



Selective improvement of global datasets for the computation of locally relevant environmental indicators: A method based on global sensitivity analysis

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ABSTRACT

Several global datasets are available for environmental modelling, but information provided is hardly used for decision-making at a country-level. Here we propose a method, which relies on global sensitivity analysis, to improve local relevance of environmental indicators from global datasets. This method is tested on nitrogen use framework for two contrasted case studies: mixed dairy supply chains in Rwanda and the Netherlands. To achieve this, we evaluate how indicators computed from a global dataset diverge from same indicators computed from survey data. Second, we identify important input parameters that explain the variance of indicators. Subsequently, we fix non-important ones to their average values and substitute important ones with field data. Finally, we evaluate the effect of this substitution. This method improved relevance of nitrogen use indicators; therefore, it can be applied to any environmental modelling using global datasets to improve their relevance by prioritizing important parameters for additional data collection.

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Software and data availability

The modelling done in this paper is performed in the R project for statistical computing. R is an open source statistics software and can be downloaded from <https://www.r-project.org>. Data from a global dataset were obtained from the Global Livestock Environmental Assessment Model (GLEAM) version 2, which was developed by the Animal Production and Health Division (AGA) of Food and Agriculture Organization of United Nations (FAO). The description of GLEAM can be found at <http://www.fao.org/gleam/en/>. The code is programmed in R and is available at <https://github.com/uaimable/GSA>.

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1. Introduction

The sustainability of agricultural systems depends on many social, economic and environmental factors related to technology, practices, and innovation, including a proper management of nutrient flows, such as nitrogen (N) (Sutton et al., 2013). Insight into the efficiency of nutrient use along livestock supply chains can help to identify targeted nutrient management interventions (Uwizeye et al., 2016a). Recently, Uwizeye et al. (2016a) proposed a comprehensive framework to assess nutrient use performance along livestock supply chains. This framework includes three complementary indicators: life-cycle nutrient use efficiency (life-cycle-NUE), life-cycle net nutrient balance (life-cycle-NNB) and nutrient hotspot index (NHI). Quantification of these indicators, however, is quite data intensive and its application on a regional or global level can be laborious because livestock supply chains are relatively long, internationalized and diverse (Gerber et al., 2013; Henderson et al., 2015). Moreover, data on livestock production is scarce, often outdated and does not reflect the spatial and temporal variability of the livestock systems. Given the limited availability

and quality of data, regional averages, default parameters and expert knowledge are often used in the global datasets, despite their high uncertainties and potential biases (Krueger et al., 2012; Uusitalo et al., 2015). These uncertainties in input parameters have an influence on the variance of the model output (Ferretti et al., 2016; Heijungs, 1996; Heijungs and Kleijn, 2001; Oenema et al., 2003; Saltelli et al., 2008, 2000; Sarrazin et al., 2016). Also, averaged or reference values do not reflect the heterogeneity of production units within a given system (Henderson et al., 2015). Gourley et al. (2015), for example, found that milk production per hectare varied by a factor of 12 among grazing dairy farms in Australia. Such variability can also be found for other farm parameters, such as the accumulation of the nutrients in the soil or feed intake. Overlooking this heterogeneity may lead to wrong decision-making or mitigation interventions (Anastasiadis and Kerr, 2013; Henderson et al., 2015).

The effect of the uncertainties of input parameters can be evaluated through sensitivity analysis. Generally, there are two types of sensitivity analyses. First, the local sensitivity analysis (LSA) is based on changing of input parameters around a reference (nominal) value and ranking the magnitude of the effect for each parameter (Campolongo et al., 2007). Second, the global sensitivity analysis (GSA) is based on the variation of input parameters according to their distribution function, and subsequently determine how much each parameter explains the model output variance (Pianosi et al., 2016; Saltelli et al., 2008). An example of an LSA, widely used in environmental studies (Ferretti et al., 2016), is to determine the effect of a change in one of the input parameters at-a-time on the model results (Groen et al., 2016a; Kohn et al., 1997; Oenema et al., 2003; Suh and Yee, 2011). This approach presents some shortfalls, such as assuming that environmental models are approximately linear and additive (Ferretti et al., 2016; Saltelli et al., 2000) or assuming that the variation of one parameter is not associated with any change in the space of all another parameter (Ferretti et al., 2016; Saltelli and Annoni, 2010). The GSA obviates these shortfalls and explores how much each input parameter contributes to the variance of the model output (Ferretti et al., 2016; Pianosi et al., 2016; Saltelli et al., 2008; Sarrazin et al., 2016; Sin et al., 2011; Uwizeye et al., 2016b; Wolf et al., 2016). Moreover, GSA allows to select the important input parameters and to simplify the model by fixing the non-important parameters to their average values (Saltelli et al., 2008). GSA approach, therefore, can provide more insights into the improvement of the relevance and reliability of environmental indicators.

An increasing number of global datasets are becoming available for environmental modelling, opening new opportunities for global sustainability analyses e.g. the Global Livestock Environmental Assessment model (GLEAM) (FAO, 2016a) or the ecoinvent (Frischknecht et al., 2005). Most of these datasets, however, do provide information which may not always be directly usable at a country or sub-regional level (Elduque et al., 2015). Consequently, indicators computed from available global datasets can hardly be used for a country-level decision-making, which significantly limits their relevance given that most policy decisions are made at that level.

The objective of this paper is thus to propose a method to improve the local relevance of environmental indicators computed from global datasets. We first evaluate how indicators computed from a global dataset diverge from the same indicators computed from local survey data. Second, we determine the important input parameters, which explain most of the variance of the indicators computed from a global dataset. Subsequently, we fix the non-important ones to their average values and substitute the important ones with field data. Finally, we evaluate the effect of this substitution. The method is tested in the case of N use indicators for

two contrasted case studies: mixed dairy supply chains in Rwanda and the Netherlands. In Rwanda, there is less information available on national statistics, whereas, in the Netherlands, the statistics are available in the national and European database.

2. Materials and methods

2.1. Description of the proposed method

The different steps of the proposed method are summarized in Fig. 1.

2.1.1. Indicators of N use at supply chain level

We used the nutrient use performance framework developed by Uwizeye et al. (2016a) to assess N management in mixed dairy systems of the Netherlands and Rwanda. The indicators considered are: (i) life-cycle- NUE_N , which defines the efficiency of which N inputs are recovered in the end-products; (ii) life-cycle- NNB_N , which defines the amount of N that is available for loss to the environment; and (iii) NHI_N which defines the relative distribution of N balances along the supply chain. The framework quantifies the N flows in crop/pasture production, animal production, manure management system (MMS), and processing of animal products including the internal processes and loops. The detailed description of this procedure and these indicators can be found in Uwizeye et al. (2016a).

2.1.2. Global sensitivity analysis

We described four steps to perform the GSA. Step 1, we selected the probability density function (PDF) for each input parameter. For input parameters described by an average or reference value without any information on their variability, a normal distribution is assumed, and a coefficient of variation of 20% was applied (IPCC, 2006). For input parameters described by fixed minimum and maximum and a specific likely value (e.g. emission factor (EF)), we assign a triangular distribution. Finally, we assign a uniform distribution of input parameters that are only defined by the minimum and maximum, as advised by Van Gijlswijk et al. (2004). Step 2, we performed Monte Carlo simulation (MCS), which consists of generating N random values from a specified PDF of each input parameter (Groen et al., 2014b; Saltelli et al., 2008). The sample size was set to $N=5000$. We denoted the matrix of Monte Carlo simulations of each input parameter used in the model as P , the number of the input parameters as k , the size of the MC runs, as N , and the number of the model evaluations during the GSA as r . Step 3, the uncertainties of k input parameters were propagated through the model that results in the sample of the model outputs in this case for the life-cycle- NUE_N , life-cycle- NNB_N , and NHI_N . Step 4, we used the squared standardized regression coefficients (squared SRC) method for GSA (Groen et al., 2016a; Saltelli et al., 2008) to estimate the sensitivity indices. Several examples of the application of SRC method are found in the literature (Basset-Mens et al., 2009; Cosenza et al., 2013; Groen et al., 2016a, 2014a; Sattari et al., 2016; Sin et al., 2011; Uwizeye et al., 2016b). The squared SRC method is based on multilinear regression between the model output and the input parameters, and is noted as follows:

$$Y_i = \beta_0 + \sum_{j=1}^k \beta_j P_{ij} + \varepsilon_i \quad (1)$$

where Y refers to the model output, the constant β_0 represents the intercept, β_j refers to the slope (regression coefficient), P refers to the sampling matrix of input parameters, k the number of the input parameters and ε_i is the error term, which is assumed to be

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