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# Assessment of uncertainty in emergy evaluations using Monte Carlo simulations

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ABSTRACT

Emergy evaluations most often rely on point estimates for important energy, material and solar transformity (or more generally unit emergy values, UEVs) parameters. For emergy science to continue its advancement as a tool for assessing energy and environmental sustainability, it needs to include estimates of uncertainty surrounding emergy budgets so that statistical confidence can be assessed. Here, Monte Carlo simulation was used to analyze the effect of uncertainty in the estimates of energy, material and UEVs of system-sources (e.g., sunlight, evapotranspiration, fuel, fertilizer) on the uncertainty of the UEV of the system-yield. Eight unique corn and wheat production systems, reported in the literature, provided the statistical properties (e.g., means, standard deviations, minima) of the energy, material and UEVs of the system-sources, but the probability distribution functions were assumed to be normal, log-normal, or uniform. Uncertainty from system-sources was partitioned into energy/material and UEV. The contribution that a system-source made to total emergy flow was strongly indicative of the amount of uncertainty it contributed. Out of 22 parameters (11 energy/mass and their 11 UEVs), four of them contributed more than 86% of the uncertainty to the UEV of the crop yield. The UEV of nitrogen fertilizer contributed the most uncertainty (19%), followed by the rate of soil erosion (11%), application rate of nitrogen fertilizer (4%), and labor requirements (5%). When uncertainty from all 22 parameters was included, the expected UEV of the crop yield was 118,000 sej/J with a total level of uncertainty (95% confidence interval) of ±106,000 sej/J (±90% of the mean), indicating that uncertainty was vast. However, ±50% was due to energy/mass uncertainty, while ±40% was due to UEV uncertainty, of which all but ±2% was due to the UEV of nitrogen fertilizer, indicating that little uncertainty (±12,600 sej/J) was derived from non-nitrogen fertilizer UEVs. Most of the uncertainty came from the energy/mass, rather than UEVs, indicating that as much care should be given to estimating energy and material use as to selecting or estimating UEVs. Our simulation ignored any multicollinearity that may have existed among the energy/mass use of the system-sources, which likely meant that we overestimated uncertainty. Future investigation should build in the correlations that exist among the system-sources (e.g., nitrogen fertilizer is related to water availability) to better quantify uncertainty. The simulations suggested that uncertainty from UEVs may be hierarchically organized with a few system-sources contributing a majority and most contributing little, indicating that management of uncertainty can be focused on a few parameters.



## 1. Introduction

Biophysically based environmental accounting methods, such as life cycle assessment, ecological footprint accounting (Borucke et al., 2013; Kitzes and Wackernagel, 2009), carbon footprint accounting, water footprint accounting (Hoekstra et al., 2012; Jefferies et al., 2012), ecological cumulative exergy accounting (Zhang et al., 2010a, 2010b; Ukidwe and Bakshi, 2007; Bakshi, 2002), emergy accounting (Campbell and Garmestani, 2012; Srinivasan et al., 2012; Brown and Ulgiati, 2004; Odum, 1996) and others, that strive to estimate the total consumption of natural resources required across a web of processes to provide an alternative decision-making framework to neoclassical economics, have proliferated over the last few decades. With each accounting approach there are resource intensity factors used to estimate the total resource consumption of an activity, whether it is producing a new product or delivering a service. Thus, estimates of intensity factors become paramount to accurately portraying the total resource consumption of an activity.

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In emergy accounting this intensity factor, known as the solar transformity when referring to energy, but more generally as a unit emergy value (UEV), when multiplied by the amount of energy consumed directly from a single source, provides the total indirect and direct solar emergy embodied in that single source. When an activity requires the consumption of multiple types of natural resources across a web of energy transformations, a solar transformity specific to each type of natural resource is needed for this multiplication to give the solar emergy contributed by each resource. Summing the solar emergy contributed from each resource provides the total indirect and direct solar emergy required to make a product or deliver a service.

The choice of solar transformity and estimation of direct energy consumption are key steps toward estimating the total solar emergy (or natural resource consumption). There are three major pathways for uncertainty to enter the final estimate of how much solar emergy something required. First, the list of sources required could exclude items that were actually required. Or rarely an item could be erroneously included. Second, the energy consumed during use of a source, when estimated using models, could contain some estimation error. Or, occasionally, when observed data is available, it will suffer from measurement error. Third, the solar transformity of the particular source may not be known for that specific case so it must be estimated. In emergy accounting, the approach used most often to estimate a solar transformity is to use a previously calculated value that is taken directly from the published literature or from a database of literature values (Tilley et al., 2012). For example, rather than estimate a new solar transformity for freshwater for every new emergy evaluation, a global mean solar transformity of rainfall is often used.

Often, emergy evaluations follow a tabular procedure where source flows of energy (joules, J) or mass (grams, g) are transformed to solar emergy (solar emjoules, sej) and then summed to estimate the emergy of the yield (Table S1). A point estimate of the energy or mass for each source is multiplied by a point estimate of its solar transformity (sej/J) or specific solar emergy (sej/g), respectively, to estimate the solar emergy it contributes to the total solar emergy (sej) of the system. The emergy of the sources are summed to estimate how much solar emergy was consumed to produce a yield of energy. The solar transformity of the yield can then be estimated by dividing the total solar emergy by the energy of the yield to give a point estimate.

Uncertainty associated with the parameter estimates has traditionally not been incorporated into the procedure, but there is the need to report a standardized, quantitative estimate of the uncertainty (Ingwersen, 2010). The author proposed both an analytical method and a stochastic method based on Monte Carlo for estimating UEV uncertainty. Recently, Li et al. (2011) provided two analytical methods (the Variance method and the Taylor method) to estimate the uncertainty of emergy table-based calculations to suggest that they may be better than stochastic methods like Monte Carlo because they require less information. Brown et al. (2011) demonstrated the utility of Monte Carlo simulations in estimating the range of solar transformity of petroleum and natural gas derived from geological resources.

Comparison of emergy evaluations that have been conducted for different systems that produce the same product, but in slightly different ways, clearly show that a range of estimates for the solar transformity of a single type of product exist (Coppola et al., 2009; Franzese et al., 2009; Lefroy and Rydberg, 2003; Rodrigues et al., 2003; Brandt-Williams, 2002). In addition Dynamic Emergy Accounting (DEA) has shown that the solar transformity of a product or storage will vary temporally as the system-sources and system-yield of the transformation process increase and decrease (Tilley, 2011). For example, the multiple estimates for the solar transformity of freshwater discharged from canals in Miami, Florida fit a lognormal probability distribution function (PDF) when simulated with DEA (Tilley and Brown, 2006). In addition, Cohen (2003) used DEA to show that the solar transformities of various soil properties changed during soil genesis. Campbell (2003) was one of the first to estimate the variability of a key solar transformity, rain. Other emergy analysts have also recognized that point estimates are a limitation (Brown et al., 2011; Amponsah and Le Corre, 2011; Ingwersen, 2010, 2011; Ulgiati et al., 2011; Hau and Bakshi, 2004; Campbell, 2003; Cohen, 2003; Odum, 1996), which signals the call for a practical way to include uncertainty in emergy analyses and a better understanding of the level of uncertainty that exists in emergy evaluations.

With the need to incorporate uncertainty into emergy analyses, the next question becomes what is an effective and efficient way to do this? A first step is to elucidate where most of the uncertainty arises in a typical emergy evaluation. If a vast majority of the uncertainty derives from a few parameters, then they can be the focus of more precision in future emergy evaluations. Once the nature of the uncertainty is better understood, future steps would include adjusting the emergy methodology to reduce overall levels of uncertainty and to provide, for example, the capability to estimate confidence intervals for solar transformities or other traditional emergy indices, such as the emergy yield ratio or environmental sustainability index.

The objective of this study was to delve deeper into the origins of uncertainty in emergy evaluations, and determine how much uncertainty is propagated from the uncertainty associated with the system-sources of energy or material and their solar transformities or specific emergy (referred to henceforth as unit emergy values, UEVs). A second aim was to determine which system-sources added the most uncertainty to the solar transformity of the yield. Finally, a third aim was to determine the impact that the assumed probability distribution function of the system-sources had on the uncertainty of the solar transformity of the yield.

### 1.1. Uncertainty and Monte Carlo simulation

Uncertainty is defined as having limited knowledge about the value of a parameter, while variability is the variation of the individuals in a population (Rai and Krewski, 1998). Ingwersen (2010) suggested that emergy scientists co-opt the US EPA framework (Lloyd and Ries, 2007) for classifying uncertainty, which identifies the three basic types of uncertainty as scenario, model and parameter. Scenario uncertainty regards the fit of model parameters to geographical, temporal or technological contexts. Model uncertainty derives from whether the appropriate model (e.g., mathematic model) is being used, especially if there is more than one model for representing the same system. Parameter uncertainty concerns whether appropriate values are being used (e.g., in emergy evaluation this includes the solar transformity and the energy used). Ingwersen (2010) adds that emergy evaluations can be prone to other types of error such as, errors in use of significant figures, use of UEVs that include inventory items from a large-scale source, arithmetic errors, different global baselines, and use of an inappropriate UEV.

Monte Carlo simulation is a stochastic model that uses random number generation to select values for parameters from assumed PDFs that then interact in some way to produce an output that has its own PDF. Thus, it is a technique that is well-suited to elucidate the effects of parameter uncertainty. It could also be used to explore the effects of model and scenario uncertainty, but we focused on using it for investigating parameter uncertainty. Thus, model uncertainty was not evaluated here. Rather, we focused on assessing the contribution of parameter and scenario uncertainty in the agricultural crop systems selected for this study. Certainly, model uncertainty exists since there are many ways to produce