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Uncertainty characterization for emergy values

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ABSTRACT

While statistical estimation of uncertainty has not typically accompanied published emergy values, as with any other quantitative model, uncertainty is embedded in these values, and lack of uncertainty characterization makes their accuracy not only opaque, it also prevents the use of emergy values in statistical tests of hypotheses. This paper first attempts to describe sources of uncertainty in unit emergy values (UEVs) and presents a framework for estimating this uncertainty with analytical and stochastic models, with model choices dependent upon on how the UEV is calculated and what kind of uncertainties are quantified. The analytical model can incorporate a broader spectrum of uncertainty types than the stochastic model, including model and scenario uncertainty, which may be significant in emergy models, but is only appropriate for the most basic of emergy calculations. Although less comprehensive in its incorporation of uncertainty, the proposed stochastic method is suitable for all types of UEVs. The distributions of unit emergy values approximate the lognormal distribution with variations depending on the types of uncertainty quantified as well as the way the UEVs are calculated. While both methods of estimating uncertainty in UEVs have their limitations in their presented stage of development, this paper provides methods for incorporating uncertainty into emergy, and demonstrates how this can be depicted and propagated so that it can be used in future emergy analyses and permit emergy to be more readily incorporated into other methods of environmental assessment, such as LCA.

1. 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 a 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, under review). The incorporation of uncertainty in LCA results is commonplace and furthermore prerequisite to using results to make comparative assertions that are disclosed to the public (ISO 14044: 2006).

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.

1.1. 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 repli-

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

cable fashion. The classification scheme defined by the US EPA defines three uncertainty types: parameter, scenario, and model uncertainty (Lloyd and Ries, 2007). This scheme is co-opted here to represent the uncertainty types associated with UEVs. These uncertainty types are defined in Table 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.

1.2. 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 (Huijbregts et al., 2003; Frischknecht et al., 2007a,b).

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

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

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

where σ^2_{geo} for variable a is a function of ω_a (Eq. (1)),[1] which a simple transformation of the coefficient of variation (Eq. (2)),[2] 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}, ($k \approx \sigma^2_{\text{geo}}$) is a symmetrical measure of the spread between the median, also known as the geometric mean, μ_{geo}, and the tails of the 95.5% (henceforth 95%) confidence interval (Eq. (3)).

$$\text{CI}_{95} = \mu_{\text{geo}}(x\div)\sigma^2_{\text{geo}} \tag{3}$$

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

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

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):

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

where a, b ...z are references to parameters of a multiplicative model y of the form $y = \Pi a \ldots z$. 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)).[3]

$$\text{CV}_{\text{model}} = \sqrt{e^{\{\ln(\sigma^2_{\text{geo of model}})^2/1.96^2\}-1}} \tag{6}$$

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

[1] Eq. (1) adapted from Slob (1994).
[2] Eqs. (2)–(4) adapted from Limpert et al. (2001).
[3] Eqs. (5)–(7) adapted from Slob (1994).