ADVANCES IN LIFE CYCLE ASSESSMENT AND EMERGY EVALUATION WITH CASE STUDIES IN GOLD MINING AND PINEAPPLE PRODUCTION

By

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To the memory of James H. Weeks and Blanche R. Ingwersen, two of my grandparents who passed away late in the course of my Ph.D. program, but who believed in me and forever inspire me.

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CHAPTER 1

INTRODUCTION

Production of goods and services is inextricably tied to the environment. As basic resources for modern economies are becoming more costly or less available (e.g. freshwater and petroleum) and impacts of productive activities have created local and global scale environmental change (e.g. climate change), the need to understand connections between the environment and economy has become more critical. The delegates to the UN Conference on Environment and Development, representing over a 100 of the world's nations, acknowledged in the milestone Rio Declaration on Environment and Development, or Agenda 21, that all productive processes in economies are dependent upon resources from the environment and sinks to absorb the pollution that they generate (principle 8, UN 1992). At the World Summit on Sustainable Development a decade later, it was furthered acknowledged that measurement systems are necessary to quantify these dependencies and pollution impacts for the purposes of achieving more sustainable development (chapter 3, UN 2005).

Measurement of Sustainable Production and Consumption

Measurement is the first step toward effective management and protection of the environment in the context of productive processes. But the concept of measurement of environmental impacts of production processes has been evolving with broader understandings of what, how and where impacts occur and who in turn is responsible for those impacts. The first generation of environmental policy in the United States (such as the Clean Air Act of 1970), and still the dominant from of regulation in place in

the United States, is primarily based on the regulation of environmental pollution “at the pipe”, implicitly focusing only on pollution at the point of occurrence and obligating only the party responsible at that point. This style of legislation reflects the assumption that impacts should be measured only at the point of impact. But the ultimate purpose and driver of a production processes is to provide for an end product or service, and thus the impacts of productive processes can all be related to the intermediate or end products. That product or service is demanded by a consumer, and that consumer shares responsibility for the environmental impacts that occur along the production chain. Shared producer and consumer responsibility was recognized in the Rio Declaration and reinforced at in international action plans such as the Marrakesh Process launched at the World Summit on Sustainable Development (UN DESA 2008), and is now becoming further integrated at national, regional and local scales, especially through voluntary public and private initiatives (e.g. Environmental Management Systems, Extended Producer Responsibility policies, corporate greenhouse gas accounting standards). It then becomes clear that measurement tools are needed that relate these broader impacts to products or services in a way that accounts for impacts along the full production chain such that management can involve both producer and consumer, and so that no impacts associated with production processes are left out.

Life Cycle Assessment as a Measurement Tool

Life Cycle Assessment (LCA) is an established and standardized framework for assessing impacts of production processes and for relating full life-cycle impacts to a final product (ISO 2006a). LCA is being used globally for product systems for product design, management, and communication of environmental performance (UNEP 2007), as well as to guide environmental product policy (European Commission 2003).

LCA is an appropriate framework for measuring impacts of products because it uses a full life cycle perspective, from “cradle-to-grave” thus omitting no product stages during which significant impacts might occur, including all production and consumption stages. This begins with assessing the goal and scope of a product system and continues with an inventory of inputs and emissions by product stage relevant to estimation of impacts which is used to estimate relevant environmental impacts with impact characterization factors developed from impact models. Impacts are all related to a unit of the product serving a particular functional purpose, called a functional unit. These impacts typically measure use of environmental sources (resource use indicators) or stressors on environmental sinks (impact indicators). Impact indicators depict impacts at varying points in the chain of causality from the release of an emission to its ultimate impact (end-point) on primary areas of concern (human health, natural environment, resources, manmade environment), depending upon how evolved the science is for modeling impacts along this chain (Bare et al. 2006).

LCA is arguably the strongest framework for measuring environmental impacts of production activities for the complex, global supply chains typical of modern products. Ness and colleagues (2007) categorized measures of sustainability based on their focus and their temporal aspects. In contrast with techniques such as environmental impacts assessment, which is focused on future activity and is highly-location specific, LCA is primarily focused on current systems (though can be used for design purposes) and is not limited in focus to one particular site. In contrast with sustainability indices (e.g. environmental pressure indicators) which are often retrospective indicators of larger systems, LCA is more product specific. LCA also originates from industrial ecology and

engineering, and its quantification by particular unit processes make LCA results more relevant for product management. In comparison with other systems-oriented approaches such as embodied energy or emergy analysis, LCA is multi-criteria, which provides a broader view of products and makes it less likely that important impacts are overlooked (Ulgiati et al. 2006).

Research Problems in Life Cycle Assessment

The bold intention to use LCA to relate a product to all the damages (or benefits) that occur to the environment over the life cycle of its production, use and disposal depend upon detailed inventories of complex life cycles and accurate models to estimate damages. LCA adapts understandings and models from many other fields to accurately identify and model impacts and thus is only advanced as the science and its application within this fields. LCAs are often limited by incomplete or inappropriate data and absence of relevant impact models. Two focal areas of LCA that specifically need to be addressed to better measure sustainable production and consumption in a manner applicable to global supply chains are 1) resource-use indicators and 2) LCA of non-OECD product systems. These problems and a proposed plan for addressing them are described in the following three sections.

Life Cycle Impact Assessment (LCIA) Indicators for Resource Use

As described above, indicators in LCA may be broadly split into resource use and impact indicators. Resource use indicators may be based on the use of a particular energy source or material (e.g. fossil energy use or freshwater use) or may be an aggregate measure. Futhermore they may focus on relating that use to ultimate availability (e.g. mineral resource depletion) or simply just report usage. Relating different indicators of resource use together may require use of subjective weighting

criteria when there is not a physical basis for relating the resources (Guinée 2002). But the impact of using different resources may be related together without the need for subjective judgment if resources can be characterized on a common physical basis with a common unit, which is instructive for synthesizing the effects of resource use. Various authors have argued for the need to incorporate a unified measure of resource use into LCA to limit resource consumption associated with productive processes (Finnveden 2005; Seager and Theis 2002; Stewart and Weidema 2005).

Single-unit measures of resource use has been developed extensively outside of the LCA framework, although not all of these methods have been applied as indicators in LCA. Common biophysical units may be units of mass, land area, or energy. Life cycle based methods using mass include extensions of material flow analysis (MFA) and closely related methods including ecological rucksack and material inputs per unit service (MIPS) (Brunner and Rechburger 2003; Schmidt-Bleek 1994) In essence, these methods associate a material intensity (g material/g product) to all inputs to a product over the production cycle. They have been applied predominantly in studies of dematerialization of economies (Bartelmus 2003; Matthews et al. 2000; NAS 1999) and have not been formally integrated as an impact method in life cycle assessment. The major weakness of using MFA derived units of mass as a common resource use indicator for a product is the absence of differentiation of the quality of different resource types, as well as the difference in the usage of materials that may render them useless or may not affect their ability to be used in future production processes or by the environment. These weaknesses are pointed out by Van Der Voet et al. (2004).

Area-based measures of resource use either measure solely direct and indirect occupation and transformation of land or also equivalence factors to relate different land use types and symbolic land uses together to measure a broader concept of land requirements (e.g. ecological footprint). Measures of occupation and transformation of land use are commonly employed in LCA (Guinée 2002). A measure that combines all types of land use in a single unit based on their biological capacity is the ecological footprint (Wackernagel et al. 2002). Ecological footprint has been more recently integrated as a resource-use measure in the largest commercial LCA database (Frischknecht and Jungbluth 2007). Indicators of land occupation suffer from numerous shortcomings. Neither direct land use nor the ecological footprint measure below-ground resource use (non-renewable), and neither incorporate the use of hydrologic resources. Furthermore, land-use itself it not expected to become a limiting resource in the future. Although the ecological footprint already shows that total direct and indirect use of the Earth's biocapacity has been exceeded, which is referred to as an ecological deficit (Hails et al. 2008).

Energy-based measures are potentially more comprehensive in their inclusion of resources than land-based and material-based measures. Energy-based measures are derived from the laws of thermodynamics, the first of which states that energy is consumed in every transformation process. Thus every process, both independent of and dependent on humans, involves the consumption of energy, which makes energy an ideal common unit for tracking total resource use (Odum 2007b). Some energy-based resource use measures have already been incorporated into LCA. Energy analysis (Boustead and Hancock 1978), known as cumulative energy demand (CED)

analysis implemented in a life cycle framework (Frischknecht and Jungbluth 2007), measures the total heat energy (enthalpy) in fuel and other energy carrier consumed based on their heating values. CED does not include the contribution of non-energy sources. Surplus energy, part of the Eco-indicator 99 methodology (Goedkoop and Spriensma 2001b) estimates the difference in the amount of energy required to extract resources now versus at a designated point in the future. Surplus energy is also limited to energy sources.

Another thermodynamically-based indicator already integrated into LCA that includes a broader array of resource is *exergy*, which may be defined as a sum of available energies in a material (primarily as pressure, kinetic, physical, chemical) in respect to their difference from reference conditions. Raw resources have high exergy values until processed or transformed at which time there exergy is lost as entropy. These sum of transformations of all inputs into processes in an LCA can be measured with cumulative exergy demand, or CExD (Bösch et al. 2007b). CExD is particularly valuable as a measure of the total thermodynamic efficiency of a process where the goal is to minimize total exergy consumption.

None of the aforementioned energy-based methods account for the energy required by the environment to support and recreate the resource basis of economies; they only account for energy consumed in existing resources. Thus a critical first link in the chain of resource provision (environment to resource) is missing in how resource use is accounting for in product life cycles. Tracking this first link, however, *is* possible using the emergy method to relate all resources on the basis of sunlight energy. Emergy is an energy accounting metric that may be defined as the total direct and

indirect energy used to support a system measured in a common unit of energy – conventionally sunlight equivalents (Odum 1996). The origins of all resources, both renewable and non-renewable, can all be directly or indirectly traced back to the primary energy driving the biosphere, sunlight, and can thus be tracked in units of energy of this type. Thus it becomes a biophysically legitimate way of combining different forms of resources in a common measurement unit.

Emergy evaluation is an independently developed methodology for measuring the environmental performance of an ecosystem or human-dominated system, which has also been applied to evaluating product systems. Emergy has been used in conjunction with LCA as part of a comparative or multi-criteria approach (Cherubini 2008; Pizzigallo et al. 2008). Emergy has been adapted for use in economic-based input-output LCA by Bhakshi and collegues, who define emergy as an extension of exergy called ecological exergy (Hau and Bakshi 2004b) and have used it as a measure of the contribution of ecosystem processes to sectors of the US economy (Ukidwe and Bakshi 2004a) and to evaluate individual products (Baral and Bakshi 2010). Nevertheless emergy has not been integrated into traditional process-LCA in such a manner that it can be used in conjunction with traditional life cycle inventory databases and in comparison with other LCA metrics.

A measure of the ultimate limitations that the biosphere imposes upon economic processes must relate these processes to the energetic limits of the biosphere (Odum 2007a). While such a broad concept may not highlight the scarcity of particular resources, it does provide a sufficiently wide context through which to compare any and all products with our planetary resource base; in doing so it can provide insight into

absolute sustainability of economic processes in the long-term. Emergy (in sunlight energy equivalents) can be used to measure contribution of all forms of resources and environmental processes to a product and report them with a common unit relates each resource back to the energy consumed in its origin, and as such is an optimal numeraire for measuring total resource use per unit of the product. Further clarifying the rationale for integrating emergy into LCA a measure of total resource use and as demonstrating the means of integrating emergy into a complex process-LCA typical of high volume products is a primary objective of this dissertation.

An implicit requirement for integrating emergy or any other impact metric into LCA is to quantify the uncertainty in the impact model. It has been recognized among the LCA community that the data and models used to represent complex product life cycles potentially have a significant amount of variation and uncertainty (Fava et al. 1994). Reporting average scores for products can at times be misleading to the degree of accuracy occurring. Better estimation of uncertainty in these scores is a current priority in the LCA field (Reap et al. 2008).

Uncertainty characterization should include uncertainty in model parameters, uncertainty to represent variation among different geographic, technological or other production scenarios that may be unknown, and uncertainty built into the actual impact models themselves (Lloyd and Ries 2007). When emergy is incorporated into LCA as an impact model, this should therefore include the additional model uncertainty that is added when unit emergy values (UEVs) are used to relate inputs to processes to the emergy that was used to make them.

In the practice of emergy evaluation, emergy results are not typically presented with uncertainty ranges. The originator of the emergy concept, H.T. Odum, believed that an emergy result was accurate within an order of magnitude (Brown 2009). The lack of a more clearly defined and systematic manner of characterizing the accuracy of emergy results has been a criticism of emergy work for decades (Rydburg 2010). A couple notable first attempts at characterizing uncertainty in specific UEVs were performed by Campbell (2001) and Cohen (2001). Campbell estimated the uncertainty in the transformity of global rainfall and river chemical potential based on differences in estimated global water flows. Cohen (2001) used a stochastic simulation technique to generate confidence envelopes for UEVs of various soil parameters. Both of these approaches were first-order attempts for estimating ranges of specific emergy values, but did not fully characterize this uncertainty or propose methods of propagating this uncertainty for use in future evaluations. A model for estimating uncertainty in emergy results would be useful for estimating ranges in emergy results within emergy and beyond for the estimation of the additional uncertainty related to emergy models in life cycle results that use emergy as a unit of measurement.

Applications of LCA for non-OECD country exports

LCA studies have predominantly been conducted on product systems located in the United States, EU countries, Canada, Japan, and Australia and other member of the Organization for Economic and Co-operation and Development (OECD) (Thiesen et al. 2007). As a result there has been a geographic-bias in the development of all aspects of LCA, including product system inventories, selection of impact categories, and LCA impact models. This bias has resulted in two primary deficiencies in LCA: (1) production in non-OECD countries is less well characterized and has a lesser capacity

to use life cycle management; and (2) consumption in OECD countries of non-OECD origin products are generally less well characterized than production within OECD countries. Unless this gap in life cycle management capacity is closed, increasing environmental demands on producers could marginalize non-OECD country producers with lesser capacity (Sonnemann and de Leeuw 2006). Expanding the scope of LCA to incorporate more global analysis including for products from non-OECDs is now a priority in the current phase of the UNEP-SETAC Life Cycle Initiative (UNEP Life Cycle Initiative 2007).

Export of products to OECD countries plays a significant role in the economy of many non-OECD countries. For those in Latin America and Africa, these exports are largely from the primary sectors, which include fuels, agricultural products, and minerals (Zhang et al. 2010). Mineral and agricultural sectors are both responsible for many direct environmental impacts that are site-specific, because they generally require significant transformation of the land and emissions occur often in a diffuse manner in an open environment at the site. As a result, both mineral and agricultural environmental impacts are less easily characterized than impacts from more enclosed processes with less direct interaction with the local environment (more concentrated and controlled emissions).

Characterization of diffuse emissions and related impacts in mining and agriculture often use models that account for the local environmental factors that influence emissions and their potency at production sites (spatial and temporal specificity). There have been calls for greater regionalization of impact methods in both the mining (Yellishetty et al. 2009) and agricultural sectors (Gaillard and Nemecek

2009). In agricultural systems, regional factors effect emissions and their impacts included emissions such as fertilizer derivatives and pesticides and impact emissions including eutrophication, acidification, and global warming. Local factors also effect emissions that have just recently begun to be characterized in LCA, including water loss (Pfister et al. 2009). Improvements in regional characterization can have dramatic effects on LCA outcomes.

Not all relevant environmental impacts from agricultural systems have been characterized in LCA. Two that the UNEP taskforce has identified as extremely relevant, particularly in non-OECD countries, are biodiversity impacts and soil erosion (Jolliet et al. 2003b). Models to estimate impacts from biodiversity are very much in their infancy, while some have been proposed (e.g. Maia de Souza et al. 2009; Schenck and Vickerman 2001). Erosion is the most significant cause of land degradation globally (Gobin et al. 2003). Soil erosion has not frequently been characterized in LCA, but universal methods for estimating soil erosion based on geographic, climatic, soil and management factors do exist. The most commonly applied measure of soil erosion is probably the Universal Soil Loss Equation (USLE) and its more recent developments, the Revised Universal Soil Loss Equation (RUSLE) and most recently, RUSLE2 (Foster et al. 2008). Soil erosion has in a rarely been used in LCA , and has not been customized for use in LCA of non-OECD countries, many of which have humid tropical environments, where because of heavy rainfall erosion risks can be much greater (Lal 1983).

Without a strong demand on the part of buyers or regulation imposed by governments, there is not a strong incentive to use LCA in non-OECD countries

(Sonnemann and de Leeuw 2006). However, because of the emerging life cycle perspective in countries where non-OECD exports are consumed, many of which are OECD countries, the demand for use of LCA to measure environmental performance may come from the consumers. Yet, there needs to be a standardized mechanism through which the LCA results can be conveyed to the consumers in a way that they can use this information to inform decision making. One solution is to present this LCA-based environmental performance information in the form of a product label. A Type III environmental label or environmental product declaration (EPD), as defined by ISO 14025, is designed for this purpose (ISO 2006b). EPDs are designed to convey information on product function and production of the product, and relate this information to environmental performance in a manner that one product can be compared with another product in the same category. Product category rules (PCRs) have to be specified so that results presented in EPDs are comparable. The ISO 14025 standard recommends that PCRs be based on at least one background assessment of a product, so that the product life cycle can be characterized and relevant impacts determined. This aspect of PCRs present a challenge for product systems in developing countries, because often little life cycle data and or LCA analysis of these systems exist. Another potential barrier to use of EPDs that applies not only to non-OECD countries was identified by Christiansen et al. (2006) and regards the interpretation of EPDs. These authors note that LCA data presented in EPDs are often not readily meaningful without reference to the relative performance of other products in the category. This shortcoming of EPDs is another important issue to address to make LCA more relevant for non-OECD product systems.

Research Overview

Three independent studies addressing the research problems described comprise this dissertation. The *first* study proposes a means to integrate emergy as a life cycle assessment indicator to provide a measure of long-term sustainability in LCA. This study uses the case of the Yanacocha gold mine in northern Peru. A detailed process-based life cycle assessment is carried out to track the emergy in all direct and indirect inputs to the mining process, including in the ore itself. Methods of associating emergy values with inventory data and calculating results with emergy in LCA are described. Comparisons of emergy results are made with a commonly used measure of life cycle energy requirement, or cumulative energy demand. Following presentation of these results, their potential value in the regional context and the broader value of emergy results for LCA are discussed, along with remaining questions and problems with this integration.

The problem of statistically describing the confidence of emergy results leads directly into the research needs addressed in the *second* study: estimating the uncertainty of emergy values. In this study, sources of uncertainty in emergy are explored and the likely forms of probability distributions of different types of emergy calculations are suggested. The description of the sources and forms of uncertainty lead to the proposal for a model for describing uncertainty in emergy, and two alternative procedures for estimating confidence intervals of emergy values are described. This study proceeds with an evaluation of the accuracy of the proposed model and a proposes a means of integrating confidence intervals into the tables commonly used to present emergy results.

The *third* study shifts to addressing the problems associated with broad characterization and application of life cycle assessment for poorly characterized or data-poor product categories in regions where existing regionalized emissions and impacts models are not appropriate. A multi-criteria process-LCA is conducted of fresh pineapple for export in Costa Rica (not previously characterized with LCA), based on data from a representative sample of pineapple producers. Existing universally-applicable emissions and inventory models are customized to better characterize environmental impacts. An original method for characterizing soil erosion is addressed. Variation and uncertainty in inputs and emissions among the participating producers are used to estimate the range of environmental performance in the sector for each impact category. This LCA is furthermore designed to contribute to creating the rules for an environmental product declaration in a manner applicable for uncharacterized product categories.

CHAPTER 2

EMERGY AS AN IMPACT ASSESSMENT METHOD FOR LIFE CYCLE ASSESSMENT PRESENTED IN A GOLD MINING CASE STUDY

Introduction

LCA is an established and widely-utilized approach to evaluating environmental burdens associated with production activities. Emergy synthesis has been used for similar ends, although in an emergy synthesis one tracks a single, all encompassing environmental aspect, a measure of embodied energy (Odum 1996). While each is a developed methodology of environmental accounting, they are not mutually exclusive.

Emergy in the LCA Context

LCA is a flexible framework that continues to grow to integrate new and revised indicators of impact, as determined by their relevance to the LCA purpose and the scientific validity of the indicator sets (ISO 2006d). Other thermodynamically-based methods, such as exergy, have been integrated into LCA (Ayres et al. 1998; Bösch et al. 2007a). Emergy synthesis offers original information about the relationship between a product or process and the environment, not captured by existing LCA indicators, particularly relevant to resource use and long-term sustainability, which could be valuable for LCA. However there are differences in the conventions, systems boundaries and allocation rules between emergy and LCA, which require adjustments from the conventional application of emergy, to achieve a consistent integration.

From the perspective of the LCA practitioner, the first questions regarding use of emergy would be those of its utility. Why would one select emergy, in lieu of or in addition to other indicators of environmental impact? For what purposes defined for an LCA study would emergy be an appropriate metric? Assuming the inclusion of emergy

as an indicator, what would be necessary for its integration into the LCA framework? This paper briefly describes the utility of emergy, and through a case study evaluation of a gold mining operation at Yanacocha, Peru, presents one example of how emergy can be used in an LCA framework. Finally, the theoretical and technical challenges posed by integration are discussed.

In reference to the first question, these four key points provide a theoretical justification for the use of emergy in LCA:

1. **Emergy offers the most extensive measure of energy requirements**. System boundaries in a cradle to gate LCA typically begin with an initial unit process in which a raw material is acquired (e.g. extraction), and would include raw materials entering into that process, but would not include any information on the environmental processes[1] creating those raw materials. Emergy traces energy inputs back further into the life cycle than any other thermodynamic method, summing life cycle energy inputs using the common denominator of the solar energy directly and indirectly driving all biosphere processes (Figure 1).[2] Other thermodynamic methods including exergy do not include energy requirements underlying environmental processes (Ukidwe and Bakshi 2004b).

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[1] All references to 'environmental processes' and 'environmental flows' in this paper refer to solar, geologic, and hydrologic flows that sustain both ecosystems and human-dominated systems. This is the essence of what is meant here by 'environmental contribution'.

[2] For example, growing corn requires the solar energy necessary to support photosynthesis of the corn plant. This includes all the solar energy falling on the corn field, not just the amount the corn used to fix CO2. Furthermore growing corn requires fossil inputs among others, all of which were originally created with solar energy, and thus which are included in emergy analysis.

2. **Emergy approximates the work of the environment to replace what is used**. When a resource is consumed in a production process, more energy is required to regenerate or replenish that resource. The emergy of a resource is this energy required to make it including work of the environment, and assuming equivalent conditions; this *is* the energy that is takes to replenish it. Sustainability ultimately requires that inputs and outputs to the biosphere or its subsystems balance out (Gallopin 2003). As the only measure that relates products to energy inputs into the biosphere required to create them, emergy relates consumption to ultimate limits in the biosphere, by quantifying the additional work it would require from nature to replace the consumed resources.
3. **Emergy presents a unified measure of resource use**. Comparing the impacts of use of biotic vs. abiotic resources, or renewable vs. non-renewable resources, typically necessitates some sort of weighting scheme for comparison.[3] Because there is less agreement upon characterization of biotic resources, these may not be included despite their potential relevance (Guinée 2002). Using emergy, abiotic and biotic resources are both included and measured with the same units. As follows from its nature as a unified indicator, one which characterizes inputs with a single methodology to relate them with one unit (emergy uses sejs, or solar emjoules, which are sunlight-equivalent joules), no weighting scheme is necessary to join different forms of resources (e.g. renewable and non-renewable; fuels and minerals) to interpret the results.

[3] In the IMPACT 2002+, and Eco-indicator 99 methodologies, use of non-renewable resources is included in the damage categories of resources but renewable resources are omitted (Goedkoop and Spriensma 2001a; Jolliet et al. 2003a)

The choice of measures of impact in an LCA follow from the goal and scope of the study (ISO 2006d). Emergy analyses have been used for a multitude of LCA-related purposes, including to measure cumulative energy consumption (Federici et al. 2008), to compare environmental performance of process alternatives (La Rosa et al. 2008), to create indices for measuring sustainability (Brown and Ulgiati 1997), to quantify the resource base of ecosystems (Tilley 2003), to measure environmental carrying capacity (Cuadra and Björklund 2007) and for non-market based valuation (Odum and Odum 2000). The incorporation of emergy in LCA could potentially enhance the ability of LCA studies to achieve these same and other purposes.

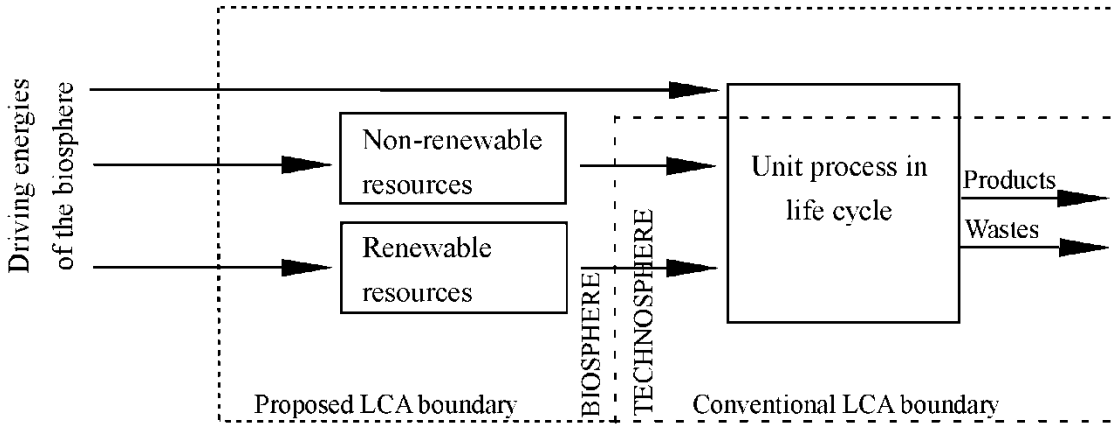

Figure 2-1. Proposed boundary expansion of LCA with emergy. Driving energies include sunlight, rain, wind, deep heat, tidal flow, etc.

This was not the first study to attempt to combine emergy and life cycle assessment. Earlier studies focused on contrasting the two approaches (Pizzigallo et al. 2008) or extending emergy to include disposal and recycling processes (Brown and Buranakarn 2003). The most comprehensive approaches probably include the Eco-LCA and SUMMA models. Although referred to as ecological cumulative exergy consumption (ECEC) rather than emergy due some slight modifications to emergy

algebra, the Eco-LCA model is an EIO-LCA model which uses emergy as an impact indicator (Urban and Bakshi 2009). The SUMMA model is a multi-criterion analysis tool which uses emergy as one measure of “upstream” impact which it combines with other measures of downstream impact (Ulgiati et al. 2006). A similar multi-criteria approach using MFA, embodied energy, exergy and emergy is used by Cherubini et al. (Cherubini et al. 2008).

In contrast with these previous studies, this study uses a more conventional process LCA approach through using an common industry software (SimaPro) and attempts to integrate emergy as an indicator within that framework as specified by the ISO 14040/44 standards, which results in adjustments to the conventional emergy methodology. This is also the first study to use emergy in a detailed process LCA where flows are tracked at a unit process level. Results from the study, addressed in the discussion, reveal insights for which emergy is suggested to be a useful metric for LCA.

A Case Study of Emergy in an LCA of Gold-Silver Bullion Production

Metals and their related mining and metallurgical processes have been a frequent subject of LCA and other studies using approaches from industrial ecology (e.g. Yellishetty et al. 2009 and Dubriel 2005), which is reflective of the critical dependence of society upon metals, as well as an acknowledgement of the potential environmental consequences of their life cycles. While these studies have addressed both downstream and upstream impacts, including resource consumption, none have used tools capable of connecting the product system to the environmental processes providing for the raw resources they require (especially because they are largely nonrenewable). An LCA is presented here of a gold-silver mining operation that uses

emergy to quantify the dependence on environmental flows. In this case study, the primary purpose could be succinctly stated as follows:

To quantify the total environmental contribution underlying production of gold-silver bullion at the Yanacocha mine in Peru.[4]

Total *environmental contribution* includes the total work required by the environment (biosphere) and the human-dominated systems it supports (technosphere) to provide for that product. As impacts in LCA are categorized as resource-related (referring to upstream impacts) or pollution-related (referring to downstream impacts) (Bare et al. 2003), environmental contribution would be categorized with the former.

The scope of this study, following from this goal, extends from the formation of the gold deposit (representing the work of the environment) to the production of the semi-refined doré, a bar of mixed gold and silver.[5] Emergy is chosen as the measure of environmental contribution, to be tracked over this 'cradle to gate' study, and to be the basis of the indicator of impact of mining. Energy is commonly used in LCA to track the total energy supplied to drive processes in an industrial life cycle. Yet the interest here is in how much work was done in both environmental systems *and* human-dominated systems to provide for it (point 2), which is not measured by just considering available energy used by energy carriers (e.g. cumulative energy demand) or by summing all available energy (exergy) in all the inputs (point 1). Additionally the energy from the

[4] The Yanacocha mine is one of the largest gold mines (in terms of production) in the world. The mine produced 3.3275 million ounces in 2005 (Buenaventura Mining Company Inc. 2006). This represented more than 40% of Peruvian production (Peruvian Ministry of Energy and Mines 2006) and approximately 3.8% of the world's gold supply in 2005, assuming 100% recovery of gold from doré and using the total of 2467 tonnes reported by the World Gold Council (2006).

[5] The system and inventory are described in detail in the appendix 'Life Cycle Inventory of Gold Mined at Yanacocha, Peru – Description'.

environment to provide for non-energy resources (materials) is part of the environmental contribution (point 2), so all need to be tracked. However, in order to directly compare the environmental contribution underlying each resource input together with the others contributing to a unit process of mining operation, the contribution should be tracked with a single indicator, for which emergy serves as this indicator here (point 3).

Using emergy allows for the introduction of more specific questions which, when used in an LCA context, are answerable where they are traditionally not in an emergy evaluation, which lumps all inputs into a single system process. The ability to track unit processes from the biosphere together with unit processes in the technosphere enables one to ask:

Is there more environmental contribution underlying the formation of the gold or the combined mining processes?

as well the more familiar (to LCA) comparisons of inputs and unit processes in the product system:

Which unit process(es) are the most intensive in terms of environmental contribution? Which inputs are responsible for this?

To address long-term sustainability, the activity surrounding this life cycle can be put in context of available resources; more specifically:

How does this relate to the availability of energy driving environmental processes in this region?

LCA results should be presented with accompanying uncertainty quantified to the extent feasible (ISO 2006c). To fit in the LCA framework, emergy results also need to

be presented with uncertainty estimations to explain the accuracy with which environmental contribution can be predicted.

Gold and silver are co-products, which may be mined separately and which have independent end-uses, so comparison of this life cycle data with alternative production routes or for end-use requires allocating environmental contribution between them, as well as between mercury, which is naturally associated with the ore body, separated during the refining stage and sold as a by-product.

This LCA is not comparative, because no other alternative solutions for providing the gold are being evaluated. Nevertheless with a universal measure of impact that does not require normalization or weighting (point 4), results can be compared with alternative product systems for which emergy evaluation has been done, if the boundaries and allocation rules for these alternative products are comparable, or put in the context of other relevant emergy flows, such as those supporting ecosystems or economic systems in the same region.

Methodology

The functional unit chosen for the study is 1 g of doré (gold-silver bullion) at the mine gate, consisting of 43.4% gold and 56.6% silver. For comparison with other gold, silver, and mercury products, results are also reported in relation to 1 g of gold, 1 g of silver, and 1 g of mercury. The inventory for these products was based on the average of annual production in 2005, the most recent year for which all necessary data were available. Annual production was reported by one of the mine partners (Buenaventura

Mining Company Inc. 2006). The total production for this year was approximately 9.40E+04[6] kg of gold and 1.23E+05 kg of silver combined as gold-silver bullion, or doré.

A process-based inventory was completed in accordance with the ISO 14040 series standards (ISO 2006a, 2006b) and included direct inputs from the environment (elementary flows), capital and nondurable goods, fuels, electricity, and transportation, along with inputs not traditionally or commonly accounted for, including the geologic contribution to mineral formation. Nine unit processes representing process stages were defined, and inputs were tracked by unit process (Figure 2-2). These were divided into background processes (deposit formation, exploration, and mine infrastructure), production processes (extraction, leaching, and processing), and auxiliary processes (water treatment, sediment control, and reclamation). A description of the inventory calculations and results is in the supplemental material.

[6] "xE+y" is the form of scientific notation used throughout this document to represent "x times 10 to the y power".

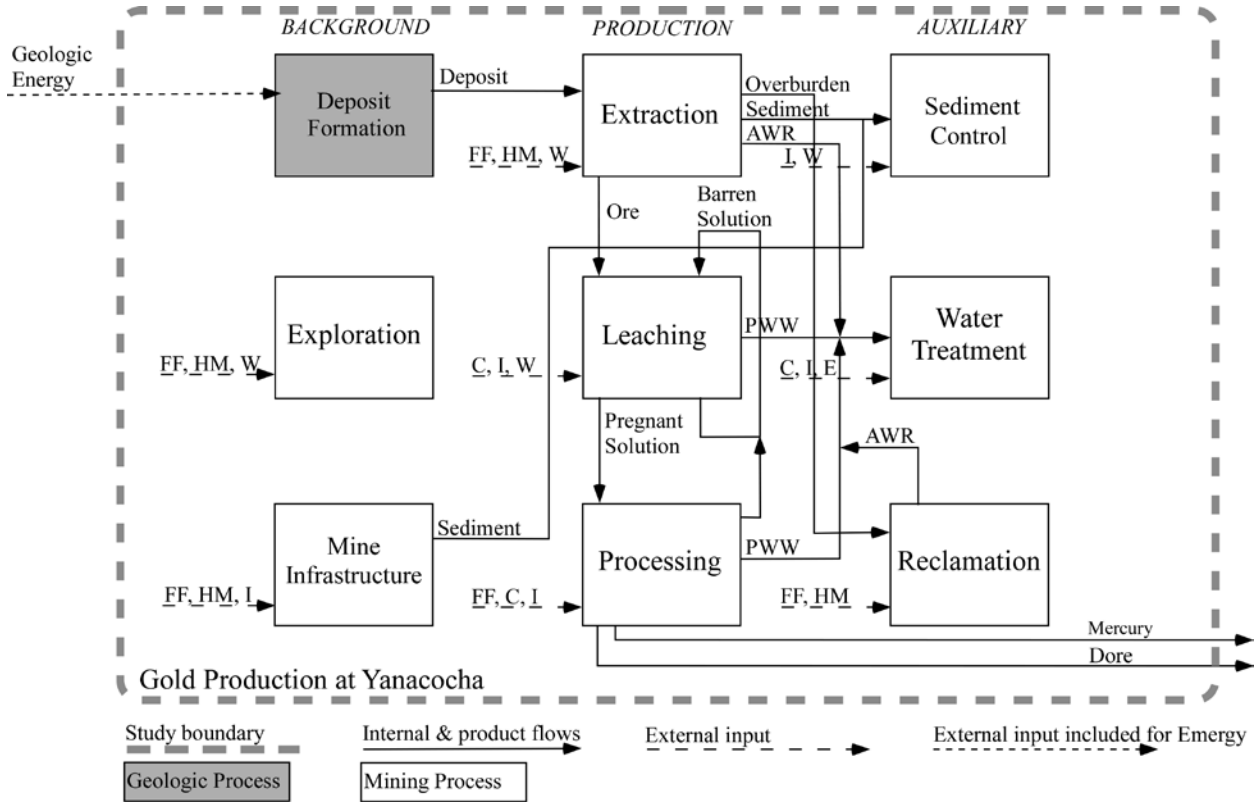

Figure 2-2. Gold production system at Yanacocha with modeled flows and unit processes. FF = fossil fuels, HM = heavy machinery, I = infrastructure, C = chemicals, W= precipitation and pumped water, E = electricity, AWR = acid water runoff, PWW = process wastewater.

Emergy and Energy Calculations

All inputs were converted into emergy values either via original emergy calculations or by using previously calculated unit emergy values which relate input flows in the inventory to emergy values (Odum 1996). An inventory cutoff for inputs consisting of 99% of the emergy for the process was declared, to be as comprehensive as possible without including all minor inputs. As the emergy of some inputs was not readily estimated prior to the inventory collection, these inputs were by default included and, even if determined to contribute less than 1% of the total emergy, were kept in the inventory.

The geologic emergy of gold, silver, and mercury (representing the work of the environment in the placement of mineable deposits) were estimated using the method of Cohen et al. (2008), who proposed a new universal model for estimating emergy in elemental metals in the ground, based on an enrichment ratio of the element, which can be described in the form:

$$UEV_i = ER_i * 1.68E+09 \text{ sej/g} \qquad (1)$$

where UEV is the unit emergy value (sej/g) for this element in the ground, ER is the enrichment ratio, and *i* denotes a particular element. The ER can be estimated with the following equation:

$$ER_i = OGC_i/CC_i \qquad (2)$$

where OGC is the ore grade cutoff of element *i*, which is the current minimal mineable concentration, and CC is the crustal background concentration of that element. This model assumes that ores with greater concentrations of metals require greater geologic work to form, without attempting to mechanistically model the diverse and random geological processes at work, conferring a general advantage of consistent and comparable emergy estimations for all mined metals. This universal method provides average UEVs for a particular metal in the ground, but was adapted here using the specific concentrations of gold, silver, and mercury at Yanacocha in place of the OGC for those elements.

Original emergy calculations were necessary for a number of mining inputs, including mine vehicles, chemicals, mine infrastructure, and transportation. When available, data on these inputs was adapted from a commercial life cycle inventory database, Ecoinvent v2.0 (Ecoinvent Centre 2007), and copied into a new process.

Inputs for these processes were replaced by processes carrying UEVs calculated from previously published emergy analyses. When the processes were adapted from Ecoinvent, emissions, infrastructure, and transportation data were not included, the latter of which was decided to be inappropriate for the mine location and calculated independently or estimated to be insignificant. For chemicals not available in Ecoinvent, synthesis processes were based on stochiometry found in literature references, and primary material inputs as well as energy sources were included. Emergy in overseas shipping and transportation within Peru of inputs was estimated for all materials comprising 99% of the total mass of inputs to the process.

The global baseline (estimate of emergy driving a planet and basis of all emergy estimates) of 15.83E+24 sej/yr was used for all original UEV calculations (Odum et al. 2000) and for updates of all existing UEVs calculated in other studies. When available, existing UEVs were incorporated without labor or services, to be consistent with the Ecoinvent data used which do not include labor inputs to processes. For comparison with emergy values, primary energy was estimated by summing the total energy content of fossil fuels and electricity consumed on site using energy values from the Cumulative Energy Demand characterization method as implemented in SimaPro (Frischknecht and Jungbluth 2007).

Uncertainty Modeling

Uncertainty was present at the inventory level (e.g. inputs to mining) and for the unit emergy values (the UEVs) used to convert that data into emergy. Uncertainty data for both direct inputs and UEV values (existing and original) were included in the life cycle model. Quantities of direct inputs to one of the nine unit processes were assigned a range of uncertainty based upon the same model defined for the Ecoinvent database

(Frischknecht et al. 2007). This model assumes data fit a log-normal distribution. Using this model, the geometric variance, was estimated for each input. Calculations of uncertainty ranges for the UEVs for inputs to the process were estimated based on a UEV uncertainty model (Ingwersen 2010). This model produces 95% confidence intervals for UEVs also based on a lognormal distribution, and is described in the form of the geometric mean (median) times/divided by the geometric variance, abbreviated in the following form:

$$\mu_{geo} \ (\times\div) \ \sigma^2_{geo} \qquad (3)$$

where μ_{geo} is the geometric mean or median and σ^2_{geo} is the geometric variance. The bounds of the 95% confidence interval are defined such that the lower bound is equal to the median divided by the geometric variance, and the upper bound is the median multiplied by the geometric variance. Original uncertainty estimations based on the analytical method (Ingwersen 2010) were performed for gold and silver in the ground.

Allocation

Two allocation approaches were adopted: the co-product rule often used in emergy analysis and a by-product economic allocation rule used when applicable in LCA. The co-product rule assumes that each product, in these case gold silver, and mercury, each require the total emergy of the mining processes for their production, and therefore the total mining emergy is allocated to each. Economic allocation is one method in LCA in which an environmental impact is divided among multiple products. Economic allocation was selected here in preference to allocation by mass because it most closely reflects the motivations of co-product metal producers (Weidema and Norris 2002). In this case, revenue from production was used to allocate environmental contribution, by determining the market value of the gold contained in the doré as a

percent of the total value of doré and mercury production. The resulting percentage was used as the percentage of total mining emergy allocated to gold. The same method was applied for silver and mercury. In both cases, geologic emergy was allocated to each product separately, since the model used for estimating geologic emergy in the products was element-specific.

Data Management and Tools

All inventory data was stored in SimaPro 7.1 life cycle analysis software (PRé Consultants 2008a). A new process was created for each input. Emergy was entered as a 'substance' in the substance library, and a new unit 'sej' was defined in the unit library and given the equivalent of 1 Joule.[7] This unit was assigned to the emergy substance. When existing UEVs were relied on (e.g. for refined oil), a 'system' process was created, for which emergy was the only input. A quantity of emergy in sejs was assigned to the output that corresponded with the unit emergy value (sej/g, sej/J, etc.). For inputs for which UEV values did not exist or were not appropriate, 'unit' processes were created that consisted of one or more system processes or other unit processes.[8] A new impact method was defined to sum life cycle emergy of all inputs to a process. To characterize total uncertainty (both input and UEV uncertainty) in the emergy of the mining products, Monte Carlo simulations of 1,000 iterations were run in SimaPro for estimates of confidence intervals of emergy in the products using both emergy co-product and economic allocation rules.

[7] For purposed of functionality in SimaPro – the integrity of the emergy algebra was not affected.

[8] 'Unit' processes as defined here correspond to the SimaPro definition, not to the unit processes defined earlier as one of the nine phases of mining.

Results

Environmental Contribution to Gold, Silver, and Mercury in the Ground

The enrichment ratio of gold was estimated as 218.8:1, based on a reported gold concentration of 0.87 ppm (Buenaventura Mining Company Inc. 2006) and a crustal background concentration of 4 ppb (Butterman and Amey 2005), which using Eq. 1 resulted in an unit emergy value for gold in the ground of 3.65E+11 sej/g. The silver concentration at the mine was not reported, but was estimated based on the silver in the product and a calculated recovery rate of gold (81.52%) to be 1.13 ppm. Using the background concentration of 0.075 ppm (Butterman and Hilliard 2004), the enrichment ratio of silver was estimated as 15.1:1, which resulted in an estimate of the UEV of silver in the ground at Yanacocha to be 1.54E+10 sej/g. The emergy of mercury in the ground was estimated to be 1.71E11 sej/g based on concentration at the mine of 8.6 ppm (Stratus Consulting 2003) and a crustal background concentration of .085 ppm (Ehrlich and Newman 2008). The total emergy in the amount of gold extracted and transformed into doré in 2005, just including the geologic contribution to gold in the ground, was 8.55E+18 (x÷) 10.7 sej (median times or divided by the geometric variance, as in Eq. 3).

Environmental Contribution to Doré

Table 2-1 shows the results of the total emergy in the mining products including for the doré, the gold and silver separately, and the mercury by-product. The total emergy in the all life cycle stages contributing to 1 g of doré was approximately 6.8E+12 sej, with an approximate confidence interval of 6.2E+12 (x÷) 2.0. Considering estimated uncertainty both in the inventory data and in the unit emergy values, the emergy in doré could with 95% confidence be predicted to be as low as 4.4 E+12 sej/g and as high as

1.3E+13 sej/g, representing an approximate range of a factor of two around the median value.

As a portion of the contribution to the total emergy in the doré, the geologic emergy in deposit formation contributes approximately 3% (Figure 2-3), but could be as high as 7% if the highest value in the range is used. The largest contributors to the total emergy of the doré include chemicals (42%) followed by fossil fuels (32%), and electricity (14%). Capital goods (mine infrastructure and heavy equipment) contribute 5%.

Table 2-1. Summary of emergy in mine products based on two allocation rules. All units are in sej/g.

Product	Geologic Emergy	Mining Emergy	Mining Allocation %	Total Emergy	95% Confidence Interval		
Emergy based on co-product allocation							
Doré	1.7E+11	6.6E+12	100%	6.8E+12	4.4E+12	-	1.3E+13
Gold in doré	3.7E+11	1.5E+13	100%	1.6E+13	1.0E+13	-	2.7E+13
Silver in doré	2.5E+10	1.2E+13	100%	1.2E+13	7.5E+12	-	2.2E+13
Mercury	1.7E+11	2.4E+13	100%	2.4E+13	1.6E+13	-	4.5E+13
Emergy based on economic allocation[1]							
Doré	1.7E+11	6.6E+12	99.90%	6.8E+12	4.4E+12	-	1.3E+13
Gold in doré	3.7E+11	1.5E+13	97.31%	1.5E+13	9.9E+12	-	2.5E+13
Silver in doré	2.5E+10	3.0E+11	2.61%	3.3E+11	2.2E+11	-	5.4E+11
Mercury	1.7E+11	2.0E+10	0.08%	1.9E+11	1.8E+11	-	2.1E+11

1 Based on 2005 Au and Ag price received of $12.69/g and $0.26/g (Buenaventura 2006); Hg market price of $0.02/g (Metalprices.com)

Relative emergy contribution of inputs is not well associated with input mass because of differences in the unit emergy values of inputs to the process. Chemicals used in the process illustrate this difference. A minor input by mass used in the

processing stage, lead acetate, contributed more emergy than did lime, whose mass input was 267 times greater.

Figure 2-3. Environmental contribution (emergy) to doré by input type.

Emergy by Unit Process

Breaking down the life cycle of a product into unit processes is not typically done in emergy analysis, but is a common step of interpretation in a life cycle assessment. Analyzing process contribution can help target where in the life cycle environmental burdens are greatest. Figure 2-4 shows the breakdown of emergy and primary energy by mining unit process.

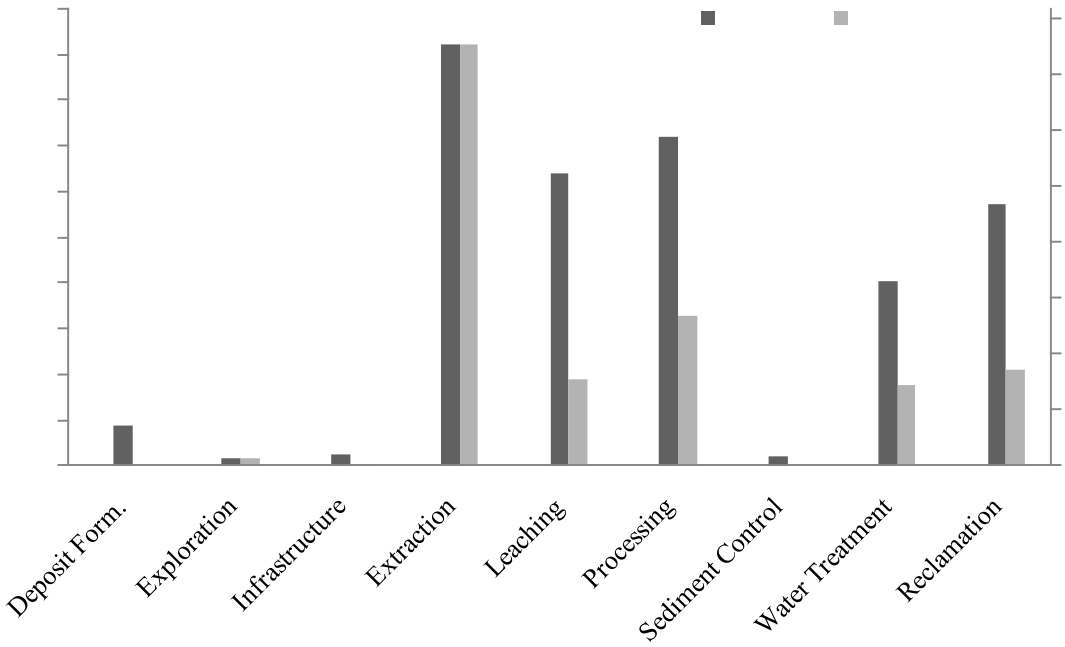

Figure 2-4. Emergy and primary energy in 1 g of doré by unit process. Primary energy is depicted on a second axis which is adjusted so that emergy and primary energy in extraction appear the same so relative contribution of each to processes can be depicted.

The largest environmental contribution comes from the extraction process. Extraction emergy is dominated by diesel fuel consumed by mine vehicles. The other production processes are chemically-intensive processes. Together the production processes represent 67% of the total emergy. Controlling for pollution to air, water and soil, which is the objective of the auxiliary processes, contribute about 30% of the total emergy. Background processes contribute little (<4%) to the emergy in the doré.

Figure 2-4 reveals differences in the absolute and relative contributions to processes as indicated by emergy and primary energy. First, the emergy for each process is six orders of magnitude greater than the primary energy in each process. Additionally the contributions of the non-extraction processes are relatively greater when measured in emergy than when measured with primary energy. Primary energy

reveals no use of energy in the deposit formation process, and relatively less energy in processes that are more chemically and materially intensive.

Allocation and Emergy Uncertainty

Table 2-1 presents the differences in the gold, silver, and mercury UEVs according to the two different allocation rules used. Because of its high value, under the economic allocation rule the gold product is allocated 97.3% of the emergy, which results in a similar UEV to that calculated under the co-product scheme, where it is allocated 100%. The big difference appears in the calculations of the UEVs for silver and mercury (3E+11 and 1.9E11 sej/g), since they are allocated small portions of the total emergy (2.61% and 0.08%) This reduces the silver UEV to 2.8% of the co-product value, and reduces the mercury UEV to only 0.8% of the co-product value.

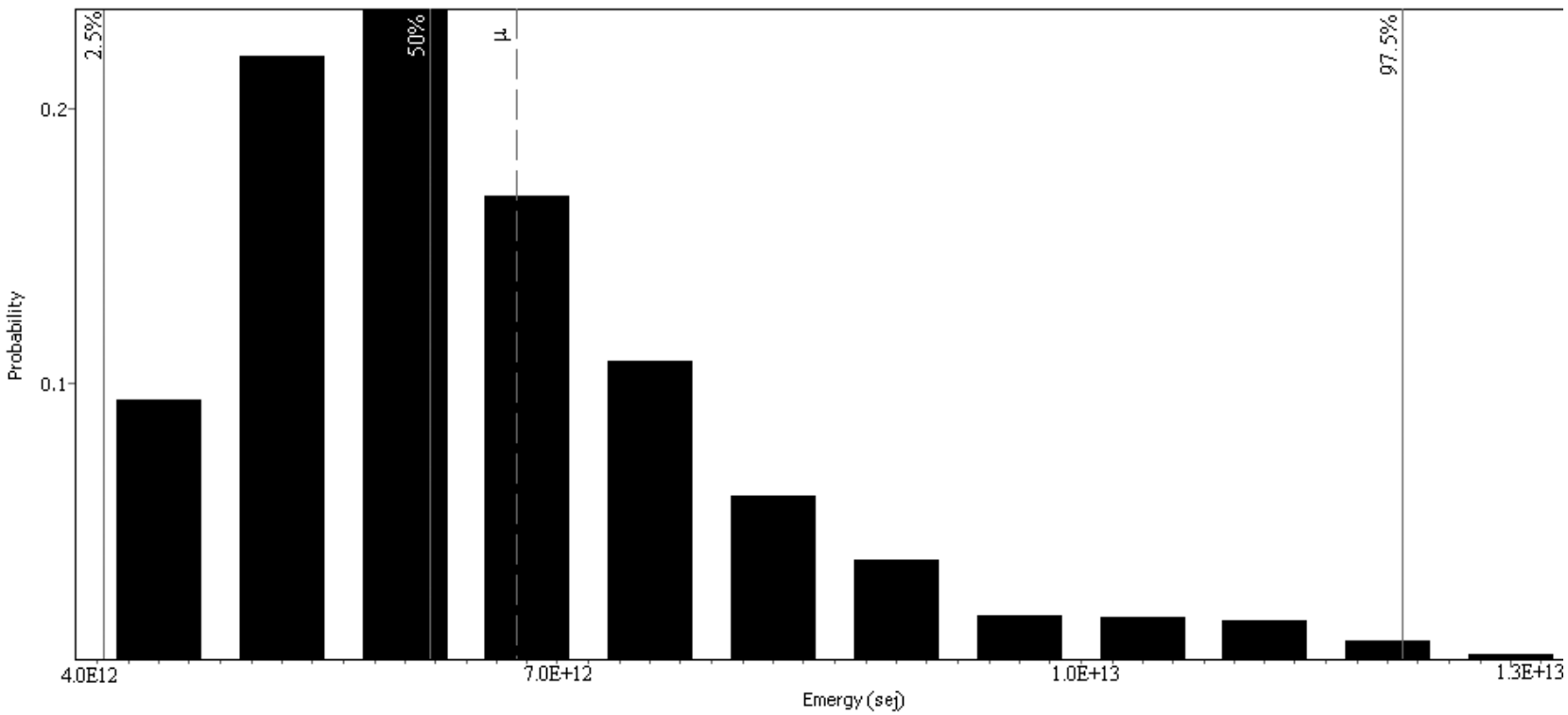

Figure 2-5. Monte Carlo analysis of 1 g of doré, showing the tails and center of the 95% CI, along with the mean (dashed line).

Uncertainties in process inputs ranged based on uncertainty in the inventory data, but primarily due to the uncertainty of the UEVs.[9] The inputs with greatest range of UEV values are the minerals and inorganic chemicals which are mineral based (see ranges in Table 2 of supplement 1). In comparison, uncertainty σ^2_{geo} values were between 1 and 1.5 for most inputs in the inventory. Figure 2-5 shows the results of the Monte Carlo analysis of the emergy in 1 g of doré, illustrating the resulting uncertainty range for the doré product. The distribution is right-skewed and resembles a log-normal distribution. Overall the combined uncertainties in the inputs lead to less uncertainty in the doré (a factor of 2) than some of the major inputs (e.g. gold in the ground with a factor of 10).

Discussion

Usefulness of Emergy Results

A significant finding of this LCA is that the environmental contribution to the mining process, dominated by fuels and chemicals, was estimated to be greater than that to the formation of the gold itself. This result holds despite the large uncertainty associated with quantification of the environmental contribution to gold in the ground. The production of doré can also be interpreted to be process with a net emergy loss, with an emergy yield ratio (EYR) of close to 1, since the emergy expended in making the product (represented here by the mining processes) is greater than the emergy embodied in the raw resource.[10] This is unfavorable in comparison with fossil energy sources and other primary sector products which generally have emergy yield ratios of

[9] Uncertainties for UEVs are shown in the first supplement. The inventory uncertainty can be found in the inventory description in the second supplement.

[10] The EYR may be defined as the total emergy in a product divided by the emergy in purchased inputs from outside the product system (Brown and Ulgiati 1997).

greater than 2 (Brown et al. 2009), but this provides no insight into the utility of the resource in society, which is much different in function and lifetime than these other products.

While primary energy would indicate that the energy in mining is heavily dominated by fuel consumption during extraction, using emergy as in indicator shows that the other more chemically- and capital-intensive processes weigh more significantly, and therefore that reducing total environmental contribution to the process would demand a broader look at the other processes and inputs. This is consistent with the trends in the results that Franzese et al. (2009) found in their comparison of gross energy and emergy in biomass.

Quantifying resource use in emergy units permits putting processes in the context of the flows of available renewable resources. Emergy used in a process can be seen as the liquidation of stocks of accumulated renewable energy in all the inputs to that process. The limit of sustainability, in emergy terms, is such that total emergy used by society be less than or equal to the emergy driving the biosphere during the same period of time. Thus the liquidation of the stock of emergy should not be greater than the flows of emergy. In this case, the amount of emergy in the doré (the stock) produced by the mine in one year is equivalent to approximately one third of the emergy in sunlight falling on the nation of Peru in one year, and one third of one percent of the emergy in all the renewable resources available annually to Peru (Sweeney et al. 2009).[11] While this does not represent a trade off for the current period (since the stock of emergy in the doré was largely accumulated in a prior time-period) it puts the total

[11] Sunlight on Peru = 5E+21 J = 5E+21 sej (Sweeney et al. 2009); since 1 sej = 1 J sunlight. 1.66E+21 sej in doré /5E+21 sej in average sunlight on Peru = 0.3.

resource use in the process and the available flows of resources on the same scale, which is a step towards quantifying the sustainability of production. The Peruvian economy is driven on average by 35% percent renewable resources, but the mining process at Yanacocha itself is only approximately 3.5% renewable on a life cycle emergy basis.[12] This result should not come as a surprise since mining and other resource extraction activities are largely using non-renewable energy sources to extract non-renewable resources.

The emergy in 1 g of doré is on the order of E+12-13 sej/g. The eventual 'London good' gold sold on the international market, which will be produced by further refining the doré, will have a minimum emergy on the order of E+13 sej/g. This is hundreds of times greater than that reported for products from other economic sectors, such as biomass-based products, chemicals, and plastics, which have UEVs consistent with the global emergy base used here on the order of E+8-E+11 sej/g (Odum 1996), reflecting the high environmental contribution underlying gold products, which is consistent with the high market value of gold.

Emergy in LCA: Challenges

The boundary, allocation and other accounting differences between emergy and LCA were dealt with here in a progressive manner. The system boundary was expanded beyond traditional LCA to included flows of energy underlying the creation of resources used as inputs to the foreground and background processes.. The inventory to the gold mining process involved a hybridization of background data from previous emergy analyses as well data from an LCI database. Numerous challenges remain for

[12] This includes only the portion of direct electricity use from hydropower. Energy sources for all other inputs are assumed to be non-renewable.

a theoretically and procedurally consistent integration of emergy and LCA and are discussed here.

Challenges of using emergy with LCI databases and software

This study revealed some of the complexities and potential inconsistencies of integrating emergy into LCA, particularly to be able to use emergy along with other LCIA indicators and to be consistent in use of accounting rules. The technical integration of emergy for the characterization of some of the processes (e.g. inventories for processes occurring off-site) implemented here in SimaPro had the shortcoming of not being able to comparatively measure other environmental aspects from background processes in the life cycle. For some of these inputs for which emergy evaluations already existed (e.g. for stainless steel used in mine infrastructure and vehicles) emergy was the only input to the item, which made computation of other full life cycle indicators for resources use (e.g. cumulative exergy demand) impossible. A better method of integrating emergy into a Life Cycle Inventory would be to associate emergy with substances, and then to allow the software to track the emergy through all the processes, rather than creating processes that store unit emergy values. Such a method would permit more accurate cross-comparison of emergy with other impact indicators.

Emergy evaluation conventionally incorporates the emergy embodied in human labor and services (Odum 1996). Adding labor as an input may be present in some forms in traditional LCA, such as in worker transportation (O'Brien et al. 2006), but energy in labor has largely been left out and its inclusion represents a potential addition to LCA from the emergy field. However, inclusion of labor, as in a typical emergy evaluation, is not included in processes in existing LCI databases including Ecoinvent 2.0. For this reason labor was not included here. ‘Services’ is the conventional means

by which the labor of background processes is included in an emergy analysis. 'Services' is the emergy in the dollars paid for process inputs, estimated using a emergy:money ratio to represent the average emergy behind a unit of money, and represents labor in background processes based on the assumption that money paid for goods and services eventually goes back to pay for the cost of human labor, since money never returns to the natural resources themselves (Odum 1996). Unit emergy values are often reported as "with labor and services" or "without labor and services". For consistent incorporation of emergy in labor in an LCA, labor would also need to be incorporated into the background processes drawn from LCI databases. Unless background processes can be "retro-fitted" with labor estimations, unit emergy values used for LCA should be those "without labor and services." This will however result in the omission of an input which is considered to be integral to holistic accounting in emergy theory, since all technosphere products rely on human input.

Reconciling rules for allocation is another necessary step for inclusion of emergy in LCA. In the LCA context, the emergy co-product allocation would be inconsistent and non-additive, because the emergy in the products would be double-counted when they become inputs in the same system (which can be as large as the global economy). Thus results based on this allocation rule should be recalculated using an allocation rule that divides up emergy before being used with existing LCIA calculation routines, to avoid the potential double-counting of emergy.[13] Allocation rules or alternatives to allocation typically used in LCA can easily be applied to allocate emergy among by-

[13] Emergy practioners also point out that emergy of co-products cannot be double-counted when they are inputs to the same system. See p. 1967 of (Sciubba and Ulgiati 2005). However in LCA all impacts have to be split according to one of the methods described in ISO 14044.

products and co-products, as was demonstrated here, but if existing UEVs for co-products are incorporated they will have to be recalculated with the chosen allocation rule before incorporation.

Allocation is not just an issue among co-products but also an issue related to end-of-life of many of the materials used. While many of the inputs to doré were transformed in such a way that they were completely consumed (e.g. the refined oil is combusted), others, particularly the gold itself, was not consumed in such as manner. Gold is a material that can theoretically be infinitely recycled and is not generally consumed in its common uses (e.g. jewelry). In emergy evaluation of recycled products, the amount of emergy that goes into the formation of the resource would be retained (i.e. deposit formation) for the materials each time its recycled (Brown and Buranakarn 2003). In contrast, it has been traditional practice for systems with open loop recycling, (like the metals industry) to split the total environmental impact between the number of distinct uses of a material (Gloria 2009). If this approach were used it would require splitting the emergy of resource formation as well as the emergy of mining among the anticipated number of lifetime uses of the gold product. But allocation in systems with recycle loops is an unresolved issue in LCA especially for products such a metals and minerals and the problem is not limited to the context of integrating emergy into LCA (Yellishetty et al. 2009).

Energy in environmental support not conventionally included in emergy evaluation

While more thorough than other resource use indicators in consideration of energy use from the environment, not all the energy required by the environment to support the doré product is included here. Geologic emergy in the clay and gravel used as a base

layer for roads and the leach pads is not included, under the assumption that these materials are not consumed in the process. Additionally, there are waste flows from the mine, some of which, such as those potentially emanating from the process sludge and residuals on the leach pads, may occur over a long period of time following mine closure. These and contemporary emissions to air, water, and soil require energy to absorb, but these are not quantified here, as they are not typically quantified in emergy analysis. Other measures to quantify damage in this waste, though they may not be numerically consistent with the analysis here, could fill in the information gap, although unless they are consistent with emergy units and methods, they will not allow for a single measure of impact. Traditional measures of impact used in LCA, such as global warming potential and freshwater aquatic ecotoxicity potential (Guinée 2002), could serve this purpose. More investigation needs to be done to relate emergy with other environmental impact metrics within the LCA framework. The outcome of emergy and other LCA metrics may not warrant the same management action, esp. those LCA metrics that measure waste flows, as they are measures of effects on environmental sinks instead of use of sources.

Uncertainty in unit emergy values

Emergy from geologic processes in scarce minerals is characterized by a high degree of uncertainty (around a factor of 10) relative to other products largely due to the differences in different models used to estimate emergy in minerals (Ingwersen 2010). However there is limited analysis of uncertainty in emergy values .The largely unquantified uncertainty associated with UEV values needs to be addressed so that use of emergy in LCA attributes appropriate uncertainty not just to inventory data, but also to previous UEVs. The uncertainty of UEVs contributing 90% of the emergy was

characterized in this paper using a method proposed in Ingwersen (2010). Using a model to estimate UEV uncertainty to couple with inventory uncertainty will help to better quantify uncertainty in LCA studies that use emergy, which will permit statistically-robust comparison of emergy in products that serve the same function (e.g. comparative LCA).

Emergy and Other Resource Use Indicators

As integrated into LCA in this analysis, emergy is suggested as one measure of resource use, defined as environmental contribution. Although primary energy use was the only other resource use metric that was quantitatively compared with emergy in this study, it would be useful to see how emergy compares with other implemented and proposed indicators of resource use in LCA, namely indicators of abiotic resource depletion, direct material input and cumulative energy demand and cumulative exergy demand.

Indicators of resource depletion are commonly used in LCA to represent how much of a particular resource is consumed in reference to its availability.[14] These are resource specific indicators and depend upon information on total reserves of various resources, which is not readily available. Emergy is not often applied to assess reserves and it is not resource-specific. Use of emergy as proposed here is therefore not closely comparable with indicators of resource depletion, which in cases of resource scarcity, convey very useful information on informing material selection.

Direct material input has been used as an indicator, particularly in the mining sector (see Giljum 2004). However it has also been argued to be of limited utility,

[14] Resource depletion indicators are build into the most common LCIA methodologies including TRACI and Eco-indicator 99 (Bare et al. 2003; Goodkoep and Springsma 2001).

primarily because it doesn't account for quality differences among resources and also includes resources that are not transformed or consumed in processes (like overburden) (Gossling-Reisemann 2008b). Emergy does take into account resource quality based on a principle that more embodied energy in creating a resource represents higher quality (Odum 1988).

Of the resource use indicators, emergy is seen by some as closely related with exergy (Bastianoni et al. 2007; Hau and Bakshi 2004b). This is in fact only the case when conventional exergy analysis is expanded to include available energy in inputs from driving energies in the environment (Figure 2-1). Otherwise the boundaries for exergy consumption are like those in conventional LCA, and still do not account for the energy driving environmental processes. Cumulative exergy consumption or a similar metric, entropy production (Gossling-Reisemann 2008a), are useful measures of efficient use of the available energy embodied in resources, and thus relative measures of thermodynamic efficiency of systems, or ultimate measures of the depletion of a the utility of resources in the process of providing a product or service (Bösch et al. 2007a). Because of the similarity between exergy and emergy, one might expect redundant results by using both exergy-based indicators and emergy-based indicators. However, a brief comparison of the result of applying the Cumulative Exergy Demand (CExD) indicator to a product from the Ecoinvent database 'Gold, from combined gold-silver production, at refinery/PE U'[15] to the emergy results here show some significant differences in the sources of exergy contribution in comparison with emergy contribution. Approximately 72% of the exergy in this product comes from electricity

[15] A detailed comparison between an inventory of this product with the inventory of Gold at Yanacocha is presented in the discussion of Supplement 2.

production and 22% from the gold ore in the ground. In comparison with the results from this study (Figure 2-2), emergy shows a much higher relative role of the fuels and chemicals used in the process[16]. This can be largely explained by the differences in the information that emergy and exergy provide. Exergy and entropy production more precisely measure embodied energy *consumption* whereas emergy is a measure of energy throughput and could be better described as measuring *use* than consumption (Gossling-Reisemann 2008b). Also exergy describes the available energy in substances (including the chemical energy in minerals), which is not the same as the amount of energy used directly and indirectly in their creation in the environment. In summary, the use of emergy provides unique information regarding resource use that does not make other resource use indicators like exergy irrelevant, but rather can augment the understanding of resource use by tailoring their use to address questions at different scales (Ulgiati et al. 2006). However, emergy is the only one of these measures that relates resources used in product life cycles back the process in the environment necessary to replace those resources, and hence the best potential measure of the long-term environmental sustainability of production.

[16] This implementation of CExD in SimaPro is incomplete and does not provide characterization factors for many of the chemicals used in the refining processes. The relative exergy contribution of chemicals to total exergy in gold would likely be higher if this were the case.

CHAPTER 3[17]

UNCERTAINTY CHARACTERIZATION FOR EMERGY VALUES

Introduction

Emergy, a measure of energy used in making a product extending back to the work of nature in generating the raw resources used (Odum 1996), arises from general systems theory and has been applied to ecosystems as well as to human-dominated systems to address scientific questions at many levels, from the understanding ecosystem dynamics (Brown et al. 2006) to studies of modern urban metabolism and sustainability (Zhang et al. 2009). Emergy, or one any the many indicators derived from it (Brown and Ulgiati 1997), is not an empirical property of an object, but an estimation of embodied energy based on a relevant collection of empirical data from the systems underlying an object, as well as rules and theoretical assumptions, and therefore cannot be directly measured. In the process of emergy evaluation, especially due to its extensive and ambitious scope, the emergy in a object is estimated in the presence of numerical uncertainty, which arises in all steps and from all sources used in the evaluation process.

The proximate motivation for development of this model was for use of emergy as an indicator within a life cycle assessment (LCA) to provide information regarding the energy appropriated from the environment during the life cycle of a product. The advantages of using emergy in an LCA framework are delineated and demonstrated through an example of a gold mining (Ingwersen accepted). The incorporation of

[17] Reprint with permission from the publisher of Ingwersen, W. W. 2010. Uncertainty characterization for emergy values. *Ecological Modelling* 221(3): 445-452.

uncertainty in LCA results is commonplace and futhermore prerequisite to using results to make comparative assertions that are disclosed to the public (ISO 2006c).

But the utility of uncertainty values for emergy is not only restricted to emergy used along with other environmental assessment methodologies; uncertainty characterization of emergy values has been of increasing interest and in some cases begun to be described by emergy practitioners (Bastianoni et al. 2009) for use in traditional emergy evaluations. Herein lies the ultimate motivation for this manuscript, which is to provide an initial framework for characterization of uncertainty of unit emergy values (UEVs), or inventory unit-to-emergy conversions, which can be applied or improved upon to characterize UEVs for any application, whether they be original emergy calculations or drawn upon from previous evaluations.

Sources of uncertainty in UEVs

Uncertainty in UEVs may exist on numerous levels. Classification of uncertainty is helpful for identification of these sources of uncertainty, and for formal description of uncertainty in a replicable fashion. The classification scheme defined by the US EPA defines three uncertainty types: parameter, scenario, and model uncertainty (Lloyd and Reis, 2007). This scheme is co-opted here to represent the uncertainty types associated with UEVs. These uncertainty types are defined in Table 3-1 using the example of the UEV for lead in the ground.

There are additional elements of uncertainty in the adoption of UEVs from previous analyses. These occur due to the following:

Incorporation of UEVs from sources without documented methods
Errors in use of significant figures
Inclusion of UEVs with different inventory items (e.g. with or without labor & services)
Calculation errors in the evaluation
Conflicts in global baseline underlying UEVs, which may be propagated unwittingly

Use of a UEV for an inappropriate product or process

These bulleted errors are due to random calculation error, human error, and methodological discrepancy, which is not well-suited to formal characterization, and can be better addressed with more transparent and uniform methodology and critical review. But uncertainty and variability in parameters, models, and scenarios can theoretically be quantified.

Table 3-1. Elements of uncertainty in the UEV of lead in the ground.

Uncertainty Type	*Definition*	*Example*	*Explanation*
Parameter	Uncertainty in a parameter used in the model	Flux of continental crust = .0024 cm/yr	Global average number. A more recent number is .003cm/yr (Scholl and von Huene, 2004)
Model	Uncertainty regarding which model used to make estimations is appropriate	See model for minerals in Table 2	Variation exists between this model and others proposed for minerals
Scenario	Uncertainty regarding the fit of model parameters to a given geographical, temporal, or technological context	Variation in enrichment ratio based on deposit type	Assumption that the emergy in all minerals of a given form is equal

Models for describing uncertainty in lognormal distributions

Different components of uncertainty in a model must be combined to estimate total uncertainty in the result. These component uncertainties may originate from uncertainty in model parameters. In multiple parameter models, such as emergy formula models, each parameter has its own characteristic uncertainty. Uncertainty in environmental variables is often assumed to be normal, although Limpert et al. (2001) presents evidence that lognormal distributions are more versatile in application and may

be more appropriate for parameters in many environmental disciplines. This distribution is increasingly used to characterize data on process inputs used in life cycle assessments (Frischknecht et al. 2007; Huijbregts et al. 2003b).

A spread of lognormal variable can be described by a factor that relates the median value to the tails of its distribution. Slob (1994) defines this value as the dispersion factor, *k*, but it is also known as the geometric variance, σ^2_{geo}:

$$\sigma^2_{\text{geo of a}} = e^{1.96\sqrt{\ln \omega_a}} \quad (1)$$

$$\omega_a = 1 + \left(\frac{\sigma_a}{\mu_a}\right)^2 \quad (2)$$

where σ^2_{geo} for variable *a* is a function of ω_a (Eq. (1)),[18] which a simple transformation of the coefficient of variation (Eq. (2)), [19] where σ_a is the sample standard deviation of variable *a* and μ_a is the sample mean. This can be applied to positive, normal variables with certain advantages, because parameters for describing lognormal distributions result in positive confidence intervals, and the lognormal distribution approximates the normal distribution with low dispersion factor values.

The geometric variance, σ^2_{geo}, ($k \approx \sigma^2_{geo}$) is a symmetrical measure of the spread between the median, also known as the geometric mean, $\mu_{geo,,}$ and the tails of the 95.5% (henceforth 95%) confidence interval (Eq. (3)).

$$CI_{95} = \mu_{geo} \ (x\div) \ \sigma_{geo}^2 \quad (3)$$

The symbol '(x÷)' represents 'times or divided by'. The geometric mean for variable *a* may be defined as in the following expression (Eq. (4)):

[18] Eq. (1) adapted from Slob (1994).

[19] Eqs. (2)-(4) adapted from Limpert et al. (2001).

$$\mu_{geo} = \frac{\mu_a}{\sqrt{\omega_a}} \tag{4}$$

The confidence interval describes the uncertainty surrounding a lognormal variable, but not for a formula model that is a combination of multiplication or division of each of these variables. The uncertainty of each model parameter has to be propagated to estimate a total parameter uncertainty. This can be done with Eq. (5):

$$\sigma^2_{geo\ of\ model} = e^{\sqrt{\ln\left(\sigma^2_{geo\ of\ a}\right)^2 + \ln\left(\sigma^2_{geo\ of\ b}\right)^2 + \cdots \ln\left(\sigma^2_{geo\ of\ z}\right)^2}} \tag{5}$$

where *a, b* …*z* are references to parameters of a multiplicative model y of the form $y = \prod a \ldots z$. Note that parameter uncertainties are not simply summed together, which would overestimate uncertainty. This solution (Eq. (5)) is valid under the assumption that each model parameter is independent and lognormally distributed.

Describing the confidence interval requires the median, or geometric mean, as well as the geometric variance. The geometric mean of a model can be estimated first by estimating the model CV (Eq. (6)) and then with a variation of Eq. (4) (Eq. (7)).[20]

$$CV_{model} = \sqrt{e^{\left\{\frac{\ln\left(\sigma^2_{geo}\right)^2}{1.96^2}\right\}} - 1} \tag{6}$$

$$\mu_{geo\ of\ model} = \frac{\mu_{model}}{\sqrt{1 + CV_{model}{}^2}} \tag{7}$$

Models for uncertainty in UEVs

Numerous methods exist for computing unit emergy values[21], but for uncertainty estimation, it is import to distinguish between them according to a fundamental

[20] Eqs. 5-7 adapted from Slob (1994)

difference in the way UEVs are calculated: the formula vs. the table-form model. The formula model is used for estimation of emergy in raw materials, such as minerals, fossil fuels and water sources (the UEV in Table 1 is of this form). The traditional table-form evaluation procedure- is typically used for ecosystem products and products of human activities. Formula models are generally multiplicative models using estimates of various biophysical flows and storages in the biosphere as parameters. In order to quantify variability within a formula model, such as an emergy calculation, the result distribution needs to be known or at least predicted. Model parameters are generally positive values multiplied to generate the UEVs. Such multiplicative formulas have been shown to lead to results approximating a log-normal distribution (Hill and Holst 2001; Limpert et al. 2001). Therefore it would be logical to assume that UEVs calculated in this manner are distributed lognormally.

The model geometric mean and variance (Eqs. (5) and (7)), used in conjunction, offer an analytical solution for estimating uncertainty for formula-type unit emergy values, with some built in assumptions, foremost being that the model parameters have a common lognormal distribution. For models with parameters of mixed and unknown distributions and large coefficients a variation, a common method for estimating uncertainty is to simulate a model distribution using a stochastic method such as Monte Carlo, and estimate uncertainty based on the model distribution's confidence interval (Rai and Krewski 1998). A notable drawback of a stochastic simulation method is that the results obtained have some variability in themselves, which, however, can be reduced by increasing the number of iterations.

[21] See (Odum 1996) for procedure for calculating UEVs, which are also known as transformities when the denominator is an energy unit, or specific emergy when the denominator is a mass unit.

Table-form UEV calculations would be more accurately described as sum products, where UEVs of inputs contributing to the total emergy in an item of interest are multiplied by the quantities of each input to get emergies in those inputs, and the emergy in each input is then added together to get the total emergy in the item of interest. This hybrid form operation is not readily amenable to an analytical solution (Rai and Krewski 1998). In the absence of a readily-available analytical model for this type of UEV, a Monte Carlo model may be adopted for modeling UEV uncertainty for table-form calculations.

Figure 3-1 provides an conceptual overview of the proposed uncertainty model. The analytical solution is used to model all quantifiable sources of uncertainty (parameter, model, and scenario) while the Monte Carlo model is used only to estimate total parameter uncertainty.

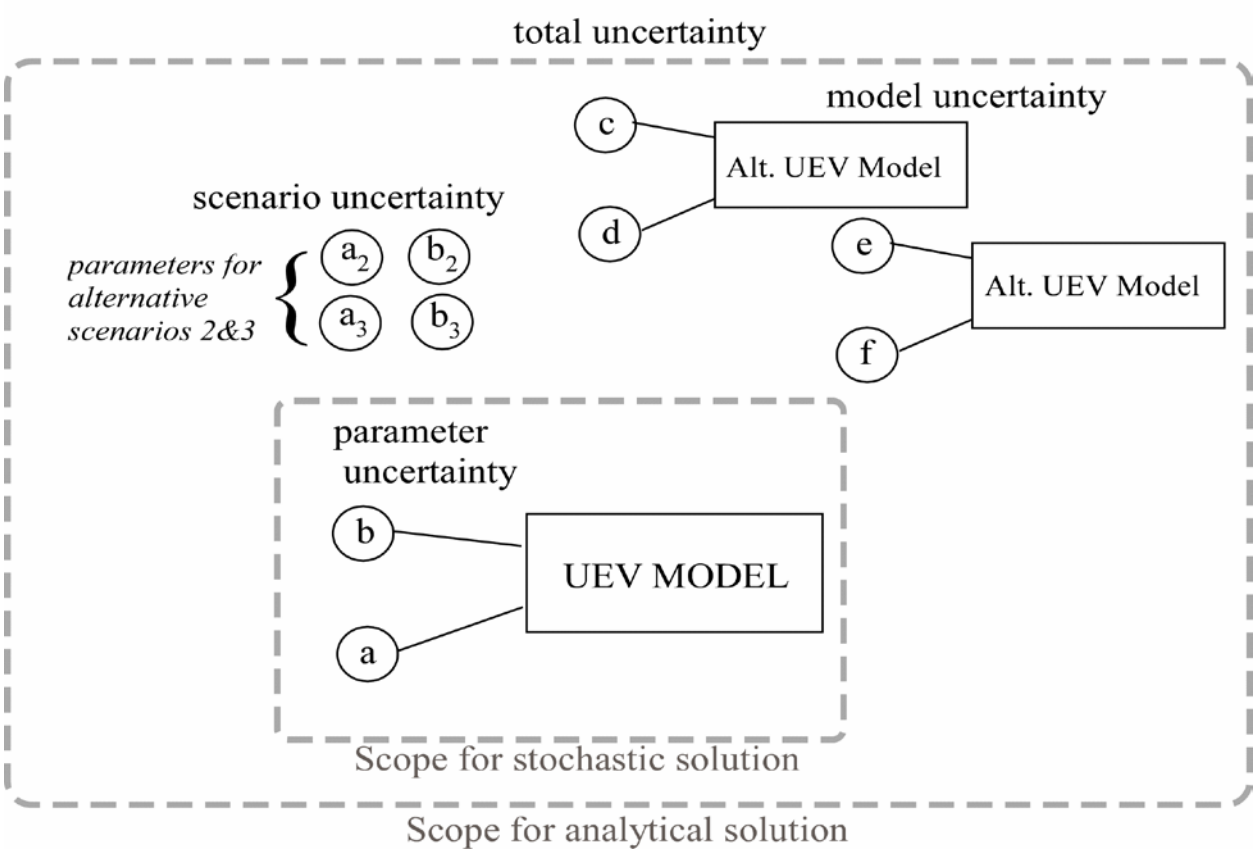

Figure 3-1. Conceptual approach to modeling uncertainty. The parameter uncertainty consists of uncertainty and variability in the parameters used to estimate the UEV; the scenario uncertainty consists of the uncertainty arising from use of parameter values for different geographic or technological scenarios; the model uncertainty from different models. Only the proposed analytical solution incorporates scenario and model uncertainty to estimate total uncertainty.

Modeling procedure and analysis

First the geometric variance and medians of five formula-type UEVs are estimated with the analytical solution to describe the type of variability and distribution of some commonly used UEVs, breaking down the uncertainty into the three classes described. Parameter uncertainty for these same UEVs is then also estimated with the stochastic model, along with two table-form UEVs. The modeling results are cross compared. As the distribution of UEVs has not previously been described, the resulting distributions from the stochastic model are tested to see how closely they fit traditional

lognormal and normal distributions, as well as a hybrid of the two. In the process of this analysis a means of reporting UEV uncertainty for future incorporation and interpretation of uncertainty is described.

Uncertainty was estimated for five formula-type UEVs: lead, iron, oil, groundwater, and labor. These UEVs were chosen because they represent categories of inputs from the biosphere (labor excepted) – scarce and abundant minerals, petroleum, water, and human input – that form the basis of many product life cycles.

Models for calculating each UEV are presented in Table 3-2 along with their sources. Parameter uncertainty was estimated as follows: ranges of values or multiple values from distinct sources when available were taken from the literature for each model parameter. The mean and sample standard deviation for each model parameter was calculated. With this value, the uncertainty factor, ω, corresponding to each parameter was calculated with Eq. (2). The UEV *parameter uncertainty* was then estimated for the combined parameter uncertainty factors with Eq. (4).

Table 3-2. Unit emergy value models used for parameter uncertainty calculations.

Category	*Model*	*Source*
Minerals	$UEV_{mineral}$ = Enrichment Ratio * Land Cycle UEV, sej/g	Cohen et al. 2008
	Enrichment Ratio = (ore grade cutoff, %)/(crustal concentration, ppm)/(1E6)[a]	"
	Land Cycle, sej/g = (Emergy base, 15.83 E24 sej/yr) / (crustal turnover, cm/yr)(density of crust, g/cm3) (crustal area, cm2)	Odum 1996
Petroleum	UEV_{Oil}, sej/J = (1.68[b] * emergy of kerogen, sej/J)(C content, %)/((Conversion of kerogen to petroleum, fraction)*(Enthalpy of petroleum, 4.19E4 J/g))	Bastianoni et al. 2000
	UEV_{carbon} in kerogen, sej/g = (emergy of C in phytoplankton, sej/g)/conversion to kerogen, fraction	"
	UEV_{Carbon} in phytoplankton, sej/g = (phytoplanton UEV, sej/J)*(Phytoplankton Gibbs Energy, 1.78E4 J/g)/ (phytoplanton fraction C)	"
Groundwater	$UEV_{groundwater}$, sej/g = (Emergy base, 15.83E24	Buenfil 2001

	sej/yr)/(Annual flux, g/yr)	
	Annual flux, g/yr = ((Precip on land, mm/yr)/(1E6 mm/km))*(Land area, km2)*(infiltration rate, %)*(1E12 L/km3)(1000 g/L)	"
Labor	Total annual emergy use model. UEV_{labor}, sej/J = ((Emergy use)[c]/(Population)*(Per capita calorie intake, kcal/day)(365 days/yr)(4184 J/kcal))	Odum 1996

[a] Omitted when concentration is reported in %
[b] Included for conversion from global emergy baseline of 9.44E24 to 15.83E24 sej/yr
[c] Emegy use for global estimate was 1.61E26 sej/yr, or a total emergy use of the world's nations (Cohen et al. 2008)

Model and/or *scenario uncertainty* was incorporated by estimation of separate uncertainty factors for these types of uncertainty. When multiple models existed for a UEV, the average and sample standard deviation of the UEVs produced by different models were calculated. Model uncertainty was estimated for lead, iron, petroleum and water. When models exist for UEVs which are specific to a set of conditions but for which those conditions are unknown in the adoption of a UEV, scenario uncertainty can be included. For instance if labor is an input in a process, but the country in which the labor takes place is undefined, there is scenario uncertainty which includes the variability of the emergy in the labor depending on which country it comes from. Two scenario uncertainties were estimated for labor UEVs (one for US labor and one for world labor) for purposes of example. Parameter along with either model or scenario uncertainty were combined for an estimate of *total uncertainty* by combining the uncertainty factors for each parameter and for scenario and/or model uncertainty according to Eq. (5). This can be summarized as:

total uncertainty = *parameter uncertainty* + *model uncertainty* + *scenario uncertainty* (8)

In order to compare the consistency of the analytical solution for the median and geometric variance with the confidence interval generated by the simulation, stochastic simulation models for the lead, iron, water, and labor UEV calculations were run. A Monte Carlo simulation was scripted in R 2.6.2 statistical software © (R Development Core Team 2008) to calculate each UEV 100 times using a randomly selected set of parameters. Randomized parameters were created with a random function using the sample standard deviation and means of each parameter. The parameters were assumed to be log-normally distributed.

The mean and standard deviations of the log-form of each parameter were used to create variables with a lognormal distribution, for which the following equations (Eqs. (9) and (10)) were used (Atchinson and Brown, 1957):

$$\sigma_{logUEV} = \sqrt{\ln \omega_{UEV}} \qquad (9)$$

$$\mu_{logUEV} = ln\,(UEV) - O.5(\sigma_{logUEV}) \qquad (10)$$

The resulting set of UEV approximations (100) provide a distribution from which the left and right sides of the confidence interval can be estimated by the 2.5 and 97.5 percentile values, respectively. In order to get a representative sample, this procedure was executed 100 times thus generating 100 distributions (for a total of 10 000 UEV values). From each distribution, the mean, median, and standard deviation values were reported, and these values were averaged across the 100 distributions to arrive at average values for each UEV. From the average mean and standard deviation, the σ^2_{geo} value for that UEV was estimated according to Eq. (1).

The stochastic simulation did not incorporate the model and scenario uncertainty components, which could only be estimated by way of the analytical solution. The

stochastic simulation recalculates the UEV by varying the parameters, but does not incorporate uncertainty from use of alternative models or on account of parameters from other scenarios. Thus to compare the stochastic and analytically-derived results from parameter uncertainty, the calculated *parameter* σ^2_{geo} (Eq. (5)) may be compared with the σ^2_{geo} value obtained from the simulation distributions.

Uncertainty was also estimated for two UEVs calculated with the table-form model -- electricity from oil and sulfuric acid made from secondary sulfur. The emergy tables used to estimate these two UEVs were simplified to include only items that contributed in total to 99% of the emergy in these items.[22] Uncertainty was estimated solely with the Monte Carlo simulation routine used for the formula UEVs, with the following change:uncertainty data in the form of σ^2_{geo} values for both inventory values (e.g. secondary sulfur in g in Table 4) and their respective UEVs (e.g. UEV for secondary sulfur in sej/g) were used in conjunction with their means to create random lognormal variables for use in the simulation. Estimation of the natural log-form of the standard deviation for these variables for generating lognormal random values was slightly different than for the formula UEV case, because it used the σ^2_{geo} value instead of the sample standard deviation (Eq. (11)).

$$\sigma_{logUEV} = \frac{\ln \sigma 2geo}{1.96} \qquad (11)$$

The uncertainty factors in the Ecoinvent Unit Processes library for geometric variance were used for the σ^2_{geo} values for the inventory data (Ecoinvent Centre 2007). For the UEVs of the inventory items, the deterministic mean and the geometric variance of the UEV for the same item calculated with the formula model were used when

[22] The table for electricity from oil was adapted from Brown and Ulgiati (2002)

appropriate as the mean and σ^2_{geo} value, respectively. This choice was based on the assumption that the inventory items (e.g. water to make sulfuric acid) had the same UEV as those calculated with formula UEV models (e.g. groundwater).

The 95% confidence interval of the simulation distributions for formula and the table-form UEVs were compared with the confidence intervals predicted by a perfect log-normal distribution (μ_{geo} (x÷) σ^2_{geo}), those predicted by a normal-lognormal hybrid distribution using the arithmetic mean as the center parameter (μ (x÷) σ^2_{geo}), and those predicted by a normal distribution ($\mu \pm 1.96\sigma$). Eqs. (1) – (3) were used to estimate the μ_{geo} and σ^2_{geo} from the μ and σ derived from the sample distribution. The percent difference between the predicted and model distribution tails was calculated to measure the how accurately the predicted distributions represented the model distribution.

Results

The details of the uncertainty calculations for lead are shown in Table 3-3. For lead, parameter and model uncertainty were estimated. The σ^2_{geo} values (approximately the upper tail of the distribution divided by the median) for the five parameters range from 1.03 to 2.25. The total parameter uncertainty (σ^2_{geo}) is larger than the largest individual parameter σ^2_{geo} value, but less than the sum of these parameter σ^2_{geo} values. The total uncertainty for lead, consisting of the combined model and parameter uncertainty (without scenario uncertainty) is dominated by the model uncertainty, which has a large σ^2_{geo} value due to large differences in previously published estimates used for the UEV of lead. The 95% confidence interval for the lead UEV using this analytical form of estimation would vary across three orders of magnitude, from 4.38E+11 sej/g to 5.38E+13 sej/g. However, if the UEV model used to estimate the mean was the only

acceptable model, the interval would shrink to 1.87E+12 – 1.26E+13, indicating considerably less uncertainty.

Table 3-3. Analytical uncertainty estimation for lead UEV, in ground.

No.	Parameters	μ	σ	σ^2_{geo}
1	crustal concentration (ppm)	1.50E+01	1.41	1.20
2	ore grade (fraction)	0.06	0.03	2.25
3	crustal turnover (cm/yr)	2.88E-03	6.77E-04	1.58
4	density of crust (g/cm3)	2.72	0.04	1.03
5	crustal area (cm2)	1.48E+18	2.1E+16	1.03
	Models			
6	Alternate Model UEVs	4.52E+11	7.25E+11	9.12
	Summary			
	Unit emergy value, μ (sej/g)	5.46E+12		
	Parameter Uncertainty Range (No. 1-5), μ_{geo} (sej/g) (x÷) σ^2_{geo}	**4.85E+12**	(x÷)	**2.59**
	Total Uncertainty Range (No. 1-6), μ_{geo} (sej/g) (x÷) σ^2_{geo}	**2.57E+12**	(x÷)	**11.09**

Sources

1 Odum (1996); Thornton and Brush (2001)
2 Gabby (2007)
3 Odum (1996); Scholl and von Huene (2004)
4 Australian Museum (2007); Odum (1996)
5 UNSTAT (2006); Taylor and McLennan (1985); Odum (1996)
6 ER method and Abundance-Price Methods (Cohen et al. 2008)

The geometric variance calculations from the analytical solution for the formula UEVs (lead, iron, crude oil, groundwater, and labor) showed a wide range of values presented in Table 3-5. Geometric variance values were dominated by model or scenario variances in the cases of the minerals and labor. The total parameter uncertainty ranged from 1.08 for labor to 3.59 for crude oil, whereas model uncertainty was as high as 9.12 for lead.

The confidence intervals estimated from the analytical and stochastic methods were of similar breadth (for all five formula UEVs), although they were not identical – the intervals from the analytical solution were all shifted slightly to the left.

The Monte Carlo simulation of the UEVs produced largely right-skewed distributions, as indicated by the means for UEVs (see column 3 of Table 5) being less than the medians. Without exception the means of the simulated UEV distributions were less than the medians.

The table-form UEV calculation for sulfuric acid appears in Table 3-4. The geometric variance values for the inputs of secondary sulfur and diesel are those calculated for oil in the ground[23]; the UEV for diesel is that calculated for oil; the UEV for electricity from oil was calculated from an emergy table and the geometric variance is the σ^2_{geo} value from the Monte Carlo simulation; and the UEV and geometric variance for water are those calculated above for groundwater. The Monte Carlo simulation resulted in a median of 6.51E7 and a σ^2_{geo} value of 1.75, which, in comparison with the formula UEVs, indicates less of a spread in the distribution for this UEV. The other table-form UEV, electricity, also had a σ^2_{geo} value less than that of its major input, crude oil, suggesting a pattern of less breadth in the confidence intervals of table-form UEVs than those of their most variable input.

Table 3-4. Emergy summary with uncertainty of 1 kg of sulfuric acid.[a]

No	Item	Data (units)	Unit	Relative Data Uncertainty σ^2_{geo}	UEV (sej/unit)	Relative UEV Uncertainty σ^2_{geo}	Solar Emergy (sej)
1	Secondary sulfur	2.14E+02	g	1.32	5.20E+09	3.59	1.11E+12
2	Diesel	3.41E+03	J	1.34	1.21E+05	3.59	4.13E+08
3	Electricity	6.30E+04	J	1.34	3.71E+05	2.77	2.34E+10
4	Water	2.41E+05	J	1.23	1.90E+05	1.95	4.57E+10
	Product						
5	Sulfuric acid	1.00E+03	g		1.18E+09	**3.31**	1.18E+12

[23] Assuming the geometric variance is the same because they share similar UEV models, which is an assumption mentioned later in the discussion.

| | | |

the right of the model with increased error, and the normal distribution often predicted a lower tail many orders of magnitude less than the model value. The smaller the standard deviation relative to the mean (reflected by the σ^2_{geo} value), the better all predicted distributions fit the model interval. In the case of the two table-form UEVs, electricity from oil and sulfuric acid, the lognormal confidence interval tended to underpredict the model lower tail more severely (suggesting that the tail is closer to the mean), but was still the best fit when considering the combined error in both tails. The left tail of these model UEV distributions was more constricted, and in these cases the quotient of the model mean and σ^2_{geo} value, reflected by the hybrid model, was a closer approximate of the lower tail.

Table 3-5. UEV uncertainty estimated from the analytical solution.

Item	UEV Den.	UEV (sej/Den.)	Parameter μ_{geo}	Parameter σ^2_{geo}	Model and/or Scenario[1] σ^2_{geo}	Total μ_{geo}	Total σ^2_{geo}	Lower UEV using parameter uncertainty	Upper UEV using parameter uncertainty	Lower UEV using total uncertainty	Upper UEV using total uncertainty
Lead	g	5.46E+12	4.85E+12	2.59	9.12	2.57E+12	11.09	1.87E+12	1.26E+13	4.38E+11	5.38E+13
Iron	g	1.06E+10	1.15E+10	2.00	6.66	7.18E+09	7.53	5.73E+09	2.29E+10	1.52E+09	8.63E+10
Crude oil	J	1.21E+05	9.78E+04	3.59	1.04	9.77E+04	3.59	2.72E+04	3.51E+05	2.72E+04	3.51E+05
Groundwater	g	9.36E+05	8.90E+05	1.86	1.28	8.83E+05	1.95	4.78E+05	1.66E+06	4.56E+05	1.74E+06
Labor	J	6.74E+06	6.73E+06	1.08	11.43	3.11E+06	11.44	6.26E+06	7.24E+06	5.89E+05	7.70E+07

[1] All values represent model uncertainty, except for labor for which this is scenario uncertainty

Table 3-6. UEV Monte Carlo results and comparison of model CI's with lognormal, hybrid, and normal confidence intervals. [1]

		Monte Carlo Results		Model 95% CI		Predicted 95% CIs					
						Lognormal CI		Hybrid CI		Normal CI	
Item	UEV Type[2]	μ_{geo}	σ^2_{geo}	Lower	Upper	Lower error	Upper error	Lower error	Upper error	Lower error	Upper error
Lead	F	5.19E+12	2.73	1.93E+12	1.38E+13	-1.5%	2.6%	12%	17%	-123%	-11%
Iron	"	1.30E+10	1.99	6.62E+09	2.53E+10	-1.8%	2.3%	4.5%	8.8%	-40%	-6.6%
Crude oil	"	1.57E+05	3.55	4.66E+04	5.44E+05	-4.5%	2.9%	18%	27%	-273%	-14%
Ground H2O	"	9.40E+05	1.92	5.06E+05	1.77E+06	-2.9%	2.4%	2.6%	8.3%	-35%	-5.8%
Labor	"	6.91E+06	1.08	6.45E+06	7.40E+06	-0.32%	0.35%	-0.25%	0.42%	-0.57%	0.12%
Electricity from oil	T	2.81E+05	2.77	1.16E+05	7.68E+05	-12%	2.4%	0.85%	17.3%	-126%	-11%
Sulfuric Acid	T	8.10E+08	3.31	2.72E+08	2.67E+09	-10%	0.50%	31%	47%	-179%	-96%

[1] Confidence intervals defined as follows: Lognormal = μ_{geo} (x÷) k; hybrid = μ (x÷) k; normal = μ ± 1.96σ.
[2] F = formula UEV; T = table-form UEV. UEVs are in sej/g for lead, iron, groundwater, and sulfuric acid, and sej/J for crude oil, labor, and electricity from oil.

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Discussion and Conclusions

To fully characterize uncertainty for UEVs, the sources of uncertainty need to be identified and quantified. The classification scheme introduced by the EPA provides a useful framework which helps in identification of quantifiable aspects of uncertainty. However in practice, describing the uncertainty in parameters, scenarios and models requires significant effort and must draw from previous applications of various models and across various scenarios. In this manuscript, the data sufficient to characterize these three types of uncertainty for each UEV was not readily available, and as a result in no cases has a total parameter uncertainty been estimated that includes all parameter, model, and scenario uncertainty for lack of either multiple models or modeled scenarios from which to include that component of uncertainty. Unless one or more of these types of uncertainty can be categorically determined to be absent for a UEV, the uncertainty measures presented here underestimate the total uncertainty in these UEVs.

Acknowledging this underestimate, how much uncertainty are in unit emergy values? Parameters for describing the uncertainty ranges inherit in 7 UEVs have been presented and analyzed here. Informally, emergy practitioners may have assumed an implicit error range of “an order of magnitude”, but this analysis reveals such a general rule of thumb is inappropriate. As quantified here the UEVs may vary with either less or more than one order of magnitude, but this is UEV specific. However, when UEVs have as their basis the same underlying models, if the parameters specific to one or more of UEVs have a similar spread, then the UEV uncertainty should be similar. Thus, as was demonstrated here, uncertainty values for a UEV may be co-opted from an UEV calculated with the same model (eg. minerals in the ground) with reasonable confidence

if original estimation is infeasible. Adoption of geometric variances from UEVs calculated with the same model would provide an advantage as a reasonable estimation of uncertainty rather than a vague or undefined measure.

Quantifying model uncertainty may have implications regarding the certainty of comparative evaluations. Figure 3-2 shows the UEVs estimated for different types of electricity in Brown and Ulgiati (2002) – all fall within the range of confidence interyal of the UEV for oil, estimated from the mean UEV reported by the authors and the geometric variance calculated for this electricity type in this paper (2.77), using equations 5 and 6 to estimate the median and equation 3 to estimate the tails. Although it appears that from this analysis the UEVs of electricity sources would be statistically similar, this ignores the fact that many of the same UEVs are used in the inputs to these electricity processes. Hypothetically, if the same UEVs are used as inputs to processes being compared, relative comparisons can still be made, all of the variance due to the UEVs of inputs is covariance. This represents a problem of applying this uncertainty model to rank UEVs where there is strong covariance, which is not addressed here.

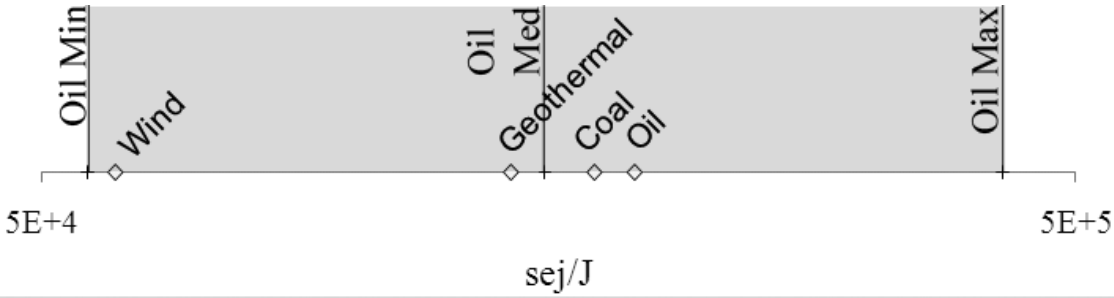

Figure 3-2. Published UEVs for electricity by source (diamonds on axis) from Brown and Ulgiati (2002), superimposed upon a modeled range of the oil UEV, using the geometric variance for electricity from oil (σ^2_{geo} = 2.77) calculated in this paper.

Comparing the analytical and stochastic solutions

Multiple advantages of proceeding with an analytical solution have been listed in the risk analysis literature. These include the ability to partition uncertainty among its contributing factors and identify factors contributing to the greatest uncertainty in a model (Rai and Krewski 1998) as well as the greater simplicity of calculation (Slob 1994). Further advantages suggested here in the context of UEVs are the ability to include other sources of uncertainty which cannot be quantified in a simple Monte Carlo analysis, and the ability to replicate the values for geometric variance.

However, because table-form UEVs are the most common form of emergy evaluation, and the stochastic simulation method is the only method presented which is functional for this form of unit emergy calculations, the stochastic method is likely to be more useful to emergy practitioners.

Model and scenario uncertainty components, which were not quantified in the Monte Carlo simulation, can be particularly significant in emergy, due to the fact that emergy values for a product are often used across a wide breadth of scenarios, computed with alternative models, and adopted in subsequent evaluations by other authors without knowledge of the context in which the original UEVs were calculated. The most desirable solution to these problems with uncertainty would be: first for model uncertainty, to agree on the use of consistent models for a UEV type to eliminate the discrepancy that occurs between competing models; for scenario uncertainty, to make UEVs more scenario specific whenever possible to eliminate scenario uncertainty. Where elimination of this model and scenario uncertainty is not possible, an alternative would be to develop a more complex version of stochastic model that would include estimation of model and scenario uncertainty in addition to parameter uncertainty.

Following from what is predicted mathematically, this study confirmed that formula UEVs as multiplicative products fit a lognormal distribution better than a normal distribution. Table-form UEVs, while they are sumproducts, also tended to be better described by lognormal distributions than normal distributions, although the two UEVs simulated both fits this distribution to a lesser degree than the formula UEVs. Using the deterministic mean as the center parameter for a multiplicative confidence interval, represented by the hybrid approach, may be a tendency of emergy practioners for simplified description of confidence intervals, but was shown here to result in more error than using the median, except for the estimate of the lower tail of the confidence interval for table-form UEVs.

Conclusions

Ultimately the accuracy of UEV uncertainty measures depend upon the representativeness of the statistics describing the model parameters. In this case a broad but not exhaustive attempt was made to describe uncertainty and variability in the model factors for the UEVs evaluated. For this reason, this author recommends sources of uncertainty be further investigated and more thoroughly quantified before they are propagated for use in future studies. The responsibility should rest with authors to diligently seek out and to summarize the uncertainty in parameters they adopt, and to perpetuate that uncertainty with the UEV uncertainty both to present the uncertainty of their own work and so that it can be adopted by those that use this UEV in the future.

By describing uncertainty associated with emergy estimates, emergy is more likely to become adopted as a measure of cumulative resource use or for other purpose in LCA. Description of uncertainty in parameters and across models and scenarios will

increase transparency in emergy calculations, thus answering one of the critiques which has hindered wider adoption (Hau and Bakshi 2004a). Uncertainty descriptors, namely the geometric variance, can be used along with inventory uncertainty data to calculate uncertainty in estimates of total emergy in complex life cycles. It can be further be used to compare different life cycle scenarios with greater statistical confidence. Pairing UEVs with uncertainty data and identifying sources of uncertainty will also help emergy practitioners understand and report the statistical confidence of their calculated emergy values and to prioritize reduction of uncertainty as a means to improve the accuracy of emergy values.

CHAPTER 4

LIFE CYCLE ASSESSMENT FOR FRESH PINEAPPLE FROM COSTA RICA – SCOPING, IMPACT MODELING AND FARM LEVEL ASSESSMENT

Introduction

Although tropical fruits and their derivative food products make up a substantial and increasing portion of the fruit consumption in the temperate countries of Europe and North America[25], little life cycle data or published life cycle assessments (LCA) of these products are available. At the same time, large areas and substantial resources in tropical countries are dedicated to growing tropical fruits, such as banana, pineapple, and mango, primarily for export (FAO 2009). Associated local and global environmental impacts need to be accounted for and better managed both locally and globally as these fruits continue to grow as a proportion of temperate-climate diets. One way to encourage better environmental management could be through LCA-based Type III environmental product declarations (EPDs), so that quantitative environmental information can be used to help producers make better management choices and help buyers and consumers make informed environmental choices that take into account the full product life cycle (Schenck 2009).

Objectives

The primary objective of this study was to conduct a background LCA of fresh pineapple production in Costa Rica to be used as a guide for creating a product category rule (PCR) for fresh pineapple, as specified by ISO 14025 (6.7.1 ISO 2006b). The development of a PCR is a mandatory step toward the process of creating an EPD.

[25] Pineapple import growth (by weight) was 248% from 1996-2006 in the EU and North America while only 56% for grapes, 33% for bananas, 27% for apples, and 14% for oranges in the same period (FAO 2009).

A goal of any product category rule is to enable comparative assertions of environmental performance between products of the same category. To create a PCR, a background LCA can be used as a reference for establishing the environmental impact categories and indicators for reporting, methods for conducting inventories and estimating impacts, and calculation parameters for these inventories and impact models. Although the objective is to create a PCR for fresh pineapple, this LCA is scoped bearing in mind the functional use of the product, to provide nutrition through fruit consumption, and thus is created with the wider intention of providing life cycle data relevant to a wider range of environmental impacts of concern in fruit-product supply chains. Impacts are estimated with methods that are as globally-valid and adaptable as possible, to permit comparable analysis with other fruit-group food products. The LCA should have sufficient coverage to represent the range of climatic, field, management, and production levels so that ranges of potential impacts can be bounded with a statistical confidence. Furthermore comparisons of environmental performance are made between fresh pineapple and other fruits through the farm scale to provide an initial analysis of how fresh pineapple from Costa Rica compares to production of other fruits consumed raw or used as the basis of processed food products.

A secondary objective is to provide a model for other such background LCAs of agricultural products, particularly for those that have yet to be performed in countries and environments where assumptions made in emission and impacts models may not hold and that hence require regional adaptation of these models for more accurate impact assessment.

The fresh pineapple system in Costa Rica

Costa Rica is the largest provider of fresh pineapple to the EU and the US. Approximately 85% of pineapples imported to the U.S. in 2005 were produced in Costa Rica; in the EU 71% of fresh pineapple imports came from Costa Rica (FAO 2009). Pineapple export has overtaken coffee to become Costa Rica's second largest agriculture export (to bananas) in terms of international exchange. This production has resulted in a rapid expansion of pineapple plantations in the Limon (Atlantic region), Alajuela (North region), Heredia (North region), and Puntarenas (Pacific region) provinces (Bach 2008). There are a number of environmental and health-related concerns surrounding this recent expansion and the modern production process. Public concerns include soil erosion, pesticide contamination of natural areas and water supplies, lowering of water tables, worker exposure to agrochemicals, and impacts of organic wastes, among others (Sandoval 2009).

Pineapples are primarily grown in three regions, hereafter referred to as the North, Atlantic, and Pacific regions, on ultisols but also on other well-drained mineral soil orders. Pineapples for the fresh export market in Costa Rica are a highly technical, non-traditional cash crop. The high level of technicality has resulted in a high degree of uniformity in production systems to meet international standards (e.g. GLOBALGAP) and produce competitive yields and fruit quality. The variety grown almost universally for export is the MD2, or "golden". A good description of the production process in Costa Rica can be found in Gomez et al. (2007). Fields are prepared with adequate drainage and raised beds. Seed materials are most often suckers (shoots from existing plants) harvested within farms. Once established pineapples require regular fertilization primarily through foliar application of fertilizers. Nematicides, herbicides and insecticides

are used to reduce pests and competition. Once mature (about 150 days on average) plants are often “forced” to begin fruiting, usually by application of ethylene gas. Fruits are ready for harvest in another six months, from where they are manually harvested and transported to packing facilities. When plants are not left to produce a second harvest, they are chopped and the field is prepared again for another planting.

Methods

System boundaries and functional units

The LCA boundaries are the farm stage though transport to the packing facility including all upstream processes.

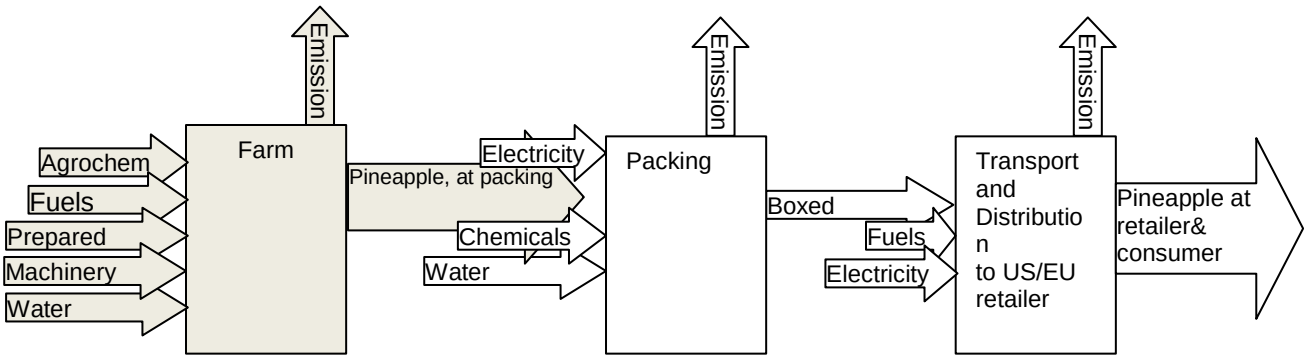

Figure 4-1 shows how this LCA integrates into a farm-to-shelf production chain.

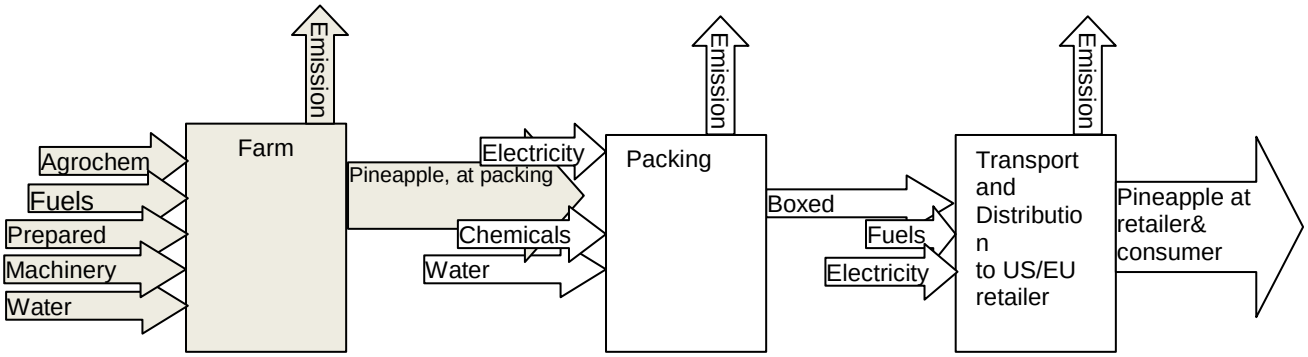

Figure 4-1. Fresh pineapple production unit processes and boundaries for the LCA. The first unit process is the focus of this paper.

The primary functional unit (FU) is 1 kg of fruit delivered to the packing facility. For comparison with other fruit products at the farm level, one serving of fruit at the packing facility is used, because it is a more relevant unit for comparison because of its functional equivalency. The USDA defines a serving of fruit as 1 cup of fresh fruit, which for pineapple is 165 g (USDA 2009). In order to estimate the number of servings that can be obtained for 1 kg of pineapple the following equation is used:

Servings/kg fresh weight fruit = (edible fraction of fruit)/(kg fruit/serving) [12]

For pineapple this results in 3.09 servings/kg fresh fruit. Life cycle inputs for all inputs of agrochemicals and machinery and related emissions are included. Permanent farm infrastructure (buildings and road) was judged to be environmentally insignificant and excluded from the study.

Data collection

A public call for producer participation in this LCA followed from a workshop organized in San Jose, Costa Rica in July 2009 for pineapple producers, government officials, LCA experts, and other potential stakeholders to present the concept of LCA-based EPDs (Ingwersen et al. 2009). Participation in the LCA was anonymous to encourage sharing of production data and evaluating environmental performance without revealing any private producer data. Farms representing all three primary producing regions of the country, with management schemes including conventional and organic, and with sizes ranging from 1 to >1000 hectares were directly solicited in order to seek a representative sample. Following agreement to participate, each producer was sent a standardized questionnaire requesting data on historical farm area, production inputs including fuels, fertilizers, pesticides, water use, agricultural machinery models and use, yield, harvest schedule, distance and means of transport to

the packing facility. Data collection was supervised through in-person meetings with producer contacts to assure common understanding of the questions for data collection. Data were later verified through comparison of data items across the entire participant pool to assure that input data were reasonably suited to pineapple production requirements. To acquire site-specific data for inventory emissions models, farms were visited and data on soils, topography, and operations were collected.

Because of the discontinuity between the non-annual production cycle and annual data collected from producers, all annual production input data had to be adjusted with the following equation.

Input, x/kg pineapple = (Annual input, x/yr)/(Farm area, ha)/(Harvest kg/ha/harvest)(harvests/yr) [13]

Because of the same reasons mentioned above, yield data were collected on a per harvest basis.

Data on all production inputs were matched with the appropriate processes in the Ecoinvent v2.0 database (Ecoinvent Centre 2007) for inclusion in the inventory and entered into SimaPro software (PRé Consultants 2008b) after being converted into EcoSpold XML format for validation. For pesticides reported, mass of the active ingredient applied was determined and used as the mass of the pesticide input from Ecoinvent of the same class (Nemecek and Kagi 2007). New processes were created for inputs without appropriate equivalents in the Ecoinvent database by assembling their active ingredients under a new process. N-P-K fertilizers were estimated by combining single or double fertilizers in quantities to match the N-P-K weight ratios of the actual fertilizers, as recommended by the Ecoinvent designers (Nemecek and Kagi 2007).

Emissions and Impact Models

Emissions and impact models were chosen based on the following criteria:

1. Universal midpoint models are used for global impacts (e.g., climate change)
2. Regionalization of universally-applicable endpoint models are used for local impacts of concern when available (e.g., USETox)

When appropriate characterization factors are not yet available, the measured impacts are reported as the quantity of relevant emissions.

Recent work in the environmental evaluation of the food sector has focused heavily on carbon footprinting, in conjunction with the development of product-level carbon footprinting standards (Sinden 2008). Acknowledging the growing importance of this effort, rules for carbon accounting in this LCA are set as synchronously as possible with the PAS 2050 standard. Land transformation from forest is a potentially significant contributor to carbon release surrounding agricultural products, especially in tropical regions (Ebeling and Yasue 2008). Carbon loss from land transformation in kg C/ha was estimated only when conversion from primary or secondary forest was reported. Loss was estimated by identifying the historical Holdridge life zones that occupied the land the farm currently occupies (Holdridge 1967) and summing the carbon in living biomass (Helmer and Brown 2000) with the estimated soil carbon (IPCC 2007) and dividing this carbon loss over 20 years. Emissions to air resulting from on-farm fuel combustion were estimated based on the same fuel-specific coefficients and equations used for agricultural data in the Ecoinvent database (Nemecek and Kagi 2007).

Estimating other emissions from farm stage processes required customization of emissions models capable of capturing, to the extent possible, the crop and field-

specific variables that affect these emission rates. Models capable of parameterization with site-specific inputs were used to estimate emissions of eroded soil, consumed water, nitrogen and phosphorus in fertilizers, and active-ingredients of pesticides. Emissions of nitrogen and phosphorus compounds to air and water are functions of crop- and field-specific factors. Pathways considered here for N include uptake, ammonia, dinitrogen oxide, and nitrous oxide formation and volatilization, and nitrate leaching and runoff . Modeled pathways for P include uptake, phosphate runoff, and loss of P bound to sediments from erosion. Uptake quantities were based on the average N and P concentration in pineapple leaf tissue. Equations and references used in estimating N and P emission can be found in the Appendix.

The PestLCI model (Birkveda and Hauschild 2006) was customized with site-specific climate and soil data to quantify the fate of pesticides applied in the field to air and water. Because drainage is present on the majority of pineapple farms, drainage was assumed to be 100% effective in the model and thus all emissions to soil that are either lost via direct runoff after application or after lost after leaching through the soil column were characterized as an emission to surface water. Pesticides not present in the default PestLCI model provided by the authors were added into the database so that fate of all pesticides applied to the field could be characterized. Characterization was farm-specific but application dates were unknown and thus the annual average of climate data was used. The plant type “2”, citrus, was chosen from the two plant types available, because the thick cuticle most resembles that of pineapple (Malézieux et al. 2003). Assumed canopy cover was 75% at time of application. All other default settings in PestLCI were maintained.

For estimating consumed water, the FAO CROPWAT model (Swennenhuis 2009) was parameterized with site-specific climatic and soil data, and plant-specific parameters. Actual water use from the “irrigation schedule option” was the quantity of water reported. Irrigation water was added through the irrigation schedule for farms that use irrigation. Farm specific climate data were taken from the FAO LocClim database based on the geographic coordinates of the farms, and coupled with farm data on irrigation practices from the questionnaires. Other general model assumptions and plant-specific parameters can be found in the appendix.

Soil erosion was estimated for each farm using the most recent ARS version of the RUSLE2 model (Foster et al. 2008), and customizing it for site-specific conditions. RUSLE2 models rain-based erosion on overland flow paths. Not included in this model are wind-based erosion and rain-based erosion from ditches or other concentrated flow areas, which are less significant sources of erosion on Costa Rican pineapple farms. Climate data required for the model were interpolated with the FAO Locclim database from the nearest 12 weather stations, including temperature, monthly rainfall, and number of days with rain per month (FAO 2010). R-values (rainfall intensity factors) were adopted from maps created in an implementation of the USLE model for the country of Costa Rica (Rubin and Hyman 2000). To parameterize the model, the following measurements were taken in representative areas of each participating farm: the percent slope and effective length of the slope were measured for each unique slope in the farm segment using a clinometer and metric tape. A unique slope consisted of a slope ± 2-3 % different from other slopes based on visual assessment or with unique drainage or contouring (e.g., bed direction) elements. In each area of the

farm with a unique soil profile, the profile was described and samples were collected for soil texture analysis (Burt 2009). Slope and soil data collected in the field were used along with farm specific management data including production schedules and other general data on pineapple morphology. One model was run for each unique combination of soil, % slope, field geometry and production schedule within each farm. Results for each farm were then averaged based on the total farm area represented by those conditions. Erosion occurring during initial conversion of the land from previous land use was not estimated. All general assumptions and parameters selected for the RUSLE2 model are reported in the appendix (**Error! Reference source not found.**).

Sensitivity analyses of the adaptations of the PestLCI, RUSLE2, FAO CROPWAT models were conducted by selecting environmental and management scenarios reported or assumed to exist based on expert knowledge of the sector. Analyses were performed using the production-weighted average of sample data (described below) and the climate variables of the North region as the default condition. Percent changes from the default conditions were reported by sequentially varying model variables within ranges naturally present in climate, field conditions, pineapple physiology, or ranges reported in management and harvest schedule.

Estimating the sector Range of Environmental Performance

In order to meet the goal of conducting an LCA representative of production in the sector and maintaining the anonymity of producers participating in the study, a single unit process was created from the inventories of the participating farms. This process was used to create a distribution of environmental impacts to characterize the sector, henceforth referred to as the sector range of environmental performance (RoEP). To create the unit process, production-weighted average input data from the individual

farms were used as means, and parameterized with confidence intervals based on ranges existing within and among farms, or moreover likely to exist within the sector. For pesticide inputs and related emissions, only inputs to conventional farms were used in the baseline because inventory data on biological control agents and their associated environmental impacts were not available.

Each of these inventory inputs was parameterized with a standard deviation based on the variation among the sample farms, and assumed to have a normal distribution. A correction of uncertainty for each input had to be made to reflect the variation in yield within and between farms. A standard deviation of yield within each farm was estimated using the reported min, max, and mean production values. A production-weighted combined uncertainty of the yield was estimated with a propagation of standard uncertainty formula (NIST 2010) of the form:

$$CV_{yield} = \sqrt{(CV^2_a * (P_a/P_{total})^2 + CV^2_b * (P_b/P_{total})^2 + \ldots CV^2_z * (P_z/P_{total})^2)} \qquad [14]$$

where CV_{yield} is the coefficient of variation of the yield for the baseline scenario, CV^2 is the square of the coefficient of variation of the yield for a farm *a*, and P_a/P_{total} is the percent of the total production of farm *a* from the total production of participating farms. The uncertainty based on variation in production inputs per hectare and uncertainty based on yield were then combined to estimate total uncertainty for each input, using the simplified form of equation 3:

$$CV_{mod,\ input,i} = \sqrt{(CV^2_{yield} + CV^2_{input,i})} \qquad [15]$$

where $CV_{mod,\ input,i}$ represents the yield-modified coefficient of variation for input *i*. The standard deviation used to parameterize a normal distribution for a given input, *i* was then estimated by multiplying $CV_{input,i}$ by the sample mean value.

For the emissions inventory, log-normal distributions were assumed and extremes from sensitivity analyses of the emissions models were assumed to represent the 2.5% and 97.5% values of these distributions. The geometric variance ($GV_{emission}$), or measure of spread of the lognormal distribution, of the modeled emission from the sensitivity analysis was estimated by taking the maximum positive % change from the tested parameter values, dividing by 100% and adding 1.[26] The variation based on the sensitivity analysis was combined with variation in farm yields and in the production input related to that emission (e.g. nitrogen fertilizers for nitrate). A variation of equation 4 for propagation of uncertainty for lognormal variables was used to combine uncertainty from sensitivity analyses with yield uncertainty using to the follow formulas:

$$GV_{mod,emission\ i} = exp(\sqrt{(ln(GV_{yield})^2 + ln(GV_{input,\ i})^2 + ln(GV_{emission\ i,})^2)} \quad [16]$$

where $GV_{mod,emission\ i}$ is the yield-modified GV of the emission, $GV^2_{yield,\ i}$ is again the GV of the yield, $GV_{input,\ i}$ is the GV of the respective input related to the emission, and $GV_{mod,emission\ i}$ is the GV of emission, *i*. For emissions related to multiple inputs, the $GV_{input,\ i}$ used was the related input with the maximum coefficient of variation. GV for the inputs and emissions were calculated from the coefficient of variation with the formula (Slob 1994):

$$GV_x = exp(1.96\sqrt{ln(1+CV_x^2)}) \quad [17]$$

where GV_x is either the GV of yield or input and CV_x is the coefficient of variation of the input or emission.

An exception to a production-weighted average of emissions was made for modeling the emission of carbon dioxide potentially resulting from land-use change. For

[26] For example, if they max percent change from the default value from the sensitivity analysis was +60%, the estimated geometric variance = 1+60%/100% = 1.6.

estimation of carbon emissions, the PAS 2050 standard dictates that, for cases where an agricultural product is from an unknown location in a country, the land use transformation allocated to the product should be the carbon lost in conversion of the most carbon-rich ecosystem of the country divided by the lifetime of the crop (default = 20 years) (Sinden 2008). The max potential kg C/ha loss was estimated by overlaying the historical Holdridge life zones on current pineapple-occupied areas (Holdridge 1967), selecting the life zone with the highest storage of above ground and below-ground carbon (Helmer and Brown 2000), adding in estimated soil carbon (IPCC 2007), and dividing this carbon loss over 20 years. The uncertainty range of carbon loss allocated to pineapples due to conversion from forest was then modeled with a uniform distribution with the min equal to 0 and the max equal to the max potential carbon loss, all in kg/ha.

Monte Carlo simulations with 1000 runs were executed in SimaPro for each impact (described below). The final RoEP was estimated by taking the ends of the 99% confidence intervals (0.5^{th} and 99.5^{th} percentiles) to represent the ends of the RoEP.

LCIA Indicators

The measures of environmental impact selected, or LCIA indicators, were chosen both because of their precedence in existing agricultural LCA and for their environmental relevance to both the geographically-specific human health and environmental concerns of the regions as well as larger concerns associated with the farm stage in production of fruit products. Characterization was done for both farm stages and upstream processes for farm inputs (e.g., manufacture and transport of agrochemicals to the farm). Impact categories selected were cumulative energy demand, potential soil erosion, potential aquatic eutrophication, water footprint and

stress-weighted water footprint, human and freshwater toxicity, carbon footprint and land use.

Soil erosion impact

Soil erosion or loss is infrequently reported as an emission and lacks a suitable LCIA methodology to relate erosion to impacts to damage to ecosystems or human communities. Soil erosion was one impact category with particular concern to experts from non-OECD countries and thus recommended for further development in LCAs studies by members of the UNEP working group on LCIA in 2003 (Jolliet et al. 2003b). Soil loss or potential has been reported as an inventory indicator in mass of soil lost or depleted per functional unit (Heuvelmans et al. 2005; Peters et al. 2010; Schenck 2007) and is done as such here.

Cumulative Energy Demand

Energy use from non-renewable resources is often considered an indicator appropriate for all product systems and has been shown to correlate well with other categories of environmental impact (Huijbregts et al. 2010). Total energy life cycle use in fuels and electricity is measured using the Cumulative Energy Demand (CED) indicator implemented in the Ecoinvent database (Frischknecht and Jungbluth 2007). Only characterization of non-renewable energy from fossil sources is implemented here. A proposed indicator (Ingwersen in Press) based on the emergy method is potentially a stronger indicator of resource use for agricultural systems, but, because characterization factors were not available for the majority of the Ecoinvent processes used in the inventory it was not applied here.

Virtual water content and stress-weighted water footprint

Freshwater consumption and its resulting impacts on water availability and quality for ecosystems and human health is a significant environmental concern, particularly in areas susceptible to drought or water scarcity from overuse. Food consumption is a strong driver of water use globally (Chapagain and Hoekstra 2004). Nevertheless, estimating freshwater consumption has only recently been developed in reference to the water required per unit of food output, and just in the last year been integrated into LCA as an LCIA method (Pfister et al. 2009). Here, water consumption is estimated both by the water footprinting method (Hoekstra et al. 2009), henceforth referred to as *volumetric water footprint* to reduce confusion of terms, and further extended as a midpoint LCIA method called *stress-weighted water footprint* (SWWF), as described by Ridoutt and Pfister (2010).

The volumetric water content, also known as virtual water, represents the total consumptive water use of green water (rainwater), blue water (water stored in surface and groundwater), and grey water (equivalent water use required to dilute polluted water to background levels). Life cycle consumptive water use in background processes is not included in this study for lack of appropriate background data, which has been acknowledged as a shortcoming of existing LCI databases (Pfister et al. 2009). However, consumptive water use has thus far been shown to be heavily dominated by agricultural processes, and upstream process are assumed not to have a significant effects on the results. The green and blue water components in the farm stage were estimated with the FAO CROPWAT model as described above; grey water was estimated as the water required to dilute the nitrate emission from the farms to 10 mg/L (Hoekstra et al. 2009).

Because the effects of water use for production are very different depending on the relationship of that use to regional water availability, the water stress index (WSI) is applied as a characterization factor to relate use to its likelihood of depraving humans and ecosystems of water in the region. A WSI for Costa Rica of 0.0163 calculated by Pfister et al. (2009) as part of the creation of global characterization factors and was applied using an equation by Ridoutt and Pfister (2010) to calculate the stress-weighted water footprint:

$$SWWF = WSI_{CR}(WF_{proc,blue}) \quad [18]$$

where $WF_{proc,blue}$ is blue water footprint in L/kg pineapple and WSI_{CR} is the unitless water stress index for Costa Rica. Ridoutt and Pfister (2010) also propose calculating the SWWF by including the grey water. However, the water represented by grey water (the water necessary for dilution) is not depriving other users of water, so it is not included in the SWWF here.

Aquatic eutrophication

Macro-nutrient excess is a threat to both terrestrial and aquatic ecosystems, however it is perhaps more of a threat in aquatic ecosystems. The process of eutrophication in aquatic ecosystems (nutrient excess leading to sharp increase in primary production and subsequent increase in microbial oxygen consumption leading to a depletion of oxygen) is closely tied with runoff of N and P in agricultural fertilizers. The effects of N and P nutrient influx are system-dependent, but freshwater systems are generally P-limited and seawater, N-limited. Studies in streams on the Caribbean side of Costa Rica have shown that P addition can have cascading ecological effects on stream ecosystems (Rosemond et al., 2001). N escaping to the Pacific and Caribbean estuaries is assumed here to have the same effects documented in other estuarine

environments, such as the Gulf of Mexico (Miller et al. 2006). As a result, quantification of the effects of N and P in runoff from pineapple farms is performed here with regard to its potential to cause eutrophication. A variation of formula has been previously used (Gallego et al. 2010; Seppala et al. 2004) to create eutrophication characterization factors for aquatic ecosystems:

$$cf_e = tf_e * af_e * nf_e \qquad [19]$$

where the characterization factor for emission *e* is cf_e (here in kg N/kg emission); tf_e is the transport factor, the probability that emission *e* will be transported to an aquatic environment where it will have an effect; af_e is the bioavailability factor for a emission *e;* nf_e is the nutritive factor for emission *e*, which is its ability to cause eutrophication relative to N. Because emissions to water from farms occur directly to freshwater environments, and because land in Costa Rica is 100% exorheic (rainfall terminates in ocean), so as for areas where this is the case in the US, as in Norris (2003), tf_e is set to 1. Most of the air currents in Costa Rica move inward toward the mountains (Daly et al. 2007), with rainfall depositing airborne emissions back to the land so for emissions to air we also set tf_e to 1. Availability factors are based on the relative proportion of readily-available inorganic forms of nutrients to organic forms – in this case only emissions of inorganic nutrients are characterized, so af_e is set to 1 for all emissions. The nutritive factors for the emissions are all based on the Redfield ratio of 116:16:1 (C:N:P) as in Norris (2003). Because the ratio of N:P has been found to vary between 13-19 in aquatic systems, the CV applied to each *nf* and propagated the final cf_e is 0.09. Each cf_e is thus equivalent to the nf_e since both the transport and availability factors are set to 1 here for all characterized emissions. The resulting values, especially for emissions to

air, are notably higher those in the Ecoinvent implementation of TRACI (Frischknecht and Jungbluth 2007), which uses the average US characterization values, because they account for transport losses assumed not to occur here.

Human and freshwater ecotoxicity

Pesticides used in pineapple farming include herbicides, insecticides, nematicides and soil fumigants. Toxicity of these pesticides to humans and ecosystems is a function of fate in the environment, lifetime, transport, intake and effect. Models were reviewed that consider the fate, incidence of contact, and effect of pesticide emissions both on ecosystems and human health. Numerous models that have been used in LCA are available for this purpose, including USES-LCA, IMPACT 2002+, CAL-TOX, and others. Despite their similarities in purpose and orientation, results of these models have been shown to be widely divergent. Recognition of this divergence prompted the cooperative development of the USEtox model (Rosenbaum et al. 2008). USEtox was therefore selected to characterize toxicity here, in line with the intent of selecting models based on international consensus. USEtox is, however, based on the European continent, and the characterization factors are based on the climate, population, land use, and other data geographically representative of Europe. Other authors have shown that characterization scores for pesticides in multimedia fate, transport and effect models are very sensitive to geographic variables (Huijbregts et al. 2003a), particularly soil erosion and fraction of surface water, which are very different in Costa Rica than in the European continent. An evaluation of sources of uncertainty in the IMPACT model showed that the misrepresentation of geographic variables can potentially result in errors of three orders of magnitude (Pennington et al. 2005). Thus all geographic and demographic variables in the USEtox default model were tailored to the Costa Rican

environment, which is henceforth referred to as USEtox-CR. Results are reported in number of disease cases for human toxicity, and potentially affected fraction of species/m3/day for freshwater ecotoxicity.

Other indicators

The IPCC global warming potential 100-year characterization factors (IPCC 2007), expressed in CO_2-equivalents, were used as characterization factors for emissions with a potential to cause global warming, which sum together to create the carbon footprint. Occupation of land is described in m2/yr without impact characterization.

Results

Pineapple Sector Inventory

Pineapple field data on geographic location, topography, management and soils were collected for areas in total representing approximately 200 ha and producing approximately 18,000 tons pineapple/harvest or 10,000 tons/yr. Participating farms represented all three primary production districts (North, Atlantic, Pacific) and included both conventional and organic, respectively represented by approximately 88% and 12% by total production of the sample. Complete data on production inputs in the questionnaires was provided for 93% of farms surveyed based on total production volume.

The production-weight average yield among farms providing complete data was 95 ± 36 tons/harvest with an average of 0.60 ± 0.24 harvests/yr. The average yield reported for the sector is 67 tons/harvest (Gómez et al. 2007). Within farm yield variation between minimum and maximum yield/ha was up to 38 tons in one case, with an overall minimum of 48 tons/ha and a maximum of 129 tons/ha. Inputs per kg pineapple by category were 0.17 ± 0.04 m^2/yr of land, 0.0075 ± 0.0030 kg fuels, 0.043 ±

0.012 kg minerals in fertilizers, 7.8E-4 ± 1.6E-4 kg pesticides and 3.3E-4 ± 1.35E-4 kg machinery. The inputs and standard deviations for 1 kg of pineapple at the packing facility are presented in the Appendix.

Soil Erosion

The estimated average soil erosion for the sampled pineapple farms varied from approximately 2.5 to 5 tons/ha/yr, which was approximately 0.05 to 0.10 kg soil/kg pineapple. There was significant variation within individual farms with erosion estimates for slope profiles within farms varying from less than 1 to 40 tons/ha/yr in one case, which equated to a range of 0.05 to 0.82 kg eroded soil/kg pineapple; a maximum of 16 times the minimum that was diluted by the averaging of erosion within farms.

For the sector range of environmental performance (RoEP), the median value was 0.02 kg eroded soil/kg pineapple with a lower confidence bound of 0.0005 and upper bound of 0.6 kg eroded soil/kg pineapple.

The results of the sensitivity analysis show that % slope was the factor most strongly influencing the erosion results. An increase in % slope alone from 2.5% to 30% caused an increase in erosion in tons/ha/yr of 1680%. The sensitivity of soil texture, in reference to percent change in erosion from the baseline (-38 to 92% of the baseline from low to highest erodibility), along with degree of contouring of the rows (-53 to 0% of the baseline from standard to no contouring), use of plastic mulch (-78%) and use of double harvesting systems (-32% of the baseline) all had significant influences on the soil erosion at the pineapple farms. Summary tables of the sensitivity analyses for the soil erosion and other emissions inventory models can be found in the appendix.

Cumulative Energy Demand (CED) of Pineapple

The RoEP for life cycle cumulative non-renewable energy demand of pineapple was 1.2 to 2.2 MJ/kg with a median value of 1.5 MJ/kg. Most of this energy is used to make production inputs (77%), particularly fertilizers (see Figure 4-2). Figure 4-3 shows a comparison with evaluations of apples (4 countries), oranges (2 countries), and strawberries (2 countries) using a serving of fruit[27] as the unit of comparison. This and forthcoming comparisons are only preliminary, as the full ROeP of these other sectors, with the exception of orange (BR) in this case, is not fully characterized. Nevertheless, the median value of pineapple is higher than the values reported for apples and oranges, although there is likely cases in production of these fruits (based on the RoEP of Brazilian oranges), where a better performing pineapple has a lower CED. This results differs from what is revealed in a comparison on a per kg basis, where the median of the RoEP for pineapple (1.5 MJ/kg) is in the middle of the RoEP of CED for the different apple sectors (1.2, 1.0, 1.67, and 2.4MJ/kg). The strawberries both show more than double the pineapple

[27] Servings/kg for fruits used for comparison in the results are: 1 kg pineapple = 3.09 servings; 1 kg apple = 8.26 servings; 1 kg orange = 4.06 servings; 1 kg mango = 4.18 servings; 1 kg cantaloupe = 2.88 servings (based on formula used for pineapple in methods, ((1 kg fruit)(edible fraction))/(weight of USDA kg/serving)). Comparisons to Pimentel and Coltro were made by calculating the CED of analogous inputs from Ecoinvent for reported inputs rather that using originally reported energy totals. See the Appendix for recalculations.

CED/serving.

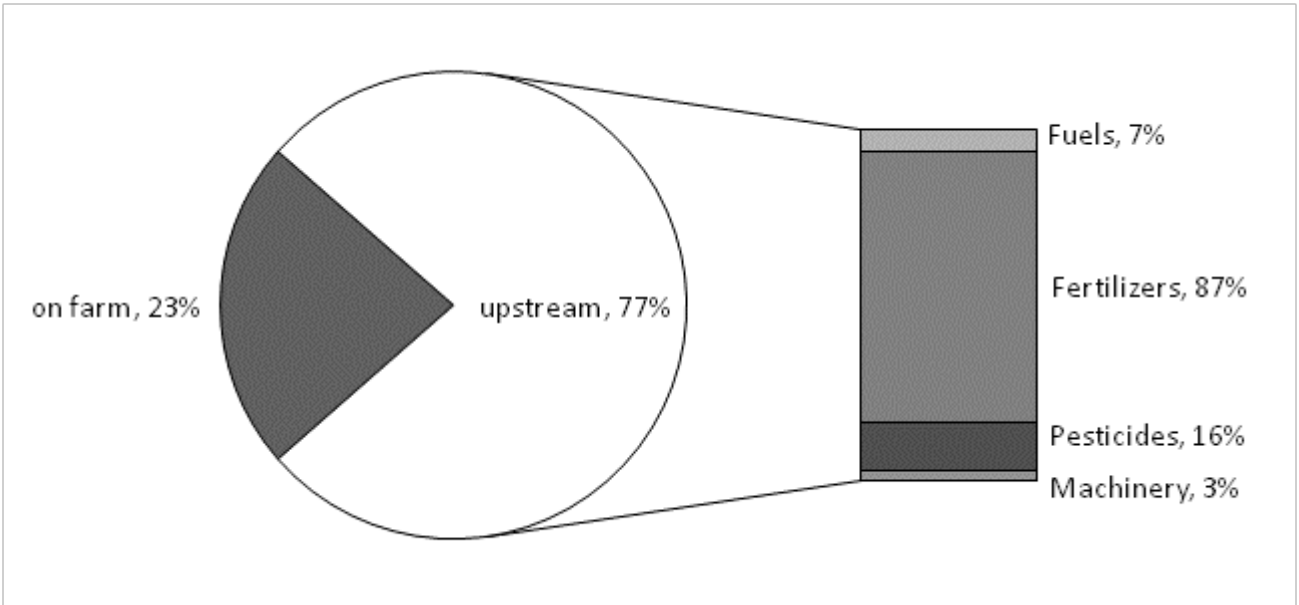

Figure 4-2. Contribution to CED for pineapple, at packing facility.

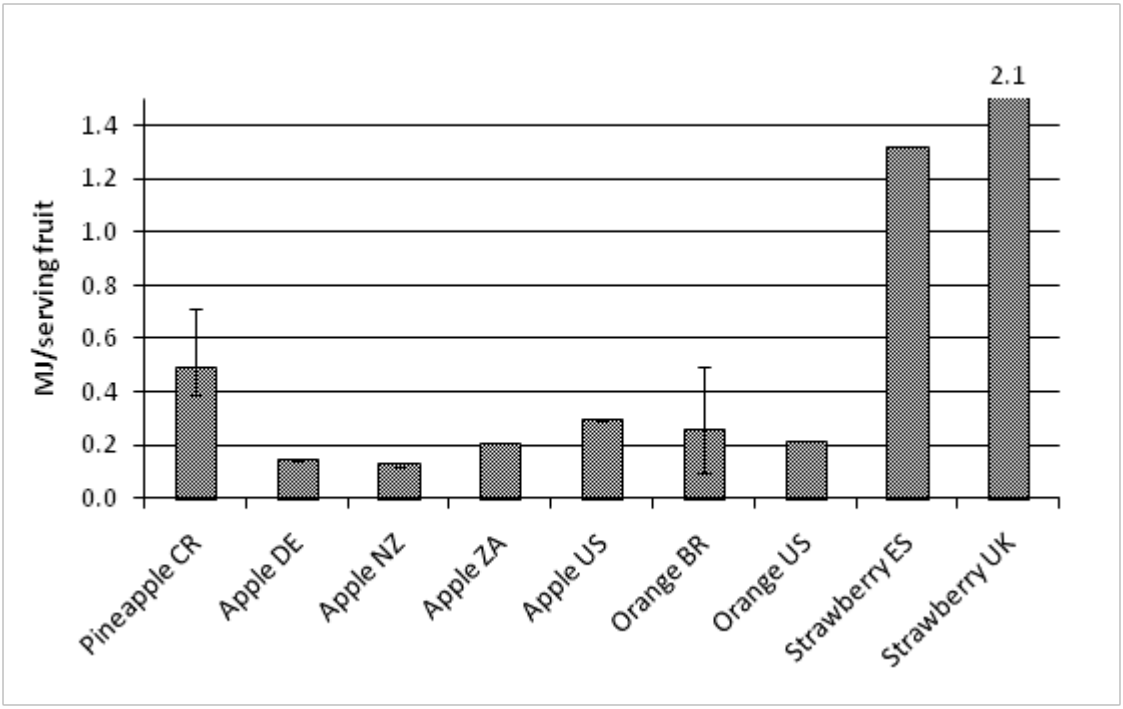

Figure 4-3. Non-renewable CED of one serving pineapple in comparison with evaluations of the farming stage of other fruits. Sources: Apple DE and Apple ZA (Blanke and Burdick 2009); Apple NZ (Blanke and Burdick 2009; Canals 2003); Apple US and Orange US (Pimentel 2009); Strawberry ES (Blanke and Burdick 2009; Williams et al. 2008); Strawberry UK ((Lillywhite et al. 2007; UoH 2005; Williams et al. 2008))

Carbon footprint

The carbon footprint RoEP for pineapple at the packing facility was between 0.16 and 1.42 kg CO_2-equivalent/kg, which is equivalent to a range of 52 to 469 g per serving. The majority of this carbon footprint could come from carbon loss from land use change, which could add up to 1.24 kg CO_2-eq./kg pineapple in the case of conversion from tropical moist forest, which was estimated to contain 394 tons C/ha. Of the sample farms, no land conversion from primary forest was reported by the producers, with no resulting loss of carbon from land use change, and as this is likely the case for many farms, an RoEP is also reported without land-use change. Not including potential carbon loss from land use change, approximately half of the carbon footprint (49%) occurred on the farm (Figure 4-4), with 34% being contributed from N_2O release from N-fertilizer and 15% from CO_2 primarily from fuel combustion. Fertilizer production (44%), followed by pesticide production (4%), fuel production (2%), and machinery production (1%) dominated upstream carbon footprint. The carbon footprint of pineapple, assuming no land use change, translates to approximately 0.03 to 0.08 kg CO_2-eq./serving. This is higher than reported for apples from New Zealand and the United Kingdom, close to that reported for strawberries from Spain but mostly lower than strawberries from the UK; noting that the full RoEP for these other fruits is not reported (Figure 4-5).

Virtual water content and stress-weighted footprint

Lower ET rates due to the physiological adaptations of the pineapple plants, along with infrequent to no use of irrigation due to high and consistent annual rainfall (with the exception of one farm) resulted in a lower evaporative portion of the virtual water content (green + blue water) for pineapple in comparison with the farm stage for other

fruits (Figure 4-6). For pineapple, the non-evaporative, grey water component is larger than the evaporative water,

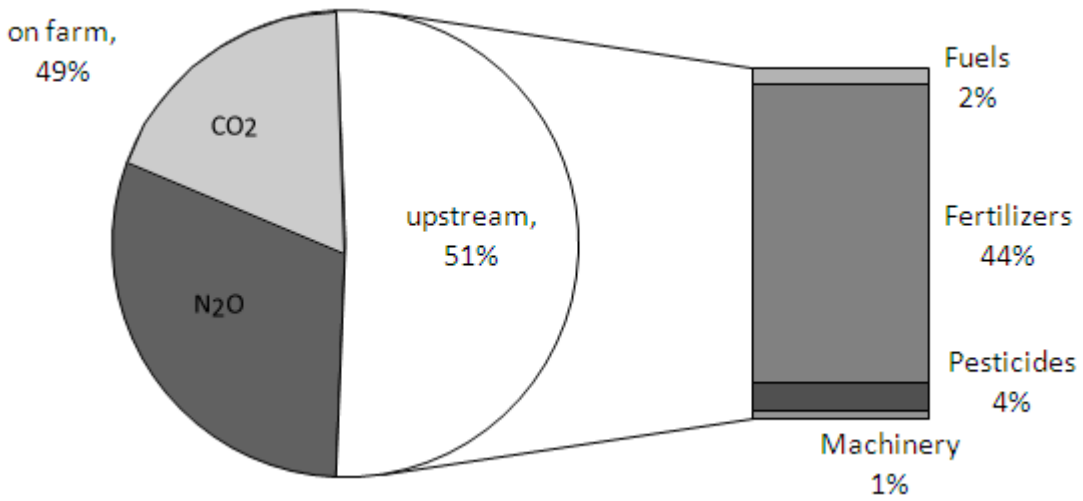

Figure 4-4. Contribution to carbon footprint for pineapple, at packing facility.

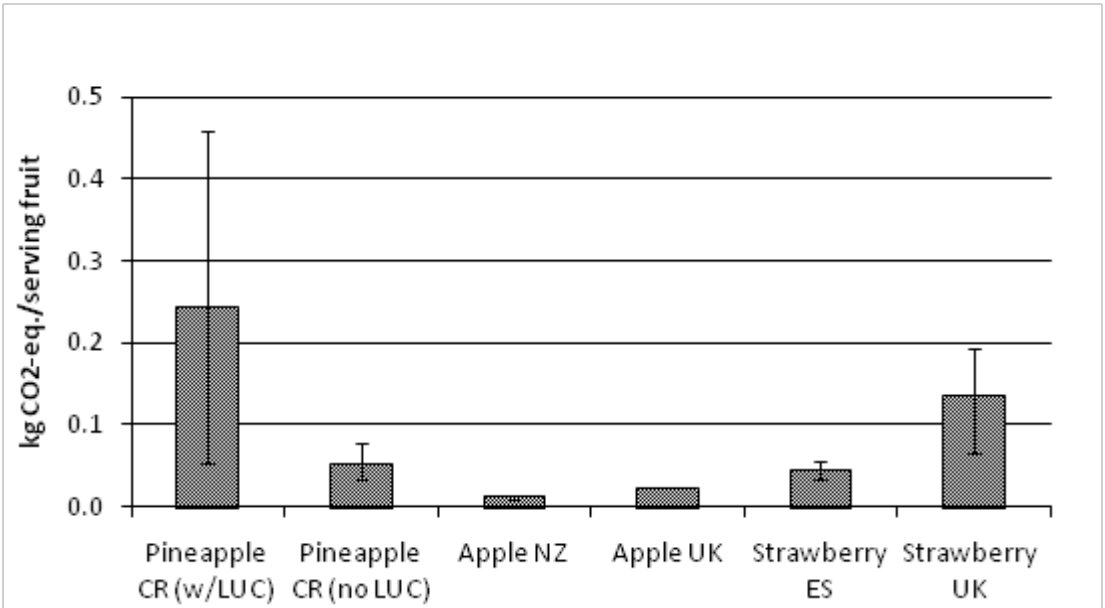

Figure 4-5. Carbon footprint of one serving pineapple in comparison with evaluations of the farming stage of other fruits. Sources: Apple NZ (Canals 2003); Apple UK (Lillywhite et al. 2007); Strawberry ES (Williams et al. 2008); Strawberry UK (Lillywhite et al. 2007; UoH 2005; Williams et al. 2008).

owing to the leaching of nitrate from use of N-fertilizers in pineapple cultivation. Most of the uncertainty in the virtual water content can be explained by the variation in the grey

water footprint due to nitrate emissions; the sensitivity analysis of the CROPWAT model for pineapple showed little regional variation in estimated ET for pineapple fields; the most significant variable is the crop coefficient (relationship of crop ET to pan ET), which has variable estimates in the literature (Malézieux et al. 2003).

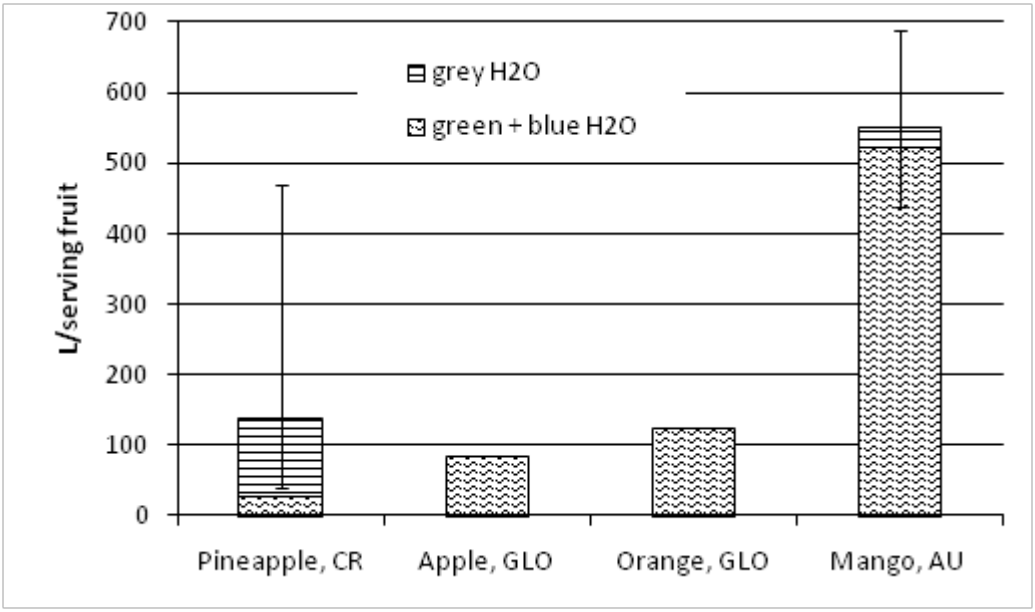

Figure 4-6. Virtual water content (VWC) for pineapple in comparison with other fruits. Evaporative and non-evaporative water are included for pineapple and mango (green + blue + grey); only evaporative water is included for apples and oranges (green + blue). Mango data is from Riddout et al. (2009); apple and orange data from Chapagain and Hoekstra (2004).

The stress-weighted water footprint (SWWF) of pineapple in the baseline scenario is negligible; the estimated confidence interval is 0.004-0.017 L/serving, because the water-stress index for Costa Rica is very low (0.02 on a scale of 0 to 1). In comparison with mango grown in AU, with a stress-weighted water footprint on average of 74 L/serving, the effect on water deprivation caused by pineapple is negligible.

Aquatic Eutrophication

The eutrophication RoEP was estimated to be between approximately 1 and 15 g N-eq./kg pineapple or 0.3 to 4.8 g N-eq/serving. More than 90% of potential

eutrophication effects were related to NO_3 leached from fields (53%), phosphorus bound to eroded sediment, and leached phosphate (10%). P in eroded soil was a the most variable of the contributors, with a cooefficient of variation of 173%, which relates to the high variability of erosion. The estimated percentage of P lost to erosion of all P applied varied between 0 and 20% among participating farms; percent of N estimated to leach from fields as NO_3-N varied between 10% and 34%.

While direct comparison among evaluations of fruits using different methods of estimating eutrophication-related field emissions is very difficult, preliminary comparisons can be made by multiplying emissions by the same TRACI characterization factors used in this study. The results are shown in

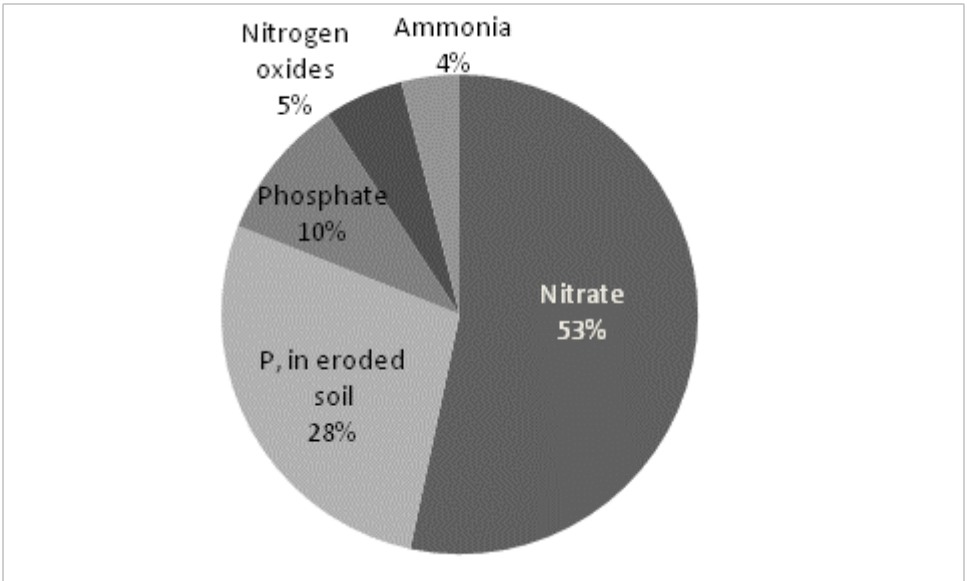

Figure 4-7. Contribution to potential eutrophication of pineapple by emission.

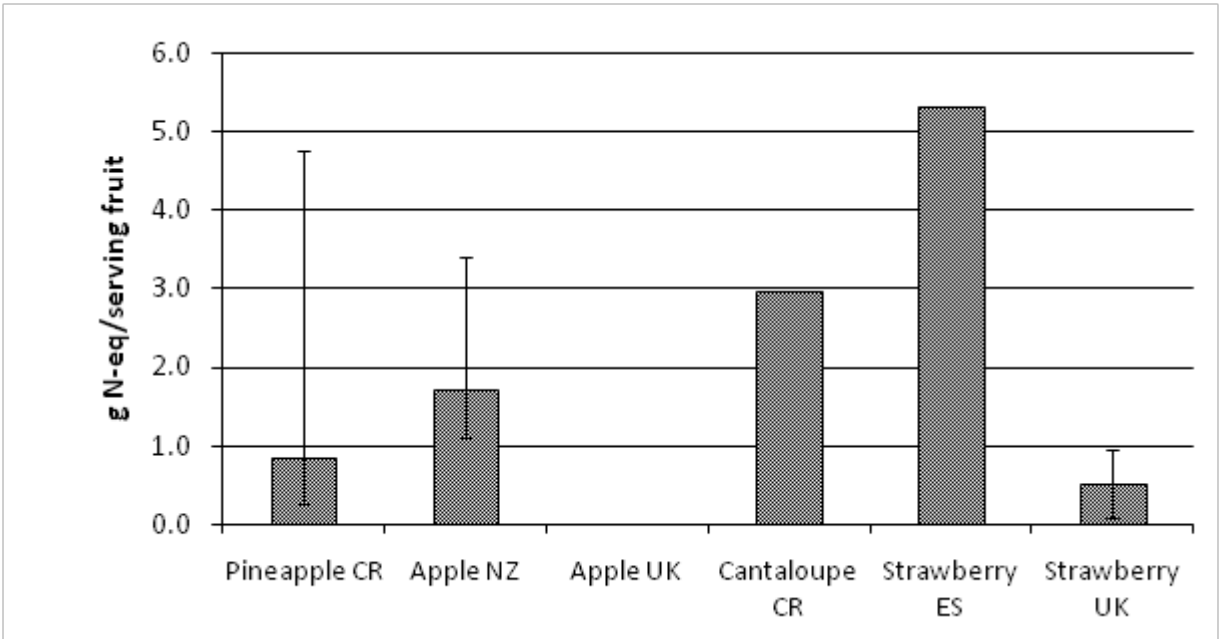

Figure 4-8. Preliminary comparison of potential eutrophication effects of one serving pineapple in comparison with evaluations of the farming stage of other fruits. Sources: (Canals 2003); Apple UK (Lillywhite et al. 2007); Cantaloupe CR (Hartley-B. and Díaz-P. 2008); Strawberry ES (Williams et al. 2008); Strawberry UK (Lillywhite et al. 2007).

Human and Ecological Toxicity

The RoEP for human toxicity was estimated to be 1.7E-10 to 1.1E-9 disease cases/kg pineapple, but could be as much as 1000 times greater or less, due to the uncertainties inherent in the USETox model. The RoEP for freshwater ecotoxicity was 0.2 to 1.4 PAF in m3/day/kg pineapple, but could be as much as 100 times up greater or less.

The pesticides contributing the most toward human toxicity are ethoprop, diuron, and diazinon, respectively applied as nematicide, herbicide, and insecticide (Figure 4-9a). The pesticides contributing the most to ecotoxicity are diuron, ametryne (herbicide), ethoprop, and paraquat (herbicide). Toxicity characterization does not necessarily correspond to quantity applied in the field; half as much ethoprop is applied as diuron and diazinon, and less of that applied is emitted from the field (5% for

ethoprop vs. 26% and 27% of diuron and paraquat), but its toxicity effects when being transported and coming into contact with humans and freshwater ecosystems is much stronger on a unit basis. Not all pesticides have demonstrated human toxicity effects although they do cause damage to freshwater ecosystems, including ametryne and bromacil.

In contrast to the temperate environment (Denmark) in which PESTLCI was originally calibrated, the Costa Rican environment has higher average annual rainfall and solar insolation which increases the estimated runoff and abiotic degradation of pesticides, respectively. The PestLCI-CR model shows a greater fraction being delivered to water, but a smaller fraction being delivered to air than in the default PestLCI model. Total emissions of pesticides are greater overall in the default model. The USETox-CR characterization model for the toxicity effects of these pesticides also shows differences from the default European parameterization. The USETox-CR characterization factors for ecotoxicity for emissions range from 1.5 to 6 times less than in USETox-EU; characterization factors for human toxicity for emissions are equal for emissions to air but 1.5 to 3 times less for emissions to water.. Despite these absolute difference, relative toxicities among these pesticides are modeled similarly.

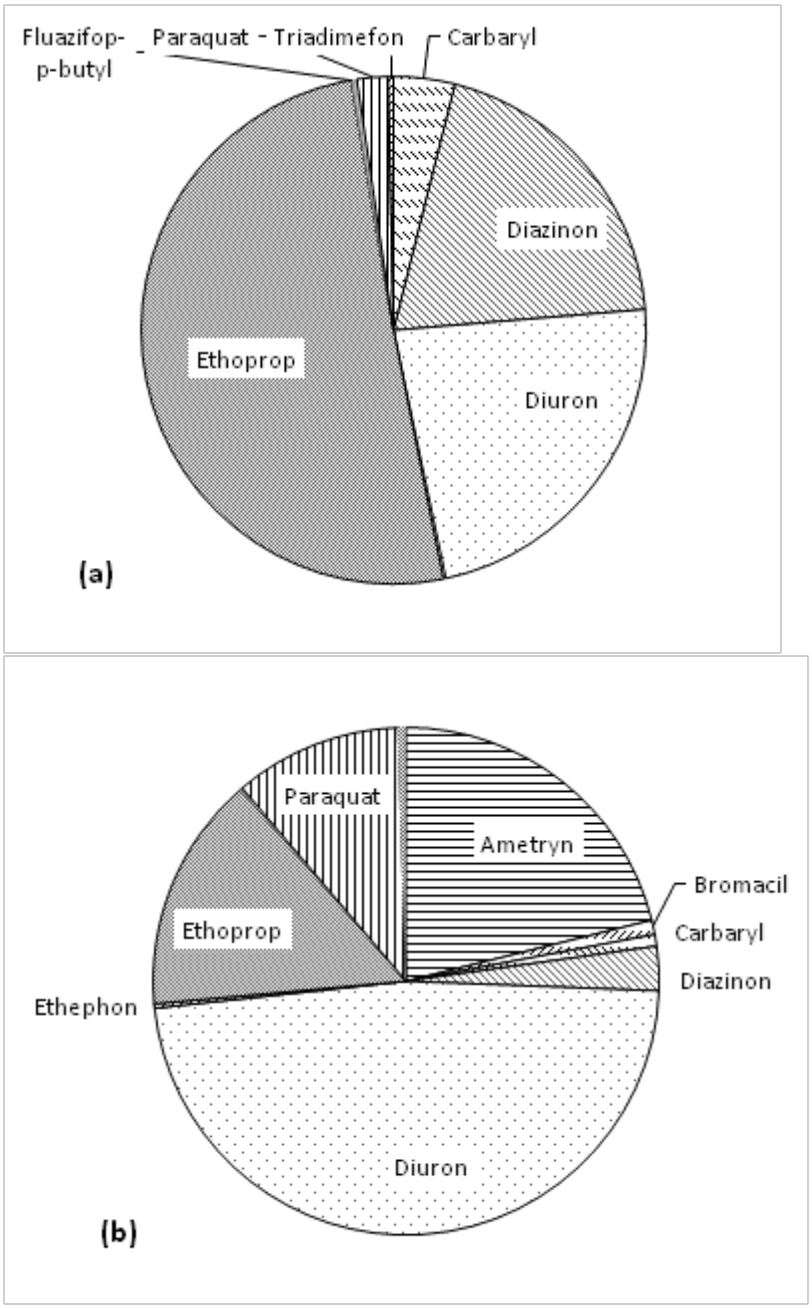

Figure 4-9. Relative contribution of active ingredients of pesticides used in pineapple production to (a) human toxicity and (b) freshwater ecotoxicity.

Results Summary

Table 4-1 presents a summary of the life cycle environmental performance of pineapple production through transport to the packing facility. On farm processes are responsible for the majority of impacts (given since some impacts were only modeled at

the farm stage due to assumption it contributes the majority of this type of impact) with the exception of the cumulative energy demand and to carbon footprint; about half of the carbon footprint occurs upstream and half on the farm. The uncertainty of each modeled impact, as measured by the coefficient of variation, varies markedly from less than 10% for land use, for which yield variation is the sole contributor to uncertainty, to human toxicity, which has a high level of uncertainty due to the large uncertainty in the toxicity characterization factors.

Table 4-1. Summary table for impacts of 1 kg pineapple delivered to packing facility.

		RoEP		Contribution to Impact		Variance of Impact	
Indicator	Unit	Min	Max	% contribution of farm stage	Most significant contributor	CV	Factor most responsible for variance[a]
Land occupation	m2/yr	0.14	0.21	100%	yield	9%	yield
Soil erosion	kg eroded soil	0.0005	0.6	100%	farm slope	165%	farm slope
NR cumulative energy demand	MJ	1.2	2.2	23%	fertilizer production	25%	yield
Carbon footprint (with LUC)	kg CO2-eq.	0.16	1.4	89%	land use change	48%	carbon loss from land-use change
Carbon footprint (no LUC)	kg CO2-eq.	0.10	0.3	49%	fertilizer production	19%	yield
Virtual water content	L	124	1450	100%	water for dilution of pollution	21%	nitrate emission
Stress-weighted water footprint	L	0.0044	0.017	100%	water for application of fert./pest.	21%	yield
Aquatic eutrophication	kg N-eq.	0.00086	0.015	96%	nitrate emission to water	62%	P in soil eroded
Human toxicity	disease cases	1.7E-10	1.1E-09	100%	Ethoprop (nematicide)	46%	amount of ethoprop applied
Freshwater ecotoxicity	PAF/m3/day	0.2	1.4	100%	Diuron (herbicide)	44%	fraction of diuron emitted to water

Notes

[a] Based on the largest CV for related inventory item among yield, associated input, or emission model. If this was the emissions model, the most sensitive variable in the sensitivity analysis was used.

Discussion

The data underlying the inventory represent medium to large size farms in the three primary geographic zones in Costa Rica. Sufficient input data from the smallest producers (<10 ha) was solicited but not acquired, likely due to less stringent bookkeeping practices and also heavier reliance upon larger producer associations for tasks, managements, and equipment. The other end of the spectrum of producers, the largest national and multi-national companies with farms >250 ha, is neither directly represented. Although solicited, none of the four largest companies agreed to provide primary data for this study.

All emissions and inventory results reveal the importance of yield in impact estimations, confirming recent findings in agricultural LCA (Roos et al. 2010). With higher yields and an equal amount of impact/area, impacts are diluted across more product, representing higher environmental efficiency. The average yield reported for the sector (67 tons/ha) falls at the 9th percentile of the yield distribution of the sample farms that contributing production data, indicating a bias toward more productive farms in the sample used to create the baseline scenario. However, because the reported average sector yield falls within the confidence intervals for yield varied here, this national average pineapple falls within the distribution modeled. It is necessary to reiterate here that the objective was to model the expected range of environmental performance in the sector, and that the range rather than the median or mean values should be the focus of the results.

The wide ranges of performance evident for all impacts categories indicate the importance of farm-level assessment to differentiate environmental performance of pineapple production among farms. In the initial comparisons of environmental

performance between farm stage production of pineapple and other fruits, where such comparisons were possible, pineapples perform within a similar range, seemingly better in some categories and worse in others, but the full RoEP for the other fruits was not published nor calculable in most cases, limiting the ability of comparison. The estimated RoEP for energy demand for pineapple showed it to be higher in energy demand than apples and oranges on a per serving basis, but lower than Spanish and British strawberries. The carbon footprint reflected a similar patterns with less of a relative difference between pineapples and other fruits. Pineapple was lower in consumptive water use than apples, oranges and mangos, but higher than mangos in its gray water requirement. Without the need for irrigation in most areas and because of its physiological adaptations to water stress, water use impacts were minimal in comparison with other fruits. The broad RoEP of eutrophication for pineapple indicates the relatively higher degree of uncertainty for this category, and considerable potential overlap in this respect with other fruits.

Because production inputs dominate energy demand and carbon footprint, the relatively high-agrochemical input intensity of pineapple cultivation (FAO 2006; Su 1968) may explain in part why these indicators are higher for pineapple in relation to other fruit. Additional explanation is provided by the fact that there are less servings of pineapple per kg than the fruits compared here, largely because of the higher non-edible potion of pineapple (about 50%).

The significance of regionalized emissions and impact models

The significance that climatic, geographic, crop, and field-specific factors have in emissions and impact models is supported by the differences in outcomes of the regionalized and the original versions of models used here. Water loss estimates from

CROPWAT are dependent on water balance calculations based on climatic, soil, and plant conditions, and estimated will differ greatly among different climate zones and by crop. The PESTLCI model showed great variation in emissions between the default conditions (Denmark) and Costa Rica. Characterization factors for pesticides differed by up to 70 times for toxicity factors between the default USETox and the USETox-CR model. Using regionalized models will likely have significant effects on LCA outcomes, and should be applied with careful attention to the capacity to accurately describe conditions, but is essential for more accurate characterization of local and regional impacts.

Although regional data was incorporated into these models, all those adapted here operate independently and use a unique set of field parameters. Attempt was made to use consistent parameterization of these models, but there is no guarantee of consistency of model calculations of common parameters (e.g. runoff is estimated in PestLCI, CROPWAT, and RUSLE2). Some models achieve a higher degree of specificity (RUSLE2) than others (CROPWAT) and thus some do not utilize all data that could theoretically influence results. However, the use of freely, publically-available models adaptable to a wide range of conditions is of high utility for likelihood of use and for comparability. The N and P fertilizers emissions model was adapted based on average pineapple nutrient uptake rates, but otherwise did not account for regional climatic conditions or soil properties. The model presented here is an improvement upon solely arbitrary designation of emissions fractions of all forms of N and P (e.g. 35% of N leaches to soil), some of which, including N leaching, has been estimated to vary between 10 and 80% of applied N (Miller et al. 2006), and may be sufficient for

relative comparison among farms, but could be replaced with a more detailed process-based model as is used here for soil erosion, water use and pesticide emissions. These models could all be improved with better parameterization based on data collection on pineapple farms in Costa Rica for variables including pineapple biomass, nutrient uptake, water use, and leaf permeability to pesticides.

Estimated environmental impacts

All estimates of environmental impacts need to be considered in light of the accuracy of their characterization and of the inputs data underlying this characterization.

Experimental quantification of soil erosion is typically marked by high variability, usually because erosion is strongly event-based and the difficulty of capturing a representative sample of eroded sediment. Data from experimental measurement of soil loss in CR are no exception to this (see Table 15-1, Rubin and Hyman 2000). In consequences models based on long-term climatic and management data may be preferable and yield more comparable results for quantification of soil erosion in LCA. However they should still be validated with existing data. The RoEP of 0.02 to 32 tons/ha soil erosion tons/ha/yr found here does confer with existing estimates of erosion of mineral soils under pineapple cultivation in Hawaii and Australia.

Land use, energy use and carbon footprint were estimated with the lowest uncertainty, however the latter two are both heavily dependent upon the quality of the input data for upstream processes. Carbon loss through land transformation has been calculated to be a dominant factor in the carbon footprint of crops occupying former tropical forest (Fargione et al. 2008), and that could possibly occur for pineapple cultivation, if it replaces tropical forest. There is, however, little evidence to suggest that pineapple expansion in Costa Rica has been a direct cause of deforestation since 1990

(Joyce 2006). Nevertheless conversion from other types of land use, including secondary forest and pasture, could also result in carbon loss but is not quantified here. As far as eutrophication and toxicity impacts are concern, which are impacts based on potentially long-range transport, persistence and availability in environmental media, the effects on ecosystems (freshwater ecotoxicity) and humans (human toxicity) should be read with appropriate skepticism of the capacity of generic models to make accurate estimations without explicit spatial data; nevertheless because these aspects (fate, transport, toxicity effects) are all relevant to their ultimate effect, they should be considered superior to just reporting quantities of pesticides released.

Potential Impacts Not Measured

The scope of this LCA was strictly limited to environmental impacts, and did not include any evaluation of social or economic impacts. Both of these impacts can potentially be accounted for in LCA, with the related tools of Life Cycle Costing (LCC) and the newly developed Social Life Cycle Assessment (SLCA).

Aside from loss of stored carbon, land use conversion and occupation can have ecosystem consequences on biodiversity across multiple scales (ME Assessment 2005), and this should be accounted for in the LCA, and has been recommended for consideration and methods are under development, but none were judged to be sufficient to capture effects on biodiversity of pineapple production in the studied environment.

Handling and application of pesticides in the field could have direct impacts on worker health, but no suitable methodology exists for measuring this in LCA. However all farms sampled reported use of protective equipment among workers in the field to reduce this risk.

Residual organic waste on pineapple fields has been blamed for ecological consequences such as providing the substrate for the larval stage development of biting flies (Sandoval 2009), which have potential consequences for local livestock. Such consequences have not been addressed here.

Conclusions and Recommendations for Farm Level LCA of Fruit Products

The development of inventories of agricultural processes and the characterization of their impacts are two separate but interdependent stages of the LCA. Since fruit products depend on further downstream processes before reaching the final consumer, inventories should include sufficient information that impacts can be characterized for their entire farm-to-disposal life cycle stages. Yet particular attention should be paid to those inventory items that need to be recorded in the farm stage because of their likelihood to dominant full life cycle impacts: these include water use, eutrophication, toxicity, and soil erosion.

Evidence here shows that it is essential to include upstream processes to fully characterize energy use for farm LCA, because energy use in agricultural inputs such as fertilizers may dominate cumulative energy use through the life cycle stage. Acknowledging this importance, life cycle data on farm input production adapted from LCI databases with a EU-focus such as Ecoinvent used here needs to be validated for its application in other world regions. Because actual farm level energy use is dominated by liquid fuels for farm equipment such as tractors, energy use is likely to be strongly correlated with other impacts during the farm stage dominated by fuel combustion, including greenhouse gas production, acidification, and photochemical oxidant production. Emissions to air causing these impacts should be included in agricultural inventories for use in full life cycle studies, but for sake of brevity and

increased interpretability of LCA users, characterization of these impacts at the farm level is likely to be unnecessary because of its redundancy. This may not be the case if other energy sources (e.g. biofuels or electricity) comprise a substantial proportion of farm stage energy use.

Use of LCIA indicators should be based both on environmental relevancy and sufficient characterization models and uncertainty estimation. In this case we recommend use of a measure of cumulative energy consumption, such as CED. Use of other broader measures of energy use, such as emergy, would present a richer picture of energy use that is more informative for measurement of long-term sustainability, but should only be used if accurately integrated into the life cycle inventory and for which model uncertainty is described. Energy use also is characterized by relatively low model uncertainty, which increases comparability of different products.

Local and regional environmental impacts related to soil erosion, water stress, eutrophication, and ecological and human toxicity are particularly relevant for farm level process and require characterization adapted to the region of production. Soil erosion is a particularly localized indicator requiring a large amount of field-specific information to accurately model. It is highly relevant for areas with sloped terrain and high rainfall. The direct downstream impact of soil erosion on water quality though sedimentation, was not quantified here but is a relevant environmental impact that deserves future investigation for LCA characterization. And as demonstrated here, accurate quantification of soil erosion can be particularly relevant for other impacts, including eutrophication, due to loss of nutrients bound to soil in erosion, and potentially for toxicity impacts, although the contribution of eroded sediments to those impacts was not

quantified here. Farm level emissions are marked by high levels of variability, especially related to yields, and uncertainty due to complex and site-specific fate, transport, and effect processes of agricultural emissions. We recommended that farm-stage LCAs reported data along with sufficient range parameters to quantify uncertainty in input data related to those emissions, uncertainty in the emissions themselves, and if characterized, uncertainty in the characterization factors. Finally, farm stage assessment data must be coupled with data on downstream life cycle stages before being fully evaluated by the end-consumer.

CHAPTER 5

CONCLUSIONS

Final conclusions will go here

LIST OF REFERENCES

Australian Museum. 2007. Structure and composition of the Earth. http://www.amonline.net.au/geoscience/earth/structure.htm. Accessed.

Ayres, R. U., L. W. Ayres, and K. Martinas. 1998. Exergy, Waste Accounting, and Life-cycle Analysis. *Energy* 23(5): 355-363.

Bach, O. 2008. *Agricultura e implicaciones ambientales con énfasis en algunas cuencas hidrográficas principales*. Decimotercer Informe de Estado de la Nacion en Desarollo Sostenible. San Jose: Consejo de Rectores.

Baral, A. and B. R. Bakshi. 2010. Thermodynamic Methods for Aggregation of Natural Resources in Life Cycle Analysis: Insight via Application to Some Transportation Fuels. *Environmental Science & Technology* 44: 800-807.

Bare, J., T. Gloria, and G. Norris. 2006. Development of the method and U.S. normalization database for Life Cycle Impact Assessment and sustainability metrics. *Environmental Science & Technology* 40(16): 5108-5115.

Bare, J., G. A. Norris, D. W. Pennington, and T. McKone. 2003. TRACI - The Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts. *Journal of Industrial Ecology* 6: 49-78.

Bartelmus, P. 2003. Dematerialization and capital maintenance: two sides of the sustainability coin. *Ecological Economics* 46: 61-81.

Bastianoni, S., A. Facchini, L. Susani, and E. Tiezzi. 2007. Emergy as a function of exergy. *Energy* 32: 1158–1162.

Bastianoni, S., D. E. Campbell, R. Ridolfi, and F. M. Pulselli. 2009. The solar transformity of petroleum fuels. *Ecological Modelling* 220(1): 40-50.

Birkveda, M. and M. Z. Hauschild. 2006. PestLCI—A model for estimating field emissions of pesticides in agricultural LCA. *Ecological Modelling* 198: 433-451.

Blanke, M. M. and B. Burdick. 2009. An energy balance (as part of an LCA) for home-grown (apple) fruit versus those imported from South Africa or New Zealand. In *LCA IX. Joint North America LCA Conference*. Boston.

Bösch, M. E., S. Hellweg, M. A. J. Huijbregts, and R. Frischknecht. 2007a. Applying Cumulative Exergy Demand (CExD) Indicators to the ecoinvent Database. *Int J LCA* 12(3): 181-190.

Bösch, M. E., S. Hellweg, M. A. J. Huijbregts, and R. Frischknecht. 2007b. Applying Cumulative Exergy Demand (CExD) Indicators to the ecoinvent Database. *International Journal of Life Cycle Assessment* 12(3): 181-190.

Boustead, I. and G. F. Hancock. 1978. *Handbook of Industrial Energy Analysis*. New York: Ellis Horwood Ltd.

Brown, M. T. 2009. Personal Communication with Brown, M. T., Gainesville, FL 2009.

Brown, M. T. and S. Ulgiati. 1997. Emergy based indices and ratios to evaluate sustainability: monitoring economies and technology to toward environmentally sound innovation. *Ecological Engineering* 9: 51-69.

Brown, M. T. and S. Ulgiati. 2002. Emergy evaluations and environmental loading of electricity production systems. *Journal of Cleaner Production* 10(4): 321-334.

Brown, M. T. and V. Buranakarn. 2003. Emergy indices and ratios for sustainable material cycles and recycle options. *Resources, Conservation and Recycling* 38: 1-22.

Brown, M. T., M. J. Cohen, and S. Sweeney. 2009. Predicting national sustainability: The convergence of energetic, economic and environmental realities. *Ecological Modelling* 220(23): 3424-3438.

Brown, M. T., M. J. Cohen, E. Bardi, and W. W. Ingwersen. 2006. Species diversity in the Florida Everglades, USA: A systems approach to calculating biodiversity. *Aquatic Sciences* 68(3): 254-277.

Brunner, P. and H. Rechburger. 2003. *Practical Handbook of Material Flow Analysis*. Vero Beach, FL: CRC Press.

Buenaventura Mining Company Inc. 2006. Form 20-F for fiscal year 2005., edited by SEC.

Burt, R. 2009. *Soil Survey Field and Laboratory Methods Manual*. Soil Survey Investigations Report No. 51. Lincoln, Nebraska: National Soil Survey Center, Natural Resources Conservation Service, U.S. Department of Agriculture.

Butterman, W. C. and H. E. Hilliard. 2004. *Silver*. Mineral Commodity Profiles. Reston, VA: U.S. Geological Survey.

Butterman, W. C. and E. B. Amey. 2005. *Gold*. Mineral Commodity Profiles. Reston, Virginia: U.S. Geological Survey.

Canals, L. M. 2003. Contributions to LCA methodology for agricultural systems: Site dependency and soil impact assessmentthesis, Universidad Autonoma, Barcelona.

Chapagain, A. K. and A. Y. Hoekstra. 2004. *Water footprints of nations*. Vol. 1, *Value of Water Research Report Series No. 16*. Delft, The Netherlands: UNESCO-IHE Delft.

Cherubini, F., M. Raugei, and S. Ulgiati. 2008. LCA of magnesium production - Technological overview and worldwide estimation of environmental burdens. *Resources Conservation and Recycling* 52(8-9): 1093-1100.

Cherubini, F., M. Raugei, and S. Ulgiati. 2008. LCA of magnesium production - Technological overview and worldwide estimation of environmental burdens. *Resources Conservation and Recycling* 52(8-9): 1093-1100.

Christiansen, K., M. Wesnæs, and B. P. Weidema. 2006. *Consumer demands on Type III environmental declarations*. Copenhagen: 2.0 LCA consultants.

Cohen, M., S. Sweeney, and M. T. Brown. 2008. Computing the Unit Emergy Value of Crustal Elements. In *Emergy Synthesis 4: Proceedings of the 4th Biennial Emergy Conference*, edited by M. T. Brown. Gainesville, FL: Center for Environmental Policy.

Cohen, M. J. 2001. Dynamic Emergy Simulation of Soil Genesis and Techniques for Estimating Transformity Confidence Envelopes. In *Second Biennial Emergy Analysis Research Conference*. Gainesville, FL: Center for Environmental Policy.

Cuadra, M. and J. Björklund. 2007. Assessment of economic and ecological carrying capacity of agricultural crops in Nicaragua. *Ecological Indicators* 7: 133–149.

Daly, G. L., Y. D. Lei, C. Teixeira, D. C. G. Muir, L. E. Castillo, and F. Wania. 2007. Accumulation of Current-Use Pesticides in Neotropical Montane Forests. *Environmental Science & Technology* 41(4): 1118-1123.

Ebeling, J. and M. Yasue. 2008. Generating carbon finance through avoided deforestation and its potential to create climatic, conservation and human development benefits. *Philosphical Transactions of the Royal Society B* 363: 1917–1924.

Ecoinvent Centre. 2007. *Ecoinvent data v2.0*. Dübendorf, CH: Swiss Centre for Life Cycle Inventories.

Ehrlich, H. and D. Newman. 2008. *Geomicrobiology*. 5th ed. Boca Raton, FL: CRC Press.

European Commission. 2003. *Communication of the (European) Commission to the Council and the European Parliament on Integrated Product Policy*. COM(2003) 302 final.

FAO. 2006. *Fertilizer use by crop*. FAO Fertilzer and Plant Nutrition Bulletin. Rome: Food and Agricultural Organization of the United Nations.

FAO. 2009. FAOSTAT Trade Database.

FAO. 2010. Web LocClim, Local Monthly Climate Estimator: FAO.

Fargione, J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. 2008. Land clearing and the biofuel carbon debt. *Science* 319(5867): 1235-1238.

Fava, J. A., A. A. Jensen, L. Lindfors, S. Pomper, B. d. Smet, J. Warren, and B. Vigon. 1994. *Lifecycle assessment data quality. A conceptual framework*. Pensacola, FL: SETAC.

Federici, M., S. Ulgiati, and R. Basosi. 2008. A thermodynamic, environmental and material flow analysis of the Italian highway and railway transport systems. *Energy* 33(5): 760-775.

Finnveden, G. 2005. The Resource Debate Needs to Continue [Stewart M, Weidema B (2005): A Consistent Framework for Assessing the Impacts from Resource Use. Int J LCA 10 (4) 240−247]. *The International Journal of Life Cycle Assessment* 10(5): 372-372.

Foster, G. R., D. Yoder, and S. Dabney. Revised Universal Soil Loss Equation 2 (RUSLE2) ARS Version May 20, 2008. USDA Agricultural Research Service, Oxford, MS.

Franzese, P. P., T. Rydberg, G. F. Russo, and S. Ulgiati. 2009. Sustainable biomass production: A comparison between Gross Energy Requirement and Emergy Synthesis methods. *Ecological Indicators* 9(5): 959-970.

Frischknecht, R. and N. Jungbluth. 2007. *Implementation of Life Cycle Impact Methods. Data v2.0 (2007)*. Ecoinvent report No. 3. Dübendorf, CH: Swiss Centre for Life Cycle Inventories.

Frischknecht, R., N. Jungbluth, H.-J. Althaus, G. Doka, R. Dones, T. Heck, S. Hellweg, R. Hischier, T. Nemecek, G. Rebitzer, M. Spielmann, and G. Wernet. 2007. *Ecoinvent report No. 1: Overview and Methodology*. Dübendorf: Swiss Centre for Life Cycle Inventories.

Gabby, P. N. 2007. Lead. In *U.S. Geological Survey Minerals Yearbook — 2005*, edited by USGS. Washingon, DC: USGS.

Gaillard, G. and T. Nemecek. 2009. Editorial. In *Proc. of the 6th Int. Conf. on LCA in the Agri-Food Sector*. Zurich: Agroscope Reckenholz-Tänikon Research Station ART.

Gallego, A., L. Rodriguez, A. Hospido, M. T. Moreira, and G. Feijoo. 2010. Development of regional characterization factors for aquatic eutrophication. *International Journal of Life Cycle Assessment* 15(1): 32-43.

Gallopin, G. 2003. *A systems approach to sustainability and sustainable development Sustainable Development and Human Settletments Division*. Santiago, Chile: United Nations Economic Commission for Latin America and the Caribbean.

Giljum, S. 2004. Trade, Materials Flows, and Economic Development in the South: The Example of Chile. *Journal of Industrial Ecology* 8: 241-263.

Gloria, T. 2009. Determination of empirical allocation measures for non-ferrous metals. In *Joint North American Life Cycle Conference*. Boston, MA: American Center for Life Cycle Assessment.

Gobin, A., G. Govers, R. Jones, M. Kirkby, and C. Kosmas. 2003. *Assessment and reporting on soil erosion - Background and workshop report* Copenhagen: European Environment Agency.

Goedkoop, M. and R. Spriensma. 2001a. *The Eco-indicator 99: A damage-oriented method for LCA*. Amersfoort, NL: PRé consultants.

Goedkoop, M. and R. Spriensma. 2001b. *The Eco-Indicator 99. A damage oriented method for LCA.* The Netherlands: PRe.

Gómez, M. P., P. P. Quesada, and K. M. Bucheli. 2007. Implementation of good practices in the production of fresh pineapples for export: Case study of the Huetar Norte region, Costa Rica. In *Implementing programmes to improve safety and quality in fruit and vegetable supply chains: benefits and drawbacks. Latin American case studies*, edited by L. B. D. R. Maya Piñeiro. Rome: Food and Agriculture Organization of the United Nations.

Gossling-Reisemann, S. 2008a. What is resource consumption and how can it be measured? Theoretical considerations. *Journal of Industrial Ecology* 12(1): 10-25.

Gossling-Reisemann, S. 2008b. What Is Resource Consumption and How Can It Be Measured? - Application of Entropy Analysis to Copper Production. *Journal of Industrial Ecology* 12(4): 570-582.

Guinée, J. B., ed. 2002. *Handbook on life cycle assessment: operational guide to the ISO standards.*, *Vol. 7, Ecoefficiency in industry and science*. Doldrecht, London: Kluwer Academic.

Hails, C., S. Humphrey, J. Loh, and S. Goldfinger, eds. 2008. *Living Planet Report 2008*. Gland, Switzerland: WWF International.

Hartley-B., M. and R. Díaz-P. 2008. *Mejoras mmbientales para el desarollo de la competitividad en tres cadenas agroalimentarias costarricenses*. Heredia, Costa Rica: Centro Internacional de Politica Economica.

Hau, J. L. and B. R. Bakshi. 2004a. Promise and problems of emergy analysis. *Ecological Modelling* 178(1-2): 215-225.

Hau, J. L. and B. R. Bakshi. 2004b. Expanding Exergy Analysis to Account for Ecosystem Products and Services. *Environmental Science and Technology* 38(13): 3768-3777.

Helmer, E. H. and S. Brown. 2000. Gradient Analysis of Biomass in Costa Rica and a First Estimate of Countrywide Emissions of Greenhouse Gases from Biomass Burning. In *Quantifying sustainable development the future of tropical economies*, edited by C. A. S. Hall, et al. San Diego: Academic Press.

Heuvelmans, G., J. F. Garcia-Qujano, B. Muys, J. Feyen, and P. Coppin. 2005. Modelling the water balance with SWAT as part of the land use impact evaluation in a life cycle study of CO2 emission reduction scenarios. *Hydrological Processes* 19(3): 729-748.

Hill, A. R. and C. V. Holst. 2001. A comparison of simple statistical methods for estimating analytical uncertainty, taking into account predicted frequency distributions. *Analyst*(126): 2044–2052.

Hoekstra, A. Y., A. K. Chapagain, M. M. Aldaya, and M. M. Mekonnen. 2009. *Water Footprint Manual - State of the Art 2009*. Enschede, The Netherlands: Water Footprint Network.

Holdridge, L. R. 1967. *Life Zone Ecology*. San Jose, CR: Tropical Science Center.

Hopper, R. 2008. Emergy Synthesis of Sulfuric Acid. In *Prepared for EES5306 Energy Analysis class, Spring 2008.* Gainesville, FL: University of Florida.

Huijbregts, M. A. J., S. Lundi, T. E. McKone, and D. v. d. Meent. 2003a. Geographical scenario uncertainty in generic fate and exposure factors of toxic pollutants for life-cycle impact assessment. *Chemosphere* 51: 501-508.

Huijbregts, M. A. J., W. Gilijamse, A. M. J. Ragas, and L. Reijnders. 2003b. Evaluating uncertainty in environmental life-cycle assessment. A case study comparing two insulation options for a Dutch one-family dwelling. *Environmental Science & Technology* 37(11): 2600-2608.

Huijbregts, M. A. J., S. Hellweg, R. Frischknecht, H. W. M. Hendriks, K. HungerbuÌˆhler, and A. J. Hendriks. 2010. Cumulative Energy Demand As Predictor for the Environmental Burden of Commodity Production. *Environmental Science & Technology* 44(6): 2189-2196.

Ingwersen, W. W. 2010. Uncertainty characterization for emergy values. *Ecological Modelling* 221(3): 445-452.

Ingwersen, W. W. accepted. Emergy as a impact assessment method for life cycle assessment presented in a gold mining case study. *Journal of Industrial Ecology*.

Ingwersen, W. W. in Press. Emergy as a impact assessment method for LCA presented in a gold mining case study. *Journal of Industrial Ecology*.

Ingwersen, W. W., S. A. Clare, D. Acuña, M. J. Charles, C. Koshal, and A. Quiros. 2009. *Environmental Product Declarations: An introduction and recommendations for their use in Costa Rica*. Gainesville, FL: University of Florida Levin College of Law Conservation Clinic.

IPCC. 2007. *Climate Change 2007. IPCC Fourth Assessment Report. The Physical Science Basis.* Geneva: International Panel on Climate Change.

ISO. 2006a. *Environmental management -- Life cycle assessment -- Requirements and guidelines (ISO 14044:2006)*. Geneva, Switzerland: International Organization for Standardization.

ISO. 2006b. *Environmental labelling and declarations – Type III environmental declarations – Principles and procedures (ISO 14025:2006)*. International Standard. Geneva, Switzerland: International Organization for Standardization.

ISO. 2006c. *14044: Environmental management -- Life cycle assessment -- Requirements and guidelines*. Geneva: International Standards Organization.

ISO. 2006d. *14040: Environmental management -- Life cycle assessment -- Principles and framework*. Geneva: International Standards Organization.

Jolliet, O., M. Margni, R. Charles, S. Humbert, J. Payet, G. Rebitzer, and R. Rosenbaum. 2003a. IMPACT 2002+: A new life cycle impact assessment methodology. *International Journal of Life Cycle Assessment* 8(6): 324-330.

Jolliet, O., A. Brent, M. Goedkoop, N. Itsubo, R. Mueller-Wenk, C. Peña, R. Schenk, M. Stewart, and B. Weidema. 2003b. *Final report of the LCIA Definition study*. UNEP/SETAC Life Cycle Initiative. United National Environmental Program.

Joyce, A. 2006. *Land Use Change in Costa Rica 1966-2006 as influenced by social, economic, political and environmental factors*. San Jose: Litografía e Imprenta LIL.

La Rosa, A. D., G. Siracusa, and R. Cavallaro. 2008. Emergy evaluation of Sicilian red orange production. A comparison between organic and conventional farming. *Journal of Cleaner Production* 16(17): 1907-1914.

Lal, R. 1983. Soil erosion in the humid tropics with particular reference to agricultural land development and soil management. In *Hydrology of Humid Tropical Regions with Particular Reference to the Hydrological Effects of Agriculture and Forestry Practice*. Hamburg: IAHS.

Lillywhite, R., D. Chandler, W. Grant, K. Lewis, C. Firth, U. Schmutz, and D. Halpin. 2007. *Environmental footprint and sustainability of horticulture (including potatoes) – A Comparison with other agricultural sectors*. UK: DEFRA.

Limpert, E., W. A. Stahel, and M. Abbt. 2001. Log-normal distributions across the sciences: Keys and clues. *Bioscience* 51(5): 341-352.

Lloyd, S. and R. Ries. 2007. Characterizing, Propagating, and Analyzing Uncertainty in Life Cycle Assessment. *Journal of Industrial Ecology* 11(1): 161-179.

Maia de Souza, D., R. Rosenbaum, L. Deschênes, and H. Lisboa. 2009. Crucial improvements needed for Land Use Impact Assessment modeling concerning biodiversity indicators. In *Life Cycle Assessment IX - Joint North American Life Cycle Conference*. Boston: American Center for LCA.

Malézieux, E., F. Côte, and D. P. Bartholomew. 2003. Crop Environment, Plant Growth and Physiology. In *The pineapple: Botany, production, and uses*, edited by D. P. Bartholomew, et al. Oxon, UK: CABI Pub.

Matthews, E., C. Amman, S. Bringezu, M. Fischer-Kowalski, W. Huttler, R. Kleijn, Y. Moriguichi, C. Ottke, E. Rodenburg, D. Rogich, H. Schandl, H. Schutz, E. V. d. Voet, and H. Weisz. 2000. *The Weight of Nations: Material Outflows from Industrial Economies*. 1st ed. Washington, DC: World Resources Institute.

ME Assessment. 2005. *Ecosystems & Human Well-being: Biodiversity Synthesis*, *Millineum Ecosystem Assessment*. Washington, DC: World Resources Institute.

Miller, S. A., A. E. Landis, and T. L. Theis. 2006. Use of Monte Carlo Analysis to Characterize Nitrogen Fluxes in Agroecosystems. *Environmental Science & Technology* 40(7): 2324-2332.

NAS. 1999. *Nature's Numbers*. Edited by W. N. a. E. Kokkelenburg. Washington, DC: National Academies Press.

Nemecek, T. and T. Kagi. 2007. *Life Cycle Inventory of Agricultural Production Systems*. Dubendorf: Ecoinvent Centre.

Ness, B., E. Urbel-Piirsalu, S. Anderberg, and L. Olsson. 2007. Categorising tools for sustainability assessment. *Ecological Economics* 60(3): 498-508.

NIST. 2010. The NIST reference on Constants, Units, and Uncertainty. http://physics.nist.gov/cuu/Uncertainty/combination.html. Accessed January 26 2010.

Norris, G. A. 2003. Impact Characterization in the Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts -Methods for Acidification, Eutrophication, and Ozone Formation. *Journal of Industrial Ecology* 6(3-4): 79-101.

O'Brien, E., B. Guy, and A. S. Lindner. 2006. Life Cycle Analysis of the Deconstruction of Military Barracks: Ft. McClellan, Anniston, AL. *Journal of Green Building* 1(4): 166-183.

Odum, H. T. 1988. Self organization, transformity, and information. *Science* 242: 1132–1139.

Odum, H. T. 1996. *Environmental Accounting*. New York: John Wiley & Sons.

Odum, H. T. 2007a. *Environment, Power, and Society*. 2nd ed. New York, NY: John Wiley and Sons, Inc.

Odum, H. T. 2007b. *Environment, Power and Society for the Twenty-First Century: The Hierarchy of Energy*. New York: Columbia University Press.

Odum, H. T., M. T. Brown, and S. Brandt-Williams. 2000. *Handbook of Emergy Evaluation Folio #1: Introduction and Global Budget*. Gainesville: Center for Environmental Policy, University of Florida.

Pennington, D. W., M. Margni, C. Ammann, and O. Jolliet. 2005. Multimedia fate and human intake modeling: Spatial versus nonspatial insights for chemical emissions in Western Europe. *Environmental Science & Technology* 39(4): 1119-1128.

Peruvian Ministry of Energy and Mines. 2006. *Annual Production 2005: Gold*. Lima, Peru:

Peters, G. M., H. V. Rowley, S. Wiedemann, R. Tucker, M. D. Short, and M. Schulz. 2010. Red Meat Production in Australia: Life Cycle Assessment and Comparison with Overseas Studies. *Environmental Science & Technology* 44(4): 1327-1332.

Pfister, S., A. Koehler, and S. Hellweg. 2009. Assessing the Environmental Impacts of Freshwater Consumption in LCA. *Environmental Science & Technology* 43(11): 4098-4104.

Pimentel, D. 2009. Energy Inputs in Food Crop Production in Developing and Developed Nations. *Energies* 2: 1-24.

Pizzigallo, A. C. I., C. Granai, and S. Borsa. 2008. The joint use of LCA and emergy evaluation for the analysis of two Italian wine farms. *Journal of Environmental Management* 86(2): 396-406.

PRé Consultants. SimaPro 7.1. PhD Version., Amsfoort, NL.

PRé Consultants. 2008b. *SimaPro 7.1. PhD Version.* Amsfoort, NL.

Rai, S. N. and D. Krewski. 1998. Uncertainty and Variability Analysis in Multiplicative Risk Models. *Risk Analysis* 18(1): 37-45.

Reap, J., F. Roman, S. Duncan, and B. Bras. 2008. A survey of unresolved problems in life cycle assessment. *International Journal of Life Cycle Assessment*.

Ridoutt, B. G. and S. Pfister. 2010. A revised approach to water footprinting to make transparent the impacts of consumption and production on global freshwater scarcity. *Global Environmental Change* 20(1): 113-120.

Ridoutt, B. G., P. Juliano, P. Sanguansri, and J. Sellahewa. 2009. Consumptive water use associated with food waste. *Hydrology and Earth System Sciences Discussions* 6: 5085–5114.

Roos, E., C. Sunderberg, and P.-A. Hansson. 2010. Uncertainties in the carbon footprint of food products: a case study on table potatoes. *International Journal of Life Cycle Assessment*.

Rosenbaum, R. K., T. M. Bachmann, L. S. Gold, M. A. J. Huijbregts, O. Jolliet, R. Juraske, A. Koehler, H. F. Larsen, M. MacLeod, M. Margni, T. E. McKone, J. Payet, M. Schuhmacher, D. van de Meent, and M. Z. Hauschild. 2008. USEtox-the UNEP-SETAC toxicity model: recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment. *International Journal of Life Cycle Assessment* 13(7): 532-546.

Rubin, B. D. and G. G. Hyman. 2000. The Extent and Economic Impacts of Soil Erosion in Costa Rica. In *Quantifying sustainable development the future of tropical economies*, edited by C. A. S. Hall, et al. San Diego: Academic Press.

Rydburg, T. 2010. Personal Communication with Rydburg, T., Gainesville, FL 2010.

Sandoval, A. C. C. 2009. Insensatez piñera. *El Financiero* [San Jose, CR], July 5, section En Portada.

Schenck, R. 2007. *Canning Green Beans - Ecoprofile of Truitt Brothers Process*. Vashon, WA: Institute for Environmental Research and Education.

Schenck, R. 2009. *The Outlook and Opportunity for Type III Environmental Product Declarations in the United States of America*. White Paper. Vashon, WA: Institute for Environmental Research and Education.

Schenck, R. C. and S. Vickerman. 2001. Developing a Land Use/Biodiversity Indicator for Agricultural Product LCAs. In *International Conference on LCA in Foods*. Gothenburg, Sweden.

Schmidt-Bleek, F. 1994. *Wieviel Umwelt braucht der Mensch? MIPS, das Mass fur okologisches Wirtschaften [How much environment do we need? MIPS, the measure for ecologically sound economic performance]*. Berlin, Boston: Birkhauser.

Scholl, D. and von Huene. 2004. Crustal Recylcing at Ocean Margin and Continental Subduction Zones and the Net Accumulation of Continental Crust. *EOS Transactions* 88(52).

Sciubba, E. and S. Ulgiati. 2005. Emergy and exergy analyses: Complementary methods or irreducible ideological options? *Energy* 30(10): 1953-1988.

Seager, T. P. and T. L. Theis. 2002. A uniform definition and quantitative basis for industrial ecology. *Journal of Cleaner Production* 10: 225–235.

Seppala, J., S. Knuuttila, and K. Silvo. 2004. Eutrophication of aquatic ecosystems - A new method for calculating the potential contributions of nitrogen and phosphorus. *International Journal of Life Cycle Assessment* 9(2): 90-100.

Sinden, G. 2008. *PAS 2050:2008 Specification for the assessment of the life cycle greenhouse gas emissions of goods and services*. Bristish Standards Institute.

Slob, W. 1994. Uncertainty Analysis in Multiplicative Models. *Risk Analysis* 14(4): 571-576.

Sonnemann, G. and B. de Leeuw. 2006. Life Cycle Management in Developing Countries: State of the Art and Outlook. *International Journal of Life Cycle Assessment* 11(Special Issue 1): 123-126.

Stewart, M. and B. P. Weidema. 2005. A Consistent Framework for Assessing the Impacts from Resource Use - A focus on resource functionality (8 pp). *The International Journal of Life Cycle Assessment* 10(4): 240-247.

Stratus Consulting. 2003. *Report on the Independent Assessment of Water Quantity and Quality near the Yanacocha Mining District, Cajamarca, Peru*. Washington, DC: IFC/MIGA Compliance Advisor.

Su, N. R. 1968. *Pineapple (Ananas comosus (L) Merr.)*. Nutritional requirements. Taipei, Taiwan: Taiwan Council of Agriculture.

Sweeney, S., M. Cohen, D. King, and M. Brown. 2009. National Environmental Accounting Database. http://sahel.ees.ufl.edu/frame_database_resources_test.php. Accessed.

Swennenhuis, J. CROPWAT Version 8.0. Water Resources Development and Management Service, FAO, Rome.

Taylor, S. R. and S. M. McLennan. 1985. *The continental crust: its composition and evolution : an examination of the geochemical record preserved in sedimentary rocks*. Palo Alto, CA: Blackwell Scientific.

Thiesen, J., S. Valdivia, G. Sonnemann, J. Fava, T. Swarr, A. A. Jensen, and E. Price. 2007. Understanding Challenges and Needs: A Stakeholder Consultation on Business' Applications of Life Cycle Approaches.CICLA 2007, Sao Paolo, Brazil.

Thornton, I. and S. Brush. 2001. *Lead: The Facts*. London: IC Consultants Ltd.

Tilley, D. R. 2003. Industrial Ecology and Ecological Engineering Opportunities for Symbiosis. *Journal of Industrial Ecology* 7(2): 13-32.

Ukidwe, N. and B. Bakshi. 2004a. Flow of natural versus economic capital in industrial supply networks and its implications to sustainability. *Environmental Science and Technology* 39: 9759-9769.

Ukidwe, N. and B. R. Bakshi. 2004b. Thermodynamic Accounting of Ecosystem Contribution to Economic Sectors with Application to 1992 U.S. Economy. *Environ Sci Technol* 38: 4810-4827.

Ulgiati, S., M. Raugei, and S. Bargigli. 2006. Overcoming the inadequacy of single-criterion approaches to Life Cycle Assessment. *Ecological Modelling* 190(3-4): 432-442.

UN. 1992. *Declaration on Environment and Development.* Rio de Jainero, Brazil: United Nations.

UN. 2005. *Johannesburg Plan of Implementation*. Johannesburg, SA: United Nations.

UN DESA. 2008. The Marrakech Process. http://esa.un.org/marrakechprocess/. Accessed May 19 2010.

UNEP. 2007. *Life Cycle Management - A Business Guide to Sustainability*

Paris: United Nations Environment Programme.

UNEP Life Cycle Initiative. 2007. *Life Cycle Initiative Phase 2 2007-2010*. UNEP DTIE Project Brief. Paris, France: United Nations Environment Programme, Division of Technology, Industry & Economics.

UNSTAT. 2006. Demographic Yearbook—Table 3: Population by sex, rate of population increase, surface area and density: United Nations Statistics Division.

UoH. 2005. *Sustainability of UK Strawberry Crop*. University of Hertfordshire.

Urban, R. A. and B. R. Bakshi. 2009. 1,3-Propanediol from Fossils versus Biomass: A Life Cycle Evaluation of Emissions and Ecological Resources. *Industrial & Engineering Chemistry Research* 48(17): 8068-8082.

USDA. 2009. National Nutrient Database for Standard Reference, Release 22: USDA.

Van Der Voet, E., L. Van Oers, and I. Nikolic. 2004. Dematerialization: Not Just a Matter of Weight. *Journal of Industrial Ecology* 8(4): 121-137.

Wackernagel, M., N. B. Schulz, D. Deumling, A. C. Linares, M. Jenkins, V. Kapos, C. Monfreda, J. Loh, N. Myers, R. Norgaard, and J. Randers. 2002. Tracking the ecological overshoot of the human economy. *Proceedings of the National Academy of Sciences* 19(14): 9266–9271.

Weidema, B. and G. Norris. 2002. Avoiding co-product allocation in the metals sector. In *Life Cycle Assessment of Metals: Issues and Research Directions*, edited by A. Dubriel. Pensacola, FL: Society of Environmental Toxicology and Chemistry.

Williams, A., E. Pell, J. Webb, E. Moorhouse, and E. Audsley. 2008. Strawberry and tomato production for the UK compared between the UK and Spain. In *International Conference on LCA in the Agri-Food Sector*. Zurich.

World Gold Council. 2006. Mine Production. http://www.gold.org/value/markets/supply_demand/mine_production.html. Accessed.

Yellishetty, M., P. G. Ranjith, A. Tharumarajah, and S. Bhosale. 2009. Life cycle assessment in the minerals and metals sector: a critical review of selected issues and challenges. *International Journal of Life Cycle Assessment* 14(3): 257-267.

Zhang, Y., Z. Yang, and X. Yu. 2009. Ecological network and emergy analysis of urban metabolic systems: Model development, and a case study of four Chinese cities. *Ecological Modelling* 220(11): 1431-1442.

Zhang, Y., S. Singh, and B. R. Bakshi. 2010. Accounting for Ecosystem Services in Life Cycle Assessment, Part I: A Critical Review. *Environmental Science & Technology* 44(7): 2232-2242.

BIOGRAPHICAL SKETCH

Wesley W. Ingwersen was born in Atlanta, GA on June 26, 1977. He went to secondary school at Woodward Academy in College Park, GA, where he developed a keen interest in Biology and Ecology. After a year at Wake Forest University he transferred to Georgetown University (Washington, DC) where he completed a B.A. with a major in Theology in 1999 along with additional coursework in Chemistry, Computer Science, and English. Wesley worked for an e-commerce company, enews.com, and a software development company, Lokitech, as a web designer and internet applications developer until 2002. While in the DC area and volunteering with the National Park Service and the Casey Tree Foundation, he became determined to work toward greater scientific understanding of the dependence of human systems upon nature and the value it provides, an returned to graduate school to the M.S. in Environmental Engineering in Systems Ecology at the University of Florida. His M.S. thesis involved an evaluation of long-term term success of wetland reclamation efforts on phosphate-mined lands. Following the completion of his M.S. degree, Wesley joined Ecologic – Institute of International and European Environmental Policy, in Berlin as a Transatlantic Fellow, and at the end of 2006 returned to the University of Florida to pursue a Ph.D. under his M.S. adviser, Mark T. Brown.