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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Life cycle assessment (LCA) is an internationally standardized framework for assessing the environmental impacts of products that is rapidly evolving to improve understanding and quantification of how complex product systems depend upon and affect the environment. This dissertation contributes to that evolution through the development of new methods for measuring impacts, estimating the uncertainty of impacts, and measuring ranges of environmental performance, with a focus on product systems in non-OECD countries that have not been well characterized. The integration of a measure of total energy use, emergy, is demonstrated in an LCA of gold from the Yanacocha mine in Peru in the second chapter. A model for estimating the accuracy of emergy results is proposed in the following chapter. The fourth chapter presents a template for LCA-based quantification of the range of environmental performance for tropical agricultural products using the example of fresh pineapple production for export in Costa Rica that can be used to create product labels with environmental information. The final chapter synthesizes how each methodological contribution will together improve the science of measuring product environmental performance.

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 sources of energy and materials 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 in economies. 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 form of regulation in place in the United States, is primarily based on the regulation of pollution "at the pipe",

implicitly focusing only on pollution at the point of occurrence and obligating only the party responsible at that point to reduce or cease the pollution. 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 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 2006c). LCA is being used globally for product systems for purposes of 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 including all 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. Estimating the impacts of these emissions is done 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 the state of the science 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 effectiveness of 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 depends upon detailed inventories of complex product life cycles as well as accurate models to estimate environmental damages related to resource used or emissions that occur with these life cycles. LCA adapts scientific theory and models from many other fields to accurately identify and model impacts and thus is only as 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) impact models for processes occurring in 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. Furthermore, 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 have been extensively developed outside of the LCA framework, but not all of these methods have been applied as indicators in LCA. These methods typically aggregate resource use using a common biophysical unit. 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 short, these methods associate a material intensity (g material/g product) with 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 use of materials that may only temporarily

sequester them (e.g. cooling water) or may completely transform them rendering them useless for future production processes (e.g. combusted fuels) (Van Der Voet et al. 2004).

Area-based measures of resource use either measure solely direct and indirect occupation and transformation of land or go further by using 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 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 2007). 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 2001) 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 the total of available energies of different types 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 some of their exergy is lost as entropy. The exergy losses associated with transformations of all inputs into processes in an LCA can be measured with cumulative exergy demand, or CExD (Bösch et al. 2007). 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. Accounting for 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 et al. 2008; Pizzigallo et al. 2008). Emergy has been adapted for use in economic-based input-output LCA by Bhakshi and colleagues, who define emergy as an extension of exergy called ecological exergy (Hau and Bakshi 2004a) and have used it as a measure of the contribution of ecosystem processes to sectors of the US economy (Ukidwe and Bakshi 2004) 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 conventional 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 2007). 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 demonstrating the means of integrating emergy into a complex process-based 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 alternative 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 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 Products

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 resulting in lesser capacity to use life cycle management; and (2) comparisons with OECD products has been hindered thus limiting ability to use LCA in OECD countries that consume products from all over the world. 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). Without improved life cycle management, the consumer demand for increasing non-OECD country products may increase environmental damage in non-OECD countries. Expanding the scope of LCA to incorporate more global analysis including for products from non-OECD countries is 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 into the environment surrounding 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).

Accurate characterization of diffuse emissions and their impacts in mining and agriculture depends on 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 mining systems, this may include the geologic work required to create a particular deposit, if the boundary of resource use is extended to include all environmental resources as suggested in the previous section. In agricultural systems, regional factors effect emissions and their impacts. This is particulary relevant for emissions such as fertilizers and pesticides and the impacts they can cause including eutrophication and ecological and human toxicity. Local factors also effect emissions that have just recently begun to be characterized in LCA, including water loss (Pfister et al. 2009). Regional characterization of models based on geographic difference can have dramatic effects on LCA outcomes (Lenzen and Wachsmann 2004).

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 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 heavy rain-based 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 is related to 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 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 emissions and impacts models are not appropriate because of differences in environmental conditions. A multi-criteria process-based 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 integrating using the RUSLE2 model. 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 yet 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 2006c). Other thermodynamically-based methods, such as exergy, have been integrated into LCA (Ayres et al. 1998; Bösch et al. 2007). 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:

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 2004).

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

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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.

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.

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.

The choice of measures of impact in an LCA follow from the goal and scope of the study (ISO 2006c). Emergy analyses have been used for a multitude of LCA-related

[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 2001; Jolliet et al. 2003a)

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.

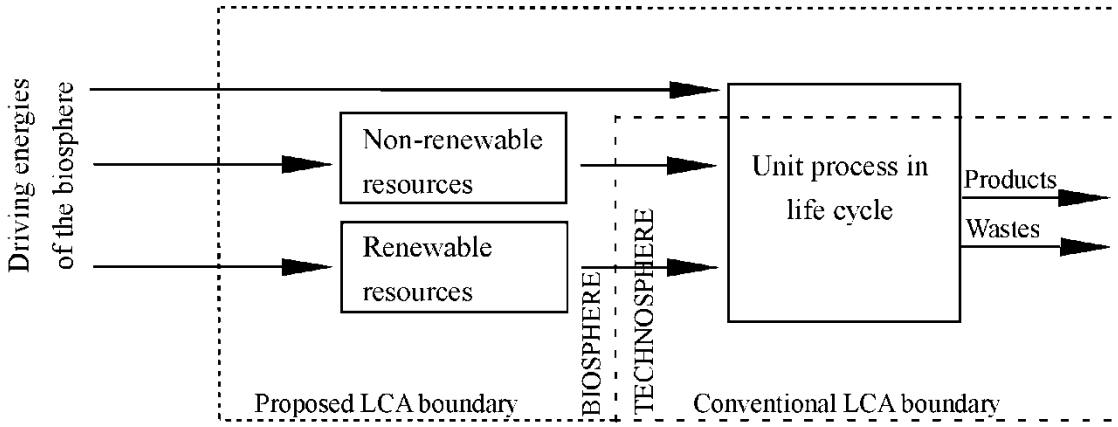

Figure 2-1. Proposed boundary expansion of LCA with emergy. Driving energies include sunlight, rain, wind, deep heat, tidal flow, etc.

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 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

[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'.

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 2006a). 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.

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

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.

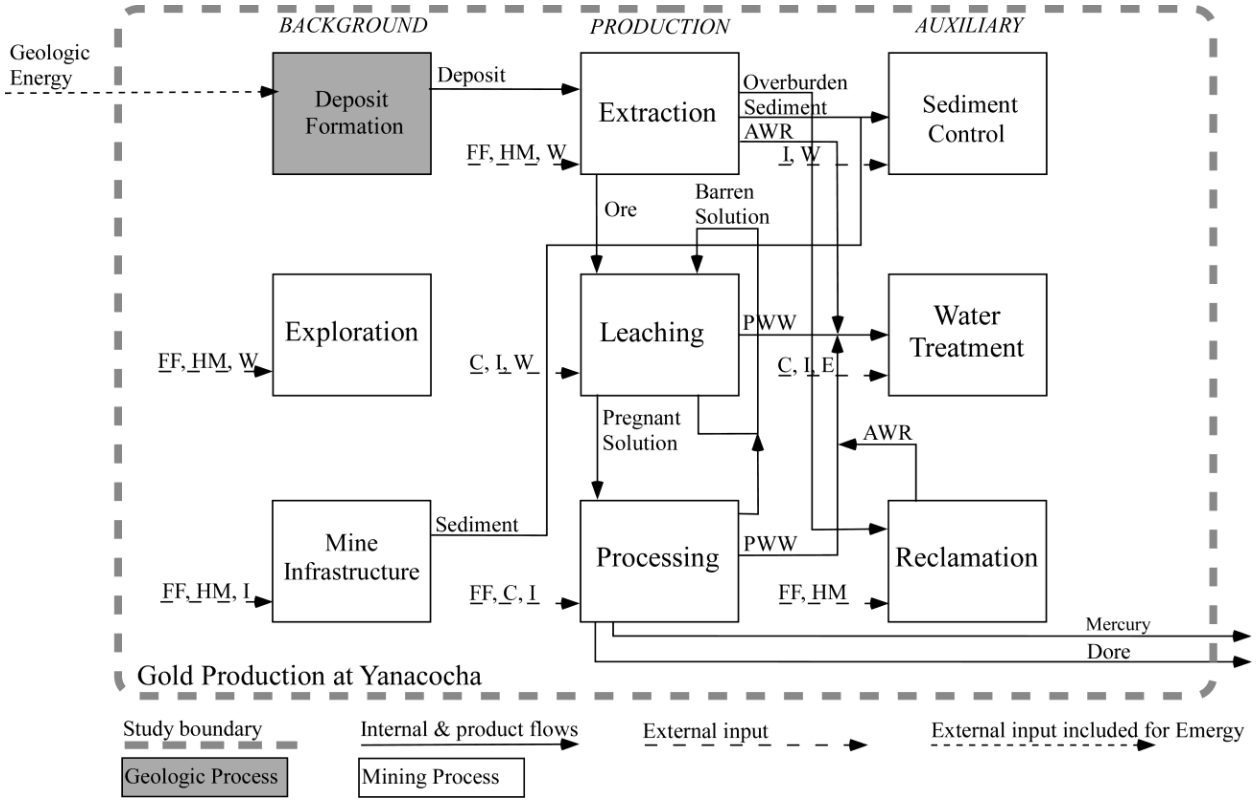

Figure 2-2. Gold production system at Yanacocha with modeled flows and unit processes. FF = fossil fuels, HM = heavy machinery, I = infrastructure, C = chemicals, W= precipitation and pumped water, E = electricity, AWR = acid water runoff, PWW = process wastewater.

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:

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

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:

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

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:

$$\mu_{geo}\ (x\div)\ \sigma^2_{geo} \tag{3}$$

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 2008). 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

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

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.

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

[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.

(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%.

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.

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)

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.

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.

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

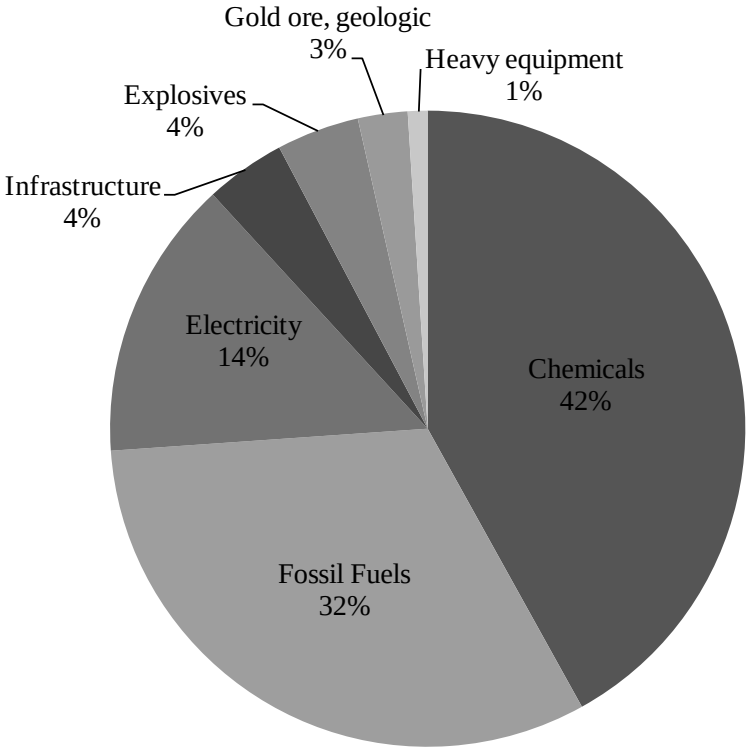

Figure 2-3. Environmental contribution (emergy) to doré by input type.

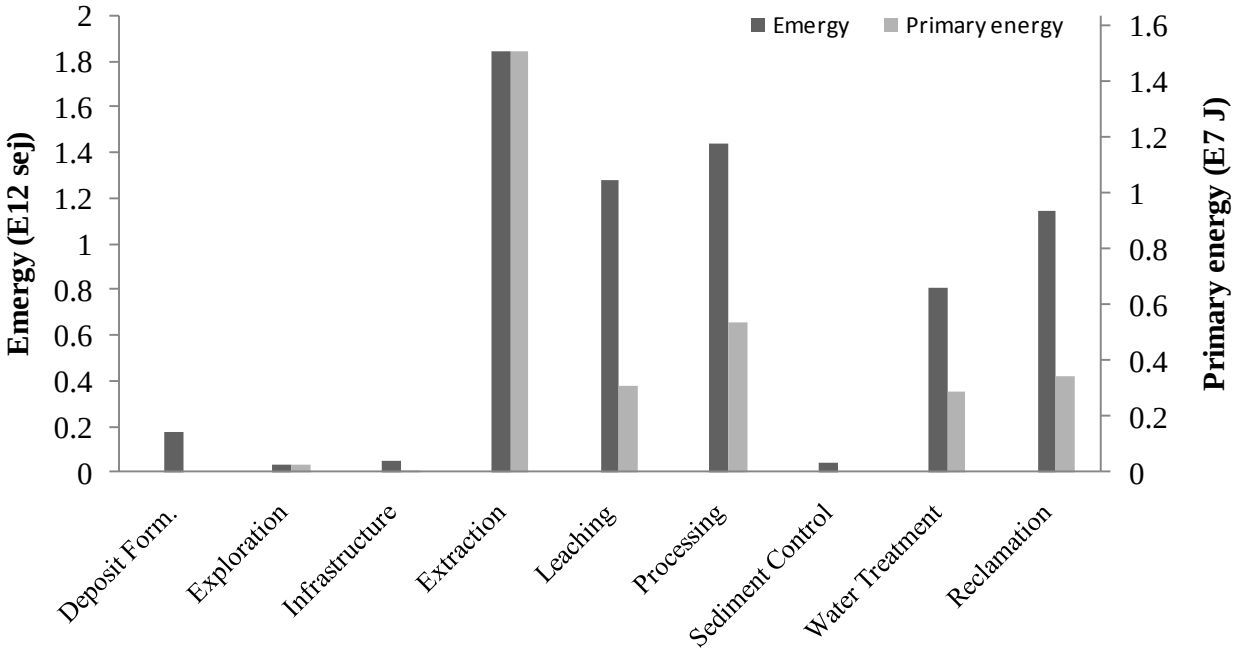

Figure 2-4. Emergy and primary energy in 1 g of doré by unit process. Primary energy is depicted on a second axis which is adjusted so that emergy and primary energy in extraction appear the same so relative contribution of each to processes can be depicted.

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

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.

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.

Uncertainties in process inputs ranged based on uncertainty in the inventory data, but primarily due to the uncertainty of the UEVs. 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 σ2geo 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.[9] This is unfavorable in comparison with fossil energy sources and other primary sector products which generally have emergy yield ratios of 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.

[9] 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).

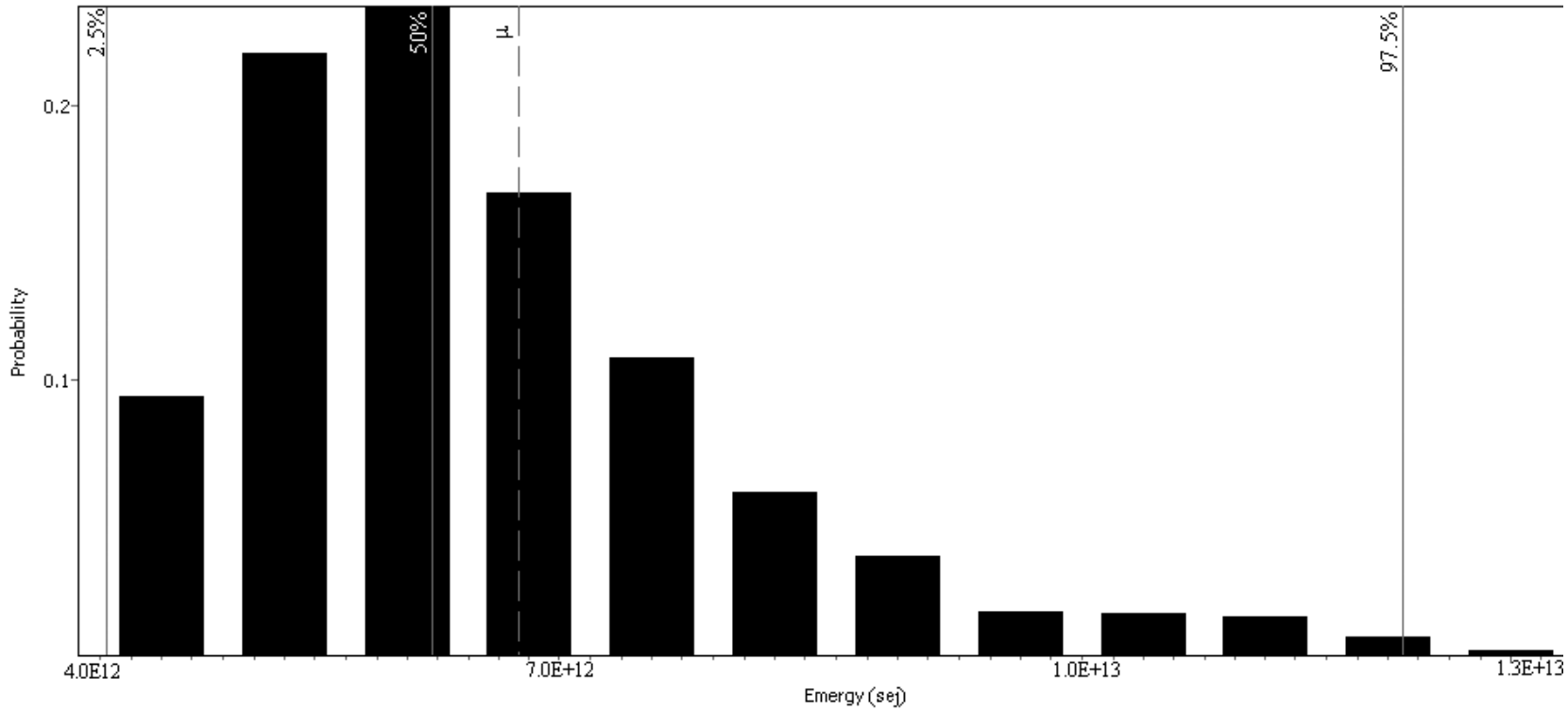

Figure 2-5. Monte Carlo analysis of 1 g of doré, showing the tails and center of the 95% CI, along with the mean (dashed line).

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).[10] 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 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

[10] 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.

process at Yanacocha itself is only approximately 3.5% renewable on a life cycle emergy basis.[11] 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 a theoretically and procedurally consistent integration of emergy and LCA and are discussed here.

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

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.[12] Allocation rules or alternatives to allocation typically used in LCA can easily be applied to allocate emergy among by-products and co-products, as was demonstrated here, but if existing UEVs for co-

[12] 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 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.[13] 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, primarily because it doesn't account for quality differences among resources and also

[13] 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).

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 2004a). 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. 2007). 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'[14] 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 production and 22% from the gold ore in the ground. In comparison with the results from

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

this study (Figure 2-2), emergy shows a much higher relative role of the fuels and chemicals used in the process[15]. 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.

[15] 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
UNCERTAINTY CHARACTERIZATION FOR EMERGY VALUES[16]

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

[16] 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 2006a).

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 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. 2003a).

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}:

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

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

where σ^2_{geo} for variable *a* is a function of ω_a (Eq. (1)),[17] which a simple transformation of the coefficient of variation (Eq. (2)), [18] 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)):

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

[18] 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):

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

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)).[19]

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

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

Models for Uncertainty in UEVs

Selecting Appropriate Methods for Uncertainty Estimations

Numerous methods exist for computing unit emergy values[20], but for uncertainty estimation, it is import to distinguish between them according to a fundamental

[19] 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.

[20] 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.

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).

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.

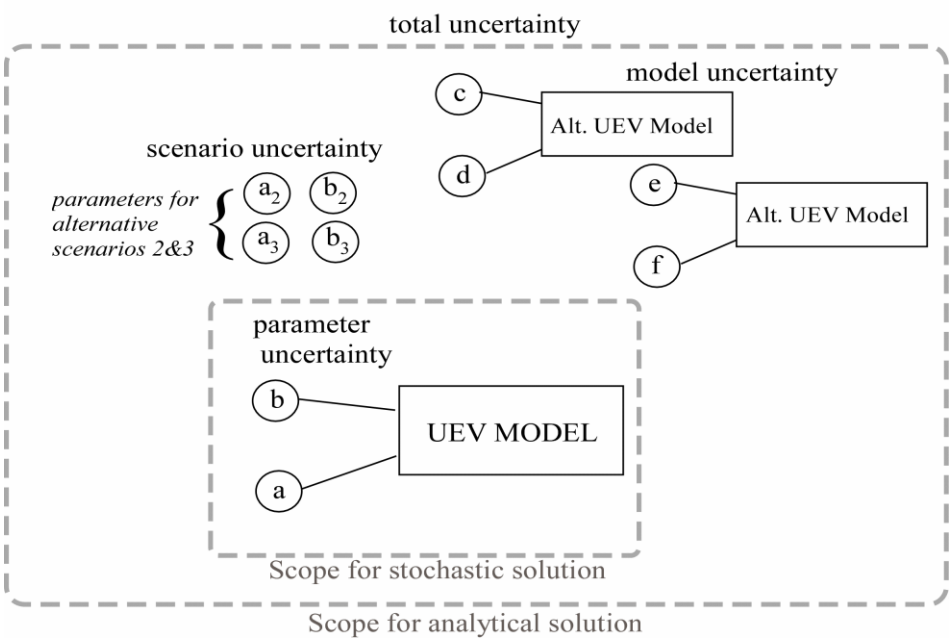

Figure 3-1. Conceptual approach to modeling uncertainty. The parameter uncertainty consists of uncertainty and variability in the parameters used to estimate the UEV; the scenario uncertainty consists of the uncertainty arising from use of parameter values for different geographic or technological scenarios;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

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

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 sej/yr)/(Annual flux, g/yr)	Buenfil 2001
	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)

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):

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

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

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.[21] Uncertainty was estimated solely with the Monte Carlo simulation routine used for the formula UEVs, with the

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

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)).

$$\sigma_{logUEV} = \frac{\ln \sigma 2geo}{1.96} \tag{11}$$

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 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.

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.

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 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 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[22]; 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

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

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
				[b]CI_{95} =	**8.10E+08 (x÷) 3.31**		

Notes:
1. UEV for secondary sulfur and diesel from Hopper (2008). Uses k-value for oil since secondary sulfur is a petroleum by-product.

4. UEV in sej/J = (UEV for global groundwater, 9.36E5 sej/g)/(4.94 J/g)

Footnotes:
[a] Inventory data from Ecoinvent 2.0 (Ecoinvent Centre 2007)
[b] Example of incorporation of a confidence interval into an emergy table assuming a lognormal distribution.

Table 3-6 summarizes the results of the Monte Carlo simulations for all UEVs when the parameter distributions were assumed lognormal, and compares the resulting confidence intervals against those that would be predicted by lognormal, hybrid, and normal distributions. A number of notable differences are present between these results and those of the calculated uncertainty values for formula UEVs in Table 3-5. The UEV means from the simulation are higher in all cases than the deterministic means presented in Table 3-5, but the simulation median values are lower than the

deterministic means. The σ^2_{geo} values from the simulation, which were calculated according to Eq. (1) from the average mean and standard deviations of the Monte Carlo distributions, are not identical to the parameter geometric variance values from Table 3-5; however, the Monte Carlo σ^2_{geo} values were always ± 5% of the analytically calculated geometric variances.

The lognormal confidence interval was the best fit for the simulated UEV distributions: error of the lognormal approximation of either the lower or upper tail was never larger than 5%. However this distribution tended to consistently overestimate the confidence interval.[23] The hybrid distribution tended to predict a distribution shifted to 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.

[23] This could be in part be explained by the fact that the equation (3) is more precisely for a 95.5% confidence, rather than a 95.0%, confidence interval (Limpert et al. 2001).

Discussion and Conclusions

How Much Uncertainty is in a UEV and Can it Be Quantified?

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.

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 2004b). 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.

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]

Item	UEV Type[2]	Monte Carlo Results		Model 95% CI		Predicted 95% CIs					
						Lognormal CI		Hybrid CI		Normal CI	
		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..

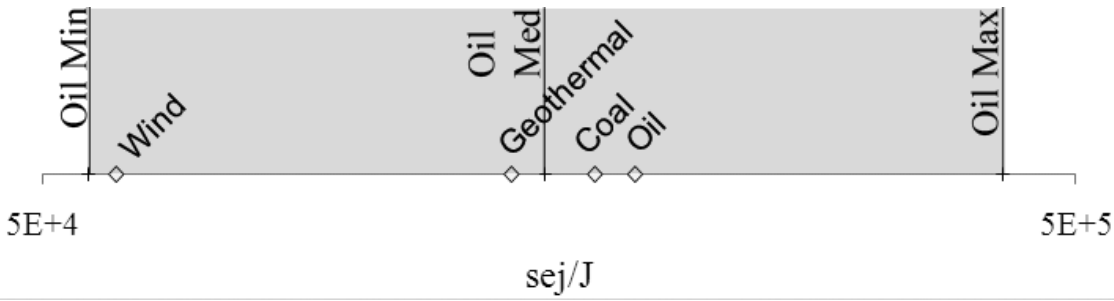

Figure 3-2. Published UEVs for electricity by source (diamonds on axis) from Brown and Ulgiati (2002), superimposed upon a modeled range of the oil UEV, using the geometric variance for electricity from oil ($\sigma^2_{geo} = 2.77$) calculated in this paper.

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[24], 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. A goal of any product category rule is to enable comparative assertions of

[24] 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).

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).

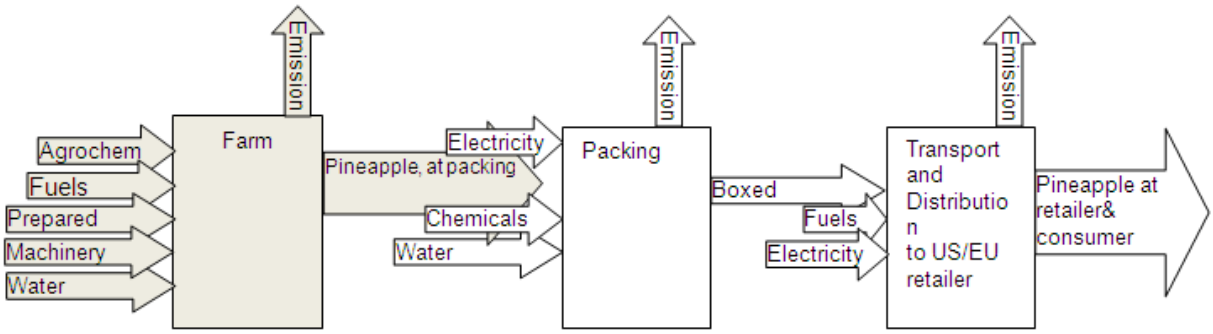

Figure 4-1. Fresh pineapple production unit processes and boundaries for the LCA. The first unit process is the focus of this paper.

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:

$$\textit{Servings/kg fresh weight fruit} = \textit{(edible fraction of fruit)/(kg fruit/serving)} \qquad (12)$$

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:

$$Input,\ x/kg\ pineapple = (Annual\ input,\ x/yr)/(Farm\ area,\ ha)/(Harvest\ kg/ha/harvest)(harvests/yr) \quad (13)$$

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 2008) 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 (Table D-7).

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 14:

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

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.[25] The variation based on the

[25] 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.

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 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 Accepted) 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:

$$cf_e = tf_e * af_e * nf_e \quad (19)$$

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. 2003b), 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[26] as the unit of comparison. This and

[26] 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.

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 CED/serving.

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 potentially 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, RoEP is also reported without land-use change. Not including land-use change, approximately half of the carbon footprint occurred upstream of the farm (51%) and (49%) of the footprint occurred on the farm, 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 (Figure 4-4).

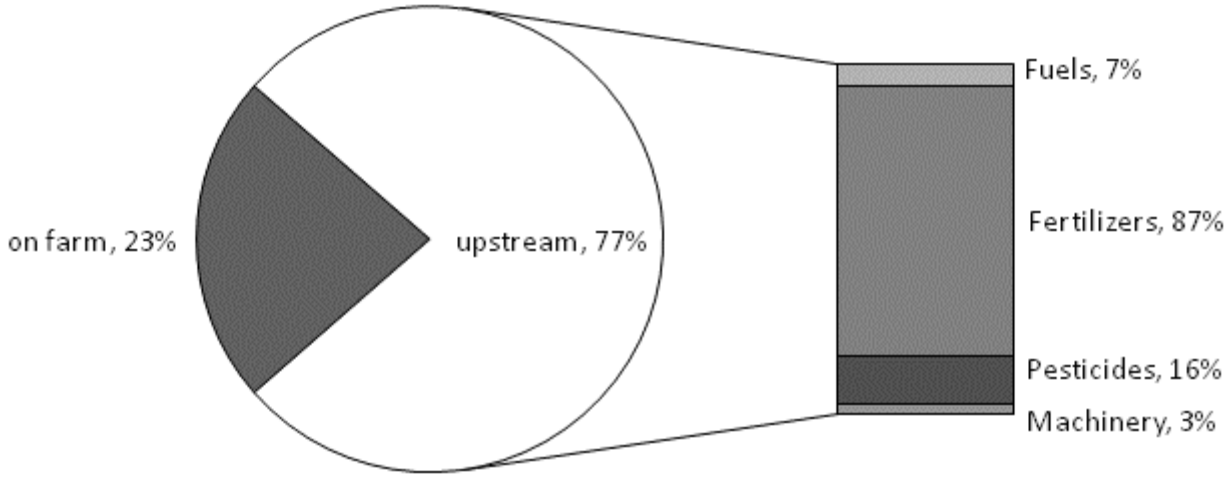

Figure 4-2. Contribution to CED of pineapple, at packing facility.

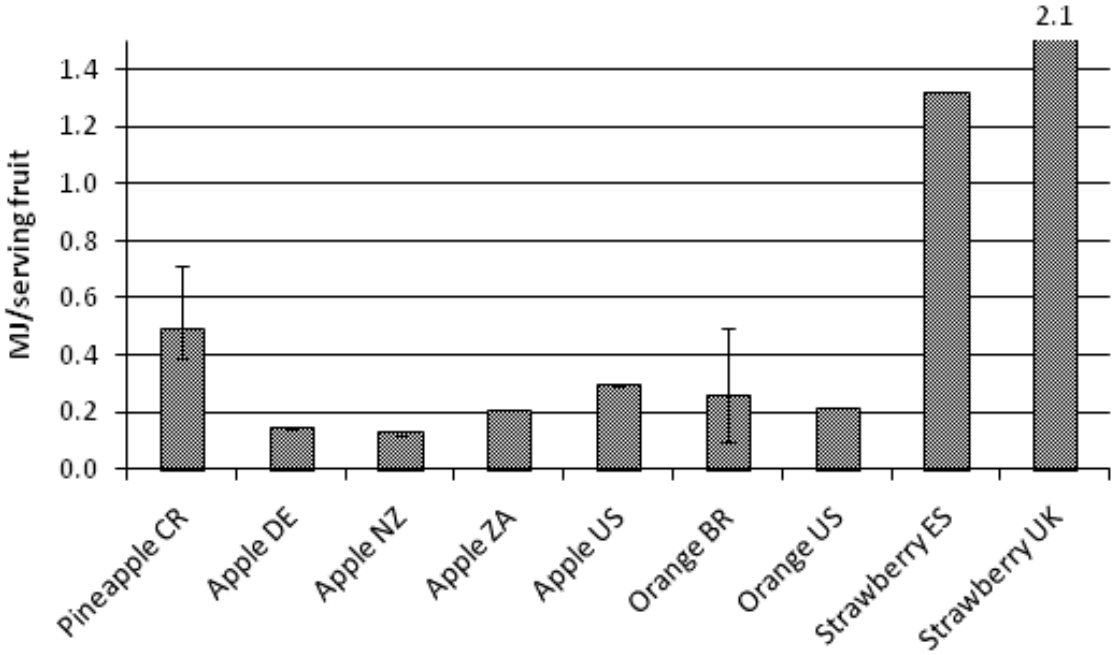

Figure 4-3. Non-renewable CED of one serving pineapple in comparison with evaluations of the farming stage of other fruits. Sources: Apple DE and Apple ZA (Blanke and Burdick 2009); Apple NZ (Blanke and Burdick 2009; Canals 2003); Apple US and Orange US (Pimentel 2009); Strawberry ES (Blanke and Burdick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

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).

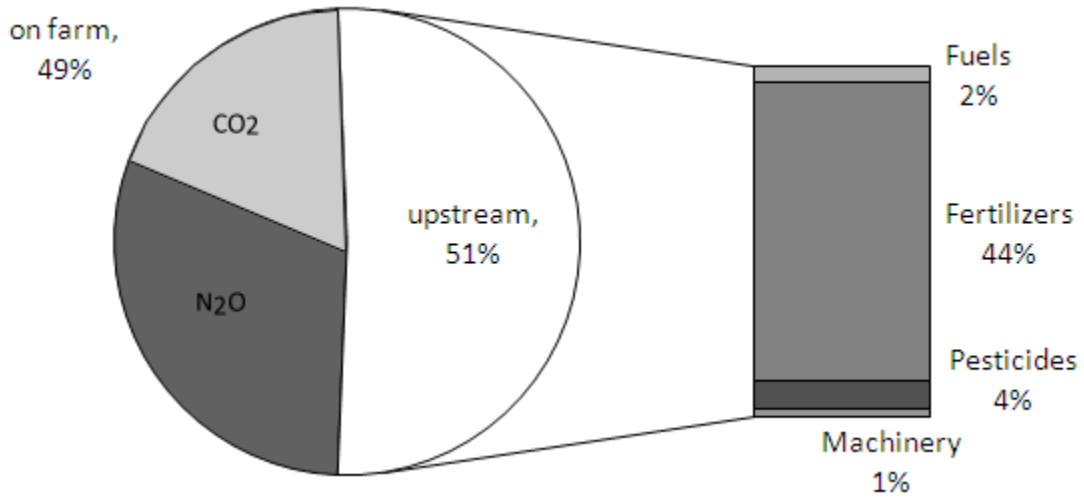

Figure 4-4. Contribution to carbon footprint of pineapple, at packing facility. Potential footprint from land-use change is not included.

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, 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).

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.

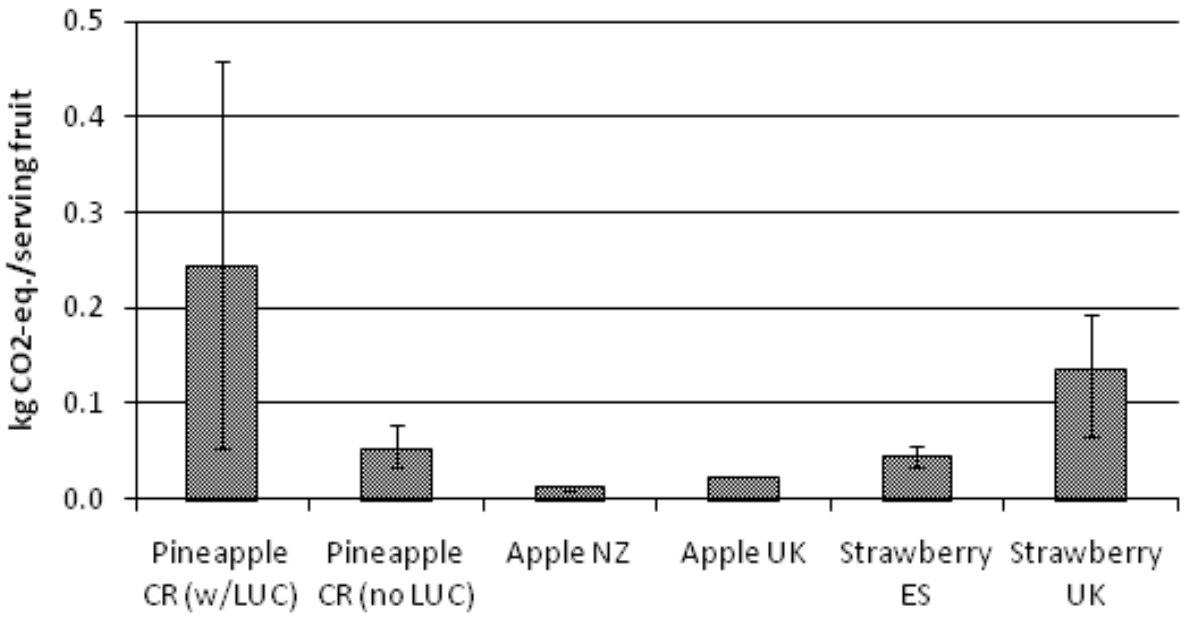

Figure 4-5. Carbon footprint of one serving pineapple in comparison with evaluations of the farming stage of other fruits. Sources: Apple NZ (Canals 2003); Apple UK (Lillywhite et al. 2007); Strawberry ES (Williams et al. 2008); Strawberry UK (Lillywhite et al. 2007; UoH 2005; Williams et al. 2008).

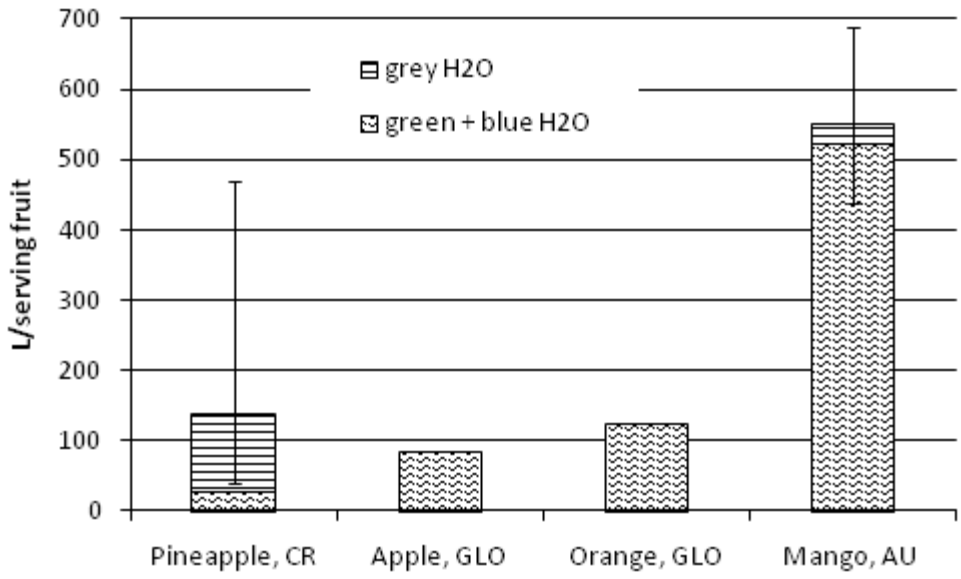

Figure 4-6. Virtual water content (VWC) for pineapple in comparison with other fruits. Evaporative and non-evaporative water are included for pineapple and mango (green + blue + grey); only evaporative water is included for apples and oranges (green + blue). Mango data is from Riddout et al. (2009);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

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%) (Figure 4-7). 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 4-8.

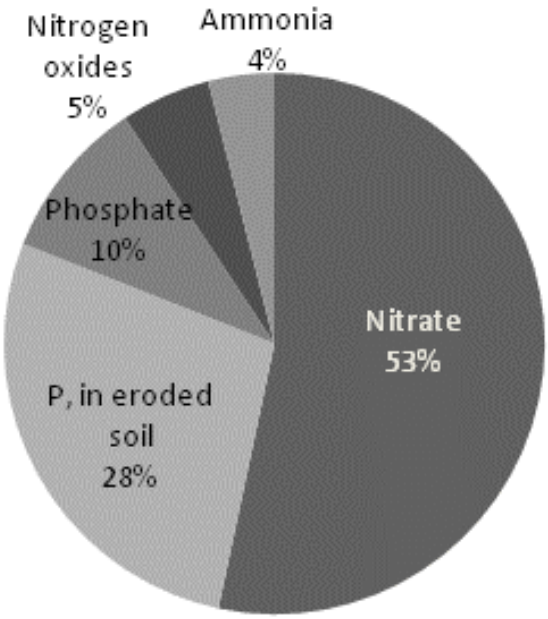

Figure 4-7. Contribution to potential eutrophication of pineapple by emission.

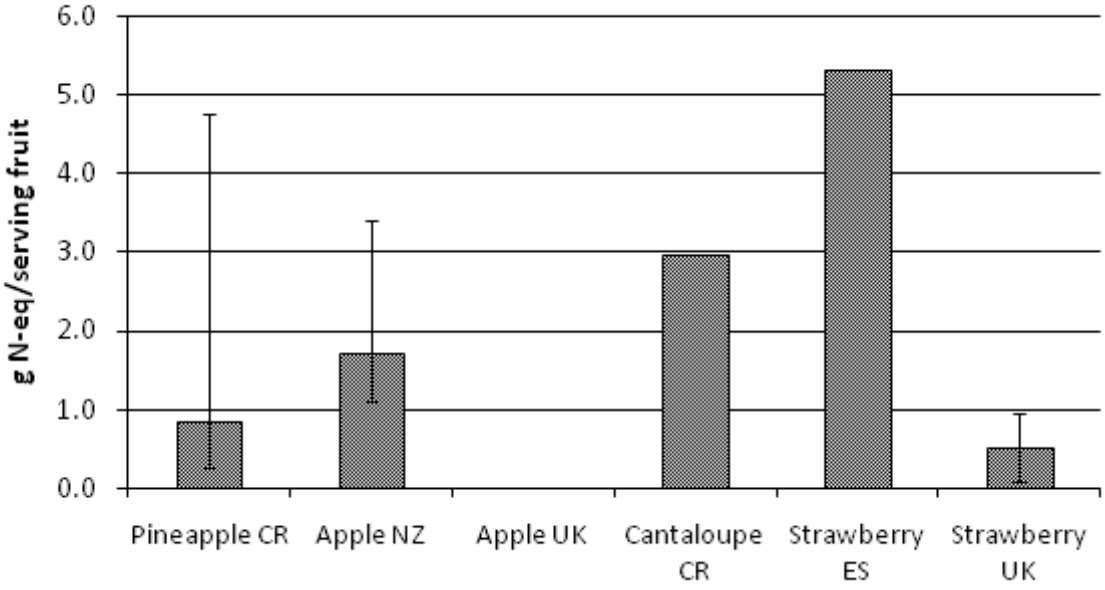

Figure 4-8. Preliminary comparison of potential eutrophication effects of one serving pineapple in comparison with evaluations of the farming stage of other fruits. Sources: (Canals 2003); Apple UK (Lillywhite et al. 2007); Cantaloupe CR (Hartley-B. and Díaz-P. 2008); Strawberry ES (Williams et al. 2008); 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 to ecotoxicity are diuron, ametryne (herbicide), ethoprop, and paraquat (herbicide) (Figure 4-9). 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.

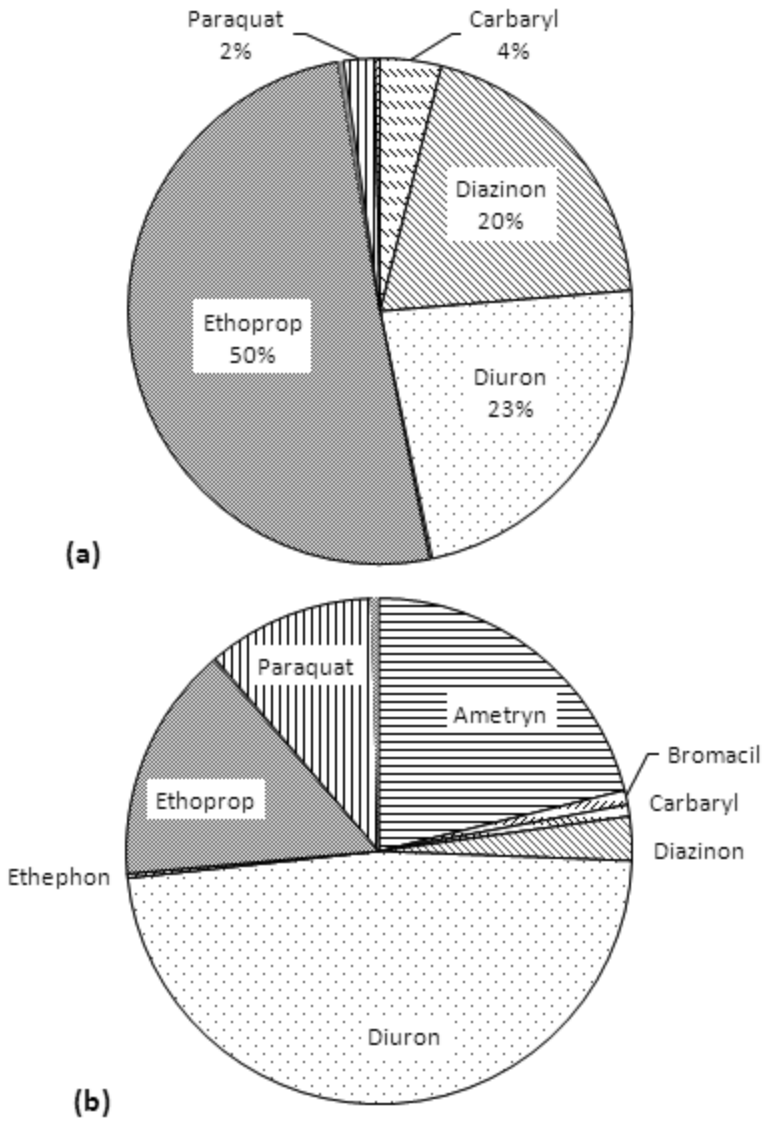

Figure 4-9. Relative contribution of active ingredients of pesticides used in pineapple production to (a) human toxicity and (b) freshwater ecotoxicity.

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.

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.

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.

CHAPTER 5
SUMMARY AND SYNTHESIS

Summary

The primary objectives of this dissertation were to better equip life cycle assessment to relate the production of goods and services to their associated environmental impacts by means of the following tasks: to provide a new process-based life cycle assessment (LCA) impact method for quantifying impacts of resource use with emergy; to provide this method with an accompanying method of uncertainty analysis; and to create a method for establishing the range of environmental performance for agricultural products with a set of indicators adapted to a tropical environment. To do so, this dissertation included two original LCA studies, one of gold-silver bullion from the Yanacocha mine and one of pineapple production in Costa Rica, and an original uncertainty model for use with emergy results. The major conclusions that can be drawn from these studies are first listed by chapter and followed by a general synthesis of the dissertation along with the ramifications of the findings.

Chapter 2 Summary

- Emergy is an ideal measure of total resource use because it traces energy directly and indirectly used in creation of products back to the driving energies of the biosphere (sunlight, tides, and deep heat) and can be used to measure environmental contribution to raw and processed resources and materials as well as direct environmental flows (e.g. sunlight, wind, rain). All indirect and direct energy can then be aggregated as emergy in sunlight energy equivalents for a single numeric value of resource use.

- Emergy can be integrated into conventional process-based LCA databases to track direct and indirect energy flows associated with complex process chains and in this manner is compatible with process-based LCA.

- In order to characterize resource use with emergy for a mining product, an LCA of the gold-silver mining operation at the Yanacocha mine in Peru was conducted using an boundary that extended from the environmental contribution to the

inputs to mining (permitted by emergy) to the creation of gold-silver bullion. A gram of gold-silver bullion was used as the functional unit.

- Total emergy in 1 gram of gold-silver bullion is in the range of 4.4E+11 to 1.3E+13 sunlight equivalent joules (sejs), which is orders of magnitude higher than most common resources, including other minerals, fuel sources, foods, and ecosystem products. 95% of the emergy in gold-silver bullion comes from inputs to mining processes rather than gold formation (and thus is based on environmental contribution that occurs off-site), despite the millennia of environmental work used to form gold deposits. The contribution of emergy to chemicals and fuels used in the mining and refining processes dominate the emergy contributing to the bullion.

- The breakdown of emergy used to make gold-silver bullion does not reflect the same pattern as cumulative energy demand, indicating the failure of the latter to characterize all indirect environmental flows to processes, and reinforcing the role of emergy in LCA to quantify these flows for a more complete measure of resource use.

- Use of allocation rules from LCA for allocating impacts among by-products and those traditionally used in emergy result in drastically divergent outcomes; allocation rules from LCA are more consistent with LCA data and should be used if results are to be adopted in future downstream LCAs (e.g., for a product that uses gold-silver bullion as an input).

- Tracking labor and information inputs into processes is not typically done in LCA and thus integrating emergy into life cycle assessment databases will not permit the quantification of emergy in labor or information which is a shortcoming to using emergy in LCA because it arguably omits important environmental contributions to final products that should be accounted for.

Chapter 3 Summary

- The range of accuracy, or uncertainty, of emergy values should be quantified so that the model uncertainty of using emergy is quantified in an LCA study, as this could be the dominate form of uncertainty present in the LCA results that use emergy as an indicator.

- Two options are demonstrated for estimating uncertainty of unit emergy values including an analytical model based on mathematical rules for propagation of uncertainty and a stochastic model using Monte Carlo analysis. Results of either approach show that unit emergy values have confidence intervals that resemble lognormal distributions and that these confidence intervals can be represented mathematically with the median value times or divided by the geometric variance.

- Three forms of uncertainty are present in emergy calculations, including parameter, scenario, and model uncertainty. All three components can be combined using the propagation of uncertainty approach to result in the broadest estimation of potential uncertainty, but depend upon the estimation of the uncertainty in parameters and existing models.

- Unit emergy value confidence intervals for table-form unit emergy value calculations, the most common calculation approach, are only renderable with a Monte Carlo model approach because there is no simplified mathematical form for estimating them analytically; thus the stochastic approach is suggested to be the most valuable of the approaches introduced.

- The estimated factor of uncertainty for emergy values does not always correspond to the presumed range of an order of magnitude. The uncertainty is variable but will be smaller than the uncertainty factor of the largest contributing input, demonstrating that uncertainty is not infinitely compounded in more highly-transformed products.

- Issues remain with using uncertainty factors for comparison of unit emergy values that share common parameters. The method requires further adaptation for handling the issue of covariance.

Chapter 4 Summary

- LCA-based environmental performance of tropical fruit production in non-OECD countries is largely uncharacterized in comparison with agricultural activities in temperate countries, yet the production of fruit has growing importance in the diet of North Americans and Europeans, and occupies increasing area in the tropics. Environmental product declarations provide one means of providing both LCA-based information and a market-based mechanism for reduction of impacts associated with production activities. A host of LCA methods need to be developed or adapted to account for the potential environmental impacts that are very relevant especially in humid tropical environments. Fresh pineapple from Costa Rica is a crop of both growing export importance and increasing environmental concerns with production.

- A farm-to-gate LCA was designed to sample representative production systems and conditions present in the Costa Rican pineapple sector. A statistical method was used to combine variability in yield, production inputs, and emissions models to estimate a range of inputs and emissions relevant to energy use, water consumption, soil erosion, land use, carbon footprint, eutrophication, and toxicity. Combined with impact characterization methods, this variability in inputs and emissions was used to create ranges of environmental performance for the sector.

- In addition to a functional unit of mass (1 kg), the functional unit of 1 USDA serving was used in order to compare LCA results with those generated for products that serve the same function – providing 1 serving of fruit.

- Soil erosion is a primary environmental concern associated with pineapple production in Costa Rica because of exposure of topsoils, sometimes on steep slopes, to high rainfall, but no commonly-used LCA method incorporates soil erosion as an indicator. USDA's RUSLE2 soil erosion model was adapted to the climate conditions and observed field parameters in Costa Rican pineapple plantations for estimating soil erosion.

- Methods developed for characterization of pesticide emissions (PestLCI), toxicity assessment (USETox), and crop water consumption (water footprint using FAO's CROPWAT), and were each adapted to the extent possible to account for the local conditions. The result of these adaptations were significant differences in characterization of impacts occurring in Costa Rica from the same characterization in the default models (developing mainly in Europe), suggesting the importance of adaptation of emissions and impacts models to the environments in which the emissions occur.

- The ranges of environmental performance for pineapple, described by the coefficients of variation, ranged from 9% for land-use to 165% for soil erosion, demonstrating significant variation within the sector, with range of performance for impacts where models incorporated local conditions being the most variable.

- The largest contributor to farm-to-gate energy use and carbon footprint was fertilizer production, thus stemming from upstream processes. On the farm level, greenhouse gas emission were dominated by N_2O. Water consumption was low because of the low water requirement of pineapple and sufficient precipitation. Soil erosion was highest (close to 0.5 kg soil/kg pineapple) in areas with steep slopes, no contouring, and erodible soils, but is potentially as low as 0.005 kg soil/kg pineapple in flat sites with good drainage, erosion-resistant soils, and management practices that involve contouring, use of plastic mulch, and minimal exposure time. Eutrophication was dominated by nitrate emissions but was highly variable due to variable emission of P in eroded sediment. The pesticides contributing the most toward human toxicity and freshwater ecotoxicity were complex factors related to transport, degradation, as well as potential health effects, and could not be predicted simply by mass applied or their specific toxicity, supporting the importance of using emissions and impact models.

- Because of the variability within the sector, as well as potential model differences for some indicators, comparisons with other fruits were inconclusive. However, pineapple largely had a higher energy use and carbon footprint than apples and oranges, but lower values than greenhouse-grown strawberries. Pineapple had a lower virtual water content than apples, oranges, and mango although it had a large grey water footprint (pollution dilution water requirement) because of significant nitrate losses.

Synthesis

LCA serves the purpose of providing a measureable link between production of goods and services and pressure on environmental resources but requires further methodological expansion and refinement to provide more relevant and accurate information for environmental decision making regarding production and consumption. Expanded methods described here include the use of emergy as an indicator of resource use accompanied with an uncertainty model for emergy, and a unique combination of LCIA indicators applied with an original method of describing the range of environmental performance of a tropical agricultural product across the product sector in a country.

The use of LCA as a tool to inform and direct sustainable production and consumption depends both on its methodological capacity to describe impacts accurately and a means of conveying complex environmental information in a form that is useful when making product design, management, or purchasing decisions as well as for informing policy making. In reference to its current methodological capacity, the incorporation of a measure of resource use that characterizes all process inputs in a common form using emergy provides a way of measuring the environmental contribution to products in the context of the availability of resources. Integration of emergy in LCA as a measure of resource use is not limited to mining products but is applicable to all products and services for which process data is available to characterize them.

The incorporation of additional or modified methodologies for impact assessment in LCA is also needed for cases where relevant indicators do not exist or are not accurate in the environments in which production processes take place. Soil erosion is

a relevant environmental concern with agricultural production in Costa Rica, but no adequate methodology for characterizing it existed in LCA. To this end the RUSLE2 model was incorporated into LCA as a measure of rain-based soil erosion. Furthermore other impacts models were adapted for use in the Costa Rican environment, including PestLCI and USETox, that had been developed for the Danish and European environments, respectively. Customization of impacts models for local conditions are not commonly performed in LCA, however, they are essential for characterizing impacts of emissions that have local or regional effects, such as eutrophication and toxicity associated with nutrient and pesticide emissions from farms. Through adapting model parameters to the local environment, strong comparability can still be achieved between products in different environments because the same model structure and its underlying physical assumptions are used. This is particularly necessary when environmental conditions are sufficiently different than those in which a baseline model was developed, to the extent that they create meaningful differences in model outcomes.

Despite the increased accuracy of LCA emissions and impact models that may be conveyed with greater environmental customization, uncertainty in the results will always be an issue because of lack of full primary data availability and because of model uncertainty. The uncertainty associated with model results can be large, as shown in some of the impact assessment results for pineapple and those for gold, which can complicate the task of selecting environmentally preferable products. Incorporation of uncertainty information should be associated with any LCA impact method. Emergy was adapted as a new impact method, but there was no associated method of measuring model uncertainty in emergy. The new methodology developed now

provides a means of characterizing the uncertainty of the emergy of a product that can accompany the use of emergy in LCA, as was demonstrated with the LCA of gold.

One of the most valuable uses of LCA is for direct comparison of the environmental performance of products that serve the same function. By incorporating data and model uncertainty into LCA results, comparisons can be more realistic and subject to statistical tests that are not possible by comparing averages. Because incorporation of uncertainty may hinder interpretability and the purposes of comparison (because comparing ranges is less intuitive than comparing points), further methodological detail and guidance can assist in the consistency of uncertainty application and its practical usage. This is the very purpose of a current UNEP working group on uncertainty management in LCA.

Another challenge related to the use of LCA for promoting sustainable production and consumption, other than the challenge of improving the accuracy of LCA data and models, is the meaningful presentation of LCA results in a form that both producers and consumers can interpret to make informed production and consumption decisions. One way to improve interpretability is to permit direct comparisons between a product and others in the same product category. Environmental performance for products within a category may include a high degree of variability that comes from differences in production practices and production site characteristics. Describing this variability can be potentially used to situate the environmental performance of individual product supply chains within the product category as an improved means of interpreting its environmental performance in addition to describing the performance range present across the sector for comparison with other products that serve the same function (e.g.

a serving of fruit). The construction of such a range is often hindered by lack of sufficient production data to describe an entire product sector. However this range can be approximated by sampling representative production processes and for accounting for variability of environmental conditions that could occur based on differences in production location, which are particularly relevant for agricultural production activities. A method for combining variation in production practice and environmental conditions to describe the range of environmental performance was developed here for pineapple production in Costa Rica, with the outcome being ranges of environmental performance for farm-level pineapple production for Costa Rica.

The production systems modeled in this dissertation were two primary sector products, gold-silver bullion and fresh pineapple, from two different non-OECD countries, Peru and Costa Rica. Product supply chains in non-OECD countries, particularly those which are largely located in the tropics, have been poorly characterized thus far through LCA. Implementation of LCA in non-OECD countries requires adaptation of data and impact assessment (LCIA) methodologies for measuring the environmental impact associated with production chains in these countries for exports that are consumed in OECD countries. LCA is uniquely appropriate for quantifying the environmental burden of this production-consumption pattern because it is only by accounting for impacts over the full life cycle that the responsibility of OECD consumers for environmental burdens in non-OECD countries is quantifiable and thus can be addressed by associated market-based or policy measures to reduce these burdens. This was demonstrated through two unique adaptations of LCA for one Peruvian and one Costa Rican export product, with implications in each

case for improved environmental management from both producer and consumer perspectives.

The availability of process data and technical capacity to use LCA in non-OECD countries is likely to be less than in OECD countries. Where the data or capacity does not exist, incentives and new mechanisms for use of LCA in non-OECD countries, particularly for products exported to OECD countries where there is a demand for environmental information, are required. The use of LCA-based labels called environmental product declarations (EPDs) could be a market-based mechanism for improvement of export production by providing information for buyers and consumers in importing nations that could be used to select the products that have the lesser impact. EPD programs for these product labels exist in a number of EU and Asian countries and are emerging in the US. Products from non-OECD countries could be registered in these programs and used to inform purchasing decisions of buyers. Alternatively or in concert with OECD programs, EPD programs could be developed in non-OECD countries as a way to gauge, publish, and promote environmental performance of export production. Thus EPDs are an application of life cycle assessment that could promote trade of more environmentally benign products by influencing both the production and consumption aspects of the supply chain. This particular application of life cycle assessment should improve LCA interpretability and function to broaden use into international markets.

APPENDIX A
SUPPLEMENT TO CHAPTER 2: PROCESS TREE AND UNCERTAINTY ESTIMATES

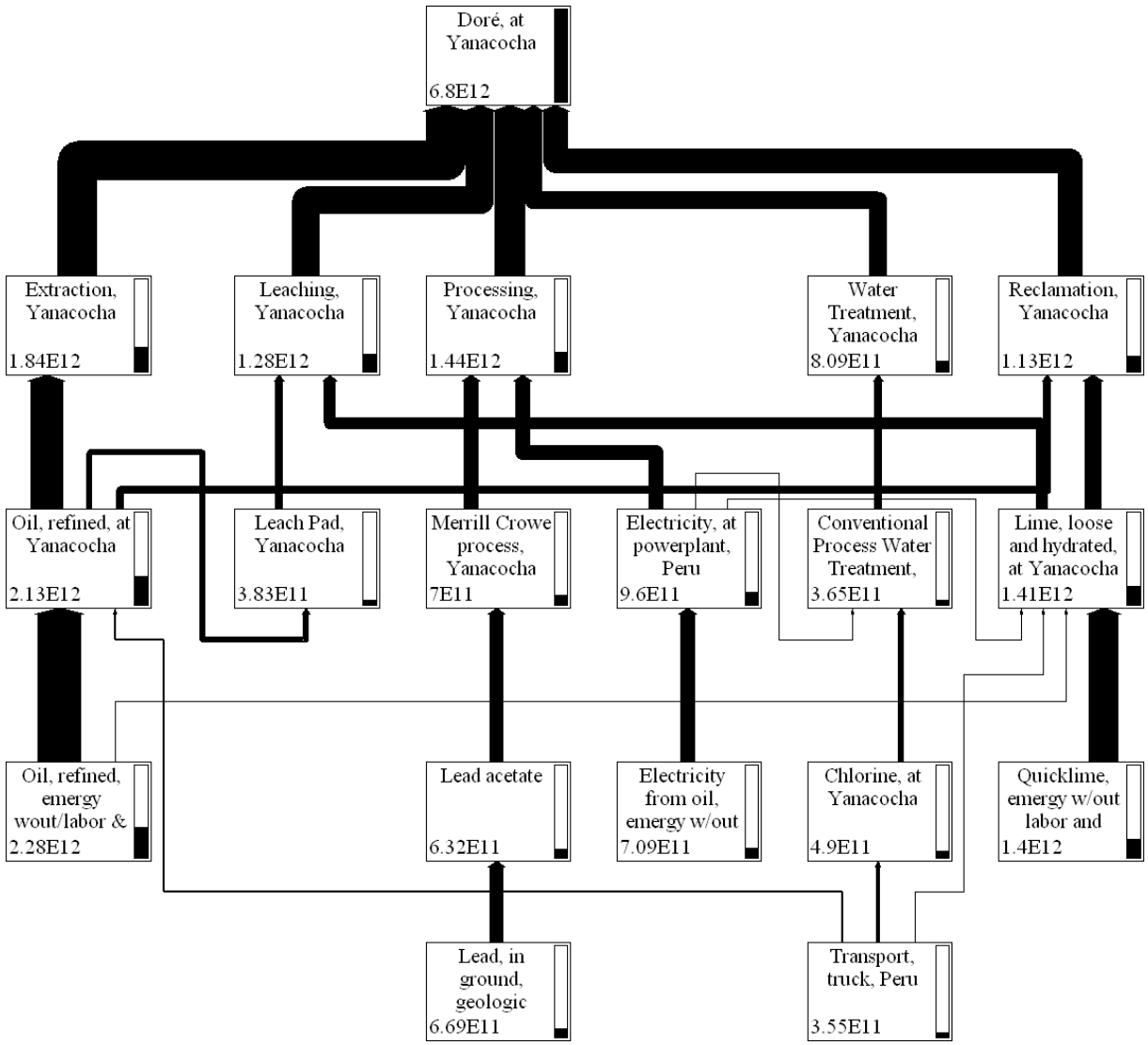

Figure A-1. SimaPro process tree of environmental contribution (sej) to 1 g doré. Inputs contributing 5% or more of the total emergy visible.

Table A-1. Uncertainty estimates for UEVs for inputs into gold-silver bullion production.

Item for which uncertainty estimated	Uncertainty estimate used for	σ^2_{geo}	Reference
Electricity, from oil	Electricity from all sources in mix	2.8	1
Gold, in ground	Gold, in ground	10.7	Table A-2
Groundwater, global	All process water	2.0	1
Iron, in ground	Pig iron, steel	7.5	1
Lead, in ground	Pb in lead acetate and Zn in zinc powder	11.1	1
Oil, crude	Crude and refined oil, natural gas	3.6	1
Silver, in ground	Silver, in ground	10.6	Table A-3
Sulfuric acid	sulfuric acid, HCl, general acids	3.3	1

Sources
1 (Ingwersen 2010)

Table A-2. Estimation of total uncertainty in gold in the ground.

No.	Parameters	μ	σ	σ^2_{geo}
1	crustal concentration (ppm)	4.00E-03	0.001	1.96
2	ore grade (ppm)	0.87	0.04	1.10
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	5.68E+14	9.22E+14	9.28
	Summary			
	Unit emergy value, μ (sej/g)	3.65E+11		
	Parameter Uncertainty Range (No. 1-5)			
	μ_{geo} (sej/g) (x÷) σ^2_{geo}	**3.35E+11**	**(x÷)**	**2.27**
	Total Uncertainty Range (No. 1-6), μ_{geo} (sej/g) (x÷) σ^2_{geo}	**1.75E+11**	**(x÷)**	**10.74**

Sources
1 Butterman and Amey (2005)
2 Newmont (2006c)
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), Odum (1991)

Table A-3. Estimation of total uncertainty of silver in the ground.

No.	Parameters	μ	σ	σ^2_{geo}
1	crustal concentration (ppm)	7.50E-02	0.007	1.20
2	ore grade (ppm)	1.13	0.06	1.10
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	4.97E+14	8.60E+14	10.03
	Summary			
	Unit emergy value, μ (sej/g)	2.54E+10		
	Parameter Uncertainty Range (No. 1-5)			
	μ_{geo} (sej/g) (x÷) σ^2_{geo}	**2.46E+10**	**(x÷)**	**1.65**
	Total Uncertainty Range (No. 1-6), μ_{geo} (sej/g) (x÷) σ^2_{geo}	**1.23E+10**	**(x÷)**	**10.59**

Sources

1 Butterman and Hillard (2004)

2-6 See Table 1 sources

APPENDIX B
SUPPLEMENT TO CHAPTER 2: LIFE CYCLE INVENTORY OF GOLD MINED AT YANACOCHA

Background

The gold mine at Yanacocha, Peru operated by Minera Yanacocha, S.R.L, is the largest gold mine in South America, and the second largest in the world in terms of production volume. Yanacocha is co-owned by Newmont Mining Company(US), Buenaventura (Peru), and the International Finance Corporation. The Yanacocha mine is one of the largest gold mines (in terms of production) in the world. The mine produced 3.3275 million ounces of gold 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 (World Gold Council 2006).

Yanacocha is an open pit mine. Ore is obtained through surface extraction. Gold and silver are extracted from ore through cyanide heap leaching and further refined through a series chemo- and pyrometallurgical processes. The output of the Yanacocha mine is a gold-silver bullion called doré, with a mercury by-product. The doré is shipped overseas for further refining.

Methodology

Scope

The scope of the life cycle inventory (LCI) included gold mining and processing from the stage of the deposit formation to the overseas export of a semi-refined gold product (doré). The purpose was to include every critical link in the mining process, including background and auxiliary processes, with the exception of administrative, community, and information and other mine support services. The choice to include all mine operations, described later, is based on the supposition that are all these operations are necessary for gold mining to occur within the current regulatory and business contexts. The scope is consistent with a cradle-to-gate LCI but extends further upstream to encompass both pre-mining activity of the company and geologic work of the environment. The downstream life cycle of gold production was not included. The inventory is based on total reported production in year 2005**.** This a *source-side LCI* – accounting for all the inputs to the process but not the emissions and wastes. Therefore this inventory would not be sufficient for characterizing pollution impacts such as air, water, or soil contamination.

Purpose

This LCI was constructed to provide a measure of total *environmental contribution* to mining. Total environmental contribution was measured as the total energy used to supply all inputs tracing back to the energies that drive the biosphere (e.g. solar, tidal, deep heat). This energy, a form of embodied energy which includes environmental inputs, was estimated following the emergy methodology (Brown and Ulgiati 2004; Odum 1996)

The aim of this LCI is generally descriptive, rather than decision-oriented (Frischknecht 1997). Neither was it completed for specific comparison. As a consequence, no inputs or processes were omitted because of redundancy with similar products or systems.

Furthermore, the purpose was to complete a detailed LCI, rather than a screening LCA. Therefore rather than relying on existing LCI data, primary data from Yanacocha was used or original calculations specific to processes at Yanacocha were performed in all main unit processes and significant[27] indirect processes.

Inventory Contents and Organization

As is customary in LCI, the inventory was grouped into a series of unit processes (National Renewable Energy Laboratory 2008). Nine primary unit processes were identified and grouped into three unit process types. These unit processes and types are identified in Figure B-1 . Background and auxiliary processes are not always included in mining LCIs, but are both essential to the mining process. A generic mining LCI model called LICYMIN includes auxiliary processes (Durucan et al. 2006). This inventory is unique among mining LCIs, in that background processes, including natural processes, are included.

Data for the mining activities are grouped by nine units processes, except in cases where data was available only at the mine level, which was the case for labor. This item is only tracked at the system level.

Water included in the inventory was water used and evaporated in the process. Other water used that is recycled or released downstream was not included, as it was not considered to be consumed.

Both raw materials inputs and core capital goods are included in the inventory. Core capital goods are defined as installations and heavy equipment critical to processes at Yanacocha. These include heavy vehicles, processing units such as ovens and reaction tanks, primary pipes, and large storage tanks. Auxiliary equipment such as connector pipes, structural skeletons, monitoring equipment are not included. The omission of small auxiliary capital is justified in the Section 'Inventory Cutoffs'.

Capital goods included elements of process infrastructure such as pad and pool geomembranes, pipes conveying process material and waste between units, and earthen materials supporting pads and used in restoration. Earthwork was not included.

Elements of non-process mine infrastructure included in the inventory are roads, steel buildings, water supply, electricity transmission line, and dams. Equipment used in mine administration and maintenance such as small trucks, computers, protective clothing, were omitted. Employee support services such as food, medical, and housing services were not included due to lack of data. Infrastructure and management of the San Jose reservoir, a reservoir for mine and community water storage within the mine boundary, was not included.

[27] 'Significance' indicates that a process falls within the inventory cutoff as described below.

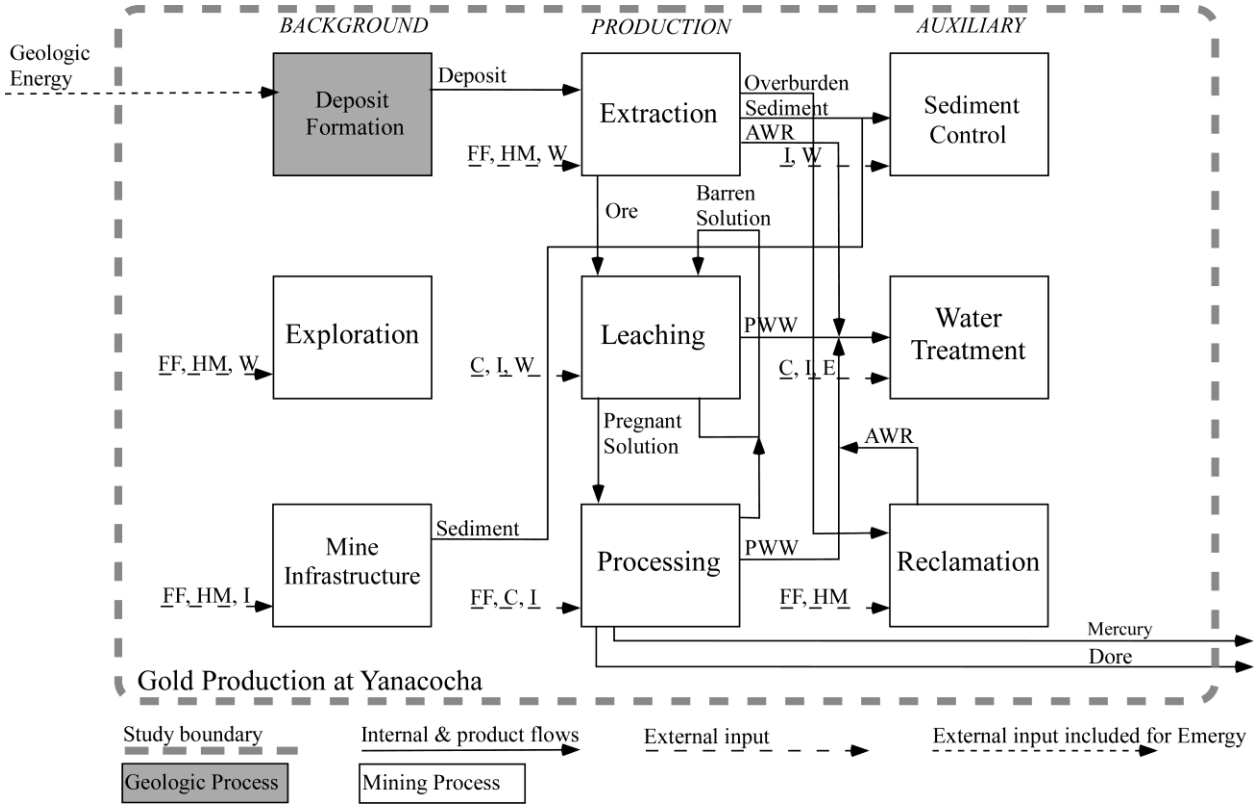

Figure B-1. Process overview . Nine unit processes (boxes) are grouped by three process types: background, production and auxiliary. Geologic processes led to deposit formation. Deposit discovery occurs during exploration. Before a deposit can be mined the necessary infrastructure such as roads, electricity and water supply, and office facilities are put in place.Mining itself begins with extraction which requires drilling and blasting away surface rock, and loading and hauling ore to leach pad. Leach pads and pools are prepared to contain and extracted ore and capture gold in solution in the leaching process. The leached solution is further refined in multiple stages, including a retort process in which the mercury is separated. Pouring into doré bars completes the processing steps that occur at the mine. Excess water from processing and acid runoff from pit is treated before release at water treatment plants. To prevent degradation of stream function sediment control structures are used to capture sediments. Once an area becomes inactive it is filled with waste rock, covered with top soil and in cases other protective layers, and replanted during reclamation.

Data Collection

The mining process was modeled based on written and graphic descriptions in corporate literature from primary sources. The model was corrected and/or confirmed through visits to the mine in July 2007 and in conversations with mine employees. Primary, public data from Newmont and partners were used as the source whenever possible. When primary data was missing, inputs were calculated or ‘back-calculated’ based on stoichometric formulas (for chemical reactions), equations in reference books

(for mine equipment, operations and infrastructure), or calculated using, when necessary, generic industry data. Areas and distances utilized in calculations, when not published in primary data, were estimated by delineating polygons of pertinent process footprints from satellite imagery in Google Earth software, saving them as KML files, and using a freely available web-based KML-polygon area calculator (GeoNews 2008).

Inventory Cutoffs

Rather than choosing a strict material, energetic or economic cutoff for data collection, inventory cutoff was based on contribution to final measure of resource impact from mining, measured in emergy. Inputs estimated to contribute to 99% of all emergy were included. In many cases items with less than 1% of contribution to impact were included, because lack of significance could not be assumed prior to calculation. Many of these inputs were left in the inventory both to demonstrate their lack of significance and to make the inventory more complete for use with other measures of impact, for which relative impact would vary.

Data Management

The inventory data was managed in SimaPro 7.1 software (PRé Consultants 2008). Original processes and product stages were created for the primary unit processes identified (Figure B-1) as well as for direct and indirect inputs to those processes. For some input data was replicated from processes available in the Ecoinvent database version 2.0 (Ecoinvent Centre 2007). The Ecoinvent database was the only third-party data used to avoid boundary issues that would result from incorporation of processes from other LCI databases available in SimaPro. Data underlying Ecoinvent processes were altered in some cases, such as for heavy vehicles, where the most analogous Ecoinvent process (e.g. lorry, 40 ton) was modified with manufacturer data on weight to make it applicable to the mining process at Yanacocha (e.g. rear dump truck). Only Ecoinvent data corresponding to ‘Inputs from Nature’ or ‘Inputs from Technosphere’ were included, since these were relevant to the scope of this LCI. Transport and excavation inputs were omitted for infrastructure items adapted from Ecoinvent.

Processes were stored either as *unit* processes or *system* processes. Unit processes were used in all cases except for those indirect processes (e.g. fabrication of infrastructure) for which emergy values already existed, in which cases system processes were used.

The process were named according to the following scheme: processes based on primary data the name ‘Yanacocha’ was attached to the end. For processes based on general estimates or calculation from the mining literature or other mines, no additional ending was attached to the name. When inputs were prepared off site but transportation to Yanacocha from their origin is included, the ending ‘at Yanacocha’ is used. For processes that only stored unit emergy values, the name ‘emergy’ was added to the end and if this unit emergy value did or did not include labor and services ‘w/labor and services’ or ‘wout/labor and services’ was attached to the names.

Results

The LCI consists of 164 SimaPro processes (Table B-16). 'Dore, at Yanacocha' is the process for the final product (Table B-1), and 'Mercury, at Yanacocha' for the by-product. All results are presented relative to the total production at the mine in 2005 of 2.17E+08 g doré which comprised 9.43E+07 g of gold, 1.23E+08 g of silver, and had by-product of 5.99E+07 g of mercury. 'Mercury, at Yanacocha' is represented by an identical process list except 'Processing, Yanacocha' is replaced with 'Processing, without smelting, Yanacocha' sincercury is removed prior to smelting, and the 'Gold at Yanacocha, geologic emergy' and 'Silver at Yanacocha, geologic emergy' processes are replaced by the 'Mercury at Yanacocha, geologic emergy' process. 100% of all mining inputs are allocated to both the doré and mercury by-products.

Table B-1. Inputs to process 'Dore, at Yanacocha'. Output is 2.17E+08 g doré.

No	Process	Amount	Unit[28]
1	Processing, Yanacocha	1	yr
2	Water Treatment, Yanacocha	1	yr
3	Gold at Yanacocha, geologic emergy	9.43E+07	g
4	Silver at Yanacocha, geologic emergy	1.23E+08	g
5	Exploration, Yanacocha	1	year
6	Mine infrastructure, Yanacocha	1/mine_lifetime	p
7	Extraction, Yanacocha	1.33E+11	kg
8	Leaching, Yanacocha	1.20E+14	g
9	Sediment and dust control, Yanacocha	1	year
10	Reclamation, Yanacocha	(6.56E+10*waste_to_reclam)+8.3E+07	kg
11	Labor, total, Yanacocha	1	p

Notes
All variables with their default values are listed in Table B-24

Descriptions of the nine primary unit processes depicted in Figure B-1 and procedures for collection of data associated with these process are presented by process below.

Deposit Formation

The gold deposits at Yanacocha were formed by the flux of hydrothermal fluids containing Au and other minerals from deeper within the crust. These fluids pushed up and crystallized on near-surface rock that had been previously altered by flows of magma. At Yanacocha, periods of volcanic activity producing magmatic flows alternated with hydrothermal flows over approximately 5.4 million years created the deposits. Greater depth and detail on the formation of gold deposits at Yanacocha is provided by

[28] All symbols for units are the same as those used in SimaPro 7.1.

Longo (2005). The inventory for this process only contains the estimated mass of gold, silver, and mercury in the final products.

Exploration

The exploration model consists of land-based exploration with a drill rig. Inventory data is presented in Table B-2. Drill rig use is based on Newmont worldwide ratio of oz reserve added to meters drilled, and reported reserve oz added at Yanacocha (Newmont 2006b). This results in 0.8 m drilled/oz reserve added. Drilling includes a diamond drill rig, diamond drills bits, and and water and diesel use for operation. Drilling calculations are based on Hankce (1991). Water use is reported by the company (Minera Yanacocha S.R.L. 2005). Initial exploration is done though aerial surveys and remote sensing techniques, but this phase was not accounted for due to lack of data. Support for exploration teams and sample processing was also omitted.

Table B-2. Inputs to process 'Exploration, at Yanacocha'. Output is 1 yr of exploration.

No.	Process	Amount	Unit	σ^2_{geo}
1	Process water, at Yanacocha	1.37E+11	g	1.2
2	Diamond exploration drill, Yanacocha	50665	hr	1.3
3	Diamond drill bit	2.00E+02	p	1.3
4	Oil, refined, at Yanacocha	5.67E+13	J	1.3

Infrastructure

Inputs to mine infrastructure are presented in

Table B-3. Land use prior to mining was predominately pasture (Montgomery Watson 2004). Loss of aboveground biomass due to clearing for mining is included. Mine roads, water and electricity supply, and buildings were included in the inventory. Total length and width of mine roads was estimated using satellite imagery. Models for road materials and constructions were created for three roads types: (1) hauling roads for use by heavy mine vehicles (approx 25m in width), (2) service roads (approx. 10 m in width), and a provincial highway connecting Cajamarca and the mine which was improved by the mining company for support of increased traffic and weight (Minera Yanacocha S.R.L. 2007). Road models were based on standards in accordance for support of vehicle weight and material type, based on California Bearing Ratios obtained from Hartman (1992). Table B-17 provides assumed road layer depths. Road materials and diesel used in transport of materials in road construction was included. Materials were assumed to be gathered on site, at an average distance of 2.5 km, based on visual estimate. Equations for transport of mine dump trucks (CAT 777C) were used to estimated trips and fuel use (see next section). Material and fuel use for the provincial highway were based on the ‘Road/CH/I U’ model in Ecoinvent (Spielmann et al. 2004).

Estimations for an electricity supply network were based on Ecoinvent’s ‘Transmission network, electricity, medium voltage/km/CH/I‘ process (Dones et al. 2003). Water supply and a pump station were also based on Ecoinvent ‘Pumpstation’ and ‘Water supply network’ processes (Althaus et al. 2004). Distance for electricity and

water supply networks were assumed equal to major mine road length (hauling road), and total water supply was reported by the company (Newmont 2006a).

Total mine building area was estimated from satellite photos to the nearest 10000 m^2. Inputs for process buildings were based on 'Building, hall, steel construction/m2/CH/I' from Ecoinvent (Althaus et al. 2004).

Table B-3. Inputs to process 'Mine infrastructure, Yanacocha'. Output is 1p. *

No.	Process	Amount	Unit	σ^2_{geo}
1	Hauling Road, Yanacocha	44	km	1.5
2	Service Road, Yanacocha	110	km	1.5
3	Highway, provincial	3.60E+06	my	1.5
4	Building, hall, steel	3.00E+04	m2	1.5
5	Pump station	6.21	p	1.2
6	Water supply network	44	km	1.2
7	Transmission network, electricity, medium voltage	44	km	1.5
8	Standing biomass before mining, Yanacocha	7895	acre	1.5

* 'p' is the symbol for 1 item or unit in SimaPro.

Extraction

The extraction phase model is based on a process descriptions reported by the mining company (Minera Yanacocha S.R.L. 2005, 2006, 2007) and third parties (Infomine 2005; International Mining News 2005; Mining Technology 2007). The extraction phase commences with the removal and onsite storage of topsoil. Drill rigs drill bore holes for placement of ANFO explosives for loosening overburden. Explosives are assumed to be ANFO type (Newmont 2006a). Large mining shovels scrape overburden and ore into large dump trucks. Overburden is transferred into waste rock storage piles. Gold-bearing ore is transported and stacked on heap leach pads. The total amount of ore mined, explosives used, percentage waste rock, and water used are reported by Newmont (Minera Yanacocha S.R.L. 2005; Newmont 2006a). Inputs are presented in Table B-4.

Table B-4. Inputs to process 'Extraction, Yanacocha'. Output is 1.99E+11 kg extracted material.

No.	Process	Amount	Unit	σ^2_{geo}
1	Scraper, Yanacocha'	596	hr	1.3
2	Drill rig, Yanacocha	2273	hr	1.3
3	Explosives (ANFO), at Yanacocha	7.71E+03	tn.sh	1.0
4	Mining shovel, Yanacocha	4.60E+04	hr	1.3
5	Rear dump truck, at Yanacocha	2.1+E+05	hr	1.3
6	Oil, refined, at Yanacocha	2.83E+15	J	1.3
7	Process water, at Yanacocha	3E+11	g	1.2

Transport of Ore and Waste Rock

Models and makes of mine vehicles were confirmed from the primary and secondary sources listed in the previous paragraph. Weight and capacity specifications for these vehicles were acquired from vehicle manufacturers. Fuel economy was estimated from data for another Newmont mine (Newmont Waihi Gold 2007). These specifications were used as parameters for vehicle production equations from the SME Mining Engineering Handbook (Lowrie 2002), for estimating total hours of use for scrapers, mechanical shovels, dump trucks, and stackers (see Table B-19). The estimated number of hours of use of each vehicle was then used to estimate fuel consumption.

Mine Vehicle Model

Fabrication and transport of mine vehicles was included in the inventory. Material composition, electricity and gas used in fabrication of mine vehicles were scaled up from a simplified version of the 'Lorry 40t/RER/I U' process in Ecoinvent v1.3 ((Spielmann et al. 2004), based upon the difference in weight. Only mass inputs into the 'Lorry 40t/RER/I U' that comprised at least 1% of the total input weight were included, with the addition of copper, lead, electricity, and natural gas. Materials were aggregated together in the case of iron (e.g. weights of wrought iron and pig iron were combined under the input 'iron'). A set percentage of the weight increase from manufacturer of larger vehicles was attributed to steel for all vehicles (40% of weight) and rubber for vehicles (7% of the weight) with larger tires including the rear dump truck and scraper. Remaining additional weight was assumed to have the same composition as the 40 ton lorry. Vehicle models including weights and lifetimes and equations for scaling weights of materials and energy in vehicle fabrication are given in Table B-20.

Leaching

The leaching process at Yanaococha is a hydrometallurgical process whereby a dissolved cyanide solution is dripped through gold and silver-bearing ore to strip these metals and collect them in lined pool before being pumped out for further processing. Total leached solution processed in 2005 was 1.21E+14 g (Condori et al. 2007). The leaching process is a circular process whereby barren solution (from CIC plant) is recycled after replenishment with cyanide. A stacker is used to stack the extracted and delivered ore on the leach pads. Estimated use is based on ore quanity and SME Reference Handbook equations (see Table B-19). A total of 4845.5 tons as of sodium cyanide as CN were consumed in this process in 2005 (Newmont 2006a). This was multiplied by molecular weight ratio of NaCN:CN to get estimated NaCN used. Calcium hydroxide, or lime, is added to raise the pH for optimal leaching. The estimated quantity of lime is based on an addition of .38 g CaOH:kg ore, which matches the total use reported by Newmont (Newmont 2006a) and is consistent with the range of 0.15-0.5 gCaOH:kg ore reported in Marsden and House (2006). Use of the leachpads and pool were based on a ratio of ore capacity to total pad area (Buenaventura Mining Company Inc. 2006). Details on leach pad and pool facilities were obtained from a mine tour and primary sources (Minera Yanacocha S.R.L. 2007; Montgomery Watson 1998). Leach pads consists of a clay layer, two layers of geomembranes, a gravel layer and collection

and conveyance pipes. These inputs were estimated based on area and specifications. Total leach pad and pool areas in 2005 were reported by Buenaventura Mining Company Inc. (2006). The leach pad process is based on the largest pad at La Quinua. Fuel used in transport of the gravel from China Linda lime plant (12 km) and of the clay from borrow pits within the mine (2.5 km) was estimated assuming dump truck equations (Table B-19), assuming use of a CAT 777C with a fuel economy of 129L/hr. Pipe network for leachate irrigation was not included. Leach pools for collecting leachate prior to processing consist of three layers of geomembranes, a geotextile, pipes for collection and pumping to treatment, and storage tanks for NaCN and mixing.

Table B-5. Inputs to process 'Leaching, Yanacocha'. Output is 1.21E+14 g leachate.

No.	Process	Amount	Unit	σ^2_{geo}
1	Stacker, Yanacocha	1.54E+05	hr	1.3
2	Sodium cyanide, at Yanacocha	6.74E+09	g	1
3	Lime, loose, hydrated, at Yanacocha	4.6E+10	g	1.2
4	Process water, at Yanacocha	4.23E+12	g	1.2
5	Leach Pad, Yanacocha	6.69E+05	m2	-
6	Leach Pool, Yanacocha	3.28E+04	m2	-
7	Recycled leach solution	1.25E+14	g	-

Table B-6. Inputs to process 'Leach Pad, Yanacocha'. Output is a 2.1E+6 m^2 leachpad.

No.	Process	Amount	Unit
1	Geomembrane, HPDE, 2mm thickness	2.10E+06	m2
2	Scraper, Yanacocha'	1.86E+03	hr
3	Geomembrane, LLPDE, 2mm thickness	2.10E+06	m2
4	HDPE Pipe, 40" dia.	6.67E+04	m
5	Fill material, Yanacocha	8.00E+08	kg
6	Gravel, crushed and washed, Peru	1.12E+09	kg
7	Oil, refined, at Yanacocha	1.63E+15	J

Table B-7. Inputs to process 'Leach Pool, Yanacocha'. Output is a 1.03E+05 m^2 leachpool.

No.	Process	Amount	Unit
1	Geomembrane, HPDE, 2mm thickness	4.81E+04	m2
2	Geomembrane, LLPDE, 1mm thickness	1.03E+05	m2
3	Geomembrane, HPDE, 1.5mm thickness	2.06E+05	m2
4	Steel Pipe, 36" dia., at Yanacocha	2.74E+04	m
5	Geotextile, 8 oz.	3.09E+05	m2
6	Steel Pipe, 36" dia., at Yanacocha	1.70E+04	m
7	Storage tank, steel	1.50E+04	kg

Processing

Gold-bearing leachate is further processed and refined on site into doré. The process train includes carbon-in-column adsorption and stripping, Merrill-Crowe precipitation, retorting, and smelting (Mimbela 2007). Wastes from these various stages go into process water treatment. These stages are aggregated together in an inventory process called 'Processing, Yanacocha' (

Table B-8). Processing is assumed to be the major consumer of electricity. Electricity is purchased by the mine from the national grid. Provision of electricity was modeled after the national feedstock mix for Peru (Energy Information Administration 2007).

Table B-8. Inputs to process 'Processing, Yanacocha'. Ouput is 1 yr of processing.

No.	Process	Amount	Unit
1	CIC process solution, Yanacocha	1.06E+13	g
2	Merrill Crowe process, Yanacocha	1.16E+13	g
3	Smelting, Yanacocha	2.17E+08	g
3	Retort process, Yanacocha	1.16E+13	g
4	Electricity, at powerplant, Peru	1.07E+06	GJ

The inputs included for the CIC process was activated carbon and the CIC plant infrastructure. A ration of 4 g Au: 1000g activated carbon with a reuse rate of 90% of the carbon was assumed ('Carbon in pulp', 2008). For the Merrill Crowe process, 1.89E+08 g of zinc powder and 4.45E+08 g of lead acetate are assumed to be included. Estimates are based on ratios from Lowrie (2002). The retort process is merely an empty place holder. The smelting process includes two smelters in addition to 1.68E+03 GJ natural gas, an amount based on a calculation of the energy necessary to heat gold to its melting point of 1337K, assuming a heat capacity of 25.4 J mol^{-1} K^{-1}, and the operational parameters of the smelter (see below).

Mass Balance Model

A dynamic mass balance model was used to track the fate of core species through the process train (see Table B-21). Company reported concentrations of elements in the feedstock at various stages and concentrations of reagents used were set as constants in the model (e.g. Water used in process; cyanide used; ppm CN in the leachate; gold and silver in final product). Other ranges of concentrations not reported were gathered from the literature and upper and lower limits were used as constraints. Recycle loops back to the leaching process exists at each stage, as the solution is reused in the process. Values for unknown quantities were manipulated within upper and lower limits until all mass balance conditions were satisfied, within an error of 2% for water flows, and up to 5% for constituents.

The following species were tracked through the processing stages: H_2O (including pumped water and precipitation), CN, Au, Ag, Hg, and Cu, primarily to account for the various reagents used in the treatment chain, including activated carbon, zinc and lead acetate (for precipitation in the presence of lead acetate), and to account for the quantities of reagents used in treatment of the process water.

Process Infrastructure

Significant components of processing and water treatment infrastructure were included based on estimates during a site visit and through measurements of geo-referenced aerial photographs (Google 2008). Infrastructure includes storage and processing tanks and steel buildings. Tanks were assumed to be steel and weights were estimated from formulas from The Tank Shop (2007). Other process capital components included in the inventory were 2 tilting electric-arc furnaces for smelting and a reverse osmosis membrane treatment system for process water. The tilting furnace was based on the Lindberg 61-MNP-1000 model.[29] For simplicity the furnace was assumed to be 100% steel.

Water Treatment

Water treatment at Yanacocha consists of treatment of process water and treatment of acid water from previously mined open pits and reclaimed pits. Treatment occurs in separate facilities. The process 'Water treatment' aggregates the treatment type, plus includes reported additional acid use in excess of the modeled requirements from the mass balance model (Table B-9).

Table B-9. Inputs to process 'Water Treatment, Yanacocha'. Output is 1 yr of water treatment.

No.	Process	Amount	Unit
1	Acid Water Treatment, Yanacocha	1.42E+13	g
2	Conventional Process Water Treatment, Yanacocha	7.02E+12	g
3	Reverse Osmosis Process Water Treatment, Yanacocha	4.68E+12	g
3	Acid,Yanacocha, unaccounting for	1.08E+09	g

Table B-10. Inputs to process 'Conventional Process Water Treatment, Yanacocha'. Output is 3.1E+12g treated water.

No.	Process	Amount	Unit	σ^2_{geo}
1	Chlorine, at Yanacocha	1.17E+10	g	1.2
2	Iron(III) Chloride	3.02E+08	g	1.2
3	Sodium hydrosulfide, 100%	3.62E+07	g	1.2
4	Polyacrylamide (PAM)	3.00E+08	g	1.2
5	Sulfuric acid, 98%, emergy w/out L&S	4.91E+04	g	1.2
6	Electricity, at powerplant, Peru	1.16E+06	kWh	1.31
7	Conventional Process Water Treatment Plant, Yanacocha	0.05	p	-

[29] Approx. weight 8000 lbs empty. Uses maximum of 3,100 cf per hr of natural gas based on 1,000 Btu/cf natural gas. Max load 2,800 lbs. Melt time for this load about 3 hrs (Hosier 2008).

Table B-11. Inputs to process 'Reverse Osmosis Process Water Treatment, Yanacocha'. Output is 5.55E+12 g treated water.

No.	Process	Amount	Unit	σ^2_{geo}
1	Chlorine, at Yanacocha	2.09E+10	g	1.2
2	Sulfuric acid, 98%, emergy w/out L&S	5.40E+04	g	1.2
3	Electricity, at powerplant, Peru	1.20E+14	J	1.31
4	RO System	1.71	p	-

Table B-12. Inputs to process 'Acid Water Treatment, Yanacocha'. Ouput is 1.42 E+13g treated water.

No.	Process	Amount	Unit	σ^2_{geo}
1	Lime, loose, at Yanacocha	7.96E+09	g	1.2
2	Iron(III) Chloride	7.10E+08	g	1.2
3	Polyacrylamide (PAM)	9.22E+08	g	1.2
4	Sulfuric acid, 98%, emergy w/out L&S	2.24E+04	g	1.2
5	Electricity, at powerplant, Peru	2.74E+06	kWh	1.31
6	Acid Water Treatment Plant, Yanacocha	0.05	p	-

Water treatment process models are based on site visits and personal communication with engineers at Yanacocha. Process water treatment included both conventional and reverse osmosis systems. Allocation between these systems is based on installed capacity in 2005. Chemical reagents used in these processes are included. Reagents quantities are based on reported quantities used when available or calculated based on total water treated and requirements specified in water treatment literature. Sludge waste from treatment is slurried and pumped back to the leach pads - no additional long-term management for sludge is included other than leach pad reclamation, as none is planned.

Conventional process water treatment inputs were based on the following. Chlorine calculations were based on the stochiometric calculation of 4 mol Cl per mol CN, with an excess ratio of 1.1 mol Cl (National Metal Finishing Resource Center 2007). NaSH is added to release cyanide bound to copper. Inputs is based on the stochiometric equation from Coderre and Dixon (Coderre and Dixon 1999). PAM added is based on an optimal concentration of 65 ppm (Wong et al. 2006). The sulfuric acid addition is based on a stochiometric requirement to adjust the pH of the water. Electricity of 0.193 kWh/ m^3 of process water is adapted from Ecoinvent 'Treatment, Sewage to Wastewater'. Iron chloride added is based on a concentration of 55 ppm (Abou-Elela et al. 2008).

The reverse osmosis process only requires the addition of CN to destroy cyanide and sulfuric acid to adjust the pH after treatment. It does require additional electricity. The assumed electricity requirement was 6 kWh/m^3 treated water.

Acid water treatment is assumed similar to process water treatment, without the addition of chlorine for cyanide destruction, and with the addition of additional lime for pH treatment. Lime added is based on the lime needed to adjust the pH of the influent from 2-11.

Reclamation

Reclamation models are based on primary data on restoration methods and long-term mine closure plans (Montgomery Watson 2004; Montoya and Quispe 2007). Total reclamation amount is based on the total amount of waste rock (material extracted), which is the difference between total extraction and total ore to leachpads. Inputs are all estimated relative to the mass of overburden returned to mining pits. All waste rock was assumed to be loaded from waste rock piles, transported and backfilled in pits, and limed at a ratio of 1gCaOH:1 kg fill. Fuel consumption for mining shovels and dump trucks is included and based on mining equations (Table B-19). Protective layering, capping, seeding/planting and reclamation maintenance activities were not included due to assumption of insignificance to entire process (< 1%). Inputs to reclamation are shown in Table B-13.

Table B-13. Inputs to process 'Reclamation, Yanacocha'. Output is 1 kg of returned overburden.

No.	Process	Amount	Unit	σ^2_{geo}
1	Lime, loose, at Yanacocha	1	g	1.2
2	Rear dump truck, at Yanacocha	1.32E-06	hr	1.3
3	Mining shovel, Yanacocha	2.33E-07	hr	1.3
4	Oil, refined, at Yanacocha	9.79E+03	J	1.3

Sediment and Dust Control

The primary measures taken at Yanacocha to reduce sediment in runoff are serpentine structures immediately adjacent to mine facilities and three large sediment dams. Sediment runoff is based on sediment storage capacity in dams and dam lifetime. Thirteen serpentines are reported (Campos 2007). Dimensions of a representative serpentine were estimated from satellite imagery (Google 2008).Serpentines were assumed to be constructed of 1540 m^3 reinforced concrete. Flocculants to cause sediments to drop out of the water column were not included. Reinforced concrete was also the only input included in sediment dams. Total concrete volume was reported as 7000 and 3000 m^3 for the Grande and Rejo dams, respectively (Newmont 2004). Concrete for the Azufre dam, not reported, was estimated as the average of the aforementioned dams. The contribution of these structures is annualized over the assumed mine lifetime of 25 years.

Mine roads are regularly watered to reduce particulates in the air. The amount of water used by the mine in dust control was reported (Minera Yanacocha S.R.L. 2005). An evaporation rate of 50% was assumed for water spayed on roads, and only this water, a total of 1.34 E+11 g, was included.

Table B-14. Inputs for process 'Sediment and dust control, Yanacocha'. Output is 1 yr.

No.	Process	Amount	Unit
1	Sediment control structures, Yanacocha	0.04	p
2	Dust control, Yanacocha	1	year

System Level Inputs

Because labor was not reported by unit process, it was included as a system level input, and appears in the 'Dore, at Yanacocha' process (see Table B-1. Inputs to process 'Dore, at Yanacocha'. Output is 2.17E+08 g doré.Table B-1).

Labor

Energy in labor was included based on the total hours worked and average human energetic consumption. Total hours worked by employees and contractors is reported by the company (Newmont 2006a). Total J of energy in human labor at Yanacocha was calculated as:

*(3.82E+09 J/yr avg human consumption)/(365*8 working hrs/yr)(2.3E+07 hrs worked at Yanacocha) = 3.01E+13 J/yr (1)*

A year's calorie intake is assumed necessary to support 8 hours of work daily for 365 days a year.

Transport

Transport of materials and capital goods making up 99% of the mass of all inputs was considered. Sea, land, and air transport were all included. Inputs to transport included transport infrastructure construction and operation.

Transport distance was based on origin of the item if known. If unknown, origin was first determined to be domestic or foreign by consultation of the Peru statistical companion for domestic production data and United Nation trade data for import-export data (Instituto Nacional Estadistica y Informacion 2006; United Nations 2008). If the item was produced or exported in quantities sufficient to supply the usage at Yanacocha, origin was assumed domestic and assumed to originate in Lima. If item was assumed to be of foreign origin, a sea distance of 5900 km was assumed (Los Angeles to Lima) in addition to road transport from Lima. Top ten items, mass inputs, and transport distances are given in Table B-23.

Inputs for sea and air transport were based on the Ecoinvent processes 'Transport, transoceanic freight ship/OCE U', 'Transport, transoceanic tanker/OCE U', and 'Transport, aircraft, freight, intercontinental/RER U' (Spielmann et al. 2004). An inventory of US truck transport from Buranakarn (1998) was adapted with data from Spielman and data on the Peruvian truck fleet (Instituto Peruano de Economia 2003). Data and notes are given in Table B-22. Due to complex geography, an older fleet, and significantly less transport, ton-km efficiency was assuming to be 50% of that of the United States.

Life Cycle Model Parameters

Various life cycle parameters can be switched to include or exclude input of geologic emergy of ore, to clay and gravel construction material. By default these inputs are switched to '0', indicating they are not included. Lifetime of all mine-infrastructure and long-term activities such as reclamation are based on the 'mine_lifetime' variable, which is set to 25 years, representing the time the mine area is occupied and run by the company. The 'process_lifetime' variable is used for capital goods used processes, and represents the time of active mining and processing at the mine, and is set by default to 20 yrs. 'Waste_to_reclam' is the fraction of waste rock backfilled in reclamation and is by default set to '1', representing 100%. Other parameters are (1) related to the size of leach pad and carrying capacity and are used for leach pad capital estimations; (2) related to the mine vehicle models; (3) the ore grade at Yanacocha (Au_ore_grade); (4) the percent of process water treated with reverse osmosis (per_RO_treat); and (5) the way that emergy of labor is included. Parameters are given in Table B-24.

Uncertainty

The inventory estimates were complemented with uncertainty ranges for direct inputs to the nine primary unit processes. For these inputs, uncertainty range was estimated using the same model specified for the Ecoinvent v2.0 database (Frischknecht et al., 2007). This model assumes inventory data fit a log-normal distribution, and that uncertainty can be estimated according to six factors: reliability, completeness, temporal correlation, geographic correlation, technological correlation, and sample size. The uncertainty is reported as the square of the geometric standard distribution, σ^2. Uncertainty estimates are presented in Table B-25. Model parameters related to lifetime of operations were also assigned ranges. Parameters for mine infrastructure, transport distances, and mine vehicle models were estimated with the Ecoinvent method. For processes based on Ecoinvent data, uncertainty data was perpetuated from Ecoinvent processes.

Emergy Conversions

All system processes containing in their name 'émergy' consisted solely of an emergy input, listed as an 'Input from Nature', estimated in units of solar emjoules (sej). These processes served as conversion factors between inventory units and emergy values (e.g. 1.1E+05 sej per J of refined oil), commonly called unit emergy values (UEVs). The UEVs were applied in order to calculate total environmental contribution as energy in sunlight equivalents. Sources for emergy values per unit input were based on previous emergy evaluations of an identical or similar product.

Like inventory values, UEVs were assigned an error range, due to uncertainty in the equivalence of the product, uncertainty in processes in nature, or due to methodological differences in emergy calculations. A log-normal distribution is assumed for the UEVs.

Discussion

This inventory may be directly compared with an existing process in the Ecoinvent database 'Gold, from combined gold-silver production, at refinery/PE U' (henceforth 'Gold …. /PE U') and its accompanying description (Classen et al. 2007), which is also based on production at the Yanacocha mine.

This study reports a total production of 9.43E+07 g of gold in doré while the ‘Gold …. /PE U’ process assumes 1.03E+08 g gold in doré. In the ‘Gold …. /PE U’ process, the inventory data has already been allocated between gold and silver in the doré. This process assumes an additional inputs for separating the gold from the silver in the doré. In this study, the inventory data has not been pre-allocated between gold and silver.

The structure of this inventory is much more elaborate than that of the ‘Gold …. /PE U’ process in Ecoinvent. The Ecoinvent process is essentially a system process, where inputs to doré production are all grouped under the aforementioned process. This inventory is based on nine unit processes, each of which have additional unit processes contributing to them.

The ‘Gold …. /PE U’ process does not consider any inputs into deposit formation, or exploration. Mine infrastructure in the Ecoinvent process is based on a generic Swedish mine. In this study major infrastructure, such as mine building, roads, and processing structures, are based on original analysis of the mine site. The remaining infrastructural components, included power delivery and water supply, are based on generic Ecoinvent processes. For extraction, the ‘Gold …. /PE U’ process does not estimate the contribution of mine vehicles. For leaching, the ‘Gold …. /PE U’ process does not include the leach pad and pool architecture or its construction. For processing, the ‘Gold …. /PE U’ process does not include the leach pad and pool architecture or its construction. In this inventory, reagents added during processing and water treatment are based on mass balance calculations of the process. This inventory explicitly includes some of the major components of the process, water treatment, and sediment control infrastructure at Yanacocha, which are missing from the ‘Gold …. /PE U’ process. There are other notable differences in the inventories. Land use and transformation are not included as inputs in this study, but are included in the ‘Gold …. /PE U’ process. Standing biomass from land transformation, however, is included in this inventory. This is only a source-side LCI, but the ‘Gold …. /PE U’ process includes estimates of emissions to air and water.

The electricity mix in the ‘Gold …. /PE U’ process is based on the Brazilian electricity mix. In this study a new electricity mix process specific to Peru was created. The assumed mine lifetime presents a significant difference between the inventories, which effects the contribution of all capital goods and infrastructure. The ‘Gold …. /PE U’ process assumes a mine lifetime of 50 years; this study only 25 years. A comparison of the outputs and direct non-durable inputs to mining in reference to output of 1 g of doré is presented in Table B-15.

Table B-15. Comparison of this inventory with the equivalent Ecoinvent process

No	Item	this inventory 'Dore, at Yanacocha'	Ecoinvent v2.0 'Gold …. /PE U'	Unit
Total production				
1	Gold	9.43E+04	1.03E+05	kg
2	Silver	1.23E+05	3.67E+04	kg
3	Dore	2.17E+05	1.40E+05	kg
	Rel. to dore production	100%	64%	
Direct non-durable inputs to 1 g of dore				
4	Electricity	6.77	12.3	MJ
5	Diesel	18.4	47.7	MJ
6	Sodium Cyanide	30.8	42.9	MJ
7	Lime	0.55	1.17	g
8	Sodium hydroxide	0	52.6	g
9	Activated carbon	6.73	17.1	g
10	Zinc	0.873	3.33	g
11	Sulfuric acid	6.74	7.67	g
12	Hydrochloric acid	6.75	0	g
13	Transport, truck	0.352	1.92	tkm
14	Explosives	0.032	0.416	kg
15	Water	0.022	0.016	m3
16	Lead acetate	2.05	0	g
17	Chlorine	0.203	0	kg
18	Sodium hydrosulfide	0.378	0	g
19	Iron chloride	6.430	0	g
20	Polyacrylamide	7.38	0	g

Notes

4.61E-9 p of ‘Doré, at Yanacocha’ (=1/annual production, g) and 1.006 g of 'Gold …. /PE U' (=1/99.4 % allocation to gold) were compared here as each represent 1 g of doré. Post-doré electricity and transport included in 'Gold …. /PE U' are omitted for comparison.

Item references (format: this inventory; Ecoinvent)

4 'Electricity, at powerplant, Peru'; 'Electricity Mix /BR' from Ecoinvent
5 'Oil, refined, at Yanacocha'; 'Diesel, burned in building machine /GLO U'
6 'Sodium cyanide, at Yanacocha'; 'Sodium cyanide, at plant/RER U'
7 'Limestone, loose and hydrated, at Yanacocha'; 'Lime, milled, packed, at plant'
8 NA; 'Sodium hydroxide, 50% in H2O, production mix, at plant/RER U'
9 'Activated carbon'; 'Charcoal, at plant/GLO U'
10 'Zinc, geologic emergy'; 'Zinc, primary, at regional storage/RER U'
11 'Sulfuric acid, 98%, emergy w/out L&S', 'Sulphuric acid, liquid, at plant/RER U'
12 NA, 'Hydrochloric acid, liquid, at plant/RER U'
13 'Transport, truck, Peru';'Transport, lorry >16t, fleet average/RER U'
14 'Explosives (ANFO), at Yanacocha'; 'Blasting/RER U'
15 'Process Water, Yanacocha'; 'Water, river' + 'Water, well, in ground'
16 'Lead Acetate'; NA
17 'Chlorine, at Yanacocha'; NA

18 'Sodium hydrosulfide, 100%'; NA
19 'Iron chloride'; NA
20 'Polyacrylamide'; NA

Due to the difference in output one would expect the values in the 'Gold …. /PE U' process to be 1.58 times greater than those in this inventory, but there are still discrepancies beyond this difference. Electricity, diesel, lime, activated carbon, zinc, truck transport and explosives are all greater in the Ecoinvent inventory than expected. Sodium cyanide, sulfuric acid, and water use are less than the expected difference.

Appendix

Table B-16. List of processes in the ‘Gold_Yanacocha’ project inventory.

No.	Process	Unit	No.	Process	Unit
1	Acid Water Treatment Plant, Yanacocha	p	83	Mercury, in ground, geologic emergy	g
2	Acid Water Treatment, Yanacocha	g	84	Merrill Crowe plants, Yanacocha	p
3	Acid,Yanacocha, unaccounting for	g	85	Merrill Crowe process, Yanacocha	g
4	Activated carbon	kg	86	Mine infrastructure, Yanacocha	p
5	Aircraft, long haul	p	87	Mining shovel, Yanacocha	hr
6	Airport	p	88	Natural gas, emergy w/out labor & services	J
7	Aluminum ingot, emergy w/out labor & services	g	89	Oil, crude, emergy w/out labor & services	J
8	Ammonium nitrate, emergy w/out labor & services	g	90	Oil, refined, at Yanacocha	J
9	Ammonium, emergy w/out labor and services	g	91	Oil, refined, emergy wout/labor & services	J
10	Antifreeze	g	92	Operation, aircraft, freight, intercontinental	tkm
11	Azufre Dam, Yanacocha	p	93	Operation, maintenance, airport	p
12	Bitumen, emergy w/out labor and services	g	94	Operation, maintenance, port	p
13	Brass, emergy w/out labor & services	g	95	Operation, transoceanic freight ship	tkm
14	Brick, emergy w/out labor and services	g	96	Operation, transoceanic tanker	tkm
15	Bronze, emergy w/out labor & services	g	97	Paint, emergy w/out labor and services	g
16	Building, hall, steel	m2	98	Pesticide, orthophosphate, emergy w/out labor and services	g
17	Cement, emergy w/out labor and services	g	99	Pig iron, emergy w/out labor and services	g
18	Chlorine, at Yanacocha	kg	100	Polyacrylamide	g
19	Chlorine, emergy w/out labor and services	kg	101	Polybutadeine rubber, emergy w/out labor & services	g
20	CIC plant, Yanacocha	p	102	Polystyrene, emergy w/out labor and services	g
21	CIC process solution, Yanacocha	g	103	Polyurethane	g
22	Clay, in ground, geologic emergy	g	104	Port Facilities	p
23	Concrete, at Yanacocha	g	105	Primary steel, emergy wout/labor & services	g
24	Concrete, emergy w/out labor and services	g	106	Process water, at Yanacocha	g
25	Conventional Process Water Treatment Plant, Yanacocha	p	107	Processing without smelting, Yanacocha	year
26	Conventional Process Water Treatment, Yanacocha	g	108	Processing, Yanacocha	year
27	Copper, emergy w/out labor & services	g	109	Pump station	p

28	Diamond drill bit	p
29	Diamond exploration drill, Yanacocha	hr
30	Diamond, in ground, geologic emergy	g
31	Doré from Yanacocha PE, at CH	g
32	Doré, at Yanacocha	g
33	Drill rig, Yanacocha	hr
34	Dust control, Yanacocha	year
35	Electricity from coal, emergy w/out labor and services	J
36	Electricity from hydro, emergy w/out labor and services	J
37	Electricity from natural gas, emergy w/out labor & services	J
38	Electricity from nuclear, emergy w/out labor and services	J
39	Electricity from oil, emergy w/out labor and services	J
40	Electricity, at powerplant, Peru	J
41	Electricity, at powerplant, USA	J
42	Emergy in dollar, Peru, 2004	USD
43	Ethylene-propylene rubber (EBR), emergy w/out labor and services	g
44	Exploration, Yanacocha	year
45	Explosives (ANFO), at Yanacocha	kg
46	Extraction, Yanacocha	kg
47	Fill material, Yanacocha	g
48	Generic inorganic acid, 100%, emergy w/out labor and services	g
49	Generic organic chemical, emergy w/out labor and services	g
50	Geomembrane, HPDE, 1.5mm thickness	m2
51	Geomembrane, HPDE, 2mm thickness	m2
52	Geomembrane, LLPDE, 1mm thickness	m2
53	Geomembrane, LLPDE, 2mm thickness	m2
54	Geotextile, 8 oz.	sq.yd
55	Glass, emergy w/out labor and services	g
56	Gold in doré, at Yanacocha	g
57	Gold, in ground, at Yanacocha, geologic emergy	p
58	Grande Dam, Yanacocha	g
59	Gravel, crushed and washed, Peru	g
60	Ground water, emergy	km
61	Hauling Road, Yanacocha	m
62	HDPE Pipe, 40" dia.	g
63	HDPE, emergy w/out labor & services	kg
110	PVC, emergy w/out labor and services	g
111	Quicklime, emergy w/out labor and services	g
112	Rear dump truck, at Yanacocha	hr
113	Reclamation, Yanacocha	kg
114	Recycled leach solution	g
115	Reinforced concrete, at Yanacocha	m3
116	Rejo Dam, Yanacocha	p
117	Retort process, Yanacocha	g
118	Reverse Osmosis Process Water Treatment, Yanacocha	g
119	RO membrane	p
120	RO System	p
121	Road construction, Peru	kmy
122	Road operation, Peru	kmy
123	Rock wool, emergy w/out labor and services	g
124	Salt, NaCl 100%, emergy w/labor and services	g
125	Sand, in ground, geologic emergy	g
126	Scraper, Yanacocha'	hr
127	Sediment and dust control, Yanacocha	year
128	Sediment control structures, Yanacocha	p
129	Serpentine, Yanacocha	p
130	Service Road, Yanacocha	km
131	Silt, in ground, geologic emergy	g
132	Silver in doré, at Yanacocha	g
133	Silver, in ground, at Yanacocha, geologic emergy	g
134	Smelters, Yanacocha	p
135	Smelting, Yanacocha	g
136	Sodium cyanide, at Yanacocha	kg
137	Sodium hydrosulfide, 100%	kg
138	Sodium hydroxide, 100%, at Yanacocha	g
139	Sodium hydroxide, 100%, emergy wout/labor and services	g
140	Stacker, Yanacocha	hr
141	Standing biomass before mining, Yanacocha	m2
142	Standing biomass, tropical savannah, emergy	g
143	Steel Pipe, 36" dia., at Yanacocha	ft
144	Storage tank, steel	g
145	Sulfuric acid, 98%, emergy w/out labor	g

				and services	
64	Heavy Vehicle	my	146	Sulphur hexaflouride	g
65	Highway, provincial	g	147	Surface water, emergy	g
66	Hydrochloric acid, 100%, emergy w/out labor and services	g	148	Tetrafluoroethylene	g
67	Hydrogen cyanide	g	149	Tilting Furnace	p
68	Hydrogen sulfide, emergy w/out L&S	g	150	Transmission network, electricity, medium voltage	km
69	Iron ore, emergy w/out labor and services	g	151	Transoceanic freight ship	p
70	Iron(III) Chloride	J	152	Transoceanic tanker	p
71	Labor, Peru, emergy	p	153	Transport of Dore, Yanacocha to Switzerland	g
72	Labor, total, Yanacocha	m2	154	Transport truck, operation, Peru	km
73	Leach Pad, Yanacocha	m2	155	Transport, aircraft, freight, intercontinental	tkm
74	Leach Pool, Yanacocha	g	156	Transport, aircraft, freight, Peru	tkm
75	Leaching, Yanacocha	g	157	Transport, transoceanic freight ship	tkm
76	Lead acetate	g	158	Transport, transoceanic tanker	tkm
77	Lead, in ground, geologic emergy	kg	159	Transport, truck, Peru	tkm
78	Lime, loose and hydrated, at Yanacocha	g	160	Transport, truck, USA, emergy w/out labor and services	tkm
79	Limestone, in ground, geologic emergy	g	161	Water supply network	km
80	Lumber, emergy w/out labor and services	g	162	Water Treatment, Yanacocha	year
81	Mercury, at Yanacocha	g	163	Wood preservative	g
82	Mercury, in ground, at Yanacocha, geologic emergy	g	164	Zinc, in ground, geologic emergy	g

Table B-17. Mine hauling road parameters, based on Hartman (1992).

Course	Thickness (m)	Material	Cross-sectional area (m2)
Surface	0.1	Gravel	2.5
Base	0.1	Clay-sand-silt	2.5
Subbase	0.5	Clay-sand-silt	12.5

Table B-18. Mine service road parameters, based on Hartman (1992).

Course	Thickness (m)	Material	Cross-sectional area (m2)
Surface	0.1	Gravel	2.5
Base	0.1	Clay-sand-silt	2.5

Table B-19. Mining equations

Equation	Reference[1]
Shovel and stacker loading production, loose m^3/hr = 3600(Bucket capacity, loose m^3)(efficiency)(fill factor)(propel time factor)/(load cycle time, seconds)	SME, Equation 12.21
Total shovel and stacker use, hrs = (m^3/mine/yr/ loose m^3/hr)	NA
Scraper load, m^3 = (capacity, m^3)(swell factor, ratio of bank m^3 to loose m^3)	SME, Equation 12.9

Scraper travel time, min = (distance to soil storage, m)/(speed, km/hr)(16.7 m-h/km-min)	SME, Equation 12.18
Scraper cycle time, min = (load time,min)+(travel time,min*2)+(spread time,min)	SME, Equation 12.19
Scraper production, m^3/hr= (60)(bucket capacity, m^3)(operating efficiency)/cycle time (hrs)	SME, Equation 12.21
Scraper use, hrs (Topsoil to be moved, annualized)/(scraper production)	NA
Dump truck spot and load time, min = (spot time, min)+(passes-1)(loading cycle time)	SME, Equation 12.15
Travel time to dump point, min = (Distance,m)/(speed, km/h)(16.7 m-h/km-min)	SME, Equation 12.18
Dump truck cycle time, min= (load time) + (travel time) + (travel time) + (dump time)	SME, Equation 12.19
Dump truck production, m3/hr =(60)(haulage units)(load, bank m^3)(efficiency)/(cycle time,min)	SME, Equation 12.21
Dump truck use, hrs = (ore mined, m^3/yr/ haulage production, m^3/hr)	NA
Drill rig use, hrs/yr = (holes/layer)(layers/year)(digging, hrs/hole+travel time, hrs/hole)	NA

[1]All references with SME refer to the SME Handbook (Lowrie 2002).

Table B-20. Mine vehicle data

Type	**Manufacturer/Model**	**Weight (kg)[1]**	**Lifetime (hrs)[2]**
Rear Dump Truck	CAT 793D	166866	30000
Stacker	CAT 325D w/boom	29240	14000
Scraper	CAT 651E	62000	14000
Mining shovel	Hitachi EX5500	518000	90000
Drill rig	Atlas Copco Simba 1250	11830	14000

[1] From manufacturer specifications

[2] Estimated from (Lowrie 2002)

Table B-21. Mass balance of leaching, processing, and water treatment.

STAGE	1 - LEACH					
	EXTERNAL INPUT	RECYCLED INPUT	EXTERN + RECYC	PRECIP	TOTAL INPUT	*Recycle Frac*
Input	Mass (g)	Mass (g)	Mass (g)	Mass (g)	Mass (g)	
Primary						
H_20	1.42E+12	1.25E+14	1.27E+14	1.38E+13	1.41E+14	*98.46%*
CN	4.40E+09	1.71E+09	6.35E+09		6.35E+09	*26.96%*
Au		2.31E+06			1.16E+08	*1.98%*
Ag		4.70E+07			4.66E+08	*10.10%*
Hg		1.50E+07			1.00E+09	*1.50%*
Cu					5.12E+09	*0.00%*
ppm Au						
ppm CN			50		45	
% CN solution		Ext+Rec CN (mass)	6.11E+09			
pH			11			
Ag:Au ratio		CN check	*96.18%*		4.00E+00	
Dore %Au		H20 check	*99.57%*			
Dore %Ag	Check ext+int H20	1.26E+14				
	Recycled water needed to bal	*1.26E+14*				
	H20 Recycle rate	*98.89%*				

STAGE	TO AIR		TO CARBON COL		TO MERRILL CROWE		TO LEACH		RESIDUAL	
Input	Mass frac	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)
Primary										
H_20	0.03	4.23E+12	0.75	1.06E+14	0.1	1.41E+13	0.12	1.69E+13	0	0.00E+00
CN	0.03	1.91E+08	0.75	4.76E+09	0.1	6.35E+08	0.12	7.62E+08	0	0.00E+00
Au	0	0.00E+00	0.50	5.82E+07	0.33	3.82E+07			0.172	2.00E+07
Ag	0	0.00E+00	0.22	1.01E+08	0.14	6.64E+07			0.64	2.98E+08
Hg	0	0.00E+00	0.04	4.23E+07	0.03	2.78E+07			0.93	9.31E+08
Cu	0	0.00E+00	0.60	3.09E+09	0.40	2.03E+09			0.7	3.59E+09
ppm Au				0.55		2.71				
ppm CN				45		45		45		
% CN solution			check CN:Au ratio	82		17				
pH										
Ag:Au ratio										
Dore %Au			Water check	1.20E+14						
Dore %Ag			Reported H20	1.21E+14						
			Water Difference	98.94%						

KEY

Reported or calculated from reported value	Constrained Value
Check	

STAGE	2 - CARBON COLUMNS					3 - MERRILL CROW				
	INPUT	TO MERRILL CROWE		TO LEACH		INPUT	TO RETORT		TO LEACH	
Input	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)
Primary										
H_20	1.06E+14	0.1	1.06E+13	0.9	9.51E+13	2.46E+13	0.47	1.16E+13	0.53	1.31E+13
CN	4.76E+09	0.69	3.29E+09	0.31	1.48E+09	3.92E+09	0.94	3.69E+09	0.06	2.35E+08
Au	5.82E+07	0.98	5.70E+07	0.02	1.16E+06	9.52E+07	0.988	9.41E+07	0.012	1.14E+06
Ag	1.01E+08	0.55	5.57E+07	0.45	4.55E+07	1.22E+08	0.988	1.21E+08	0.012	1.46E+06
Hg	4.23E+07	0.71	3.00E+07	0.29	1.23E+07	5.78E+07	0.988	5.71E+07	0.012	6.94E+05
Cu	3.09E+09	0.1	3.09E+08	0.9	2.78E+09	3.09E+08	0.988	3.06E+08	0.012	3.71E+06
ppm Au	0.551		5.399		0.012	4		8		0.09
ppm CN	45		311		16	159		318		18
% CN solution	4.00E+00									
pH										
Ag:Au ratio										
Dore %Au										
Dore %Ag	82		58							
C (as activated carbon	1.46E+10	0	0	0	0.00E+00					
Zn						1.42E+08	0.66	9.34E+07	0.33	4.67E+07
Pb (as lead acetate)						4.45E+08	1	4.45E+08		

STAGE	4- RETORT						
	INPUT	TO HG-PRODUCT		TO WWT		TO SMELT	
Input	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)
Primary							
H_20	1.16E+13	0	0.00E+00	1	1.16E+13	0	0.00E+00
CN	3.69E+09	0	0.00E+00	1	3.69E+09	0	0.00E+00
Au	9.41E+07	0	0.00E+00	0	0.00E+00	1	9.41E+07
Ag	1.21E+08	0	0.00E+00	0	0.00E+00	1	1.21E+08
Hg	5.71E+07	0.95	5.99E+07	0.01	5.71E+05	0.04	2.07E+06
Cu	3.06E+08	0	0.00E+00	0	0.00E+00	1	3.06E+08
ppm Au	8						
ppm CN		Check Hg	*104.84%*				
% CN solution							
pH							
Ag:Au ratio							5.26E+08
Dore %Au							
Dore %Ag							
C (as activated carbon							
Zn	9.34E+07			1	9.34E+07		
Pb (as lead acetate)	4.45E+08			1	4.45E+08		

STAGE	5 - SMELT						
	INPUT	TO DORE-PRODUCT		TO LEACH		TO WWT	
Input	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)	Mass frac	Mass (g)
Primary							
H_20	0.00E+00	0	0.00E+00	0	0.00E+00	1	0.00E+00
CN	0.00E+00	0	0.00E+00	0	0.00E+00	1	3.92E+09
Au	9.41E+07	1.00	9.43E+07	0	0.00E+00	-0.00273	-2.60E+05
Ag	1.21E+08	1.02	1.23E+08	0	0.00E+00	-0.02067	
Hg	2.07E+06	0	0.00E+00	1	2.07E+06	0	0.00E+00
Cu	3.06E+08	0	0.00E+00	0	0.00E+00	1	3.09E+08
ppm Au							
ppm CN							
% CN solution		Check recovery % Au	*81.04%*				
pH		Check recovery % Ag	*26.44%*				
Ag:Au ratio							
Dore %Au		Percent Au in dore	*43.38%*				
Dore %Ag		Percent Ag in dore	*56.62%*				

KEY

Reported or calculated from reported value	Constrained Value
Check	

Table B-22. Inventory of Peruvian road transport.

No.	Item	Flow	Unit
1	Trucks	4.44E+10	g
	Road Construction		
2	Concrete	6.00E+09	g
3	Bitumen	1.75E+10	g
4	Gravel	2.42E+11	g
5	Electricity	4.92E+11	J
6	Diesel	1.18E+12	J
	Road operation		
7	Electricity	7.31E+09	J
8	Paint	6.04E+03	g
9	Herbicide	3.37E+02	g
	Transport		
10	Diesel consumption	8.90E+15	J
	Product		
11	Annual yield of trucks	1.50E+09	ton-km

NOTES

Input references from Spielman et al. (2004)

Trucks

1 (Class 8 weight lb)(class 8 trucks)*(Class 6 weight lb)(class 6 trucks)*(454 g/lb) / (10 yr lifetime)

4.44E+10 g Truck weights from Buranakarn (1998)

UEV from heavy mine vehicle model

Highway construction

Demand by trucks of infrastructure creation

Good transport percent road wear 0.424 Based on Swiss situation. Table 5-117.

road length=(length of road network, km)(14.4% paved)

Highway	km	11351	(Economic Commission of Latin American and the Carribbean 2006)
Improved unpaved	km	18634	
Concrete	kg/ (m*yr)	37	
Bitumen	kg/ (m*yr)	15.4	
Gravel for highway subbase	kg/ (m*yr)	470	
Gravel for unpaved road surface	kg/ (m*yr)	101.25	
Lifetime			
Concrete	yr	70	
Bitumen	yr	10	
Gravel for highway subbase	yr	100	
Gravel for unpaved road surface	yr	10	

Standard Equation for road materials

(Good transport percent road wear)(material kg/m*yr)(road length km) (1000m/km) (1000g/kg) / (material lifetime yr)

2	Concrete	g	6.00E+09
3	Bitumen	g	1.75E+10
4	Gravel	g	2.42E+11

	Electricity for highway constr.	MJ/m*yr		98.7	Motorway. Table 5-94.
	Electricity for unpaved road constr.	MJ/m*yr		2.18	2nd class road. Table 5-94.
	(Good transport percent road wear)(energy MJ/m*yr)(road length km) (1000m/km) (1E+6 J/MJ)				
5	Electricity for construction	J	4.92E+11		
	Diesel for highway construction	MJ/m*yr		192	Motorway. Table 5-94.
	Diesel for unpaved road construction	MJ/m*yr		33	2nd class road. Table 5-94.
	(Good transport percent road wear)(energy MJ/m*yr)(road length km) (1000m/km) (1E+6 J/MJ)				
6	Diesel	J	1.18E+12		
	Operation				
	Demand by trucks of infrastructure operation				
	Good transport percent road use			0.103	Based on Swiss situation. Table 5-117.
	Electricity for highway operation	KWH/m*yr		0.67	Motorway. Table 5-101.
	Electricity for unpaved road operation	KWH/m*yr		3.4	2nd class road. Table 5-101.
	(Good transport percent road use)(electricity use KWH/m*yr)(road length km) (3600000 J/KWH)				
7	Electricity for operation	J	7.31E+09		
	Paint for highway operation	kg/m*yr		0.00517	
	(Good transport percent road use)(paint usekg/m*yr)(road length km) (1000 kg/g)				
8	Paint	g	6.04E+03		
	Herbicide for highway operation	kg/m*yr		2.88E-04	
	(Good transport percent road use)(herbicide usekg/m*yr)(road length km) (1000 kg/g)				
9	Herbicide	g	3.37E+02		
	UEV for orthophosphate from Nepal (2008)				
	Transport				
	Mid-size truck fuel economy	diesel kg/vkm		0.25	(Kodjak 2004)
	Tractor trailer truck fuel economy	diesel kg/vkm		0.37	(Kodjak 2004)
	Mid-size truck vkm/ton-km	vkm/ton-km		0.62	Lorry 3.5-16t. Table 5-119.
	Tractor trailer vkm/ton-km	vkm/ton-km		0.12	Lorry >16t. Table 5-119.
	Tractor trailer ton-km percentage			0.88	Table 5-119.
	Mid-size truck ton-km	ton-km	1.75E+08		Lorry >16t. Table 5-119.
	Tractor trailer ton-km	ton-km	1.32E+09		Lorry 3.5-16t. Table 5-119.
	Truck fuel use = (Truck ton-km)(ton-km/vkm)(diesel kg/vkm) (4.36E+07 J/kg)				
	Mid-size truck fuel use	J	1.20E+15		1.08E+08
	Tractor trailer fuel use	J	2.53E+15		1.56E+08
10	Total diesel fuel use	J	3.73E+15		2.64E+08
11	No. trucks= total vehicles* portion of trucks in import data (Economic Commission of Latin American and the Carribbean 2006; United Nations 2008) (5.04E+04 Ton-km/truck/yr USA)(.5 Peru/US productivity)(142872 trucks in Peru fleet)				
	Annual truck transport	ton-km	1.50E+09		

Table B-23. Assumed origins and transport distances for inputs to mining.

Input	Mass (kg)	Assumed Origin	Data Source	Sea Distance (km)	Road Distance (km)
Refined Oil	9.75E+07				
Imported	2.34E+07	Balao, Ecuador	1	1148	250
Domestic	7.41E+07	Chimbote	1	0	250
Lime	7.36E+07	China Linda	2	0	12
Chlorine	4.41E+07	Lima	3	0	850
Caustic soda	2.52E+07	Lima	1	0	850
Explosives (ANFO)	7.00E+06	Lima	3	0	850
Sodium cyanide	6.69E+06	US	3	5900	850
Concrete	4.68E+06	China Linda	2	0	12
Steel pipe	2.97E+06	US	3	5900	850
Other	1.27E+07	Local	NA	0	0
TOTAL	2.74E+08				

Notes
Only inputs comprising 1% of total mass input are listed.
Data Sources
1. (Instituto Nacional Estadistica y Informacion 2006))
2. (Buenaventura Mining Company Inc. 2006)
3. (United Nations 2008)

Table B-24. System-level parameters.

Parameter	Default Value	σ^2_{geo}	Units and Comments
include_geo	1	NA	1=Include geologic emergy of gold ore; 0=do not include
include_clay_em	0	NA	1=Include geologic emergy of clay for roads and leach pads; 0=do not include
include_grav_em	0	NA	1=Include geologic emergy of gravel for roads and leach pads; 0=do not include
mine_lifetime	25	1.3	yrs. 1993-2018. End date estimate from http://www.newmont.com/csr05/protest_yanacocha/1.html
process_lifetim	20	1.3	yrs. Avg process lifetime for all processing facilities. Less than mine_lifetime
waste_to_reclam	1	NA	Fraction of waste rock used to refill pits. 1=All waste rock used for backfilling
lima_yan_distan	850	1.1	km. (1.05,1,1,1.01,1,NA)
Au_output	3327500	1	oz/yr, Buenaventura 2006
Hg_output	5.5	1	short tons/month, Newmont 2006a
veh_add_steel	0.4	1.2	Additional fraction steel for heavy vehicles. (1.2,1,1.03,1,1,NA)
veh_add_rubber	0.07	1.2	Additional fraction rubber for heavy vehicles. This is substituted with steel for track vehicles. (1.2,1,1.03,1,1,NA)
veh_weight	15500	1.2	kg. Based on 40ton Lorry (Ecoinvent). (1.2,1,1.03,1,1,NA)
kgore_topadarea	198891	1.5	kg/m2. Based on avg of 5 leach pad areas and capacities. Actual SD*2
kgoretopoolarea	4057275	1.5	kg/m2. Based on avg of 5 leach pad areas and capacities. Actual SD*2
per_RO_treat	0.4	1	Fraction of excess water treatment using reverse osmosis
tot_excess_wat	1.2E+13	1	G
Au_ore_grade	0.028	1	oz/ton
labor_use_J	0	NA	1 = include labor by using sej/J emergy in labor. See emergy in labor process. 0= Do not use
labor_use_dol	0	NA	1 = include labor using emergy/$ ratio. 0=do not include.
sea_transport	5900	1.1	km. Los Angeles to Lima sea distance. Used for generic sea transport distance. (1.05,1,1,1.01,1,NA)

Table B-25. Uncertainty estimates for inventory data using Ecoinvent method (Frischknecht and Jungbluth 2007)

Unit Process(es)	Input or Variable	reliability	completeness	temporal correlation	geographic correlation	other tech-correlation	sample size	Uncertainty score
Exploration, Extraction, Reclamation	Oil, refined	1.2	1	1	1.1	1.2	NA	**1.3**
Exploration, Extraction, Sed. & Dust control	Water for process	1.2	1	1	1	1	NA	**1.2**
Extraction, Reclamation, Mine Infrastructure	Heavy Vehicle Use	1.2	1	1.1	1.1	1	NA	**1.3**
Mine infrastructure	Infrastructure based on visual estimates	1.05	1	1	1	1.5	1.2	**1.5**
Extraction	Explosives	1	1	1	1	1	NA	**1.0**
Leaching	CN	1	1	1	1	1	NA	**1.0**
Processing	Natural gas	1.2	1	1	1.1	1.2	NA	**1.3**
Water treament, Reclamation	Chemicals for water treatment (CaOH, Cl, FeCl3, PAM, H2SO4); and reclamation (CaOH)	1.2	1	1	1	1	NA	**1.2**
Variables	Distance variables	1.05	1	1	1.01	1	NA	**1.1**
Variables	Mine vehicle model variables	1.2	1	1.03	1	1	NA	**1.2**

APPENDIX C
SUPPLEMENT TO CHAPTER 3: R CODE FOR STOCHASTIC UNCERTAINTY MODELS

The following sections contains code for stochastic uncertainty models for both the formula and table-form uncertainty models, as described in chapter 2. This code can be run in R statistical software.

Code for Formula UEV Uncertainty Estimation

```
#A script for a Monte Carlo simulations of formula-type unit emergy values to estimate uncertainty
#Author: Wes Ingwersen, wwi@ufl.edu
##Do a Monte Carlo simulation for a formula UEV calculation, with uncertainty expressed for all variables

#################Instructions####################
#Prepare a tab separated table of items in your emergy table in the form of:
#variable_name	average	standard deviation
#the following is a sample  for the lead UEV  – this can be copied and pasted into a new .txt file
crust_conc_ppm	15	1.41
ore_grad_frac	0.06	0.03
crust_turn_cm_yr-1	2.88E-03	6.77E-04
den_crust_g_cc-1	2.72	0.04
crustal area_sqcm	1.48E+18	2.1E+16
#This file has to be saved at C:\RData\UEV\ directory unless the path name is changed in the script for the script to function.

##################Import Data####################
#Input data in the form of a tab-delimited txt file with var name, mean, sd, on 1 line
#Uncomment lines related to UEV of interest
#To see the table that translates into this format, see Table 3 in Ingwersen (2009)

#UEV for lead
#fname <- "C:\\RData\\UEV\\lead.txt"
#item <- "lead"
#fractions <- c(1,2)
#den_unit <- "g"
#mag <- 12   #Order of mag of deterministic mean UEV

#UEV of iron
#fname <- "C:\\RData\\UEV\\iron.txt"
#item <- "iron"
#fractions <- c(1,2)
#den_unit <- "g"
#mag <- 10   #Order of mag of deterministic mean UEV

#UEV of oil
#fname <- "C:\\RData\\UEV\\oil.txt"
#item <- "oil"
#fractions <- c(2,3,4,5)
#den_unit <- "J"
#mag <- 5   #Order of mag of deterministic mean UEV
```

```
#UEV of groundwater
#fname <- "C:\\RData\\UEV\\gw.txt"
#item <- "gw" #Groundwater
#fractions <- c(2)
#den_unit <- "g"
#mag <- 5   #Order of mag of deterministic mean UEV

#UEV of labor
#fname <- "C:\\RData\\UEV\\labor.txt"
#item <- "labor"
#fractions <- c()
#den_unit <- "J"
#mag <- 6   #Order of mag of deterministic mean UEV

#Loads the text file, stores it in a data frame
cols <- c("var","mu","sig")
df <- read.delim(fname,header=FALSE,strip.white=TRUE,row.names=1, col.names=cols)
df

#Verify that the data loaded properly

#########Set Initial Parameters####################
#Run the following code
##Number of MC results
n <- 100

#Number of MC's to run from which to calculate the uncertainty
j <- 100

##Case 1: Assume variables are normally distributed
##Case 2: Assume varibales are log-normally distributed
case <- 2
#Note - Model only stable using case 2

###########Functions for MC - just load on first use#####################

##Function to return logforms of mean and standard dev
returnlogforms <- function(mu,sig) {
	lamda <- 1+(sig/mu)^2
	logformsig <- sqrt(log(lamda))
	logformmu <- log(mu)-0.5*logformsig
	return(c(logformmu,logformsig))
}

#n will also be the number of replicates of each variable in the model chosen

#Make a matrix to hold n of each model parameter)
make_params <- function()
{
mc_vars <- matrix(nrow=nrow(df),ncol=n)
	for (x in 1:nrow(df))
	{
	#Put the mean and sd in a matrix
	m <- df[[1]][x]
	s <- df[[2]][x]
		if(case==2)
```

```
		{
		logforms <- returnlogforms(m,s)
		mc_vars[x,] <- rlnorm(n,meanlog=logforms[1],sdlog=logforms[2])

		} else {
		mc_vars[x,] <- rnorm(n,mean=m,sd=s)

		}
	}
	return(mc_vars)
}


clean <- function(parameters) {
	a <- 0
	b <- 0
	for (a in 1:length(fractions)) {
		ind <- fractions[a]

		for (b in 1:n) {
			if ((parameters[ind,b]<=0 || parameters[ind,b]>=1) && !is.na(parameters[1,b])) {
				parameters[,b] <- NA
			}
		}
	}
}

#######################Unit emergy value model#######################################
#Run the desired model, or enter your own model

#Model for land cycle is
#ER <-  2.ore_grad_frac/(1.crust_conc_ppm/1E6)
#ER
#Land_UEV <- 15.83E24/(3.crust_turn_cm_yr-1)*(4.den_crust_g_cc-1)*(5.crust_area_sqcm)
#Mineral_UEV <- ER*Land_UEV

#Model for water = UEVwater, sej/g = (global emergy base, 15.83E24 sej/yr)/Annual Flux, g/yr)
#turnover time = (Global groundwater resevoir)/
#(Global precip on land, mm/day)(365days/yr)/(1E6 mm/km)*(global land area (km2)*(infiltration rate)

#Function to do the model calculation
mod <- function (mat)
{
res_vec <- c() #Result vector
for (i in 1:n)
	{
		UEV <- NA
		if ((item=="lead" || item=="iron")&& !is.na(mat[1,i])) {
			pred <- 2.64 # Predicted sq_sig_geo for lead_UEV
			pred <- 2.03 # Predicted for iron_UEV
			#Formula for Mineral UEV calc
			if (item=="lead") {
			er <- mat[2,i]/(mat[1,i]/1E6)#when conc is in ppm
			} else {
			er <- mat[2,i]/(mat[1,i]) #when conc is a frac
			}
```

```
                        land_UEV <- 15.83E24/(mat[3,i]*mat[4,i]*mat[5,i])
                        UEV <- er*land_UEV  #For mineral calcs
                }
                if (item=="oil" && !is.na(mat[1,i])) {
                                #Formula for oil
                                #Deterministic solution
                                #mat <- df
                                #i<-1
                        ep_c <- (mat[1,i]*1.78E4)/mat[2,i]
                        ek <- ep_c/mat[3,i]
                        UEV <- (1.68*ek*mat[5,i])/(mat[4,i]*4.19E4)
                                #UEV
                        #If UEV is negative take absolute value
                }
                if (item=="gw" && !is.na(mat[1,i])) {
                        #Formula for groundwater
                                #Deterministic solution
                                #mat <- df
                                #i<-1
                        global_land_area <- mat[3,i] #km2
                        precip <- mat[1,i] #mm/yr
                        infiltration <- mat[2,i]
                        annual_flux <- ((precip/1E6)*global_land_area*infiltration*1E12*1000)
                        UEV <- 15.83E24/annual_flux
                }
                if (item=="labor") {
                        #Formula for labor
                        #(Global emergy use per yr/global population)/(Daily per capita calorie
intake*365 days*        4184J/kcal)
                        #mat <- df
                        #i<-1
                        UEV<-(1.61E26/mat[1,i])/(mat[2,i]*365*4184)
                }
                if (UEV<0) {
                        UEV <- NA
                        }
                res_vec[i] <-  UEV
        }
        return(res_vec)
}

##################RUN SIMULATION####################
#Hightlight and run the following code

#Run the Monte Carlo, j times
mc <- c() #Store the results of one Monte Carlo here
Quot_upper_by_med <- c() #Store the results of the upper limimit divided by the median for each MC
upperlims <- c()
lowerlims <- c()
medians <- c()
means <- c()
sds <- c()
all_mc <- matrix(nrow=j,ncol=n)#Store each mc result in a row for graphing later
for (a in 1:j)
{
        params <- make_params()
```

```
        if (length(fractions)) (clean(params)) #Removes values <0 or >1 for fractions
        mc <- mod(params)
        all_mc[a,] <- mc
        med <- median(mc,na.rm=TRUE)
        std <- sd(mc,na.rm=TRUE)
        CIs <- format(quantile(mc, probs = c(0.025,0.975),na.rm=TRUE, digits=3, scientific=TRUE))
        upperlim <- as.double(as.vector(CIs["97.5%"]))
        lowerlim <- as.double(as.vector(CIs["2.5%"]))
        up <- upperlim/med
        #low <- med/lowerlim
        upperlims[a] <- upperlim
        lowerlims[a] <- lowerlim
        medians[a] <- med
        medians[a] <- med
        sds[a] <- std
        Quot_upper_by_med[a] <- up

}

#Take averages of medians of distributions and geometric variances
med <-mean(medians)
geo_var <- mean(Quot_upper_by_med)
lower_bound <- mean(lowerlims)
upper_bound <- mean(upperlims)
#Print the results
c('Median=',med)
c('Geometric variance=',geo_var)
c('Lower bound',lower_bound)
c('Upper bound', upper_bound)
```

Code for Table-form UEV Uncertainty Estimation

```
#A script for a Monte carlo simulations of table-form unit emergy values to estimate uncertainty
#Author: Wes Ingwersen, wwi@ufl.edu
##Do a Monte Carlo simulation for a table-form UEV calculation, with uncertainty expressed for all
variables

##################Instructions#####################
#Input data in the form of a tab-delimited txt file with
var-name        flow_quanity_mean       flow_quanity_geo_var    UEV_mean        UEV_geo_var
#the following is a sample  for the sulfuric acid UEV  – this can be copied and pasted into a new .txt file
Secondary_sulfur        214     1.32    5200000000      3.59
Diesel  3410    1.34    121000          3.59
Electricity     63000   1.34    371000          2.77
Water   241000          1.23    189572.5914     1.95
#This file has to be saved at C:\RData\UEV\ directory unless the path name is changed in the script for
the script to function.

##################Import Data#####################
#UEV for electricity
#fname <- "C:\\RData\\UEV\\electricity.txt"
#item <- "electricity"
#den <- 3.6E6 #Joules of electricity This is the denominator for the UEV calculation
#den_unit <- "J"
#mag <- 5   #Order of mag of deterministic mean UEV
```

```
#UEV for sulfuric acid
fname <- "C:\\RData\\UEV\\sulfuric_acid.txt"
item <- "sulfuric acid"
den <- 1000 #g of H2SO4 This is the denominator for the UEV calculation
den_unit <- "g"
mag <- 7 #Order of mag of deterministic mean UEV


cols <- c("param","value","k_value","UEV","k_UEV")
df <- read.delim(fname,header=FALSE,strip.white=TRUE,row.names=1, col.names=cols)
df

#########Set Initial Parameters####################

##Number of MC results
n <- 100

#Number of MC's to run from which to calculate the uncertainty
j <- 100

##Case 2: Assume varibales are log-normally distributed
#Now it only works for log-normally distributed variables
case <- 2

###########Functions for MC - just load on first use#####################

##Function to return logforms of mean and standard dev #Only used for formula UEVs - copied here for
reference
returnlogforms <- function(mu,sig) {
	lamda <- 1+(sig/mu)^2
	logformsig <- sqrt(log(lamda))  #Source: Wikipedia, "Lognormal distribution"
	logformmu <- log(mu)-0.5*logformsig #Wikipedia
	return(c(logformmu,logformsig))
}

##Function to return logforms of with determininstic mean and k value (ref: Slob (1994))
returnlogforms_withKvalue <- function(mu,k) {
	logformsig <- sqrt((log(k)/1.96)^2)
	logformmu <- log(mu)-0.5*logformsig
	logformsig
	logformmu
	return(c(logformmu,logformsig))
}

#Make a matrix to hold n of each model parameter)
make_params <- function()
{
#Create a matrix to store n random values(3rd dimension) of both the value and UEV (2nd dimension) of
each variable (1st dim)
mc_vars <- mc_vars <- array(NA,dim=c(nrow(df),2,n))
	for (x in 1:nrow(df))
	{
	#Gets the values from the input matrix
	val <- df[[1]][x]
	k_val <- df[[2]][x]
	uev <- df[[3]][x]
```

```
		k_uev <- df[[4]][x]
		#Call the script to get the logforms of mu and sigma
		val_logforms <- returnlogforms_withKvalue(val,k_val)
		uev_logforms <- returnlogforms_withKvalue(uev,k_uev)
		#Use the log-forms in a lognormal distribution random generator function
		mc_vars[x,1,] <- rlnorm(n,meanlog=val_logforms[1],sdlog=val_logforms[2])
		mc_vars[x,2,] <- rlnorm(n,meanlog=uev_logforms[1],sdlog=uev_logforms[2])

		}
		return(mc_vars)
}


#Function to do the model calculation
mod <- function (mat)
{
res_vec <- c() #Result vector
for (i in 1:n)
		{
			UEV <- NA
			#Calculate the UEV for that random set of params

			em <- 0
			for (r in 1:nrow(df)) {
				#Multiply the value and UEV
				var_em <- mat[r,1,i]*mat[r,2,i]
				#Add the emergy to the sum
				em <- em + var_em
			}
			UEV <- em/den #UEV is sum of emergy divided by denominator (usu. J or g)
			res_vec[i] <-  UEV
		}
		return(res_vec)
}

##################RUN SIMULATION####################


#Run the Monte Carlo, j times
mc <- c() #Store the results of one Monte Carlo here
Quot_upper_by_med <- c() #Store the results of the upper limimit divided by the median for each MC
upperlims <- c()
lowerlims <- c()
medians <- c()
means <- c()
sds <- c()
all_mc <- matrix(nrow=j,ncol=n)#Store each mc result in a row for graphing later
for (a in 1:j)
{
		params <- make_params()
		mc <- mod(params)
		all_mc[a,] <- mc
		med <- median(mc,na.rm=TRUE)
		m <- mean(mc,na.rm=TRUE)
		std <- sd(mc,na.rm=TRUE)
		CIs <- format(quantile(mc, probs = c(0.025,0.975),na.rm=TRUE, digits=3, scientific=TRUE))
```

```
        upperlim <- as.double(as.vector(CIs["97.5%"]))
        lowerlim <- as.double(as.vector(CIs["2.5%"]))
        up_by_med <- upperlim/med
        upperlims[a] <- upperlim
        lowerlims[a] <- lowerlim
        medians[a] <- med
        means[a] <- m
        sds[a] <- std
        Quot_upper_by_med[a] <- up_by_med
}


#Take averages of medians of distributions and geometric variances
med <-mean(medians)
geo_var <- mean(Quot_upper_by_med)
lower_bound <- mean(lowerlims)
upper_bound <- mean(upperlims)
#Print the results
c('Median=',med)
c('Geometric variance=',geo_var)
c('Lower bound',lower_bound)
c('Upper bound', upper_bound)
```

APPENDIX D
SUPPLEMENT TO CHAPTER 4: ADDITIONAL TABLES AND FIGURES

Table D-1. Inputs to one kg pineapple at the packing facility.

Category	Input name	Country	Sr c	Unit	Amount	SD	Active Ing.
Energy	Diesel, at regional storage	RER	e	kg	7.29E-03	2.97E-03	n/a
	Petrol, unleaded, at regional storage	RER	e	kg	2.40E-04	2.20E-04	n/a
Fertilizer	Ammonium nitrate, as N, at regional storehouse	RER	e	kg	1.92E-03	1.08E-03	n/a
	Boric acid, anhydrous, powder, at plant	RER	e	kg	1.73E-04	1.89E-04	n/a
	Calcium nitrate, as N, at regional storehouse	RER	e	kg	1.72E-04	4.66E-05	n/a
	Compost, at plant	CH	e	kg	4.33E-03	2.43E-03	n/a
	Dolomite, at plant	RER	e	kg	2.03E-04	4.58E-05	n/a
	Fosfomax (0,30,0) fertilizer	CR	o	kg	4.51E-04	3.67E-04	n/a
	Iron sulphate, at plant	RER	e	kg	2.97E-04	2.45E-04	n/a
	Kaolin, at plant	RER	e	kg	8.20E-04	6.74E-04	n/a
	Lime, hydrated, packed, at plant	CH	e	kg	1.63E-03	3.68E-04	n/a
	Magnesium ammonium nitrate, (22,0,0,0,7)	RER	o	kg	2.11E-03	1.19E-03	n/a
	Magnesium sulphate, at plant	RER	e	kg	2.03E-03	2.09E-03	n/a
	NPK (12,24,12) fertilizer	RER	e	kg	1.18E-02	9.63E-03	n/a
	NPK (18,5,15) fertilizer	RER	o	kg	2.11E-03	1.72E-03	n/a
	NPK (2,10,10) fertilizer	RER	o	kg	7.93E-05	6.46E-05	n/a
	Potassium chloride, as K2O, at regional storehouse	RER	e	kg	5.82E-03	4.74E-03	n/a
	Potassium sulphate, as K2O, at regional storehouse	RER	e	kg	4.33E-03	3.52E-03	n/a
	Single superphosphate, as P2O5, at regional storehouse	RER	e	kg	5.54E-05	4.51E-05	n/a
	Sugar, from sugarcane, at sugar refinery	BR	e	kg	2.51E-04	5.67E-05	n/a
	Urea, as N, at regional storehouse	RER	e	kg	3.62E-03	2.04E-03	n/a
	Zinc monosulphate, ZnSO4.H2O, at plant	RER	e	kg	2.74E-04	7.58E-05	n/a
fungicide	benzoic-compounds, at regional storehouse	RER	e	kg	5.63E-05	3.55E-05	Metalaxil
	pesticide unspecified, at regional storehouse	RER	e	kg	1.49E-04	9.40E-05	Fosetyl-aluminium
	triazine-compounds, at regional storehouse	RER	e	kg	1.20E-06	7.54E-07	Thiazole, 2-(thiocyanatemethylthio)benzo-
	triazine-compounds, at regional storehouse	RER	e	kg	6.58E-06	4.15E-06	Triadimefon
growth	organophosphorus-compounds, at regional storehouse	RER	e	kg	2.58E-05	3.69E-05	Ethephon
herbicide	diphenylether-compounds, at regional storehouse	RER	e	kg	6.58E-06	3.43E-06	Fluazifop-p-butyl
	diuron, at regional storehouse	RER	e	kg	1.12E-04	5.83E-05	Diuron
	glyphosate, at regional storehouse	RER	e	kg	3.76E-05	1.96E-05	Glyphosate
	pesticide unspecified, at regional	RER	e	kg	6.60E-05	3.44E-05	Bromacil

	storehouse					
	phenoxy-compounds, at regional storehouse	RER	e	kg	1.38E-06	7.21E-07Quizalofop-P
	triazine-compounds, at regional storehouse	RER	e	kg	7.96E-05	4.14E-05Ametryn
insecticide	[thio]carbamate-compounds, at regional storehouse	RER	e	kg	3.08E-05	1.60E-05Carbaryl
	organophosphorus-compounds, at regional storehouse	RER	e	kg	1.24E-04	7.84E-05Diazinon
nematicide	organophosphorus-compounds, at regional storehouse	RER	e	kg	6.80E-05	5.47E-05Ethoprop
Machinery	tractor, production	CH	e	kg	3.13E-04	1.35E-04

Table D-2. Emissions from one kg pineapple at the packing facility.

Substance	To	Amount	GV	Note
Ametryn	air	4.90E-06	3.0	from pesticide application. Includes yield and pesticide input uncertainty.
Ametryn	water	9.87E-06	5.9	“
Ammonia	air	1.55E-07	2.3	from fuel combustion
Ammonia	air	1.10E-04	2.9	volatilized from N fertilizers
Benzene	air	2.33E-06	2.3	from fuel combustion
Benzo(a)pyrene	air	2.28E-10	2.3	from fuel combustion
Bromacil	air	9.62E-06	2.1	from pesticide application. Includes yield and pesticide input uncertainty.
Bromacil	water	5.42E-06	4.8	“
Cadmium	air	7.53E-11	5.9	from fuel combustion
Carbaryl	air	5.16E-06	4.3	from pesticide application. Includes yield and pesticide input uncertainty.
Carbaryl	water	1.78E-07	7.5	“
Carbon dioxide, fossil	air	2.35E-02	2.1	from fuel combustion. Combines uncertainty of diesel input, diesel emission factor, and yield
Carbon dioxide, fossil	air	6.45E-04	2.8	from urea application
Carbon dioxide, land transformation	air	1.00E-10		from land use change
Carbon monoxide, fossil	air	2.05E-04	5.9	from fuel combustion
Chromium	air	3.77E-10	5.9	from fuel combustion
Copper	air	1.28E-08	5.9	from fuel combustion
Diazinon	air	6.01E-06	3.0	from pesticide application. Includes yield and pesticide input uncertainty.
Diazinon	water	3.60E-07	5.9	“
Dinitrogen monoxide	air	9.06E-07	2.3	from fuel combustion
Dinitrogen monoxide	air	1.78E-04	2.9	from N fertilizers
Diuron	air	6.55E-06	1.8	from pesticide application. Includes yield and pesticide input uncertainty.
Diuron	water	2.20E-05	4.5	“
Ethephon	air	1.51E-05	8.4	from pesticide application. Includes yield and pesticide input uncertainty.
Ethephon	water	2.27E-07	12.8	“
Ethoprop	air	2.25E-06	6.6	from pesticide application. Includes yield and pesticide input uncertainty.
Ethoprop	water	1.13E-06	10.4	“

Fluazifop-p-butyl	air	1.73E-06	8.4	from pesticide application. Includes yield and pesticide input uncertainty.
Fosetyl-aluminium	water	1.59E-05	2.8	“
Glyphosate	air	2.17E-05	8.4	from pesticide application. Includes yield and pesticide input uncertainty.
Glyphosate	water	2.95E-06	12.8	“
Lead	air	3.51E-08	5.9	from fuel combustion
Metalaxil	water	1.82E-06	2.4	from pesticide application. Includes yield and pesticide input uncertainty.
Metalaxil	air	4.92E-07	5.1	“
Methane, fossil	air	1.64E-06	2.3	from fuel combustion
Nickel	water	5.27E-10	5.9	from fuel combustion
Nitrate	air	6.84E-03	3.0	leached from N fertilizers
Nitrogen oxides	air	2.79E-04	2.3	from fuel combustion
Nitrogen oxides	water	8.57E-08	2.8	from N fertilizers
NMVOC, non-methane volatile organic compounds, unspecified origin	air	1.87E-05	2.3	from fuel combustion
PAH, polycyclic aromatic hydrocarbons	air	2.31E-08	3.8	from fuel combustion
Paraquat	air	4.44E-07	8.4	from pesticide application. Includes yield and pesticide input uncertainty.
Paraquat	air	2.17E-06	12.8	“
Particulates, < 2.5 um	air	1.27E-05	3.8	from fuel combustion
Phosphate	water	1.15E-04	4.3	runoff of P fertilizers
Phosphorus	air	1.17E-04	18.7	P in eroded soil. Uncertainty includes soil erosion, P content in soil, and yield uncertainty
Quizalofop-P	water	6.88E-08	8.4	from pesticide application. Includes yield and pesticide input uncertainty.
Quizalofop-P	water	1.48E-07	12.8	“
Sediment, eroded	air	6.28E-02	18.2	estimated with RUSLE2 model. Includes yield and emission uncertainty
Selenium	water	7.53E-11	5.9	from fuel combustion
Sulfur dioxide	water	7.38E-06	2.1	from fuel combustion
Triadimefon	air	1.16E-06	8.4	from pesticide application. Includes yield and pesticide input uncertainty.
Triadimefon	air	3.38E-08	12.8	“
Water	air	1.62E+00	1.5	evaporated blue water. Includes yield and emission uncertainty
Zinc	air	7.53E-09	5.9	from fuel combustion

Table D-3. Emissions estimations for mineral-N in applied fertilizers.

No.	Pathway	Equation		Source
1	Uptake	0.018	* dry biomass	Su (1968)
2	NH_3-N to air	1-15	% * N applied	Brentrup and Kusters (2000)
3	N_2O-N to air	1.25	% * N applied	IPCC 2007, for estimating direct N_2O emissions
4	NO_2-N to air	0.001	% * N_2O-N	Nemecek and Kagi (2007)
5	NO_3-N to water	1	* residual N in soil	Brentrup and Kusters (2000)
	Item notes			
1	Based on percent concentration of N in dry pineapple biomass			
5	Assuming exchange ratio (rainfall/field capacity) = 1, all residual N leaches			

Table D-4. Emissions estimations for mineral-P in applied fertilizers.

Item	Pathway	Equation		Source
1	Uptake	0.18%	*biomass	Su (1968)
2	P_2O_5-P to water	2.5%	of applied	Powers (2007)
3	P in erodible sediment	0.00186	kg P/kg soil	Nemecek and Kagi(2007)

Table D-5. General assumptions used in the FAO CROPWAT model.

CROPWAT Component	Assumption
Climate	Penman ET based on geographically specific data from LocClim
Rain	Rainfall from LocClim; calculation with USDA S.C. Method
Soil	Medium (loam) from CROPWAT database
Crop water requirement	See Table X
Schedule	Irrigate at user-defined intervals; 70% (default) efficiency

Table D-6. Crop water requirement variables for CROPWAT.

Parameter	Value	Source
K_c init	0.9	Bartholomew (2003) p. 95, for non-mulched system
K_c mid and end	0.4	Bartholomew (2003) p. 95, for non-mulched system
Kc init1	0.5	Allen et al. (1998), refers to plastic mulched system
Kc mid	0.3	Allen et al. (1998), refers to plastic mulched system
Stage - initial, days	90	Based on average reported harvest schedule
Stage - development, days	180	"

Stage - mid-season, days	120	"
Stage - late season, days	180	"
Yf (all stages)	1.0	Estimated based on crops with similar critical depletion
Rooting depth, m	0.45	Smith (1992), p. 61,
Critical depletion, p	0.5	Smith (1992), referred to as fraction of available soil water p. 61
Crop height, m	0.9	Bartholomew (2003), average height

Table D-7. RUSLE2 parameters for Pineapple in Costa Rica

RUSLE2 Component	Parameter	Value/Setting	Notes
Introduction	Template	ARS Basic Uniform Slope	
Profile	Horiz. overland flow path length, m	16.1	production-weighted average
	Avg. slope steepness, %	2.1	production-weighted average
	Contouring	Up and down slope	
	Strips/barriers	None	
	Diversion/terrace, sediment basin	None	
	Subsurface drainage	none	
	Adjust res. burial level	Normal	
Climate	How to get erosivity	Enter R & choose EI zone	
	R factor, US units	450	for North zone
	Standard EI	Enter half-montly EI based on relative intensity of storm events during the month	
	How determine runoff?	based on 10-yr 24 hr ppt	
	10-yr, 24-hr rain (mm)	from FAO Clim	
	Annual precip	from FAO Clim	
Soils	Erodibility	get from standard nomograph	
	Erodibility, SI	0.036	production-weighted average of samples
	Hydrologic class	C - mod. high runoff	
	Hydrologic class w/subsurface drainage	B - mod. low runoff	drainage decreases runoff
	Rock cover%	0	
	Cal. Consolidation from precip	Yes	
	Normal consolidation time, yrs	7	Default
Management	Rel. row grade %	100	

	Long-term natural rough, mm	6	
	Normally used as a rotation?	No	
	Duration, yr	NA	
	Operations Dates for 1st complete cycle		
	Cropland\disks\disk, tandem heavy primary op.	1/1/2000	
	Cropland\bedders/hippers\hipper	2/1/2000	
	Add mulch	NA	
	basic/general\begin growth	3/1/2000	
	basic/general\harvest pineapple	5/1/2001	
	basic/general\harvest pineapple	NA	
	basic/general\kill vegetation	11/1/2002	
Operation: harvest pineapple	Portion of total biomass effected	0.4975	Assume all pineapples harvested at once, with fruit and 25% of plant being effected. Assuming 1.5 green biomass:fruit weight, 33% is the removed fruit. Of the remaining 66%, assumed 25% is chopped. 33%*22%
	Portion of effected left on surface	0.17	Portion of biomass effected - removed fruit
	Portion of effected left as standing residue	0	0
Vegetation	First yield for biomass conversion (kg/ha)	67000	
	1st above ground biomass at max canopy (kg/ha)	16000	
	Biomass-yield ratio	0.097	
	Develop growth chart for a production (yield) level other than base level	Yes	
	Adjust fall height based on canopy shape?	NA	
	Adjust biomass-yield relationship	NA	
	Adjust senescence relationship	see Senescence relationship	
	Adjust yield/flow-retardance relationship	see Vegetation_retardance	
	Setup long-term veg	NA	
Residue	Responds to tillage like	non-fragile-med (corn)	default
	Decomp. half-life, days	130	Use exponential decay equation with average lifetime from Bartholomew (2003) mean life * ln(2)
	Weight required for area covered, 60%, kg/hec	4000	calculation (above ground biomass) (percent chopped)

	0	0	Assume of plant mass 25% is chopped and used to cover 60% of area. The mass can be related to the harvest
	Decomposition half-life	0	
	Time until decay, weeks	26	from Bartholomew (2003)
	Halflife, weeks	18.02182669	mean life*ln(2)
Senescence Relationship	Above ground biomass subject to senesence, %	0	Plant continues growing until killed
Vegetation retardance	Type of row spacing	Veg. on ridges	
	Max. expected retardance	High	
	Avg. yield for this expect. Retardance	67000	
	Does 'no retardance' apply for yields >0	No	
	Retard class at zero yield	Low	

Table D-8. Parameters modified for USETox-CR model.

Item	Name	USETox-CR	USETox-Default	Source
1	Continent, Area land, km2	5.11E+04	9.01E+06	INEC 2009
2	Continent, Area sea, km2	5.00E+04	9.87E+05	Humbert et al. 2006
3	Continent, Areafrac, freshwater	8.61E-03	3.00E-02	Humbert et al. 2006
4	Continent, Areafrac, natural soil	4.60E-01	4.85E-01	INEC 2009
5	Continent, Areafrac, ag soil	5.29E-01	4.85E-01	
6	Continent, Areafrac, other soil	9.78E-03	1.00E-20	
7	Continent, Temperature, C	2.50E+01	1.20E+01	Humbert et al. 2006
8	Continent, Rain rate, mm/yr	3.24E+03	7.00E+02	Humbert et al. 2006
9	Continent, Soil erosion, mm/yr	4.20E-01	3.00E-02	Rubin and Hyman 2000
10	Human pop., Continent	4.45E+06	9.98E+08	INEC 2009
11	Human pop., Urban	2.80E+06	2.00E+06	INEC 2009
12	Exposed produce, continent, kg/day/capita	2.38E+00	7.53E-01	Humbert et al. 2006
13	Unexposed produce, continent, kg/day/capita	8.62E-01	2.35E-01	Humbert et al. 2006
14	Meat, continent, kg/day/capita	1.11E-01	8.39E-02	Humbert et al. 2006
15	Dairy products continent, kg/day/capita	4.25E-01	2.50E-01	Humbert et al. 2006
16	Fish freshwater, kg/day/capita	5.43E-03	1.26E-02	Humbert et al. 2006
17	Fish marine, kg/day/capita	1.76E-03	3.57E-02	Humbert et al. 2006

Item Notes

4 Based on total protected area

5 Remainder of other land area fractions

6 Assume 500 km2 of urban area + semi-urban

11 63% of population lives in urban areas

14 Pork+beef+chicken+goat

Table D-9. Sensitivity analysis of the RUSLE2 model customized for pineapple in CR.

Category	Variable changed	New Parameter Set/Value	Erosion (MT/ha/yr)	% Change	Note
Baseline	NA	NA	**7.3**	NA	
Climate	Geographic location	Pacific climate	7.5	3%	
		Atlantic climate	7.1	-3%	
Profile	% slope	1	3.3	-55%	Smallest slope among sites
	% slope	5	20	174%	
	% slope	10	41	462%	
	% slope*	20	89	1119%	
	% slope*	30	130	1681%	Approximately largest slope among visited sites
Soil	Soil erodibility, SI	0.071	9.4	29%	Silt loam with 80% silt. Estimate of most highly erodible soils present in pineapple zone
	Soil erodibility, SI	0.022	3.0	-59%	Loamy sand with 10% silt. Estimate of least erodible soils present in pineapple zone
	Contouring	Cross-slope moderate	4.3	-41%	
	Contouring	Standard contouring	4.0	-45%	
Management	Management schedule	Double harvest	4.9	-33%	Double harvest
	Management schedule	Initial preparation during rainy season-rainfall	9.3	27%	
	Mulch	Add plastic mulch	1.6	-78%	Typical in organic practice
Vegetation	Residue half-life, days	260	5.2	-29%	
	Residue half-life, days	65	8.9	22%	
	Yield, tons/ha	33.5	14	92%	Half of average yield, assume limits of competitve production
	Yield, tons/ha	110	4.1	-44%	Max yield reported, Gomez et al. 2007
	Above ground dry biomass: harvest weight ratio	0.0647	7.4	1%	Lowest plant biomass; based on highest fruit:biomass fresh weight ratio of 1 (Bartholomew 2003)
	Above ground dry biomass: harvest weight ratio	0.144	6.8	-7%	Highest plant biomass; based on lowest fruit:biomass fresh weight ratio of 0.45 (Bartholomew 2003)
		Max for farm of unknown origin		1681%	
		Geometric variance		17.8	

Table D-10. Sensitivity analysis of the FAO CROPWAT model to variables found in pineapple cultivation.

Category	Variable changed	New Parameter Set/Value	ET (mm/ crop cycle)	% Change
Baseline	NA	NA	**767.6**	NA
Climate	Geographic location	Pacific climate	811.7	6%
		Atlantic climate	712.8	-7%
Field	Soil texture	Clay	763.0	-1%
		Sand	723.0	-6%
	Add plastic mulch	kc init= 0.6, kc mature=0.3	565.0	-26%
Vegetation	Higher relative crop transpiration	kc init= 0.9, kc mature=0.74	1335.0	74%
	Root depth	depth = 1m	770	0.3%
	Critical depletion, p	High (p=0.75)	768	0.1%
	Yield in response to water	High (Yf = 1.25)	765	-0.3%
		High (Yf = .75)	767	-0.1%
	Crop height, m	Tall (height = 1.25 m)	767.7	0.0%
			Max	74%
			Geo var	1.74

Table D-11. Sensitivity analysis of PestLCI model for pineapple conditions.

Category	Variable changed	New Parameter Set/Value	Sensitivity ratio	% Change, fair	Sensitivity ratio	% Change, fsw
Climate	Solar radiation, MJ/m2/yr	6595	-1.32	-5.8%	n/a	n/a
	Solar radiation, MJ/m2/yr	6271	-1.32	1.0%	n/a	n/a
Field	farm average % slope	1		n/a	1.1	-66.0%
	farm average % slope	5		n/a	1.1	110.0%
	farm average % slope	10		n/a	1.1	330.0%
	Sand content (top layer) %	82		n/a	-2.0	-177.8%
	Sand content (top layer) %	10		n/a	-2.0	150.4%
	% canopy cover when applied	20%	-0.75	55.3%	3.01	-220.5%
	% canopy cover when applied	97%	-0.8	-22.1%	3.0	88.2%
			MAX	55%		330%
			Geo var	1.55		4.30

Table D-12. Recalculation of Pimentel (2009) energy demand for US oranges.

Input	Quantity	Unit	CED (1E3 kcal)
Machinery	50	kgc	1206.172
Diesel	337	La	3739.454
Nitrogen	196	kga	2687.112
Phosphorus	98	kga	374.5104
Potassium	196	ka	337.0593
Lime	1,120	kga	1051.304
Herbicides	0.8	kga	34.39381
Insecticides	0.3	kga	12.89768
Fungicides	1.5	kga	64.48839
Electricity	40	kWha	86.36668
Transport	228	kga	0
Yield	48,000	kg	
Total without labor		kcal	9593758
		MJ	40167.15
		MJ/kg	0.84

Table D-13. Recalculation of Pimentel (2009) energy demand for US apples.

Input	Quantity	Unit	CED (1E3 kcal)
Machinery	88	kga	2123
Diesel	2,000	Ld	22193
Nitrogen	50	kge	685.5
Phosphorus	114	kga	435.7
Potassium	114	kga	196
Lime	682	kga	640.2
Herbicides	6	kgi	258
Insecticides	47	kgi	2021
Fungicides	49	kga	2107
Electricity	40	kWh	86.37
Transport	3,000	kgk	0
Yield	54,000	kg	
Total without labor		kcal	3E+07
		MJ	1E+05
		MJ/kg	2.4

Table D-14. Recalculation of Coltro (2009) energy demand for BR oranges.

Input	Quantity	Unit	CED (MJ/kg)
Diesel	4.19	kg	53.4
Fertilizers (NPK)	11.75	kg	48.4
Bactericide	0.017	kg	180
Acaricide	1.12	kg	180
Fungicide	0.049	kg	180
Herbicide	0.149	kg	180
Insecticide	0.0093	kg	180
Lime	17.75	kg	3.93
Yield	1000	kg	
		MJ	1005.73
		MJ/kg	1.0

Table D-15. CED values for inputs used in recalculations of Orange BR, Orange US and Apples US.

Process	Amount	Unit	NR fossil CED (MJ)
pesticide, unspecified	1	kg	180
ammonium nitrate, as N	1	kg	57.4
diesel, at regional storage	1	kg	53.4
single superphoshate, as P2O5	0.436	kg	16.0
tractor, production	1	kg	101
lime, hydrated, packed, at plant	1	kg	3.9
electricity, US	1	kWH	9.0
potassium chloride, as K2O	0.837	kg	7.2

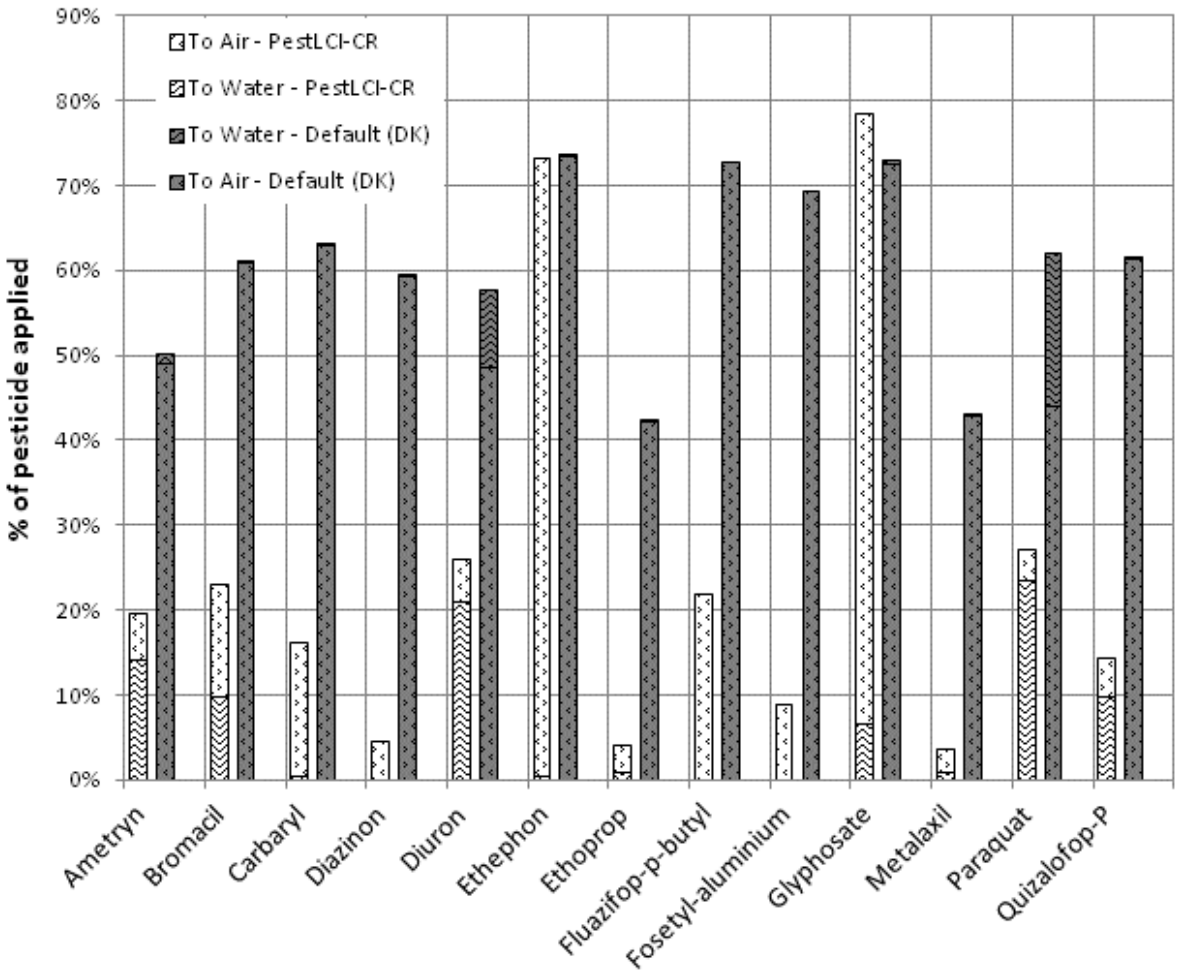

Figure D-1. Emission fractions of applied pesticides in PestLCI-CR vs. the PestLCI default.

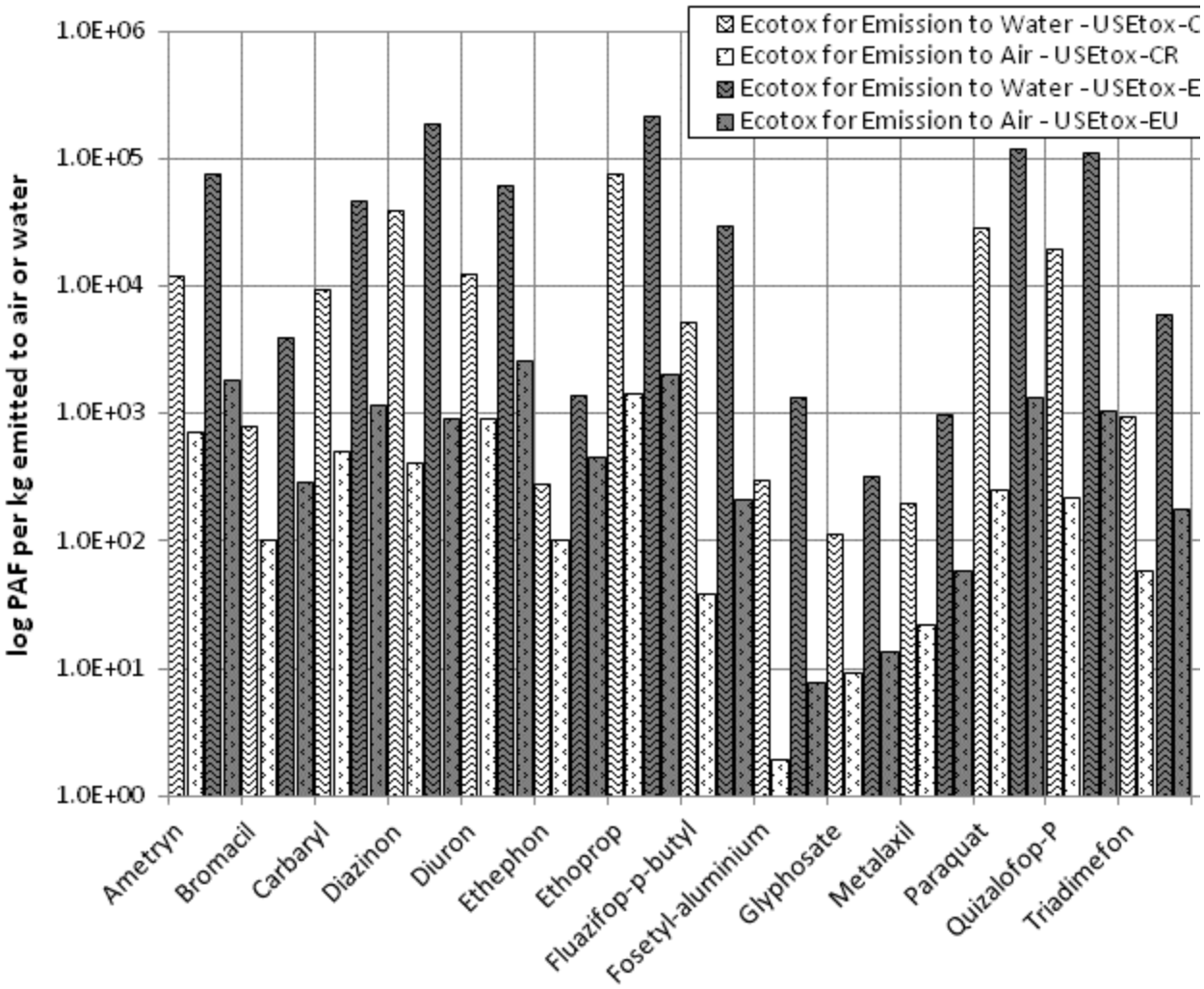

Figure D-2. Freshwater ecotoxicity characterization factors for pesticides in USETox-CR vs USETox-Default

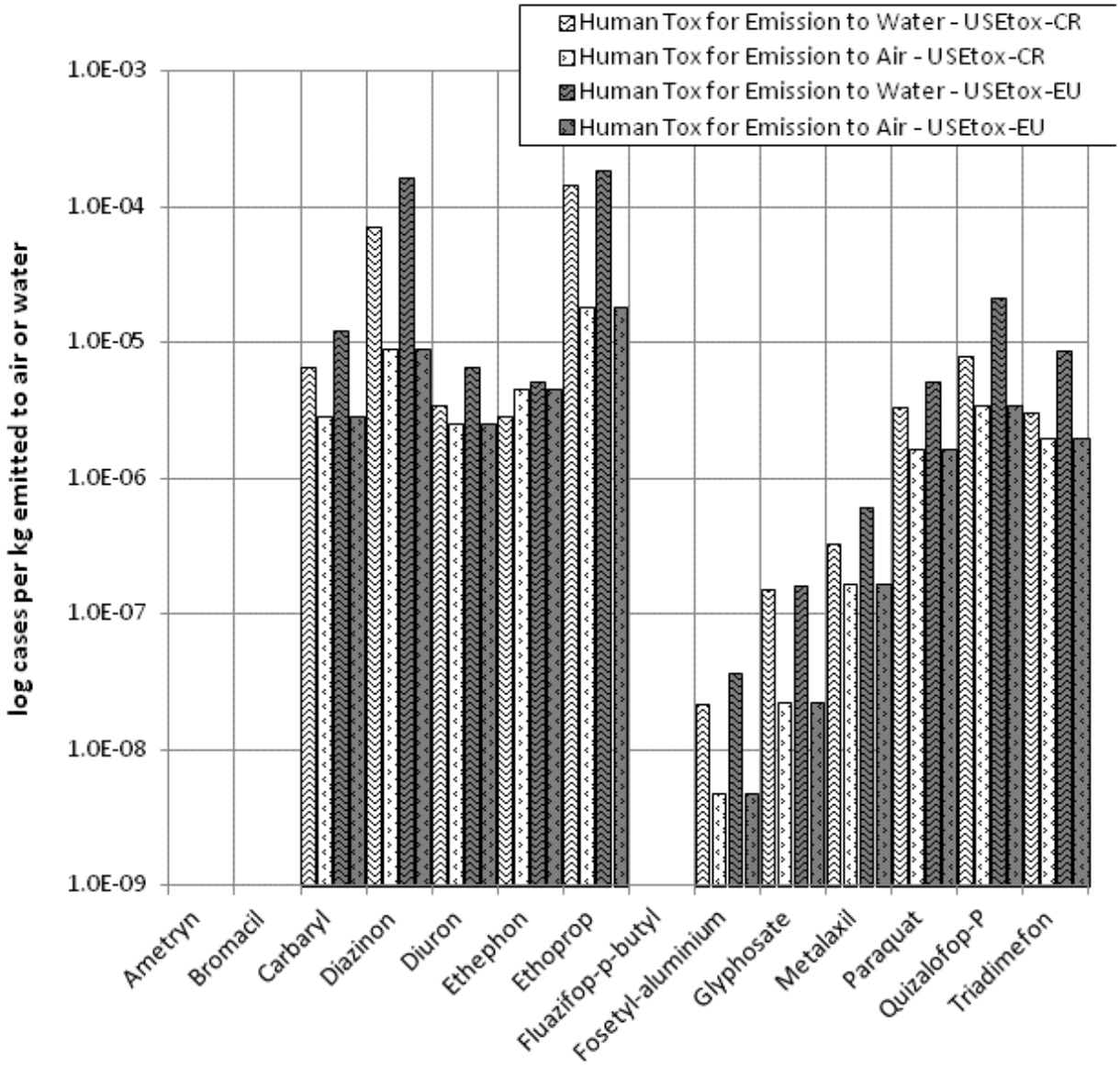

Figure D-3. Human toxicity characterization factors for pesticides in USETox-CR vs USETox-Default

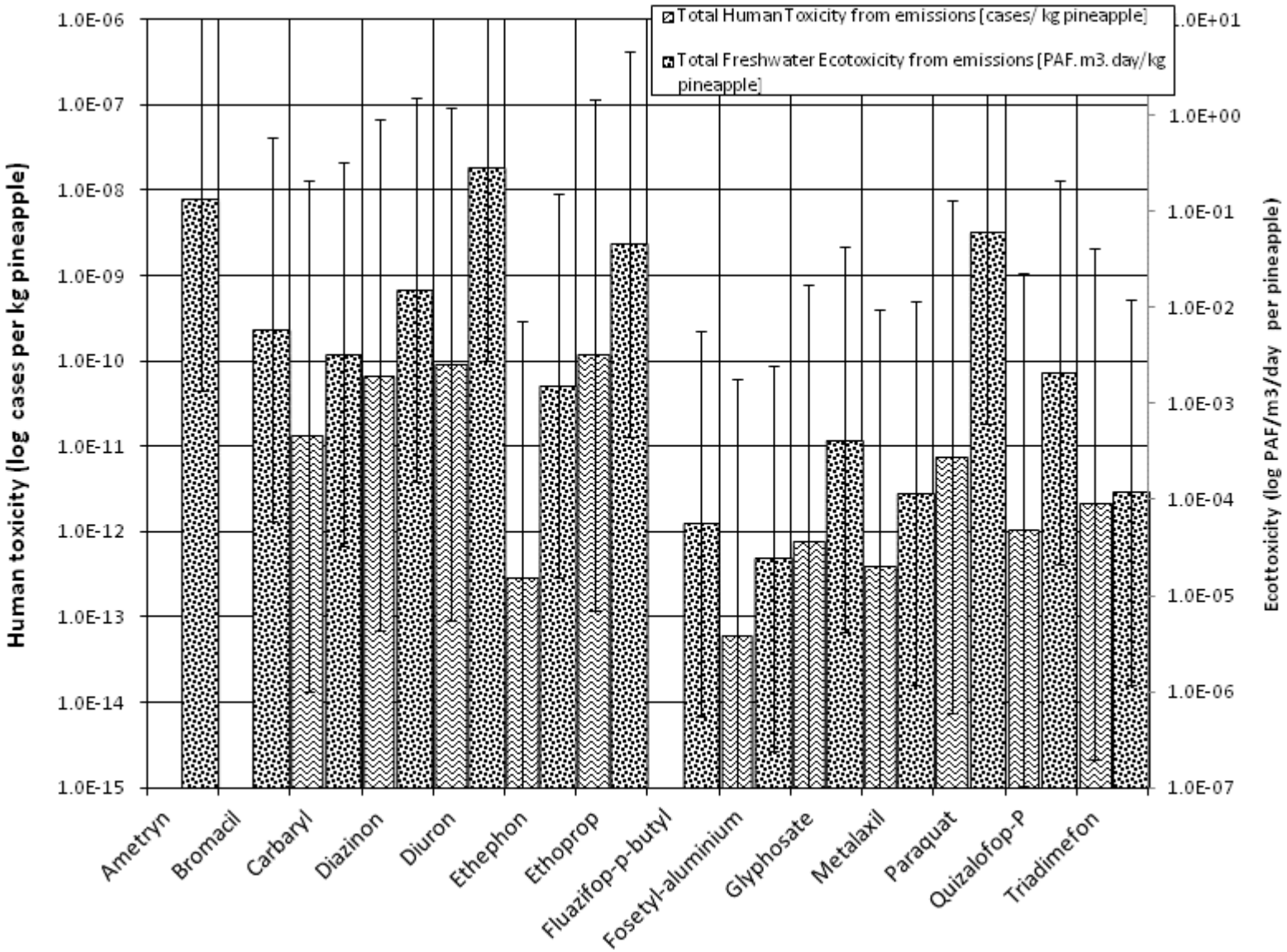

Figure D-4. Human toxicity and freshwater ecotoxicity for pesticide emissions from pineapple production in the baseline scenario.

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BIOGRAPHICAL SKETCH

Wesley W. Ingwersen was born in Atlanta, GA in 1977 and grew up in the Stone Mountain area. He went to secondary school at Woodward Academy in College Park, GA, where he developed a keen interest in environmental science. After a year at Wake Forest University he transferred to Georgetown University (Washington, DC) where he completed a B.A. in 1999. 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, and returned to graduate school to pursue an M.S. in Environmental Engineering at the University of Florida. His M.S. thesis was 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, and environmental policy think-tank in Berlin as a Transatlantic Fellow, and at the end of 2006 returned to UF to pursue a Ph.D. under his M.S. adviser, Mark T. Brown.

Wesley is a Life Cycle Assessment Certified Professional. In addition to the LCA work in this dissertation, he contributed to a study of future transportation-related GHG emissions for the state of Florida, led a feasibility study of environmental product declarations (EPDs) in Costa Rica, and is involved in the development of national guidance standards for EPDs in the US. He has published book chapters, peer-reviewed journal articles, and presented papers for conferences on issues of trade and the environment, environmental assessment, life cycle assessment, uncertainty modeling, and emergy analysis.