Two sides of the same coin: consequential life cycle assessment based on the attributional framework

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ABSTRACT

Process and Input–Output based methods are standard models used in attributional life cycle assessment (ALCA). These are linear models that, when used to estimate environmental consequences of a decision that involves changes, rely on linear extrapolation to approximate the changes. Behind this linearity are several assumptions such as fixed input/output relationships and unlimited supply of inputs. These assumptions expose the limitations of the attributional framework when used for consequential modeling. For example, if a product system faces supply constraints and an additional output would induce input substitution, a simple linear extrapolation from existing situations would fall short of estimating the environmental consequences of the additional output. These assumptions, however, can be relaxed to better reflect reality and the attributional framework can provide more relevant and accurate estimates for consequential modeling and decision making. Drawing insights from LCA studies on biofuels and the rich literature of Input–Output Analysis, this paper presents a two-step approach to consequential life cycle assessment (CLCA) based on the attributional framework. The first step compiles inventories and conducts attributional analysis to evaluate the status quo of the system under study, identify hotspots on which to focus on subsequently, and construct business-as-usual scenarios. The second step introduces the decision in question, evaluates possible changes to take place, builds scenarios representing associated environmental consequences, and modifies the original inventories accordingly. This paper demonstrates that the attributional framework can serve the purpose of addressing change-oriented questions when it is used properly and its assumptions and limitations are recognized.

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1. Introduction

A recent study has frustrated those who intend to eat healthier and help save the environment (Tom et al., 2015). The study finds that on a caloric basis vegetables and fruits in the United States—mostly grown in California (CA)—consume much more water than meat over their life cycles. The authors thus conclude that a dietary shift toward more vegetables and fruits and less meat would put further stress on water systems. Granted, if the dietary shift leads to more vegetables and fruits grown in CA, this will exacerbate the water issues there given its ongoing drought. But what if we grow the extra vegetables and fruits in states with abundant rainfall? What if we grow them locally with reclaimed water? What if we grow them in our own gardens? Unfortunately, none of these possible scenarios following a dietary shift are analyzed in the study. Thus their conclusion that a healthier diet would make the environment worse does not necessarily follow from their presentation of the status quo of crop production (Cucurachi et al., 2016).

The study by Tom et al. (2015) is not a special case, but represents the standard way we do Life Cycle Assessment (LCA). We begin by compiling inventories that mostly reflect existing situations, analyze them with a set of attributional rules, and then make suggestions or policy implications that involve or lead to changes (Weidema, 2003). Too often, however, the changes to take place are not adequately captured in the initial inventories compiled and analyzed (Cucurachi et al., 2016; Searchinger et al., 2008; Tillman, 2000; Yang and Suh, 2015a). In other words, attributional LCA (ALCA) that describes an existing and presumably static state may fall short of providing relevant and meaningful information for a decision that brings about changes.

Recognizing the problems of ALCA, Weidema (1993) were among the first to introduce what has come to be known as consequential LCA (CLCA). CLCA estimates how relevant flows change in response to a decision (Curran et al., 2005). But for a long time LCA scholars...
were debating over the two approaches without reaching a consensus (Finnveden et al., 2009). Recently there seems to be a growing awareness of the inadequacy of ALCA for decision making, and an evolution toward CLCA has been observed (McManus and Taylor, 2015). Perhaps the most explicit and salient criticisms of ALCA thus far came from Plevin et al. (2014). The authors argued that ALCA is not predictive of real-world impacts and thus should not be used for policy making. They further advised LCA scholars against drawing the conclusion that because the carbon footprint of product A is X% lower than that of product B, producing more of A would result in an X% reduction in carbon emissions. Interestingly, there was a similar realization by Ferng (2009) in Ecological Footprints, who demonstrated that land multipliers—an index similar to carbon footprint—are inadequate to capture the impact on land due to incremental changes in consumption.

In advocating for CLCA, the use of economic methods such as computable general equilibrium (CGE) models are often recommended (Earles and Halog, 2011; Ferng, 2009; Plevin et al., 2014). These nonlinear optimization models are presumably more sophisticated than the linear models that have been used in ALCA, such as process- and input–output (IO) based LCA (Heijungs and Suh, 2002). They account for a broader range of market and institutional aspects such as input substitution, factor constraints, and price effects (Lundie et al., 2007; Rose, 1995). On the other hand, they are also grounded on restrictive, unrealistic assumptions (e.g., rational expectation) that undermine the relevance and accuracy of their estimates (see, e.g., Barker, 2004; DeCanio, 2003; Thaler, 2015) for detailed critique. My focus, however, is not to argue which class of models is superior. A more interesting question I seek to address is how we can better estimate environmental consequences, or do CLCA, based on the more familiar attributional framework that we have been using in LCA (Heijungs and Suh, 2002).

I begin with a brief review of corn ethanol LCA studies to further illustrate the inadequacy of ALCA for estimating consequences of decision making when the methodology is used without recognizing its limitations. The reason I single out corn ethanol is that biofuels have played a key role in the debate between ALCA and CLCA (McManus and Taylor, 2015; Plevin et al., 2014), and corn ethanol is arguably the most contentious part of the discourse as reflected in multiple debates (Anex and Lifset, 2009; Babcock, 2009; Mathews and Tan, 2009; Searchinger et al., 2008). It is also an interesting case that, besides revealing many of the limitations of ALCA, casts light on how we can better conduct LCA to address change-oriented questions and support decision making. Then, from a methodological point of view, I analyze the assumptions involved in using ALCA to estimate changes.

Next, I present a two-step approach to CLCA based on the attributional framework. As to be shown, the approach treats attributional analysis as an important and indispensable part of the overall consequential modeling for purposes of, e.g., evaluating the status quo of the system under study and identifying hotspots on which to focus on subsequently. For this, the approach differs from much of the CLCA literature that view themselves in stark contrast to ALCA (Ekvall and Weidema, 2004; Plevin et al., 2014; Suh and Yang, 2014; Weidema, 2003). I conclude with discussions on issues like development of marginal coefficients. This paper demonstrates that the attributional framework can serve our purpose of addressing change-oriented questions when we use it properly and recognize its assumptions and limitations.

2. A brief history of corn ethanol LCA and some reflections

Driven by policies in the United States (Runge and Johnson, 2008), corn ethanol has become a major source of biofuels worldwide (Fig. 1). Its use was partly justified by the potential to reduce greenhouse gas (GHG) emissions by displacing gasoline (Keeney, 2008). Whether corn ethanol generates lower GHG emissions than gasoline, however, has to be evaluated on a system wide, or life cycle, basis. This means emissions from vehicle operation, fuel refining, feedstock production, and fuel transportation and distribution, as well as emissions from supply chains such as fertilizer production.

A typical LCA study would sum emissions across all life cycle stages and then compare the totals. Early LCA estimates differed as to which fuel performed better (Farrell et al., 2006). Notably, research by Pimentel and colleagues was all-negative for corn ethanol (Pimentel, 2003; Pimentel and Patzek, 2005). The results, together with concern over soil, air, and water pollution associated with corn production, led them to strongly oppose the use of corn ethanol (Pimentel et al., 2008). But subsequent studies, with updated data and ethanol coproducts accounted for, converged on the fact that corn ethanol had moderately lower life cycle GHG emissions than gasoline (about 70 versus 90 g CO2eMJ−1) (Farrell et al., 2006; Hill et al., 2006; Kim and Dale, 2008; Wang et al., 2007). It was then concluded that corn ethanol could reduce about 20% GHG emissions, or 20 g CO2eMJ−1, by displacing gasoline (Farrell et al., 2006).

Next came the two game-changing articles published in Science (Fargione et al., 2008; Searchinger et al., 2008). Fargione et al. (2008) used process-based LCA to investigate the direct land use change (LUC) effects of biofuels expansion; e.g., farmers in the US clear grassland to grow corn for ethanol use. Searchinger et al. (2008), by contrast, explored the indirect LUC effects using process-based LCA together with partial equilibrium analysis (PEA) (see Maruvuglia et al., 2013; Vázquez-Rowe et al., 2013) for more discussion of the methodology. For example, in response to increasing corn demand from ethanol industry, US farmers could reallocate their land to produce more corn at the expense of reduced soybean production. This could drive up global soybean prices and lead farmers across the world to produce more soybeans by clearing forest and grassland. In both direct and indirect LUC, large amounts of carbon would be released from land conversion, offsetting any carbon benefits that corn ethanol may provide for decades to come. Indeed, over the past few years we have observed significant corn expansion into grassland and cropland like cotton (Johnston, 2013; Wallander et al., 2011; Wright and Wimblerly, 2013; Yang and Suh, 2015b). Since publication, the two studies have changed the discourse of bioenergy LCA research, culminating in amendments to biofuels policies that took land use change effects into consideration (Farber, 2011).

Why were LUC effects systematically neglected in previous LCA studies? In hindsight, it was mainly because they used the attributional LCA (ALCA) approach without realizing its limitations. What
these ALCA studies did was take a “snapshot” of existing conditions, e.g., existing corn grown on long-standing cornfield. But when they calculated that corn ethanol had lower life cycle emissions than gasoline (about 70 versus 90 CO₂ MJ⁻¹), their conclusion that corn ethanol could reduce GHG emissions by 20 g CO₂e MJ⁻¹ (Farrell et al., 2006) was not merely descriptive of existing corn ethanol but implicative of additional corn ethanol. Above all, that is what policies like the renewable fuel standard (RFS) in the United States aims for, namely, a large increase in ethanol production. In other words, these seemingly attributional studies were implicitly involved in consequential reasoning. The question then arises: would the conclusion hold true for additional corn ethanol, or would 1 additional MJ of corn ethanol reduce 20 g CO₂e?

Before answering this question, let us first examine what would need to happen in order for the conclusion to hold true for additional corn ethanol. For simplicity, let us assume that of the 70 g CO₂e MJ⁻¹ GHGs for corn ethanol, 30 g come from corn farming and 40 g from ethanol refining, with tail pipe emissions canceled out by plant carbon uptake. For gasoline, of the 90 g CO₂e emitted per MJ of fuel, 5 g are from crude oil extraction, 15 g are from crude oil refining, and 70 g are from tail-pipe emissions. Thus in order for 1 additional MJ of corn ethanol to reduce 20 g CO₂e, the following would need to happen:

1) 1 additional MJ of corn ethanol would cause additional 40 g CO₂e emissions to be generated from the biorefining stage, including direct GHG emissions at biorefineries from, e.g., energy use, and indirect emissions from production of additional energy, enzyme, yeast, etc.;

2) The additional MJ of corn ethanol would require a certain amount of additional corn to be produced, generating 30 g CO₂e emissions along with it, including N₂O emissions from additional fertilizers applied and CO₂ emissions from additional energy used in machinery, as well as indirect emissions due to production of additional fertilizers, pesticides, energy, etc.;

3) The additional MJ of corn ethanol would take the place of 1 MJ of gasoline that could have been produced and used, thus avoiding 90 g CO₂ GHGs to be released into the atmosphere.

In summary, every process involved in the corn ethanol system would need to expand proportionally in response to an increase of 1 MJ in ethanol demand. Likewise, every process involved in the gasoline system would need to shrink proportionally in response to a decrease of 1 MJ in gasoline demand. But would all these assumptions happen in the real world?

Regarding 1), the answer is likely “Yes.” Regarding 2), however, the answer is likely “No” because of land constraints as discussed above. Corn expansion would likely result in the clearing of natural habitats directly or indirectly. It is arguable that additional corn could come from yield increase through intensification without land expansion. But in this case the amount of additional fertilizers and pesticides applied to produce additional corn would be much higher than that applied to produce existing corn (Searchinger, 2010). Be it extensification or intensification, therefore, the GHG emissions associated with additional corn would be significantly higher than that of existing corn estimated by the non-LUC studies cited above. And regarding 3), the answer is also likely no, due to the complexity of markets and human behaviors (Geyer et al., 2013; York, 2012; Zink et al., 2015).

3. Assumptions behind applying ALCA for decision making

From a methodological point of view, when we apply such linear models as process- and IO-based LCA to address change-related questions, they are based on a strict linear or proportional relationship (Fig. 2). That is, if the life cycle GHG emissions of corn ethanol are estimated at 70 g CO₂ MJ⁻¹, 1 additional MJ of Gj, and Tj of corn ethanol would induce 70 g, kg, and t CO₂e. Underlying this simple linear extrapolation are a number of assumptions, among which are fixed input/output coefficients and an unlimited supply of inputs (West, 1995). These assumptions are reflected in Equations (1) and (2) for process-based LCA. Note that here I do not differentiate between process- and IO-based LCA. The two differ in aspects such as system boundary and the level of aggregation (Sub and Huppes, 2005), but on a fundamental level they are both linear models. For simplicity let us focus on the process-based LCA method.

\[
m = BA^{-1}f
\]

(1)

\[
\Delta m = BA^{-1}\Delta f
\]

(2)

In Equations (1) and (2), A is the technology matrix with columns representing processes and rows products, and elements along a column denoting products consumed (negative values) or produced (positive values). B is the environmental matrix in which a column vector shows emissions or natural resources emitted or consumed by a process in A. f is a column vector related to the functional unit of a study, and m shows the life cycle emissions. \(\Delta f\) indicates changes in functional unit resulting from a decision in question, and \(\Delta m\) indicates total additional emissions caused by \(\Delta f\). Note that Equations (1) and (2) yield the same results when \(\Delta f = f\).

From a consequential perspective, let us reformulate Equation (2) using the power series expansion (Sub and Heijungs, 2007), which reflects the round-by-round effects of \(\Delta f\), as shown below,

\[
\Delta m = B\Delta f + B(I - A)\Delta f + B(I - A)^2\Delta f + \cdots + B(I - A)^n\Delta f
\]

(3)

where I is the identity matrix, and the first term B\(\Delta f\) shows the additional direct emissions from producing \(\Delta f\); the second term B\((I - A)\Delta f\) shows the additional first-round indirect emissions from producing the inputs used in producing \(\Delta f\); and the third term B\((I - A)^2\Delta f\) shows the additional second-round indirect emissions, so forth. Again, the technology and environmental matrices, A and B, remain constant throughout. This constancy indicates that all processes have adequate capacity to accommodate any expansion
in output as a result of $\Delta f$ and that additional outputs are produced in a set of fixed coefficients.

In reality, however, the human-economy-environment system is faced with many constraints such as the scarcity of certain resources and the biophysical limits of the environment. Besides, many of the processes in the system may be highly nonlinear and cannot be adequately represented by fixed input/output relationships. As a result, ALCA based on a simple linear extrapolation from existing situations may fall short of approximating changes. In fact, in Input–Output Analysis (IOA) the limitations of imputation analysis, which is equivalent to ALCA, have been long recognized (Ghosh, 1964; Tilanus, 1967). In tourism IOA, for example, multipliers derived from imputation analysis were found to significantly misrepresent the economy-wide impact of incremental changes in tourism expenditure (Bryden and Faber, 1971; Frechtling and Horvath, 1999; Ohagan and Mooney, 1983).

4. A two-step approach to CLCA based on the attributional framework

The inadequacies of ALCA described above, however, do not mean we should do away with the attributional framework altogether. Above all, there are cases where linear extrapolation may adequately approximate marginal changes, e.g., when major processes of a product system have sufficient capacity to accommodate additional outputs. In this section, I present a two-step approach to CLCA based on the attributional framework (Fig. 3). Section 4.1. explains the approach, Sections 4.2.-4.4. focus on the second step of scenario analysis, and Section 4.5. provides an example illustrating how the approach works.

4.1. A two-step approach to CLCA

The first step is consistent with the way we have been doing ALCA, namely, compiling inventories and conducting attributional analysis (Fig. 4). This step helps us evaluate the status quo of the system under study and identify hotspots on which we can focus subsequently. The second step introduces the decision in question, evaluates possible changes to take place, builds scenarios representing associated environmental consequences, and modifies the original inventories accordingly. (Fig. 4). In the second step, we may need to collect more data (e.g., capacity utilization, supply constraints, and marginal technologies) for the key processes to be affected to estimate how they may respond to changes in output.

Fig. 3. A two-step approach to consequential life cycle assessment based on the attributional framework. The yellow box reflects how the two steps work. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Eventually, the approach yields range estimates rather than point estimates of decision outcomes. The range may be narrowed with further information before a decision is made (e.g., from possible outcomes to probable or likely outcomes). Or it may be revisited and narrowed with observations of what has happened after the decision. In any event, because predicting future outcomes is inherently uncertain, it is untenable to give only point estimates, which are known to be ‘incredible certitude’ in policy analysis (Manski, 2013).

Correspondingly, this approach entails us to be more specific and clear about the research question we address (Zamagni et al., 2012). As discussed above, many of the questions LCA addresses are consequential in nature (Weidema, 2003). In the case of corn ethanol, for example, the question was commonly posed as “what is the carbon footprint of corn ethanol as compared to gasoline?” But it should have been more appropriately framed as a set of related questions such as “what is the carbon footprint of corn ethanol, per MJ used, compared to gasoline given existing technologies”, followed by “how much carbon would we save if we increase the production of corn ethanol by 100 TJ or 100 PJ?”

Within this approach, the first step is familiar to LCA practitioners and analysts. Below I focus on the second step and discuss some of the important modifications we can make to better estimate the environmental emissions of changes in outputs due to the decision in question. The core idea is to relax the major assumptions of ALCA and linear extrapolation.

4.2. Deriving marginal coefficients

The first modification is to derive marginal input/output coefficients that are different from the average coefficients compiled in the first step. Previous studies (Weidema et al., 1999; Weidema, 2003, 1993) have discussed in detail the procedure of identifying marginal technologies in the context of process-based LCA. In IOA, problems with using average coefficients have been long recognized; efforts to derive marginal coefficients for better economic impact analysis and forecasting date back to half a century ago (Ghosh, 1964; Tilanus, 1967).
Two scopes of marginal coefficients can be differentiated, depending on the effect of $\Delta f$. The first is when $\Delta f$ does not affect existing situations, e.g., changing causes to the coefficients of the process that produces only $\Delta f$, as shown below,

$$\Delta m = B_1 A_1^{-1} \Delta f$$  \hfill (4)$$

$$B_1 = \Delta B + B_0$$  \hfill (5)$$

$$A_1 = \Delta A + A_0$$  \hfill (6)$$

where $A_1$ and $B_1$ contain marginal coefficients, as opposed to the original $A_0$ and $B_0$ compiled in the first step which include average coefficients. $\Delta A$ and $\Delta B$ indicate changes in the technological and environmental coefficients from the average as a result of $\Delta f$. An example of this case is agricultural intensification: additional crops grown on marginal land are likely to differ from, but will not affect, existing crops grown on long-standing cropland in terms of yield and inputs.

The second is broader, where $\Delta f$ affects also existing situations, e.g., causing changes to the coefficients of the process that produces both $\Delta f$ and $f_0$, as shown below,

$$\Delta m = B_1 A_1^{-1} \Delta f + \Delta B A_0^{-1} f_0 + B_0 \Delta A^{-1} f_0 + \Delta B \Delta A^{-1} f_0$$  \hfill (7)$$

an example of which is agricultural intensification: additional production would increase the overall nutrients application and runoff rates. In either case (Equations (4) and (7)), $A_1$ and $B_1$ could be partially or entirely different from the original $A_0$ and $B_0$ depending on if, for example, marginal coefficients are derived for one process (Equations (8) and (9)) or for all the processes involved (Equations (10) and (11)). Bars in Equations (8)–(11) indicate marginal coefficients that are different from the average coefficients in $A_0$ and $B_0$. Those without bars indicate they are the same as average coefficients. The circumstance in which marginal coefficients are needed for all processes (Equations (10) and (11)) is rare. Most likely, they are needed only for several key processes identified in the first step that would be affected due to the decision in question.

$$A_1 = \begin{bmatrix} a_{11} & \bar{a}_{1i} & \cdots & a_{1n} \\ \vdots & \ddots & \ddots & \vdots \\ a_{n1} & \bar{a}_{ni} & \cdots & a_{nn} \end{bmatrix}$$  \hfill (8)$$

$$B_1 = \begin{bmatrix} b_1 & \bar{b}_j & \cdots & b_n \end{bmatrix}$$  \hfill (9)$$

$$A_1 = \begin{bmatrix} \bar{a}_{11} & \bar{a}_{1i} & \cdots & \bar{a}_{1n} \\ \vdots & \ddots & \ddots & \vdots \\ \bar{a}_{n1} & \bar{a}_{ni} & \cdots & \bar{a}_{nn} \end{bmatrix}$$  \hfill (10)$$

$$B_1 = \begin{bmatrix} \bar{b}_1 & \bar{b}_j & \cdots & \bar{b}_n \end{bmatrix}$$  \hfill (11)$$

\subsection*{4.3. Dynamic CLCA}

In LCA, the standard way an inventory is compiled resembles taking a snapshot of a system, with little regard to its temporal characteristics. This static treatment may be suited to systems that are relatively stable in input/output structures. But it may misrepresent systems that experience rapid changes, especially when outdated data are used (Yang and Suh, 2015c). In accounting for a changing system, dynamic LCA (Collinge et al., 2013) creates multiple life cycle inventories (LCIs) that represent the system in different times (see, e.g. (Hertwich et al., 2015)). The use of dynamic LCIs, however, resembles taking multiple “snapshots” without explicitly addressing the question of “what would happen if or if not …” Thus, this approach still falls within the domain of ALCA. To conduct CLCA in this dynamic context entails first establishing emission trends without the decision in question (i.e., business-as-usual), and then estimating new emission trends resulting from that decision with all else being equal. Fig. 5 illustrates this dynamic process. Again, using process-based LCA the total additional emissions caused by a decision over time can be calculated by (based on Equation (4)):

$$\Delta d = \sum_{t=0}^{n} \Delta m_t$$  \hfill (12)$$

$$\Delta m_t = B_1 t A_1^{-1} \Delta f_t$$  \hfill (13)$$

where $\Delta d$ denotes the total additional emissions over time and subscript $t$ indicates time unit, commonly a year. Equation (4) and (7) and Equations (12) and (13) resemble what are known as comparative statics and comparative dynamics in economics. Both are applicable depending largely on the goal and scope of a study and the system being studied. Comparative statics (Equations (4) and (7)) is more suited to short-term, incremental changes and when the system is stable without the perturbation of the decision in question. By contrast, comparative dynamics (Equations (12) and (13)) is more suited to mid- to long-term analysis of potentially large changes and when the system is unstable with or without the perturbation of the decision in question.

\subsection*{4.4. A more realistic displacement ratio}

In LCA, another widely used assumption is the one-to-one perfect displacement or substitution ratio. In the case of corn ethanol, for example, 1 MJ of corn ethanol is assumed to displace 1 MJ of gasoline. While there is no theoretical foundation for this perfect displacement ratio, it possibly stems from the use of the same functional unit in ALCA as the basis of comparison between alternatives. It makes sense, for example, to compare the carbon footprint of corn ethanol and gasoline on the same basis (e.g., per MJ consumed or per mile driven). But this does not mean producing an

![Fig. 5. An illustration of dynamic consequential life cycle assessment (CLCA).](image-url)
extra TJ of corn ethanol will prevent an equal amount of gasoline from being produced. It is more likely that the additional ethanol will put downward pressure on gasoline prices, leading to a higher consumption of the fuel, such that less than 1 TJ of gasoline is displaced in the end.

The logic behind a more realistic, less than the one-to-one displacement is similar to that of the rebound effect (Borenstein, 2013), both due to the complexity of market mechanisms and human behaviors (York, 2012). There is a growing body of studies on displacement ratio based on economic analysis or partial equilibrium analysis (Chalmers et al., 2015; Geyer et al., 2015; York, 2012; Zink et al., 2015). In fact, there has been a relatively long tradition in IOA of incorporating econometric techniques to better take into account market mechanisms such as price effects and supply constraints (Almon, 1991; Joun and Conway, 1983; West, 1995). It is beyond the scope of this study to go into detail about how to derive a more realistic displacement ratio, but once derived it can be used in place of the one-to-one prefect displacement ratio to better quantify environmental consequences of a decision. For example, if it is estimated that 1 additional MJ of corn ethanol would generate 100 g CO2e, it would displace 0.6 MJ of gasoline, and the carbon footprint of producing that gasoline is 120 g CO2e MJ\(^{-1}\), then the consequence of the additional MJ of corn ethanol would be 100−0.6 × 120 = 28 g CO2e emissions.

4.5. A hypothetical example illustrating the two-step approach

In this section, we use a hypothetical example to illustrate the two-step consequential approach. Suppose we are to reevaluate the climate impact of corn ethanol before its expansion in early 2000s (Fig. 1). Our functional unit is specifically an additional kg of ethanol instead of 1 kg of ethanol. The first step is a standard attributional analysis including compilation of inventory data reflecting market situations. Suppose we find that

\[
A_0 = \begin{bmatrix}
1 & -5 & 0 & 0 \\
0 & 1 & -2 & 0 \\
0 & 0 & 1 & 0 \\
-5 & -2 & -1 & 1 \\
\end{bmatrix}
\]  \hfill (14)

\[
B_0 = [1 \ 3 \ 4 \ 0.1] \hfill (15)
\]

\[
f_0 = \begin{bmatrix}
0 \\
0 \\
1 \\
0 \\
\end{bmatrix}
\]  \hfill (16)

where \(A_0\) indicates the major processes involved in the life cycle of corn ethanol. Rows in \(A_0\) represent nitrogen (N) fertilizers, corn, ethanol, and coal (in kg), and columns represent N, corn, ethanol, and coal production. The second column, for example, means to produce 1 kg of corn uses 0.5 kg of N and 0.2 kg of coal. \(B_0\) shows the CO2 emissions (in kg) of each process, and the functional unit, \(f_0\) in this step is to produce 1 kg of ethanol. Using Equation (4) we calculate the life cycle CO2 emissions of 1 kg of corn ethanol at

\[
m_0 = B_0A_0^{-1}f_0 = [11.2]. \hfill (17)
\]

Next, we identify the key inputs to be corn and ethanol using:

\[
m_0 = B_0 \text{diag}(A_0^{-1}f_0) = [1 \ 6 \ 4 \ 2]. \hfill (18)
\]

where \text{diag} means diagonalization. Now we move on to the second step, focusing on the corn and ethanol processes and how they would respond to increases in output. Suppose we further find that ethanol is produced by two types of refiners, a wet mill and dry mill. The dry mill is more efficient and more likely to expand its production in response to a rise in ethanol demand. For corn, land is a constraint, and one possibility is to expand into set-aside land, also known as direct land use change (Fargione et al., 2008). We investigate this scenario and derive marginal coefficients for both processes, as shown in Equations (19)–(21).

\[
A_1 = \begin{bmatrix}
1 & -8 & 0 & 0 \\
0 & 1 & -1.5 & 0 \\
0 & 0 & 1 & 0 \\
-5 & -3 & -8 & 1 \\
\end{bmatrix}
\]  \hfill (19)

\[
B_1 = [1 \ 10 \ 4 \ 0.1] \hfill (20)
\]

\[
\Delta f = \begin{bmatrix}
0 \\
0 \\
1 \\
0 \\
\end{bmatrix} \hfill (21)
\]

Again, \(\Delta f\) represents the goal of understanding the climate impact of corn ethanol expansion. Now compare Equations (19) and (14). The reason an additional kg of corn uses more N and coal is that it is grown on marginal land with lower fertility, and the reason inputs for additional ethanol are lower is that it is produced using the dry-mill technology that is more efficient than the average. Next compare Equations (20) and (15). The reason CO2 emissions from corn production are much higher is because of the loss of soil and plant carbon from land conversion. We proceed to calculate the life cycle CO2 emissions of 1 additional kg of corn ethanol using Equation (4):

\[
\Delta m = B_1A_1^{-1}\Delta f = [20.4] \hfill (22)
\]

This result shows that if set-aside land is converted to grow corn for ethanol, its life cycle CO2 emissions could be much higher than that of existing corn ethanol. This simple example is aimed to illustrate how the two-step approach works. In an actual case study, other scenarios such as intensification and indirect land use change should also be considered. To apply this approach in a dynamic context entails compiling multiple inventories over time and deriving corresponding marginal coefficients (Yang and Suh, 2015a). To study the full consequences of corn ethanol expansion, including displacing gasoline, would involve applying the two-step approach to the gasoline system as well and estimating realistic displacement ratios as discussed in Section 4.4.

5. Discussion

LCA is a decision-supporting tool and many of the questions LCA addresses involve changes (Weidema, 2003). ALCA in its standard form, based on a set of attributional rules and inventories describing mostly an existing world, may fall short of examining changes and informing decision making. To understand the consequences of a decision entails estimating what would happen with and without the decision in question (Manski, 2013). Nevertheless, ALCA is instrumental in structuring a complex system, identifying hotspots, and constructing business-as-usual scenarios. In addition, linear extrapolation based on ALCA sometimes may provide an adequate approximation for marginal changes, or serve as one of the possible consequences of a decision (Fig. 4). This is why ALCA is an indispensable part of the two-step consequential approach.
proposed here, which differs from CLCA studies that view themselves in stark contrast to ALCA (Ekvall et al., 2005; Plevin et al., 2014; Weidema, 2003).

The two-step approach proposed in this paper enables us 1) to be specific about the question addressed, e.g., whether it induces changes and how large would they be and where would they take place, and 2) to examine if the inventory data collected are adequate to capture the changes. Too often the inventory data collected are a static description of an existing system and thus fail short of capturing important changes, hence modifications needed. In the example of dietary shifts, the question Tom et al. (2015) address concerns the environmental impacts of increasing consumption of vegetables and fruits, among other healthier food items. What matters in conducting an LCA of these dietary shifts is where and how the additional vegetables and fruits would be produced. However, the data collected by the authors are only a portrayal of the status quo of crop production, and thus say little about the impacts of additional vegetable and fruit production. From the perspective of the two-step approach proposed here, Tom et al. (2015) have only completed the first step. To answer the question of dietary shifts in more complete manner, the second step of scenario analysis would help to identify where and how the additional crops would be produced and to derive marginal coefficients for their production.

It is also important to point out that there are different circumstances that may benefit from the development of marginal coefficients in LCA. These circumstances depend on the social and economic context (e.g., if it is constrained) in which a question is posed, the geographic boundary (Yang, 2016), the temporal scale selected, the magnitude of the changes to take place, and the method used (IO- or process-based). For example, a particular decision may increase the total generation of electricity in a country, in which case average data including all electricity-generating technologies seem applicable. But it is possible that some of the technologies are constrained such that increases in total generation will be met by the other technologies (e.g., hydropower in California due to the drought (Gleick, 2016)). In this example, marginal coefficients would represent the emission factors for technologies projected to meet the increase in electricity demand. Sometimes, a two-step approach is also presented in ALCA studies (see, e.g., Jolliet et al. (2015)). It is worth clarifying how it differs from the two-step approach proposed here. Regarding the former approach, the first step often provides a screening-level analysis or rough estimates based on, e.g., commercial databases or industrial average data. Then the second step involves more detailed analysis with perhaps refined geographic, temporal, and technological resolution for the foreground processes directly related to the functional unit defined. This is a process leading to more accurate estimates but still falls within the domain of ALCA. By contrast, the two-step approach proposed here is for CLCA, with the second step introducing a decision, estimating potential changes as a result of the decision, and building scenarios to estimate associated environmental emissions.

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