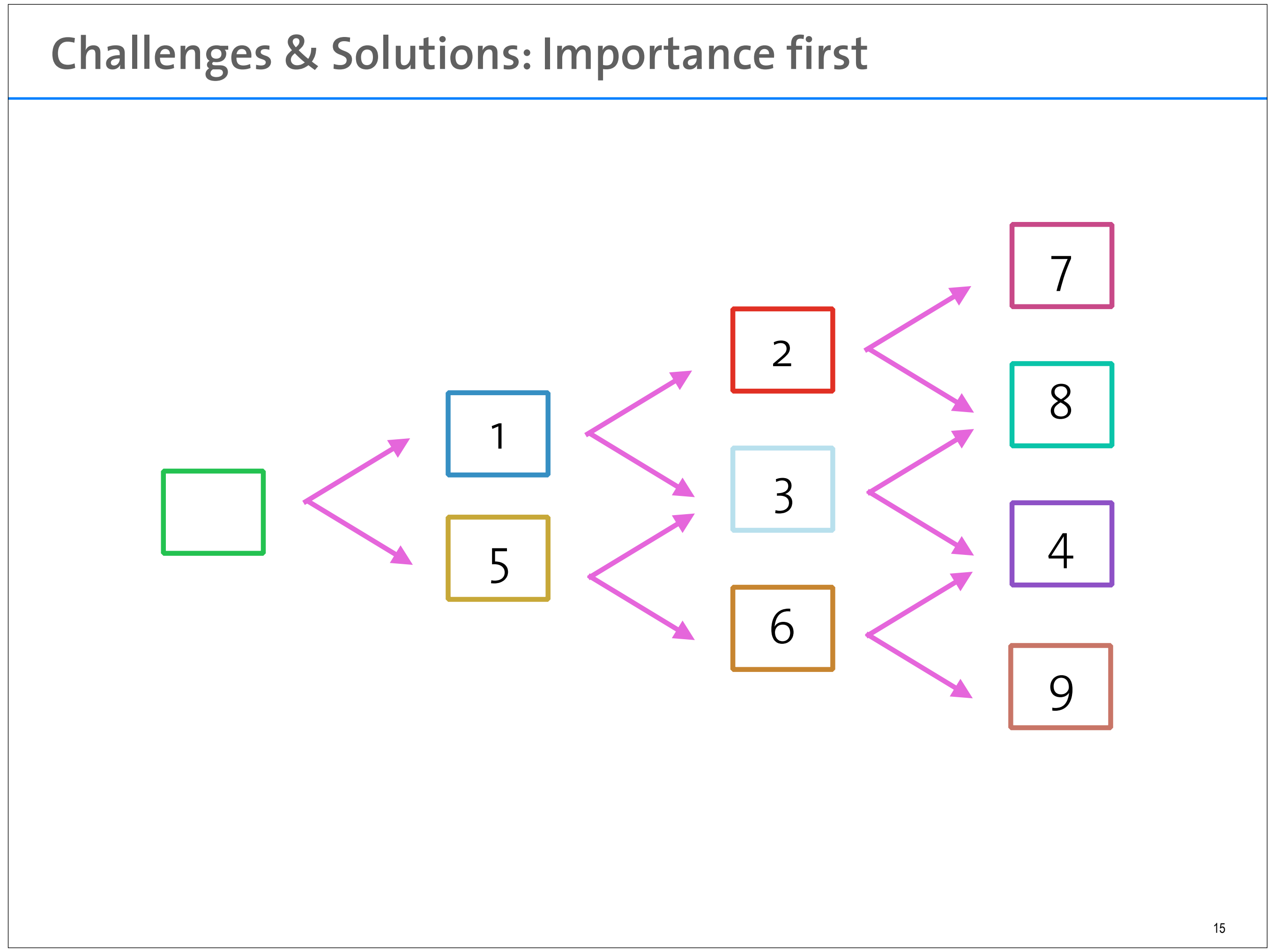
One way of doing this is do the power series expansions, but include convolution. We can’t use traditional matrix math, as each element in the technosphere matrix is (potentially) a distribution instead of a number, so we need to convolute instead of just multiplying.



ESPA is a breadth first graph traversal algorithm. Each layer in the supply chain is another power in the previous slide's equation.

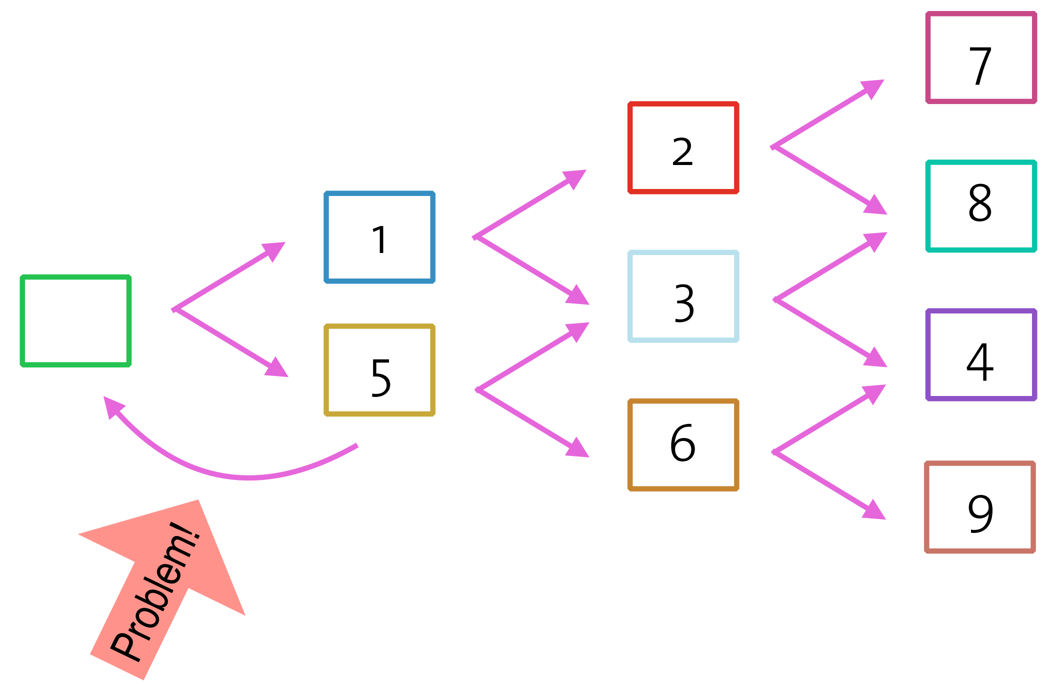


There are other graph traversal algorithms. Depth first instead goes down the supply chain instead of across. This doesn’t work well in LCA, as our graphs are cyclic (i.e. have loops), and can be quite deep.



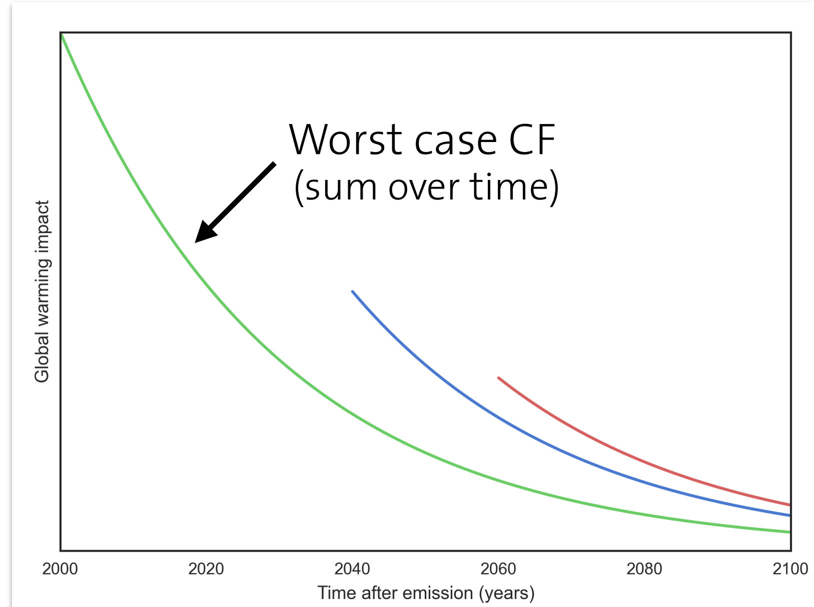
Instead, brightway2-temporalis uses a different graph traversal algorithm. I am sure this exists somewhere, but I am not sure what it is called. I call it “importance-first”. We use the potential total LCA scores of each branch to evaluate the traversal order, and stop after reaching a cutoff criteria.

Challenges & Solutions: Importance first



Cyclic graphs prevent a challenge - our graph can never be exhaustively searched. Remember, the values change each time we visit a node, as we are shifting forwards and backwards in time as we traverse temporal exchanges.

Supply chain graph traversal: Cutoff



Some authors propose using temporal cutoffs, i.e. ignore processes that occur outside of a certain time window. Instead, we cutoff based on worst-case characterised results; we calculate the worst values each CF can possibly be, and can use that to evaluate whether a branch of the supply chain graph could possibly be important.

What do we want?

1. No arbitrary temporal resolution
2. Computational efficiency
3. Transparent and flexible model representation

```
{
    "type": "biosphere",
    "amount": 87,
    "input": ("biosphere", "co2"),
    "input": ("ecoinvent", "some process"),
    "temporal distribution": [
        (0, 50),
        (1, 20),
        (2, 10),
        (3, 5),
        (4, 2)
    ]
}
```


For our data format, we want to avoid arbitrary restrictions on timescales, as well as be efficient and transparent. Flexibility is key, as we don't know what and how is really needed. The temporalis format is just an array of years (can be fractional) and amounts…

What do we want?

1. No arbitrary temporal resolution
2. Computational efficiency
3. Transparent and flexible model representation

```
In [1]: def make_it_funky():
            return [(x, 10 - x) for x in range(10)]

        my_exchange = {
            "type": "biosphere",
            "amount": sum([x[1] for x in make_it_funky()]),
            "input": ("biosphere", "co2"),
            "input": ("ecoinvent", "some process"),
            "temporal distribution": make_it_funky()
        }

        my_exchange

Out[1]: {'amount': 55,
         'input': ('ecoinvent', 'some process'),
         'temporal distribution': [(0, 10),
          (1, 9),
          (2, 8),
          (3, 7),
          (4, 6),
          (5, 5),
          (6, 4),
          (7, 3),
          (8, 2),
          (9, 1)],
         'type': 'biosphere'}
```


… but you can also use functions.

How to pick processes to temporalize?

Compare timescales of processes and impact categories

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DOI 10.1007/s11367-013-0636-7

LCI METHODOLOGY AND DATABASES

How to take time into account in the inventory step: a selective introduction based on sensitivity analysis

Pierre Collet · Laurent Lardon · Jean-Philippe Steyer · Arnaud Hélias

Received: 23 January 2013 / Accepted: 18 July 2013 / Published online: 21 August 2013

Abstract
Purpose Life cycle assessment is usually an assessment tool, which only considers steady-state processes, as the temporal and spatial dimensions are lost during the life cycle inventory (LCI). This approach therefore reduces the environmental relevance of certain results, as it has been underlined in the case of climate change studies. Given that the development of dynamic impact methods is based on dynamic inventory data, it seems essential to develop a general methodology to achieve a temporal LCI.
Methods This study presents a method for selecting the steps, within the whole process network, for which dynamics need to be considered while others can be approximated by steady-state

flows: 0.1 % in the sugarcane ethanol production and 0.01 % in the palm methyl ester production. Future developments of time integration in the LCI and in the life cycle impact assessment (LCIA) are also discussed in order to deal with the need of characterization functions and the recurrent problem of waiting times.
Conclusions This work provides a method to select specific flows where the introduction of temporal dynamics is most relevant. It is based on sensitivity analyses and on the relationship between the timescales of the flows and the timescale of the involved impact. The time-distributed LCI generated by using this approach could then be coupled with a dynamic LCIA proposed in the literature.

Int J Life Cycle Assess
DOI 10.1007/s11367-014-0783-5

LCI METHODOLOGY AND DATABASES

Temporal differentiation of background systems in LCA: relevance of adding temporal information in LCI databases

Ariane Pinsonnault · Pascal Lesage · Annie Levasseur · Réjean Samson

Received: 20 November 2013 / Accepted: 8 July 2014

Abstract
Purpose Because the potential impacts of emissions and extractions can be sensitive to timing, the temporal aggregation of life cycle inventory (LCI) data has often been cited as a limitation in life cycle assessment (LCA). Until now, examples of temporal emission and extraction distributions were restricted to the foreground processes of product systems. The objective of this paper is to evaluate the relevance of considering the temporal distribution of the background system inventory.
Methods The paper focuses on the global warming impact

foreground system is temporally differentiated, and (2) systems in which temporal information was also added to the background system. For 8.6 % of the database product systems, adding temporal differentiation to background unit processes affected the global warming impact scores by more than 10 %. For most of the affected product systems, considering temporal information in the background unit processes decreased the global warming impact scores. The sectors that show most sensitivity to the temporal differentiation of background unit processes are associated with wood and biofuel sectors.

Meta-analysis of database, per impact category

A final question is how to determine which inventory processes or exchanges need temporal information. Two nice papers have been published on this, looking at the timescales of impact categories, and doing meta-analysis of ecoinvent 2.2.

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Feel free to contact me for questions or polite criticism.