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Sensitivity analysis of greenhouse gas emissions from a pork production chain

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ABSTRACT

This study aimed to identify the most essential input parameters in the assessment of greenhouse gas (GHG) emissions along the pork production chain. We identified most essential input parameters by combining two sensitivity-analysis methods: the multiplier method and the method of elementary effects. The former shows how much an input parameter influences assessment of GHG emissions, whereas the latter shows the importance of input parameters on uncertainty in the output. For the method of elementary effects, uncertainty ranges were implemented only for input parameters that were identified as being most influential based on the multiplier method or that had large uncertainty ranges based on the literature. Results showed that the most essential input parameters are the feed-conversion ratio, the amount of manure, CH_4 emissions from manure management and crop yields, especially of maize and barley. Combining the results of both methods allowed derivation of mitigation options, either based on innovations (e.g. novel feeding strategies) or on management strategies (e.g. reducing mortality rate), and formulation of options for improving reliability of the results. Mitigation options based on innovations were shown to be most effective when directed at improving the feed-conversion ratio; decreasing the amount of manure produced by pigs; improving maize, barley and wheat yields; decreasing the number of sows or piglets per growing pig needed and improving efficiency of N-fertiliser production. Mitigation options based on management strategies were shown to be most effective when farmers strive to reduce feed intake, reduce application of N fertiliser to maize and barley, and reduce the number of sows per growing pig needed towards best practices. Finally, the method of elementary effects showed that reliability of assessing GHG emissions of pork production could be improved when uncertainty ranges are reduced, for example, around direct and indirect N_2O emissions of the main feed crops in the pig diet and the CH_4 emissions of manure. Also the reliability could be improved by improving data quality of the most essential parameters. Combining two types of sensitivity-analysis methods identified the most essential input parameters in the pork production chain. With this combined analysis, mitigation options via innovations and management strategies were derived, and parameters were identified that improved reliability of the results.

1. Introduction

Environmental impacts of the agri-food industry have been of increasing concern; in particular, awareness about environmental impacts of animal production are increasingly acknowledged (Steinfeld et al., 2006). The livestock sector, for example, is responsible for about 15% of the total anthropogenic emissions of greenhouse gases (Gerber et al., 2013). Worldwide, pork production explains about 9% of greenhouse gas (GHG) emissions of the livestock sector (Gerber et al., 2013). In general, the environmental impact of pork production is quantified using life cycle assessment (LCA) (Bauman and Tillman, 2004). To quantify GHG emissions of the entire pork production chain, we need to define values for input parameters, such as feed-conversion ratios, crop yields, nitrogen application ratios, and emission factors. Uncertainty around these input values can cause a large variation in GHG emissions estimates. For example, within the IPCC tier 1 framework, direct N_2O

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emissions of N from fertiliser and manure and crop residues vary by a factor of ten: 0.003–0.03 kg N_2O per kg N applied (IPCC, 2006b).

To quantify to what extent environmental impacts of pork production chain varied and to explore the robustness of the results, Basset-Mens and van der Werf (2005), Basset-Mens et al. (2006), and van der Werf et al. (2005) identified ranges of some of their input parameters and assessed the effect of these ranges on the output. Basset-Mens and van der Werf (2005) for example, concluded that N_2O emissions of feed crops caused large uncertainty around estimates of total GHG emissions, indicating that the impact of the feed crops is high, as are the uncertainty ranges around their emissions. None of these studies systematically explored the effect, or contribution, of each individual input parameter to the output. However, it is possible to assess the importance of each individual parameter in an LCA model by performing a sensitivity analysis.

Most LCA studies that performed a sensitivity analysis used a straightforward method, i.e. a one-at-a-time (OAT) approach. An OAT approach selects an input parameter and changes it e.g. 10%, and subsequently quantifies the effect on model output (Suh and Yee, 2011; van Middelaar et al., 2013; van Zanten et al., 2015a; Yang et al., 2011). By exploring the impact of input parameters on the output, the robustness of the results in explored. The input parameters that cause most change in model output are considered to be the most *influential parameters*. The OAT approach is often chosen because of its simplicity as it is not necessary to gather additional data or to derive, for example, ranges or distribution functions for all input parameters (Bjorklund, 2002). However, the OAT approach has two weaknesses. First, the number of input parameters assessed is usually a subset of all input parameters, implying that potential influential parameters might be overlooked. Second, the arbitrary choice of 10% may not reflect the actual uncertainty range of the input data. Some input parameters may vary only 5%, while others may vary by a factor of ten. Therefore, the actual effect on the output might be under- or overestimated.

Two methods for sensitivity analysis are available that overcome these weaknesses. The multiplier method (MPM) determines the influence of all input parameters in an LCA model, and, therefore, accommodates the first weakness. MPM was first introduced in LCA by Heijungs (1994) but to our knowledge has not been applied to an agricultural case study in LCA. MPM can be used to determine areas of potential mitigation options (Heijungs, 1996) but does not take into account the actual ranges over which the input parameters can vary. In contrast, the method of elementary effects (MEE) does include an uncertainty range for each input parameter, and, therefore, accommodates the second weakness mentioned. MEE calculates the importance of the input parameters based on their actual ranges, by exploring model outputs within these ranges. MEE can be used to determine how much the uncertainty around the input parameters affects the output. The parameters that affect the output most, based on their uncertainty range, are referred to as the most *important parameters*. It should be noted that although MEE provides a sampled model output, it is primarily used for sensitivity analysis belonging to the area of screening methods (Saltelli et al., 2008a). MEE was originally designed by Morris (1991) and expanded by Campolongo et al. (2007). To our knowledge, MEE has only been applied to LCA studies outside livestock production e.g. cocoa production by Mutel et al. (2013) and detergent production by de Koning et al. (2010).

This study aims to identify the most *essential parameters* in an LCA model of GHG emissions of pork production by combining results of the two sensitivity-analysis methods. First, MPM is applied, including all input parameters in the model, and second MEE is applied, which explores consequences of actual ranges in uncertainty. Combining results of both methods may help to formulate potential mitigation options and increase reliability of LCA results.

2. Material and methods

2.1. Matrix formulation in LCA

To facilitate the use of the sensitivity-analysis methods applied in this study, we used matrix-based LCA (Heijungs and Suh, 2002). The inventory totals equal:

$$\mathbf{g} = \mathbf{B}\mathbf{A}^{-1}\mathbf{f} \tag{1}$$

Input parameters of an LCA consist of technical parameters and emissions or resource use. The technology matrix **A** contains the technical parameters of various production processes included in the chain, such as production of feed or storage of manure, presented as a set of linear equations. Each column represents a production process. The associated emissions are found in the **B**-matrix, e.g. the kg CH_4 per kg manure storage per year. The **A**-matrix is scaled to produce the amount given by the functional unit **f** (e.g. kg of growing pig). To calculate the total environmental impact per impact category (**h**), the inventory result (**g**) is multiplied by the characterisation matrix (**Q**):

$$\mathbf{h} = \mathbf{Q}\mathbf{g} \tag{2}$$

In this case, **Q** contains the characterization factors of GHG emissions for global warming potential (GWP) on a 100-year time interval: carbon dioxide (CO_2), biogenic methane ($CH_{4,\ bio}$): 28 kg CO_2 e/kg biogenic methane, fossil methane ($CH_{4,\ fossil}$): 30 kg CO_2 e/kg fossil methane; and nitrous oxide (N_2O): 265 kg CO_2 e/kg nitrous oxide (Myhre et al., 2013), thus reducing to a vector **q'** and **h** to a scalar h. All modelling in this paper was performed in MATLAB, and the code is available online at http://evelynegroen.github.io. We only considered elements in **A** and in **B** to contain uncertainty; **f** and $\mathbf{q}'$ remained fixed.

2.2. Multiplier method

MPM predicts the change in the result h of a small change around the default value of each input parameter in **A** or **B**. A derivation of the method can be found in Heijungs (2010). MPM uses first-order partial derivatives $\left(\frac{\partial(h,m)}{\partial(A,i,j)}\right)$ and $\left(\frac{\partial(h,m)}{\partial(B,i,j)}\right)$ to estimate the influence around each input parameter. To compare the influence of the input parameters, the partial derivatives are normalized with respect to their original value A_{ij} and B_{kj}, where A_{ij} and B_{kj} are elements of **A** and **B** respectively, and h_m are the impact categories in h. The multipliers equal:

$$\eta(h,m;A,i,j) = \frac{A_{ij}}{h_m}\frac{\partial(h,m)}{\partial(A,i,j)} \tag{3}$$

$$\eta(h,m;B,k,j) = \frac{B_{kj}}{h_m}\frac{\partial(h,m)}{\partial(B,kj)} \tag{4}$$

Full expressions of the multipliers of Equations (3) and (4) are given in Heijungs (2010). The multiplier will give not only the magnitude but also the direction of change, and can either be positive or negative. The multipliers can be interpreted as how much a 1% change in the input will affect the output (in %). For illustrational purposes, we will also use the absolute effect, given by $|\eta|$.