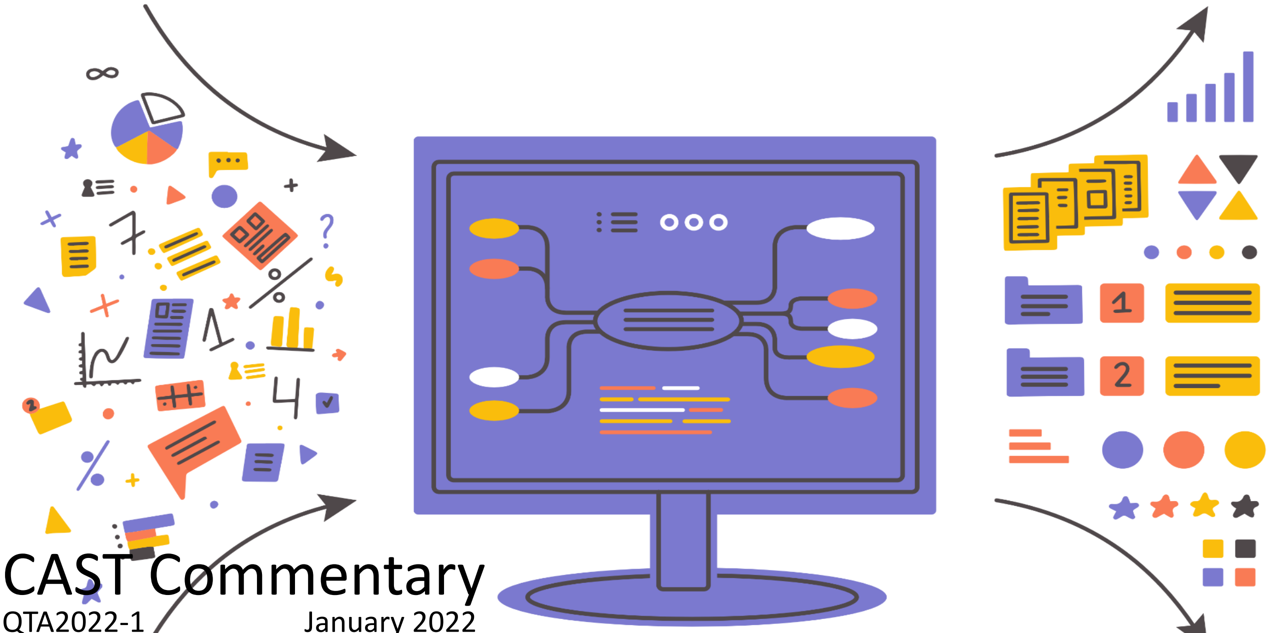

CAST Commentary
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Goals, Strengths, and Limitations Governing the Use of Life Cycle Assessment in Food and Agriculture

Authors:

Marty Matlock (Chair)
University of Arkansas

Stephen Pfister
ETH-Zurich

Brad Ridoutt
Commonwealth Scientific and Industrial Research Organisation Agriculture and Food
Clayton South, Victoria, Australia

Kurt Rosentrater
Iowa State University
Ames, IA

Greg Thoma
University of Arkansas
Fayetteville, AR

Yuan Yao
Yale University
New Haven, CT

Reviewers:

Thomas Battagliese
BASF
Florham Park, NJ

Ermias Kebreab
University of California-Davis
Davis, CA

Michael Wang
Argonne National Laboratory
Lemont, IL

CAST Liaison:

Juan Tricarico
Innovation Center for US Dairy
Rosemont, IL

Introduction

Understanding the impacts of the decisions we make in complex systems like agricultural supply chains is very difficult. Agricultural supply chains are best described as interconnected systems within systems, or metasystems. They are characterized by feedback and feedforward information flow that changes rapidly, with non-linear and difficult to predict outcomes. The global scope of the agricultural supply chain amplifies this complexity.
In spite of this complexity the demand for food supply chain transparency across social networks is increasing. Food system brands are being held responsible for consequences of decisions multiple steps above their direct

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control. Agricultural producers are being asked to report on regional and national environmental impacts of their production practices. These demands are driving the need for coherent, consistent, and defendable assessment methodologies for local-to-global environmental impacts across the entire agricultural supply chain.

The methodologies used in LCA originated from risk assessment, reduction, and mitigation strategies in hazardous materials management more than 40 years ago.

Life cycle assessment (LCA) is one of the tools being used to assess impacts across environmental, social, and economic domains. The methodologies used in LCA originated from risk assessment, reduction, and mitigation strategies in hazardous materials management more than 40 years ago. The concepts and methods are not new, but the applications in agriculture have emerged over the past 25 years (Audsley et al. 1997).

Questions LCA Can Answer

The quantitative elements of LCA are effectively based on supply chain mass and energy flow accounting linked to impact assessment models. As such, LCA can answer questions that any accounting method can answer. These include how much of a thing is accumulated at discrete points in the supply chain, what impacts result from discrete inputs in the supply chain, and what happens to the impacts if those inputs are changed.

LCA can answer questions for holistically addressing environmental sustainability of products and systems.

The most common questions addressed by LCAs are related to environmental assessment, especially environmental impacts such as global warming potential or water embodied in a product or process. Historically LCAs were used for process improvement to identify hot spots of environmental discharges and risk factors such as hazardous chemical use in a process or product life cycle. Because LCA is so powerful at defining explicit processes and inputs that result in undesirable outputs, they are also used in policy analysis and making to provide common benefits to society through policies and risk mitigation. They are similarly powerful tools for strategic planning and risk management for corporations and governments.

In order to answer a question using an LCA the question must be explicitly composed prior to conducting the assessment.

In order to answer a question using an LCA the question must be explicitly composed prior to conducting the assessment. Many assumptions are made in the LCA process that significantly influence the outcomes. Understanding why the LCA is being conducted in the first place and which question(s) it is designed to answer is key to effective implementation. The following sections of this document describe the process of problem formulation, defining goals and scopes, setting systems boundaries, defining allocation rules for multiple system products, and identifying the impact categories that the LCA will be used to quantify.

Questions LCA Cannot Answer

While LCAs are very powerful tools for analyzing entire supply chain systems for impacts, there are some questions LCAs cannot answer. These include normative value decisions, ethical framing, and risk mitigation. Normative decisions are made based upon norms, values, and morals. These are the most important decisions humans make. The outcome of an LCA cannot make this decision for you.

Questions LCAs cannot answer include normative value decisions, ethical framing, and risk mitigation.

However, an LCA can be very informative in the decision process. For example, almost all products in the supply chain have some negative impact on human health in their life cycle. These are measured in several ways, but the most common is disability adjusted life years (DALYs), which is a measure of the loss of expected length of life for a person or community due to exposure to the process or activity in the life cycle of the product. One DALY is the loss of one year of life. This information can tell a manager what the DALY impact of their products are across each step of the life cycle, if substituting elements in a production process will reduce or increase the impact, and how one product compares with another across supply chains. Recently, LCA is used extensively to address greenhouse gas footprints of products along their supply chains.

This critical information from life cycle assessments and associated impact assessments can inform these decisions, but the information does not make the decision. Compounding this complexity is the reality that any product or process has negative and positive impacts. Manufacturing nitrogen fertilizer creates several negative impacts, including DALYs, greenhouse gas emissions, eutrophication of fresh and marine waters, ocean acidification, and soil acidification. Nitrogen fertilizers also support adequate nutrition for 7.85 billion people while leaving some land for habitat to support other life. The decisions about the relative values of a process or product are very complicated. These decisions are made based upon a combination of values, ethics, and risk mitigation. The utility of LCA is in expanding our common understanding of these myriad impacts from our decisions, and in helping managers, policy makers, consumers, and others make more informed and effective decisions about the things we produce and how we produce them.

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Life Cycle Assessment Methods

LCA can be used to address a variety of information needs and individual LCA studies can differ greatly depending on their purpose. It is therefore important that organizations commissioning LCA studies—to be undertaken internally or by an external LCA consultant—consider carefully the decision-making context to be informed by the study as well as the intended audience. In some cases, LCA studies can be undertaken quickly and inexpensively where existing models are adapted using broadly representative data. The results of such studies may be adequate to identify significant issues and guide internal decision-making. On the other hand, where LCA studies are intended to support public environmental statements, higher levels of data quality will likely be required along with various completeness, sensitivity and consistency checks. This section outlines the general approach to LCA, along with relevant international standards and the main types of LCA studies. It is intended to support users of LCA information and facilitate engagement with LCA practitioners.

Methodological framework for LCA

While LCA studies may differ greatly in complexity and scope, they all adhere to common principles and share a common methodological framework. The International Organization for Standardization (ISO) standard 14040 describes the principles of LCA, which include:

While LCA studies may differ greatly in complexity and scope, they all adhere to common principles and share a common methodological framework.

- **The life cycle perspective**: LCA studies include upstream and downstream processes so as to avoid reducing environmental impacts in one life cycle stage, only to increase them in another. For food products, LCA studies should include the upstream processes of agricultural production and primary processing of commodities, as well as the energy and material inputs required at each stage. Some studies model the system only as far as the farm gate or the factory gate; others continue all the way to consumption, recycling of packaging and disposal of wastes. The included life cycle stages depend entirely on what is relevant to the question at hand.
- **A relative approach**: Across the life cycle of a product, environmental impacts can occur in many places and over long timeframes. An LCA study uses environmental models to assess potential environmental impacts relative to the unit of analysis or the functional unit in LCA

terms.. This unit of analysis could be product-based, such as a t of paddy rice, process-based, such as a hectare of land cultivated for rice production, or function-based, such as the provision of dietary protein. Defining the unit of analysis such that it is relevant to the question at hand is one of the first tasks in undertaking an LCA.

- **Transparency**: Because of the complexity of modeling a life cycle, with the various inputs and outputs and interactions with the environment, a large number of modeling decisions are inevitably taken by the LCA practitioner. Transparency of data sources and modeling choices is necessary to enable reliable interpretation of results.
- **Comprehensiveness**: In recent years, assessments of carbon footprints and water footprints have become common in agriculture and the food industry. These studies are valuable. However, there is always the risk that actions to reduce one environmental impact could, without intention, lead to higher impacts in another. For this reason, LCA studies seek to apply a broad range of environmental models covering as many relevant environmental aspects as possible.

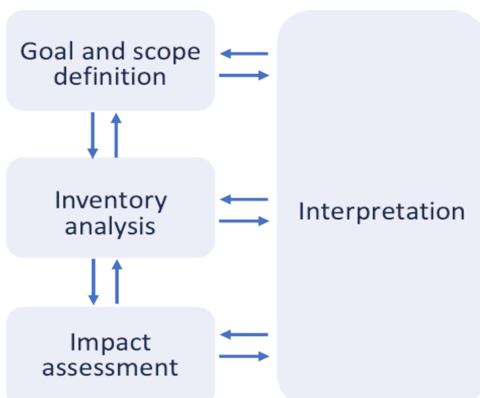

Figure 1. The four phases of an LCA study.

LCA studies also follow a common methodological approach involving four phases: goal and scope definition, inventory analysis, impact assessment and interpretation (Figure 1). The inventory analysis phase is often the most time consuming and expensive as this is where data is collected on resource use and emissions at each life cycle stage. Ideally, data is collected for the specific system under study. However, depending upon the goal and scope, data from LCA databases can also be used. The impact assessment phase is where environmental models are used to evaluate the significance of the resource use and emissions compiled in the inventory phase. Here, it is important to note that there is a wide variety of impact assessment models to choose from and new and improved models are being developed continually. To assist industry, the Life Cycle Initiative, a global collaboration under the auspices of the United Nations, periodically makes recommendations about best practice impact assessment models (https://www.lifecycleinitiative.org/).

The LCA approach is iterative whereby outputs from one phase informs the next. However, insights obtained in later phases may also point to the need to revisit earlier work. For example, impact assessment may indicate that certain inventory flows are more important than originally thought, justifying additional effort in obtaining more accurate inventory data.

International standards

To support the use of LCA in reliable and responsible ways, the International Organization for Standardization has developed a variety of standards covering the discipline. These include:

- ISO 14040:2006 describes LCA principles and methodological

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The impact assessment phase is where environmental models are used to evaluate the significance of the resource use and emissions compiled in the inventory phase.

framework

- ISO 14044: 2006 describes specific methodological and reporting requirements as well as requirements for critical review
- ISO 14046: 2014 concerns water footprint calculations
- ISO 14067: 2018 concerns product carbon footprint calculations
- ISO 14044 Amendment 1: 2017 expands the scope of 14044 to cover all footprints
- ISO 14071: 2014 provides additional coverage of LCA critical review processes
- ISO 14072: 2014 extends the application of LCA to organizations

In addition, there are ISO standards that address the communication of LCA-based information in the form of environmental claims, labels and declarations. These documents play an important role in protecting businesses and consumers from misleading environmental information and they are used in some countries to support consumer and competition laws.

Most LCA and footprint studies adopt the so-called attributional approach whereby inputs and outputs of resources and emissions are compiled and evaluated based on historical records.

Types of LCA studies

Most LCA and footprint studies adopt the so-called attributional approach whereby inputs and outputs of resources and emissions are compiled along the supple chain of a product and evaluated based on historical records. For agricultural production, where there can be considerable variability from crop to crop, data is usually used that covers a few recent seasons.

LCA studies can also take a consequential or change-oriented approach where marginal data is used to characterize what is expected to be the change in environmentally relevant physical flows arising from a decision. For example, when a process increases demand for electricity, the marginal electricity generator is studied, which may have a different environmental profile compared to generators supplying the base load. Ekvall (2020) offers an informative discussion of the differences between the attributional and consequential approaches.

Sometimes, LCA studies are designed to directly compare two different production systems or products. This is termed a comparative LCA. In such cases it is essential that all relevant stages of the life cycles are included and that equivalent methods are applied. This is easier to achieve when comparing two similar products from the same organization. However, it can be a challenge when comparing two products that might provide a similar function (e.g., a paper towel and an electric hand dryer) which involve very different industries.

Even thoughLCA is not a cure-all for environmental issues, it is a tool that, if correctly and completely used, can logically and methodically examines environmental impacts for specific products, processes, systems, and even entire supply chains.

Life Cycle Assessment of Agricultural Supply Chains

Even though LCA is not a cure-all for environmental issues, it is a tool that, if correctly and completely used, can logically and methodically examines environmental impacts for specific products, processes, systems, and even entire supply chains. To properly conduct a life cycle assessment will entail four core activities, including: (1) defining the goal and scope of the study, (2) life cycle inventory, (3) life cycle impact assessment, and (4) interpretation. This section will specifically discuss the first component of this framework.

Defining Goal and Scope

The first stage to pursuing a life cycle assessment study is to define the goal and scope of the study. There are many issues to consider here, and clearly defining what to investigate, why, and how you are going to do it is critical to successfully bringing an LCA to a meaningful conclusion. It is particularly important to unambiguously state the intended application for the LCA, the reasons for carrying out the study, the intended audience, the functional units, system boundaries, allocation rules, data sources, and clearly defining the methodologies to be used.

Some examples of goals for an LCA may include:

- To support broad environmental and sustainability assessments by an organization
- To establish baseline information for a product, process, or system
- To rank the relative contributions of individual steps or processes in the supply chain vis-à-vis environmental impacts
- To identify gaps in understanding or data
- To help guide product and process development to achieve environmental impact targets
- To provide information and direction to decision-makers / management

After setting the goals for the study, clearly defining the scope is crucial step in LCA.

After setting the goals for the study, clearly defining the scope is crucial step in LCA. All environmental impact categories (i.e., performance indicators) that will be used should be determined here, as well as any calculation methods which will be used to quantify them. Often the environmental impacts of the study will relate back to the LCA goals which have been established. Scope items must also include what portion of the supply chain will be analyzed, the functional unit to be used (so that all environmental impacts have a common metric for reporting), system boundaries, primary and secondary data to be modeled, estimated, and/or collected, how these data will be validated and used for calculations, any assumptions that might be used in the study—especially as these relate to the boundaries and data. The procedures that will be used to allocate environmental impacts must also be defined at this stage. Furthermore, acknowledging the limitations of the LCA should be done, as this will help readers understand the applicability of the results. Any other items that may impact the approach, application, and results should be discussed at the outset as well.

Defining Functional Units

As part of the Goal and Scope definition stage, it is important to unambiguously state what the functional units for the study will be.

For the sake of consistency throughout the study, as part of the Goal and Scope definition stage, it is important to unambiguously state what the functional units for the study will be. In other words, on what common basis (i.e., denominator) will you report the environmental impacts/indicators. Depending upon the goals, this functional unit may be an upstream input, or more often, will be a downstream output of the system under study.

There are three types of functional units that are commonly used for LCA studies: mass, energy, content, and economic value.

There are three types of functional units that are commonly used for LCA studies: mass (kilogram, pound, ton, etc.—which has traditionally been used), energy content (MJ, BTU—often used for fuel studies and other combustible products), and economic value (dollar, Euro, yen, pound, etc.—which is often used when multiple products have vastly differing monetary values [e.g., meat vs. rendered co-products]).

Some examples of mass functional units for an LCA study could include:

- Beverage manufacturing— bottling 355 mL (12 oz.) of a beverage (an output)
- Aluminum ingots for can production— 1 kg aluminum (an input)
- Biofuel fermentation— producing 1 gal bio-based ethanol (an output)
- Corn grain for ethanol processing—1 kg corn (an input)
- Wood production— producing 1 m3 of plywood (an output)

- Wood transported into the lumber mill— 1 m3 of pine tree (an input)
- Food manufacturing—1 kg of candy (an output)
- Chocolate for candy production—1 kg of cacao beans (an input)

Defining the system boundary, or control volume, within which the user will be working as he or she conducts an LCA is another key aspect of establishing the Goal and Scope of the project.

Establishing the functional unit or units to be used at this stage is critical as this will allow comparability amongst all subsequent LCA results, will allow comparisons with other LCA studies and publications, and will also allow for systematically relating system inputs to outputs.

Defining System Boundaries

Defining the system boundary within which the user will be working as he or she conducts an LCA is another key aspect of establishing the Goal and Scope of the project. This is important because it will help ascertain what stages or activities to be included in an LCA a person will conduct mass and energy balances into and out of the system. Sometimes the boundaries will be selected for convenience; other times the boundaries will be defined due to constraints of the study. Either way, boundary definition should be directly tied to the goals that want to be achieved by the LCA. Examples of system boundaries are shown for an LCA of a farm field, for modeling both water flow and gaseous emission flow (Figures 2 and 3). Figure 3 illustrates how the control volumes can then be used to establish the flows of mass and energy into and out of the field system. Note that in the case of this farm system, the LCA is concerned with flows which occur near

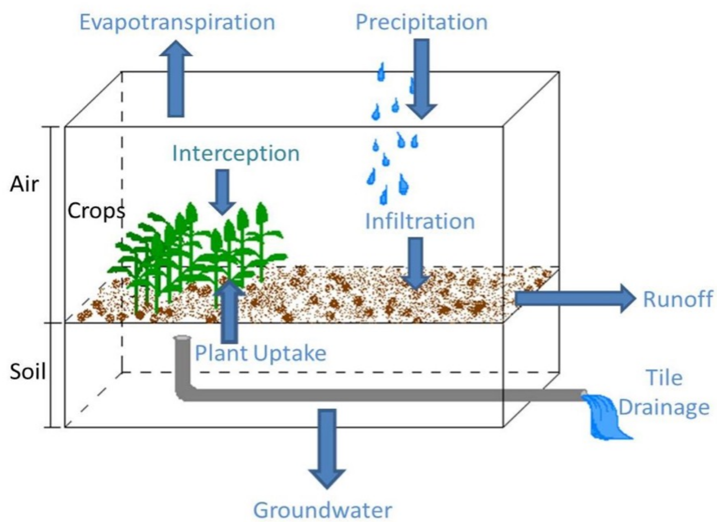

Figure 2. Example control volume for assessing net water flows into/out of a field system.

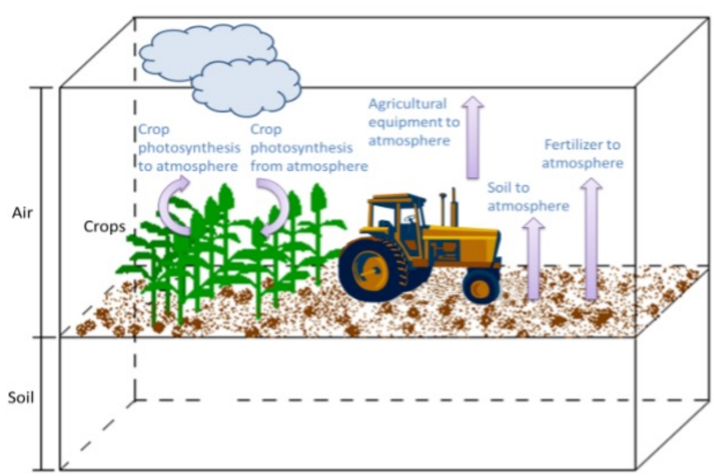

Figure 3. Example control volume for assessing net GHG flows into/out of a field system.

System boundaries can be established for any portion of a supply chain, such as a factory, a household, or even the entire supply chain.

the soil/atmosphere interface.

System boundaries can be established for any portion of a supply chain, such as a factory, a household, or even the entire supply chain, as shown in Figure 4. Depending upon goals and scope of the study, the portion of the supply chain which is analyzed will lead to differing results. If the LCA considers the full supply chain, the boundary would be considered cradle-to-grave. This is the most comprehensive approach to setting system boundaries. Many LCA studies concern raw commodity production activities on the farm only, and end at the farm gate. This type of scenario would also be appropriate for all raw production-type studies, including fisheries, mining, etc. An LCA which has boundaries from the farm to the factory would be considered cradle-to-

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An LCA which has boundaries from the farm to the factory would be considered cradle-to-plant gate.

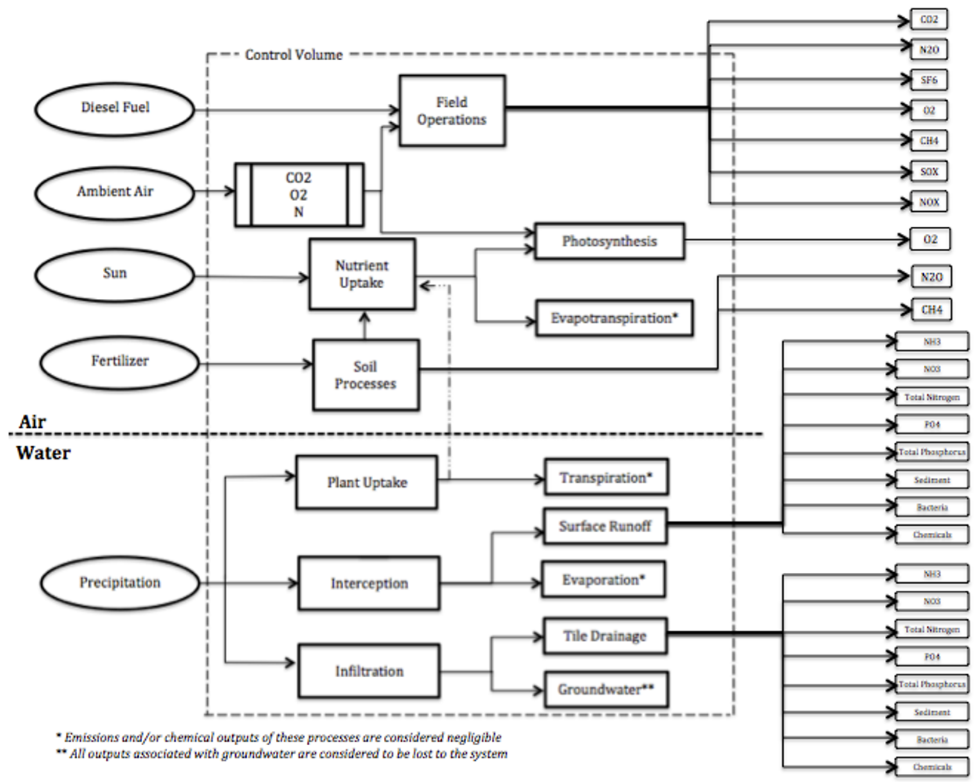

Figure 4. Establishing a logical system boundary/control volume is an important step to identifying and quantifying the net flows into/out of a system – in this case water and greenhouse gas flows in a field.

plant gate. This type of LCA could be used to help identify issues on the upstream side of the supply chain. From the factory to end of life would be considered a gate-to-grave LCA. Use-to-grave would entail consumer use and end of life activities. These types of LCAs focus on the downstream side of products.

Defining Allocation Rules

During the Goal and Scope stage, it is also important to decide how the net environmental emissions and impacts (which are determined at a later stage of the LCA methodology) will be allocated. If there is only one product being produced, then all impacts will be assigned to that product. If, however, there are multiple products (e.g., ethanol, compressed CO_2, and distiller's

During the Goal and Scope stage, it is also important to decide how the net environmental emissions and impacts (which are determined at a later stage of the LCA methodology) will be allocated.

dried grains with solubles [DDGS] in the case of corn ethanol manufacturing; steaks, roasts, spareribs, meat and bone meal, blood meal, hide leather, etc. in the case of beef processing) then it will be important to decide how the environmental impacts will be allocated, or subdivided, among the various products which are being produced. This allocation is typically done using a

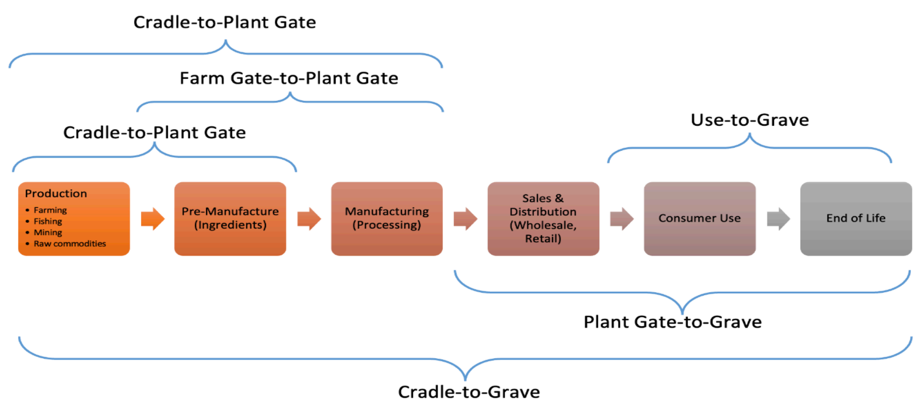

Figure 5. Example of entire supply chain for a food product, and some common types of system boundaries that might be used for LCA.

weighted average approach. If a person is using mass-based functional units, then a mass-basis for allocating impacts may be used; if a person is using an energy basis, then subdividing the impacts according to energy content of the products may be used; if a person is using economic value as a functional unit, then it would make sense to allocate according to the value of each product leaving the system boundary.

At the outset of an LCA, it must be decided as to whether existing software will be used for the analysis (there are many available for use—some more expensive than others), or if the user will build their own LCA based on either collecting primary data or using secondary sources.

Data Quality

At the outset of an LCA, it must be decided as to whether existing software will be used for the analysis (there are many available for use—some more expensive than others), or if the user will build their own LCA based on either collecting primary data or using secondary sources (i.e., published literature or databases). Whichever approach is used, the following issues should be considered for the data sets that will be utilized to estimate environmental impacts. These include the completeness of information for the products and processes in your study, the accuracy of measurements, precision with which they were measured, how the data were acquired, the timeliness of the data (which can be affected by technology and efficiency evolutions over time) and impacts that geography may have on the system. It is also important to consider how to incorporate data distributions in the LCA estimations, as all of these aforementioned issues will impact mass and energy flows as well as consequent environmental impacts, and what level of certainty (or probability) will encapsulate your computed results.

As with all other aspects of LCA the first stage is iterative in nature and will likely change and become more refined after the project is begun, and data availability (or lack thereof) becomes apparent, as well as alterations in management goals and timelines occur.

Life cycle inventory (LCI) data collection is the second phase of an LCA, following the ISO 14044 standard.

Life Cycle Inventory

Life cycle inventory (LCI) data collection is the second phase of an LCA, following the ISO 14044 standard. This phase of LCA is generally the most time intensive because of the large data requirements needed to perform an LCA. Broadly there are two classes of lifecycle assessment: (1) bottom-up or process-based LCA and (2) top-down or input-output (I/O) LCA. Both classes of LCA are built on the concept of unit processes which represent the fundamental building block of the system being simulated. One can envision model representing the production of a good or provision of a service to entail numerous activities working in concert or sequence to provide the functional unit of the study. Each of these individual connected activities are known as unit processes in the jargon of LCA.

Unit Process Characteristics

For both process and I/O models unit processes are characterized by four types of flows:

1. Inputs: raw materials provided as outputs of other unit process activities;
2. Extractions: extractions are a special type of input flow directly from nature (such as well water);
3. Outputs: the goods or services which need the unit process and may be either directly consumed or used as an input to another process;
4. Emissions: a special type of output flow directly to nature (such as carbon dioxide or nitrous oxides from combustion of fuels).

In process based LCA, a unit process will ideally satisfy material and energy balance requirements so that a full accounting of the activity's impact is available. Unit processes can represent quite simple or very complex activities, and the scale is frequently a function of data availability. For example, the process of pasteurization for milk processing could be a distinct unit process in a system within a milk processing plant, or the entire processing facility could be considered as a single activity.

In process based LCA, a unit process will ideally satisfy material and energy balance requirements so that a full accounting of the activity's impact is available.

For I/O LCA unit processes are built from an inventory of economic activity associated with the production of a good or service. These models are generally constructed from national statistics and linked with data regarding resource consumption and emissions via a wide variety of sources, including, for example, fuel prices. These unit processes also account for consumption and production flows as well as providing emissions estimates based on the economic activity (e.g., calculating that purchased fuel is combusted releasing combustion products to the atmosphere).

For I/O LCA unit processes are built from an inventory of economic activity associated with the production of a good or service.

Process Flows

Each unit process accounts for material and energy flows through a system of connected unit processes. Unit processes are connected in a manner such that the output product of one unit process is frequently used as the input to another. For example, the output of electricity from a power plant could be the input to a unit process for a home refrigerator. These flows are generally classified as techno-sphere flows, such as the example just given, and elementary flows which refer to the direct extraction of materials from the environment or the emission of materials to the environment. Unit processes are linked via their flows to construct a model of a supply chain which results in the delivery of a specified function, defined by functional unit discussed earlier. In LCA, practitioners categorize process flows as foreground and background processes. Generally speaking, foreground processes refer to activities under the direct control of the study or activities in the segment of the supply chain of direct and primary interest of the study. Background processes refer to activities in other parts of the supply chain, which may be

Unit processes are connected in a manner such that the output product of one unit process is frequently used as the input to another.

upstream-the production of electricity at a hydropower plant, or downstream, for example the disposal of packaging waste in a landfill or municipal incinerator. Numerous databases of unit process inventory exist, and these are commonly adapted to specific studies so that, for example, data regarding electricity production or transportation does not have to be collected for every single new lifecycle assessment study.

There are two fundamental sources of uncertainty and lifecycle inventory data: inherent variability and lack of knowledge.

Data Uncertainty

There are two fundamental sources of uncertainty and lifecycle inventory data: inherent variability and lack of knowledge. The former is a fundamental characteristic of all systems and can be quantified through direct measurement, like rainfall amount or temperature, or through process simulation such as crop modeling. Generally, inherent variability cannot be significantly reduced or eliminated by an LCA practitioner and therefore must be included in the accounting. Lack of knowledge, of course, can be corrected by more fully studying and characterizing the system to ensure that activities which are not measured are somehow estimated (see data gap discussion). LCA practitioners have developed techniques for estimating lifecycle inventory data uncertainty based on characteristics of the data including representativeness in regards to both temporal and geographic character, and whether the data is measured or estimated either by expert opinion or through simulation. One common approach for quantifying inventory uncertainty is use of Monte Carlo simulation in which random variance from a distribution for each inventory flow are used in a simulation leading to a distribution of impact outcomes which can be used to evaluate robustness of conclusions.

One of the consequences of the availability of multiple databases providing background data for LCA studies is that novice practitioners are tempted to mix unit processes from different databases as a means to fill any gaps in their lifecycle inventory.

Data Gaps

One of the consequences of the availability of multiple databases providing background data for LCA studies is that novice practitioners are tempted to mix unit processes from different databases as a means to fill any gaps in their lifecycle inventory. However, this is not generally appropriate because of database-specific characteristics regarding selection of system boundaries and the choice of technique for modeling multi-functional unit processes. Some databases use an economic allocation, some use mass-based allocation, while others may adopt a consequential paradigm and use market substitution to account for multi-functionality. Thus, the conclusions drawn from a study in which data gaps have been filled by selection of unit processes from multiple databases are significantly less robust. One approach to ameliorate this difficulty is to adapt inventory from one database to harmonize with the underlying assumptions and structure of the primary database selected for the study.

Another common approach to fill data gaps for flows which are not readily measured is to perform simulations of these processes using detailed mathematical models.

Even with the adaptation of other databases it is extremely common for data gaps to exist in both foreground and background unit processes. Thus, the practitioner is challenged to find suitable surrogate, proxy, or estimated inventory flow information. In some instances, surrogate or proxy data can be found in existing databases that are compatible with the primary database. As a simple example, one could select a generic process for provision of electricity rather than a process specific to the study location; while this will provide an adequate set of unit processes for characterization of impact, the impacts of the portfolio of power sources (coal, oil, nuclear, solar, wind, hydroelectric) from a specific power pool are lost. Another common approach to fill data gaps for flows which are not readily measured, for example nitrous oxide emissions from fertilizer application to crops, is to perform simulations of these processes using detailed mathematical models. It is imperative in the interpretation of an LCA to examine the potential influence of the modeling choices used for filling data gaps to characterize the robustness of the study's conclusions given the option of multiple approaches for filling data gaps.

Life cycle impact assessment (LCIA) converts the emissions and resource uses into units of potential environmental impacts.

Life Cycle Impact Assessment

Life cycle impact assessment (LCIA) converts the emissions and resource uses into units of potential environmental impacts. For this purpose, a cause-effect model is built. For emissions, this includes a fate and effect model. The fate model assesses the distribution and residence time of the pollutants in different environmental compartments (e.g., air, water, and soil). The effect model assesses the impact of the pollutant distributed in the environment on human health and/or ecosystem quality. An example can be a toxic emission (e.g., a pesticide) that ends up in the soil and freshwater (fate) and leads to adverse impact on ecosystem quality (effect). For fossil and mineral resources, impacts are assessed as resource depletion, which account for the fact that resource availability is limited. For land and water use, impacts address the limited access to resource in present time (i.e. the competition for a renewable resource leading to a reduction of natural land and water ecosystems and potential deprivation of other human users).

While endpoint level quantifies all impacts as a damage towards human health, ecosystem quality or resource depletion, midpoint indicators quantify stressors in a common unit for a specific impact category.

Mid-point versus End-point Assessment

The impacts can be quantified on so called mid-point or end-point level. While endpoint level quantifies all impacts as a damage towards human health, ecosystem quality (mainly biodiversity loss) or resource depletion, midpoint indicators quantify stressors in a common unit for a specific impact category. Impact categories are for instance the global warming potential (climate change impacts or "carbon footprints"), land use, water consumption, eco-toxicity, human toxicity or respiratory health impacts (mainly from particulate matter), and resource depletion. Midpoint categories can either lead to only one endpoint (e.g., resource depletion to natural resources) or multiple endpoints, such as climate change (affecting ecosystem quality and human health). In general, endpoint assessments have higher uncertainty as it requires additional modeling (e.g. how does climate change affect ecosystems), but provide results that are more graspable and comparable. This allows for better assessments of trade-offs among impact categories, since they quantify damages to humans, ecosystem and resources. However, it has to be noted that even though endpoints indicators have the same units for different impact categories, the results are not always consistent. For instance, human health impacts related to climate change are based on future models of

In general, endpoint assessments have higher uncertainty as it requires additional modeling, but provide results that are more graspable and comparable.

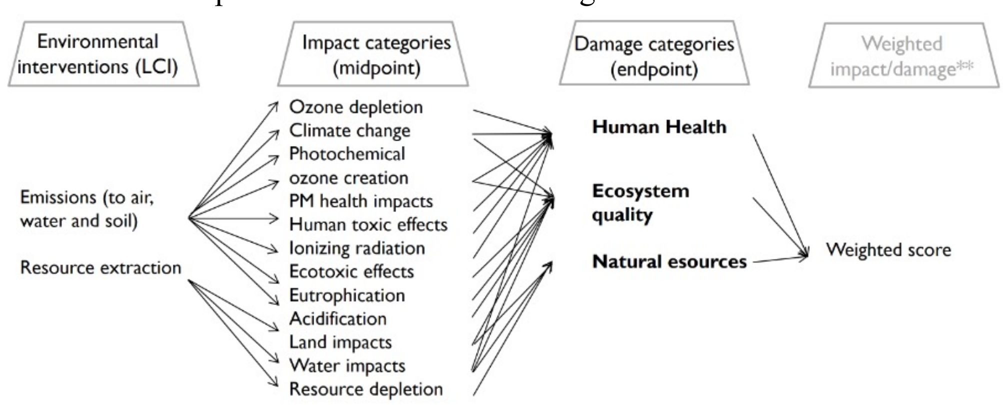

Figure 6. LCIA framework connection midpoint assessments and endpoint assessments.

future temperature increase and resulting malnutrition and spread of diseases over the next decades, while particulate matter emissions assess lower respiratory infections, stroke etc. based on epidemiological studies. Even with these challenges present, endpoint indicators can be aggregated into single-score results by normalizing and weighting steps in order to provide an overall score for the environmental impacts, which is attractive for communication purposes to laypersons and decision makers.

While a common unit or human health impacts it the DALYs reported by WHO in the global burden of disease reports, damages on ecosystem quality and resource depletion differ.

LCIA Endpoint Models

Several endpoint assessment model exists, which have a common underlying model for some and differing ones for other impact categories. While a common unit or human health impacts it the DALYs reported by WHO in the global burden of disease reports, damages on ecosystem quality and resource depletion differ. For ecosystem quality, the principle is to quantify a potentially disappeared fraction (PDF) or potentially affected fraction (PAF) of species resulting form the pollution or habitat loss due to land and water use, multiplied by the duration of the effect and the volume or area of habitat affected. Newer research has proposed to assess global species loss, which accordingly avoids the quantification of the volume or area affected (as it is global) and only has the units of species loss and duration. Common endpoint methods are ReCiPe 2016 (building upon ReCiPe and eco-indicator 99), LC-IMPACT, Impact World+ (loosely building upon Impact 2002+) and LIME3 (mainly in Japan).

Social LCIA Models

In addition to environmental impacts, life cycle sustainability assessment (LCSA) includes assessment of economic and social impacts.

In addition to environmental impacts, life cycle sustainability assessment (LCSA) includes assessment of economic and social impacts. Typically, economic impacts are measured as total costs using a Life cycle costing (LCC) approach, also known as whole-life cost or lifetime cost. This accounts for all the costs occurring over the whole life cycle, typically calculating net present costs of a product or service by applying discount rates. Social impacts are generally addressed through work hours required from and work conditions present in each process of the life cycle. Work hours are the inventory flow, while the work conditions are used to characterize the results.

When analyzing LCIA results at the midpoint level, typically 10–20 impact categories are covered separately.

Interpreting LCIA Results

Since interpretation of the LCIA results is of key importance for three reasons: (1) LCIA results are usually the main results for communication, (2) it allows to identify the important processes and flows that contribute to the impacts, and (3) the information on the contributions to overall results help to advance the analysis, since important flows can be investigated in detail and improved to enhance the robustness of the LCA.

When analyzing LCIA results at the midpoint level, typically 10–20 impact categories are covered separately. It is therefore important to assess trade-offs, since often comparison of products or product systems are not ranked unanimously among all impact categories. In general, the decision context and priorities of impact categories provide a guidance to the relevance of impact categories, which is a normative choice. There is normalization and weighting schemes to aggregate midpoint results to a single score, in which case default normative choices are made. Other options to interpret the multi-dimensional results is through multi-criteria decision analysis (MCDA), which is not commonly done.

When analyzing endpoint results, the impacts are aggregated as damages to human health ecosystem quality and natural resources, which allows more direct discussions of safeguard objects.

When analyzing endpoint results, the impacts are aggregated as damages to human health ecosystem quality and natural resources, which allows more direct discussions of safeguard objects. For instance, a decision maker might want to give higher weights to human health than natural resource depletion or ecosystem quality. Commonly, endpoint methods also include normalization and weighting that aggregates the results to an overall score.

In any case, it is important to avoid just reporting one result like a single score or a single impact category result, since the main purpose of an LCA is not a single result, but an understanding of the system analyzed, including which processes, and what emissions and resource uses are important for environmental impacts. Therefore, trade-offs should be explicitly discussed to identify problem shifting (e.g., from climate change to land use impacts, when switching from fossil to bio-based fuels).

> Although big data definitions have evolved rapidly, big data often refers to large collections of variable data that require advanced techniques to capture, process, and analyze.

> It is necessary to build data capacity for broader applications of big data analytics in LCA. Open-access, centralized LCI data repositories such as the Federal LCA Commons provides a platform to share and disseminate diverse datasets useful to LCI and LCIA modeling.

> The majority GHG emissions from the U.S. agriculture sector are methane and nitrous oxide. Estimating these two types of GHG emissions is critical to food and agriculture LCA.

Research Needs in Life Cycle Assessment

Big Data Integration into LCI

"Big data" is a ubiquitous term getting popular since 2011 (Xu, Cai, and Liang 2015). Although big data definitions have evolved rapidly, big data often refers to large collections of variable data that require advanced techniques to capture, process, and analyze (Gandomi and Haider 2015). Big data analytics, the process of using big data to support decision-making, have been used to fill LCI data gaps and characterize uncertainties. Previous studies estimated LCI data of chemical manufacturing by mining large, open-access, environmental datasets (Cashman et al. 2016; Meyer, Cashman, and Gaglione 2020). Other studies used literature datasets to train machine learning models to estimate the LCI of chemicals (Wernet et al. 2008) and biomass-derived materials (Liao, Kelley, and Yao 2019). In addition to LCI modeling, big data has been used to characterize dynamics and uncertainties associated with human behavior, such as travel patterns for transportation LCA (Cai and Xu 2013) or farmers' decisions on crop selection and fertilizer usage for agriculture LCA (Lan and Yao 2019).

It is necessary to build data capacity for broader applications of big data analytics in LCA. Open-access, centralized LCI data repositories such as the Federal LCA Commons (https://www.lcacommons.gov/) provides a platform to share and disseminate diverse datasets useful to LCI and LCIA modeling. However, submissions to data repositories are not required by most academic journals. Tremendous LCI data are still buried in LCA publications. Open data has been a trend across different disciplines, a culture shift towards better data sharing and transparency is needed in the LCA community. In addition, recent development in information technology and artificial intelligence offer new opportunities to ease and automate data collection and analytic process (Liao and Yao 2021). For instance, IOT (Internet of Things) have received increasing interest in agriculture, and some environmental data collected by IOT devices could support high-resolution LCI modeling across different temporal and geographic scales (Tzounis et al. 2017). Successful applications of those emerging technologies will need more exploration and case studies for real-world demonstration.

Advanced Greenhouse Gas Inventory Assessment

The majority GHG emissions from the U.S. agriculture sector are methane and nitrous oxide (U.S. EPA 2020). Methane is mostly generated during enteric fermentation and manure management, and nitrous oxide mainly comes from agriculture soil management. Thus, estimating these two types of GHG emissions is critical to food and agriculture LCA.

Enteric methane emissions are often estimated as a fraction of the gross energy intake using a generic approach developed by the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2014). However, prior research indicates large

> For accurate LCI data of nitrous oxide emissions, efforts are needed for nation-wide, region-specific data collection, emission monitoring, verification, and inventory assessment.

> Common methods for estimating soil carbon dynamics caused by land use change include the use of emission factors from literature, carbon balance models, dynamic crop-climate-soil models, or direct measurement, which have increased certainty but decreased applicability.

> The environmental impact of agriculture systems often varies in different locations due to differences in local practices, energy and material supplies, and environmental conditions.

variations of enteric methane emissions caused by different diets and animal characteristics (van Lingen et al. 2019). Advanced prediction models have been developed to estimate country-specific enteric methane emissions of cattle, such as models for the United States (Kebreab et al. 2008) and Australia (Charmley et al. 2016) and models based on international evaluations across different regions (Niu et al. 2018). Depending on the locations of the GHG inventory assessment, different models could be used to estimate methane LCI. The consistency and compatibility of those models will further be explored. The IPCC provides guidelines on estimating direct nitrous oxide emissions as a fraction of soil nitrogen input (De Klein et al. 2006) using default values derived from a global dataset that contains more than 800 observations (Bouwman, Boumans, and Batjes 2002). Recent research have focused on developing country- and region-specific nitrous oxide emissions by considering spatial dynamics related to soil and climate conditions, farm management practices, and nitrogen sources (Liang et al. 2020, Shepherd et al. 2015; Buckingham et al. 2014). For accurate LCI data of nitrous oxide emissions, efforts are needed for nation-wide, region-specific data collection, emission monitoring, verification, and inventory assessment (Ogle et al. 2020).

Another significant GHG emission source is land-use change (Pan et al. 2011). Quantifying the land-use change GHG emissions in agriculture LCA could be challenging, mostly due to the lack of LCI data. Common methods for estimating soil carbon dynamics caused by land use change include the use of emission factors from literature, carbon balance models, dynamic crop-climate-soil models, or direct measurement, which have increased certainty but decreased applicability (Goglio et al. 2015). Consensus has not been made on the procedure of quantifying GHG fluxes of land use change in LCA, but some recommendations on standardizing land use elementary flows (Koellner et al. 2013) and using process-based, spatially explicit, and dynamic models are promising (Schmidinger and Stehfest 2012; Hörtenhuber et al. 2014).

Geospatial Data Analysis in LCA

The environmental impact of agriculture systems often varies in different locations due to differences in local practices, energy and material supplies, and environmental conditions. Acquiring regionalized LCI data is challenging, therefore aggregated (e.g., market or country-wide average) or technology-representative LCI are often used (Hellweg and Milà i Canals 2014). Recent efforts include using extrapolation to estimate regionalized LCI data (Canals et al. 2011), using farm-related geospatial data (Cooper and Cooper 2015), leveraging process-based farm models (Romeiko et al. 2020) and Geographic Information Systems (GIS) (Reinhard, Zah, and Hilty 2017), and using spatially explicit models for land use change and ecosystem services (Chaplin-Kramer et al. 2017). Regionalized LCIA methods have also been developed as many impact categories (e.g., eutrophication) are location-dependent, such as TRACI for the United States (Bare 2011), and LC-IMPACT with high resolution of spatial details (Verones et al. 2020).

Recent discussions revealed the challenges in linking LCI and LCIA given the differences in geospatial scales, practical barriers in implementing high-resolution geospatial analysis in LCA software, and the lack of standards to ensure the comparability, reproducibility, and transparency of regionalized LCA (Frischknecht et al. 2019). Possible solutions include the use of standardized formats to facilitate transparent and consistent documentation of regionalized data and metadata and support the direct match of regionalized LCI and LCIA methods (Pfister, Oberschelp, and Sonderegger 2020). Other strategies include prioritizing the future research and development of regional

LCI and having validity and uncertainty check for regionalized LCIA methods (Mutel et al. 2019).

> Monte Carlo is the most popular approach for uncertainty analysis in LCA. MC is sampling-based and needs an explicit probability distribution for each uncertain parameter with an assumption that those parameters are independent of each other.

> Given the diverse sources of uncertainty and a large variety of uncertainty analysis methods, consensus and standardization are needed to guide the uncertainty identification and method selection.

Advanced Uncertainty Analysis in LCA

Uncertainty analysis quantifies the uncertainties of LCA results and provides a level of likelihood and confidence in LCA results (Mendoza Beltran et al. 2018). Uncertainty in LCA includes parameter, scenario, and model uncertainty. Parameter uncertainty is typically associated with the data of process inputs and outputs or technical features (Lloyd and Ries 2007). Scenario uncertainty is caused by different modeling choices (e.g., functional units and allocation methods) (Ziyadi and Al-Qadi 2019). Model uncertainty is related to models for developing LCI data or characterization factors for LCIA (Lloyd and Ries 2007).

Monte Carlo (MC) is the most popular approach for uncertainty analysis in LCA (Heijungs 2020). MC is sampling-based and needs explicit probability distribution of each uncertain parameter with an assumption that those parameters are independent of each other. MC has been mostly used for parameter uncertainty (Bamber et al. 2020). Many LCI databases like EcoInvent provide probability distribution information, and most LCA software is capable of running MC simulations, although the computational speed is a concern given the large number of iterations needed (e.g., 1,000 to 10,000 times). Recent development includes applying other faster and more accurate sampling methods (e.g., latin hypercube and quasi-Monte Carlo) (Groen et al. 2014) and developing new techniques to account for dependencies and correlations among parameters (Wei et al. 2015; Lesage et al. 2018; Groen and Heijungs 2017). Scenario and model uncertainty are more challenging than parameter uncertainty. Researchers have used discrete choice analysis and scenario analysis to simulate each combination of modeling choices (van Zelm and Huijbregts 2013) or used sensitivity analysis to quantify the impacts of modeling decisions (Bamber et al. 2020). Most LCA studies with uncertainty analysis focus on parameter uncertainty and only a few studies simultaneously modeled all three types of uncertainties. (Ziyadi and Al-Qadi 2019; van Zelm and Huijbregts 2013).

Given the diverse sources of uncertainty and a large variety of uncertainty analysis methods, consensus and standardization are needed to guide the uncertainty identification and method selection. Such guidance may need to be developed for different sectors and types of LCAs, because recent studies indicate the inherent differences of uncertainty sources among various sectors (e.g., transportation versus agriculture) and different types of LCA (e.g., attributional LCA and consequential LCA) (Bamber et al. 2020). For the food and agriculture sector, a common uncertainty source is farm characteristics driven by geographic and temporal factors (Yang, Tao, and Suh 2018). Geospatial analysis (Mutel, Pfister, and Hellweg 2012) and dynamic modeling approaches (Lan et al. 2020) could help address those uncertainties unique to agriculture LCA.

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