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UNCERTAINTIES IN LCA

Assessing greenhouse gas emissions of milk production: which parameters are essential?

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Abstract
Purpose Life cycle assessment (LCA) studies of food products, such as dairy, require many input parameters that are affected by variability and uncertainty. Moreover, correlations may be present between input parameters, e.g. between feed intake and milk yield. The purpose of this study was to identify which input parameters are essential to assess the greenhouse gas (GHG) emissions of milk production, while accounting for correlations between input parameters, and using a systematic approach.
Methods Three diets corresponding to three grazing systems (zero-, restricted and unrestricted grazing) were selected, which were defined to aim for a milk yield of 10,000 kg energy corrected milk (ECM) cow^{-1} year^{-1}. First, a local sensitivity analysis was used to identify which parameters *influence* GHG emissions most. Second, a global sensitivity analysis was used to identify which parameters are most *important* to the output variance. The global analysis included correlations between feed intake and milk yield and between N fertilizer rates and crop yields. The local and global sensitivity analyses were combined to determine which parameters are *essential*. Finally, we analysed the effect of changing the most important correlation coefficient (between feed intake and milk yield) on the output variance and global sensitivity analysis.
Results and discussion The total GHG emissions for 1 kg ECM ranged from 1.08 to 1.12 kg CO_2 e, depending on the grazing system. The local sensitivity analysis identified milk yield, feed intake, and the CH_4 emission factor of enteric fermentation of the cows as most influential parameters in the LCA model. The global sensitivity analysis identified the CH_4 emission factor of enteric fermentation, milk yield, feed intake and the direct N_2O emission factor of crop cultivation as most important parameters. For both grazing systems, N_2O emission factor for grazing also turned out to be important. In addition, the correlation coefficient between feed intake and milk yield turned out to be important. The systematic approach resulted in more parameters than previously found.
Conclusions By combining a local and a global sensitivity analysis, parameters were determined which are essential to assess GHG emissions of milk production. These parameters are the CH_4 emission factor of enteric fermentation, milk yield, feed intake, the direct N_2O emission factor of crop cultivation and the N_2O emission factor for grazing. Future research should focus on reducing uncertainty and improving data quality of these essential parameters.

Keywords Correlation · Dairy · Life cycle assessment · Monte Carlo simulation · Sensitivity analysis

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1 Introduction

Due to a growing human population and changing consumption patterns, the environmental impact of food production is increasing (Gerber et al. 2013). Dairy products, such as milk or cheese, are an important source of protein in human diets. Global protein consumption from dairy products increased from 7 g capita^{-1} day^{-1} in 2001 to 8 g capita^{-1} day^{-1} in 2011 and is expected to increase further (FAO 2015). Dairy cattle across the world, however, are responsible for approximately 20 % of the global greenhouse gas (GHG) emissions produced by the livestock sector, which is almost 3 % (1.4 gigatonnes CO_2 e) of all anthropogenic emissions (Gerber et al. 2013). In 2013, approximately one third of all global milk was produced in Europe (FAO 2015). Many studies, therefore, aimed to assess and monitor GHG emissions of European dairy production systems (Crosson et al. 2011; de Vries and de Boer 2010; Yan et al. 2011).

At present, life cycle assessment (LCA) is a commonly accepted method to quantify GHG emissions of dairy production systems (de Vries and de Boer 2010). An LCA quantifies the use of resources and emissions to air, water and soil of a product over the entire life cycle (ISO 2006a, b). Quantification of GHG emissions, therefore, is a single-issue LCA, also referred to as a carbon footprint analysis.

Performing an LCA of food products requires many input parameters, which are rarely easy to obtain and are often affected by natural variability and contain epistemic uncertainty (Walker et al. 2003). Natural variability relates to observable variation, resulting from, for example, variation in weather conditions or differences in farm management, whereas epistemic uncertainty originates from a lack of knowledge about input parameters, including errors resulting from the instrument or those introduced by the observer (Walker et al. 2003). To accurately assess and monitor GHG emissions from dairy production systems, we, therefore, need to identify sources of variability and uncertainty of input parameters and incorporate their impact in the GHG assessment.

Several studies examined the impact of natural variability (Henriksson et al. 2011; Lovett et al. 2008) or epistemic uncertainty on the GHG assessment of milk production (Flysjo et al. 2011; Gibbons et al. 2006), whereas others explored the combined impact of natural variability and epistemic uncertainties (Basset-Mens et al. 2009; Chen and Corson 2014; Ross et al. 2014; Zehetmeier et al. 2014). These studies, however, explored only a limited number of input parameters and did not systematically explore all parameters, which might imply that potential essential parameters are overlooked. Moreover, the above-mentioned studies did not account for potential correlations between input parameters, which might result in an under- or overestimation of the output variance and an underestimation of the most important parameters (Groen 2016, chapter 5).

The aim of this study is to use a systematic approach to identify which input parameters influence the GHG emissions of milk production most, and which parameters contribute most to the output uncertainty of GHG emissions while accounting for correlations between input parameters. To this end, we combined a local and a global sensitivity analysis to determine the influence of the input parameters and the effect of variability and uncertainty on the total GHG emissions of German milk production and a future milk production of 10,000 kg energy corrected milk (ECM) cow^{-1} year^{-1}. A local sensitivity analysis addresses what happens to the output variance when input parameters are slightly changed, whereas a global sensitivity analysis addresses how much of the uncertainty around each input parameter contributes to the output variance (Saltelli et al. 2008). Flysjo et al. (2011) found that by comparing grazing systems of dairy production, a different set of essential parameters showed up for each grazing system. Therefore, we included three different grazing systems based on the main grazing systems in Germany.

For these parameters and for parameters that contained high uncertainties based on literature, we constructed distribution functions to be able to propagate uncertainties through the LCA model and apply the global sensitivity method. We combined the results of this local sensitivity analysis with a global sensitivity analysis to determine which input parameters were essential in the LCA model of milk production.

2 Materials and methods

2.1 Milk production system

GHG emissions were analysed for modelled dairy production systems in Germany, from cradle-to-farm gate. A cradle-to-farm gate assessment implied that emissions are included for relevant processes up to the moment that the milk left the farm gate (Fig. 1). The production of diesel, seeds, fertilizer, lubricants, energy, feed and milk were included in the system, whereas the production of machinery, buildings, and water required for cleaning and as drinking water were excluded. We assumed a stable dairy herd, and fattening of surplus calves occurred outside the farm.

The functional unit was 1 kg ECM (4 % fat and 3.4 % protein, Spiekers and Potthast (2004)) leaving the farm gate. All GHG emissions were allocated to this functional unit. In case of a multifunctional production process of feed ingredients, such as production of rapeseed oil and meal, GHG emissions were allocated to these multiple outputs based on their economic values (i.e. economic allocation). Economic allocation of feed ingredients is the most common method used in LCA studies for livestock products (de Vries and de Boer 2010).

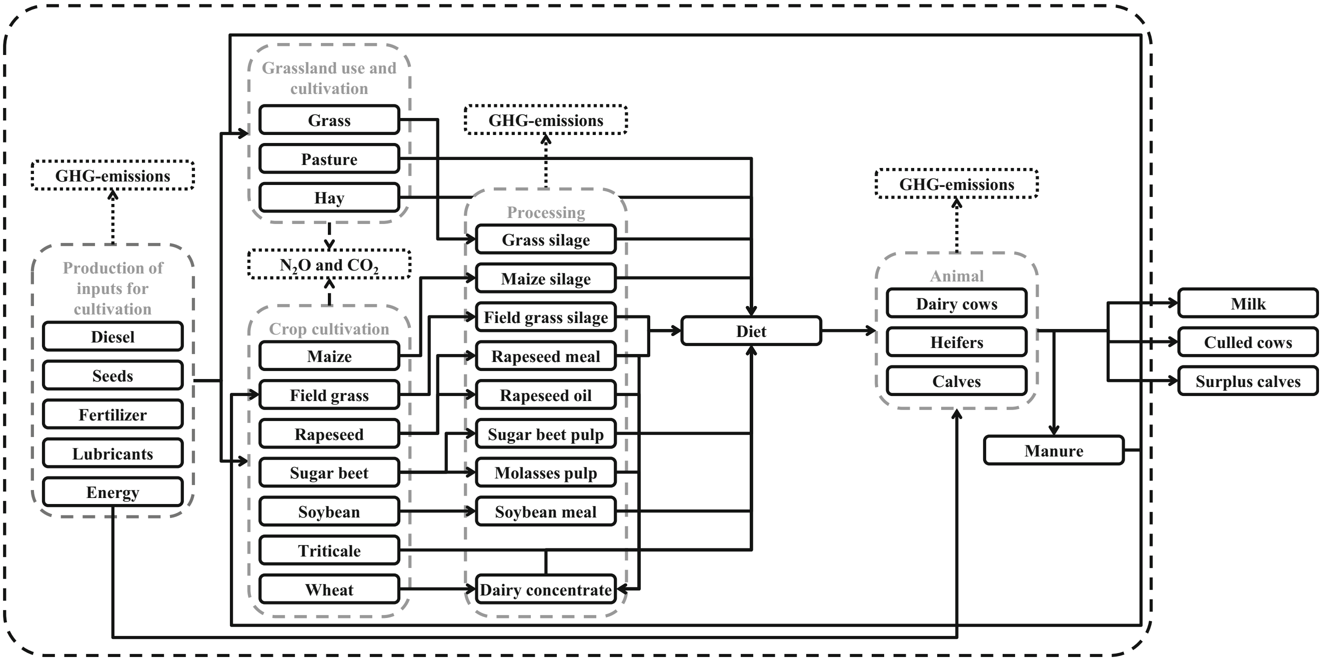

Fig. 1 System boundaries and production processes involved in the production of 1 kg of energy corrected milk)

We modelled a typical German dairy system with 120 Holstein-Friesian cows. A 305-day milk production of 10,000 kg ECM was assumed, anticipating an increase in milk yield after abolition of milk quota (EC 2009), with a dry period of 60 days. The replacement rate was 40 % (Zehetmeier et al. 2012); age at first calving was 25 months. Dairy cows and heifers were loosely housed in stables with cubicles and slatted floors, being most common in Germany, implying slurry-based manure management (Haenel et al. 2014). During their first 60 days, calves were housed in groups, on a solid floor bedded with straw, as imposed by law (Haenel et al. 2014). It was assumed that the slurry of all cattle is untreated and stored in a slurry tank with natural crust, which is most common in Germany (Haenel et al. 2014). The manure produced by the cows and the replacement heifers was applied to the grassland used for the cultivation of silage, pasture and hay as well as to cropland for the cultivation of field grass silage, replacing artificial fertilizer based on N content. The share of manure applied to the grasses and crops depended on the grazing system.

Emissions from crop cultivation, i.e. CO_2 emission from calcium ammonium nitrate (CAN) fertilizer and lime application, direct and indirect N_2O emissions from application of artificial fertilizer, manure and crop residues were included according to IPCC Tier 2 (IPCC 2006b), using German (average) data for crop yields and N fertilizer rates and German emission factors (Haenel et al. 2014). Approximately 23 % of the CAN fertilizer

Table 1 Diets for the dairy cows and replacement heifers in a zero-grazing, restricted grazing and unrestricted grazing system

	Dairy cows			Replacement heifers	
	ZG	RG	UG	ZG	UG
Feed intake[a] (kg dry matter)	7292	7228	7236	5397	5192
Grassland based feed, except pasture (%)	27	15	14	53	34
Pasture (%)	0	22	38	0	28
Field grass silage (%)	11	8	6	–	–
(High quality) maize silage (%)	26	21	13	43	34
Sugar beet pulp (%)	7	4	4	–	–
Soybean meal (%)	1	1	1	–	–
Rapeseed meal (%)	6	5	3	–	–
Triticale (%)	5	11	14	–	–
Dairy concentrate[b] (%)	16	13	8	4	4

ZG zero-grazing system, *RG* restricted grazing system, *UG* unrestricted grazing system

[a] Feed intake replacement heifers: kg dry matter (760 days)$^{-1}$; dairy cows: kg dry matter year^{-1}

[b] Rapeseed meal (32 %), rapeseed oil (1 %), sugar beet molasses (32 %) and wheat (36 %) (Spiekers and Potthast 2004) and is assumed to be equivalent to calf rearing fodder

is assumed to consist of $CaCO_3$ which contributes to CO_2 emissions (UBA 2014). The direct N_2O emissions from grazing, CH_4 and direct N_2O emissions from manure storage were included according to IPCC Tier 2, and CH_4 emissions from enteric fermentation of the cows were included according to IPCC Tier 3 (IPCC 2006a, b), using German average data for feed content characteristics and German emission factors (Haenel et al. 2014). CH_4 from enteric fermentation of the replacement heifers was included according to IPCC Tier 2 (IPCC 2006a), adapted for Germany in 2014 (Haenel et al. 2014).

2.2 Diets

We compared three grazing systems, i.e. zero-grazing (i.e. 0 h day^{-1}; ZG), restricted grazing (i.e. 10 h day^{-1}; RG) and unrestricted grazing (i.e. 20.5 h day^{-1}; UG), grazing time from April until October (182 days year^{-1}), that reflected the most common pasture types in Germany, resulting in three distinct diets. All three diets were formulated to ensure a milk yield of 10,000 kg ECM. The diets consisted of grass-based feed ingredients, such as grass silage, pasture and hay, and crop-based feed ingredients, such as field grass silage, maize silage, beet pulp silage, soybean meal, rapeseed meal, triticale (*Triticosecale* Wittm.) and dairy concentrate (Table 1). The exact composition of the diets was formulated according to feed content characteristics, such as useable crude protein and net energy for lactation, based on Krauß et al. (2015).

The diets for the replacement heifers from birth to age of first calving (760 days) were calculated according to Kirchgeßner et al. (2011), Spiekers and Potthast (2004) and Weiß et al. (2011). They covered a daily gain of at least 700 g body weight per day. Based on a combination of dry matter intake, need for metabolized energy and raw protein, two diets were formulated for the replacement heifers. One diet was formulated for replacement heifers that are housed indoor the whole year round. These heifers are assumed to replace dairy cows in the ZG system. The second diet was formulated for replacement heifers having unrestricted pasture access in summer. These heifers are assumed to replace dairy cows in both the RG and UG system. The feed intake for replacement heifers until the first calving is presented in Table 1.

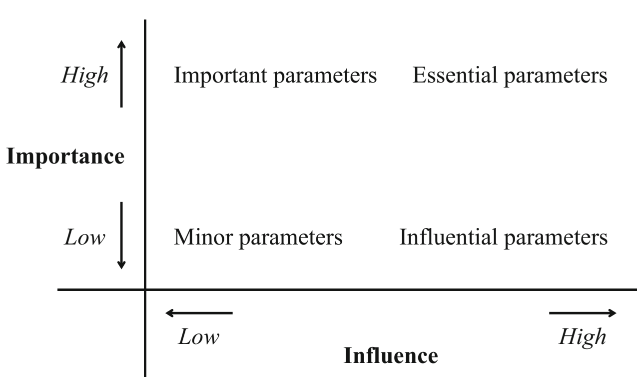

Fig. 2 Framework for combining MPM and MEE. The *horizontal axis* shows the influence of input parameters, the *vertical axis* shows the importance of input parameters. Parameters that are both influential and important are shown in the *top right corner* (essential parameters) (figure from Groen et al. (2016), originally adapted from Heijungs (1996)

2.3 Use of matrix formulation to assess GHG emissions

To facilitate the local and global sensitivity analyses, we used a matrix-based approach commonly applied in LCA calculations (for more detail see Heijungs and Suh (2002)). In matrix notation, each individual production process (e.g. the production of 1 kg fertilizer) is represented as a column in the technology matrix **A**. Parameters that are given in **A** are referred to as technical parameters. The accompanying resource use and emissions, in this case the GHG emissions corresponding to the amount of fertilizer produced in the **A** matrix, are found in the supporting matrix **B**. The production processes are linked to each other, e.g. production of seeds is used for the production of one kg of sugar beets. The **A** matrix is scaled to produce the amount defined as the functional unit (**f**); likewise, the **B** matrix is scaled to quantify the total resource use and emissions (**g**):

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

Subsequently, the impact category totals are quantified by multiplying the **g** vector with the characterization factors:

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

In our 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 per kg methane; fossil methane ($CH_{4,\ fossil}$), 30 kg CO_2 e per kg methane; and nitrous oxide (N_2O), 265 kg CO_2 e per kg nitrous oxide (Myhre et al. 2013). Because we only consider GHG emissions, as this is a single-issue LCA, **Q** is reduced to a row vector **q'** and the scalar h gives the total amount of GHG emissions expressed in CO_2 e per kg ECM.

2.4 Quantifying the effect of uncertainty

2.4.1 Sensitivity analysis

In general, a distinction can be made between two types of sensitivity analysis: a local and a global sensitivity analysis (Saltelli et al. 2008). A local sensitivity analysis looks at small changes around the original input values (or default values) and assesses the effect of those small changes on the output. Parameters that influence the output most are referred to as the most *influential* (Fig. 2) input parameters. A local sensitivity analysis requires only information about the mean;

information of the uncertainty around the input parameters is not needed. In LCA, a local sensitivity analysis can be quantified by means of the multiplier method (MPM). MPM was first introduced by Heijungs (1994) and is applied in LCA by Groen et al. (2016), Jung et al. (2014) and Wei et al. (2015). A global sensitivity analysis decomposes the output variance to the individual input parameters. It can be used to assess which parameter contributes most to the output variance, which are referred to as the most *important* (Fig. 2) input parameters. To apply a global sensitivity analysis, full knowledge of the input parameters is required, in the form of probability density functions. In LCA, the most common method for global sensitivity analysis is calculating the standardized regression coefficients (de Koning et al. 2009; Geisler et al. 2005; Mutel et al. 2013). As we will consider correlated input parameters, we will use standardized regression coefficients for correlated parameters as described in general by Xu and Gertner (2008) and applied in LCA by Wei et al. (2015) and Groen (2016, chapter 5). Figure 2 illustrates influence and importance of input parameters and shows that parameters that influence the output most and contribute most to the output variance are the most *essential* input parameters.

Because we were unable to determine distribution functions for all input parameters, a local sensitivity analysis was performed first, to capture the most influential parameters in the model. For the parameters that were most influential and for parameters that contained high uncertainties based on literature, we constructed distribution functions to be able to propagate uncertainties through the LCA model and apply the global sensitivity method.

2.4.2 Local sensitivity analysis

MPM quantifies the effect of a small change around the default value of each input parameter in **A** or **B** on h (Heijungs 2010). The partial derivatives $\left(\frac{\partial h}{\partial a_{ij}}\right)$ and $\left(\frac{\partial h}{\partial b_{kj}}\right)$ 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. The normalized partial derivatives are called multipliers and are used as estimators of local sensitivity around each input parameter. The multipliers equal:

$$\eta(a_{ij}) = \frac{a_{ij}}{h}\frac{\partial h}{\partial a_{ij}} \tag{3}$$

$$\eta(b_{kj}) = \frac{b_{kj}}{h}\frac{\partial h}{\partial b_{kj}} \tag{4}$$

The expression of the multipliers in Eqs. 3 and 4 can be found in Heijungs (2010). The multipliers in these equations can be interpreted as the relative effect of a marginal increase (i.e. 1 %) of each input parameter. For illustrational purposes, we will also use the absolute effect, given by $|\eta|$.

2.4.3 Global sensitivity analysis

The global sensitivity analysis consists of five steps: The first two steps relate to the data collection and the last three steps are a description of the algorithm and the sensitivity analysis and are described below: (1) determine distribution function of input parameters, which is explained in Section 2.5; (2) determine correlations between input parameters, also explained in Section 2.5; (3) propagation of uncertainty through the LCA model using Monte Carlo simulation with a correlated sampling design; (4) determine the output variance and (5) determine the contribution to the output variance (i.e. global sensitivity analysis) using standardized regression coefficients corrected for correlated input parameters. Step 3 to 5 are described in detail below.

Uncertainty propagation for correlated input parameters (step 3) We made use of a correlated sampling design that also allowed us to incorporate a covariance matrix. Based on the covariance matrix, the random values are drawn from the distribution functions described in Section 2.5, preserving the correlations between the input parameters. For each run, a random number is drawn for each input parameter and the output is calculated according to Eq. 2.

Determine the output variance (step 4) Based on the uncertainty propagation, a distribution function of the output h is generated. The sampled output h contains N response values, the sampling matrix contains $N\,x\,k$ random values, where $i = 1$ to N is the sample size and $j = 1$ to k are the amount of input parameters. The output variance $\left(\hat{\sigma}_h^2\right)$ is calculated as follows:

$$\hat{\sigma}_h^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(h_i - \overline{h}\right)^2 \tag{5}$$

where $\overline{h}$ is the mean: $\overline{h} = \frac{1}{N}\sum_{i=1}^{N} h_i$.

Determine the contribution to the output variance (step 5) We calculated the standardized regression coefficients adjusted for correlated input parameters, based on the paper of Xu and Gertner (2008). The main idea behind this theory is that the total partial variance ($\widehat{\sigma}_T^2(h;p_j)$) caused by parameter p_j can be split into an uncorrelated (U) and a correlated (C) part:

$$\widehat{\sigma}_T^2\left(h;p_j\right) = \widehat{\sigma}_U^2\left(h;p_j\right) + \widehat{\sigma}_C^2\left(h;p_j\right) \tag{6}$$

Based on Eq. 6, the total partial variance is estimated first; the correlated partial variance ($\widehat{\sigma}_C^2(h;p_j)$) can be estimated by subtracting the uncorrelated partial variance from the total partial variance (see Groen (2016, chapter 5) for more detail). The total sensitivity index is given by

$$\widehat{S}_T\left(h;p_j\right) = \widehat{\sigma}_T^2\left(h;p_j\right)/\widehat{\sigma}_h^2 \tag{7}$$

Also, the correlated and the uncorrelated sensitivity index can be calculated, but they are not discussed in this paper.

2.5 Uncertainties in input data

Determine distribution functions of input parameters (step 1) Both the technical parameters in **A** and the GHG emissions in **B** contain uncertain input parameters. Based on the local sensitivity analysis (Section 3.2), we implemented distribution functions for 33 (35 in case of a grazing system, due to N excretion during grazing of cows and replacement heifers) input parameters. Distribution functions related to crop cultivation were constructed for the following:

- Artificial N fertilizer rates for all feed ingredients (Table 2)
- Yield per hectare of all feed ingredients (Table 2)
- Emission factors of direct and indirect N_2O emissions due to application of artificial N fertilizer (Table 3)
- Emission factors of direct and indirect N_2O emissions due to application of manure (Table 3)
- Emission factors of direct and indirect N_2O emissions from crop residues (Table 3)
- Emission factors of direct N_2O emissions due to application of manure during grazing of cows and replacement heifers (only for RG and UG, Table 3)

Distribution functions related to animal production were constructed for the following:

- Dry matter feed intake cow^{-1} year^{-1} (Table 4)
- Milk production cow^{-1} year^{-1} (Table 4)
- Annual replacement rate (Table 4)
- Emission factor of CH_4 emissions from enteric fermentation of cows and replacement heifers (Table 3)
- Emission factor of CH_4 emissions from the storage of manure of cows and replacement heifers (Table 3)
- Emission factor of N_2O emissions from the storage of manure of cows (Table 3)

The mean and standard deviation of the yields and N fertilizer rates for all crops, except soybeans, were obtained from KTBL (2015). Mean and standard deviation of soybean, which we assumed to originate from Brazil, were based on Garcia-Launay et al. (2014). KTBL (2015) only provided data for low, medium and high yields for the feed ingredients as well as fertilizer rates; we interpreted the data for low and the high production of crops as the 95 % confidence interval and assumed a normal distribution (Table 2).

The mean and the standard deviation from emission factors of crop cultivation (i.e. direct and indirect N_2O emissions from application of artificial fertilizer, manure and crop residues), direct N_2O emissions from grazing, CH_4 and direct N_2O emissions from manure storage and CH_4 emissions from enteric fermentation were included according to ranges given by IPCC Tier 3, adapted for Germany in 2014 (Haenel et al. 2014) (Table 4).

Variation of dry matter feed intake cow^{-1} year^{-1} was assumed to be ±5 %, reflecting health issues among cows of one breed, housing and weather conditions (Gruber et al. 2005). We assumed that the variation of the dry matter feed intake corresponded to a 2.5–97.5 % interval of a normal distribution; hence, the coefficient of variation ($CV = \sigma/|\mu|$)

Table 2 Mean and standard deviation of crop yields, N from fertilizer. The distributions functions are assumed to be normal (Haenel et al. 2014)

	Yield (kg dry matter ha^{-1}) Mean[a] (std dev)	Artificial fertilizer (kg N ha^{-1}) Mean[a] (std dev)
Grassland		
Grass silage	8663 (1455)	169 (34)
Pasture	10,170 (1699)	162 (34)
Hay	7756 (1464)	109 (26)
Cropland		
Maize silage	14,500 (1276)	197 (17)
High-quality maize silage	14,500 (1276)	197 (17)
Field grass silage	14,632 (862)	201 (24)
Sugar beet	14,100 (1199)	108 (11)
Triticale	5146 (877)	89 (15)
Soybean	2400 (112)	9 (2)
Rapeseed	3159 (323)	119 (11)
Wheat	30,624 (3906)	197 (26)

Std dev standard deviation, *ha* hectare, *N* nitrogen

[a] Based on KTBL (2015) and Garcia-Launay et al. (2014), adapted for a normal distribution

Table 3 Mean and standard deviation of the emissions factors regarding crop cultivation, manure storage and enteric fermentation of the cows and replacement heifers

Emission factor	Crop cultivation Mean (std dev)	Manure storage Mean (std dev)	Enteric fermentation Mean (std dev)	N excreted during grazing Mean (std dev)
Direct N_2O	0.0125 (0.0051)	0.005 (0.003)	na	0.02 (0.02)[b]
Indirect N_2O, leaching	0.0075 (0.0088)[a]	na	na	na
Indirect N_2O, deposition	0.01 (0.005)	na	na	na
CH_4 (kg CH_4 per kg N excreted)	na	ZG 0.18 (0.037) RG 0.15 (0.031) UG 0.12 (0.024) RH ZG 0.19 (0.039) RH UG 0.08 (0.016)	na	na
CH_4 (kg CH_4 per kg dry matter feed)	na	na	AG 0.021 (0.0043) RH 0.052 (0.0106)	na

Std dev standard deviation, *N* nitrogen, *ZG* zero-grazing system, *RG* restricted grazing system, *UG* unrestricted grazing system, *RH ZG* replacement heifers, zero-grazing system, *RH UG* replacement heifers, unrestricted grazing system, *AG* all grazing systems, *na* not applicable

[a] We used emission factors (EFs) according to Haenel et al. (2014), which mostly relies on IPCC (1996), representing country specific data for Germany. However, the EF for leaching (0.025 kg N_2O-N (kg N)$^{-1}$ (IPCC 1996)) seems to be rather high compared to the new value of 0.0075 kg N_2O-N (kg N)$^{-1}$ (IPCC 2006b). IPCC (2006b) argues that EF has been changed because the EF for groundwater and surface drainage as well as the EF for rivers was too high. We decided to use the latter factor, as this EF is also used in the comparable studies of Chen and Corson (2014), Flysjo et al. (2011) and Ross et al. (2014)

[b] The amount of N excreted during grazing is 0 for the zero-grazing system

equalled approximately 2.5 % for all grazing systems and was used to calculate the standard deviation (Table 4). We assumed that the composition of the diets, however, remained fixed. The variation around milk yield was assumed to be ± 7 % due to genetic variations (Veerkamp et al. 2000). We assumed the variation of milk corresponded to a 2.5–97.5 % interval of a normal distribution; the coefficient of variation equalled approximately 3.5 % for all grazing systems (Table 4). The variation around the replacement rate was assumed to be ±10 % (Zehetmeier et al. 2012). We assumed the variation of the replacement rate corresponded to a 2.5–97.5 % interval of a normal distribution; the coefficient of variation equalled approximately 13 % (Table 4). Furthermore, a maximum replacement rate of higher than 50 % was assumed to be an unrealistic model output because we assumed that raising of own replacement heifers imply a maximum of replacement rate of 50 %. Random values drawn higher than 50 % in the Monte Carlo simulation were therefore removed.

Determining dependencies and correlations (step 2) Before we can propagate the uncertainties trough the LCA model, we first need to take into account that there might be dependencies between input parameters and correlations between the variances around the input parameters (step 2 of the global sensitivity analysis). In this study, we made a distinction between three types of dependencies:

I. A proportional relation was assumed between feed intake and manure production (Haenel et al. 2014) because the diet composition remained fixed. For example, if feed intake increased by 5 %, manure production of the dairy cow also increased by 5 %. The feed intake of the replacement heifers was assumed fixed; therefore, no such relation was applied.

II. The equations for the emissions for crop cultivation of the IPCC, i.e. the direct and indirect N_2O emissions, were also implemented in the sample design. For example, the sampled values of the crop yields were used to calculate the direct N_2O emissions of the crops.

Table 4 Mean and standard deviation of feed intake, milk yield and replacement rate of three grazing systems

Grazing system	Feed intake (kg dry matter cow^{-1} year^{-1}) Mean[a] (std dev)	Milk yield (kg ECM cow^{-1} year^{-1}) Mean (std dev)	Replacement rate Mean (std dev)
ZG	7292 (186)	10,036 (345)	0.4 (0.051)
RG	7228 (184)	10,068 (322)	0.4 (0.051)
UG	7236 (185)	10,042 (322)	0.4 (0.051)

ECM energy corrected milk, *Std dev* standard deviation, *ZG* zero-grazing system, *RG* restricted grazing system, *UG* unrestricted grazing system

[a] Based on Gruber et al. (2005)

III. We included a correlation between the N fertilization rate and crop yield. We took data from KTBL (2015) and LEL (2014) and found a correlation of $\rho = 1$ between all crop yields and fertilizer applications. In addition, we assumed a correlation between feed intake and milk production because the milk production depends on the intake of useable crude protein and net energy with feed. A correlation of $\rho = 0.5$ (Henriksson et al. 2011) between the dry matter feed intake and milk production was included. However, the emission factors of the N_2O emissions of crop cultivation and grazing are still assumed to vary independently from the N fertilization and crop yield because the emission factors also depend on other factors, such as the N content of crop residues, soil type and weather conditions. Also, the N_2O and CH_4 emission factors from manure management and enteric fermentation varied independently from the amount of manure and the feed intake because the emission factors did not only depend on the amount of manure but also on other external factors such as climate conditions (IPCC 2006a).

In theory, correlations may appear between all input parameters that vary, but we assumed that correlations only appear between parameters of the same part of the dairy production systems, so only between parameters belonging to crop cultivation (Table 2) and animal production (Table 4).

The replacement rate and the milk yield were not correlated because we already assumed a replacement rate that is related to the milk yield of 10,000 kg ECM cow^{-1} year^{-1} and the breed of Holstein-Friesian. The variation of the milk yield was too small to find a valid correlation between milk yield and replacement rate in the literature.

2.6 The effect of correlation on uncertainty analysis and global sensitivity analysis

Data regarding the correlation coefficient between N fertilizer rate and crop yield, and between dry matter feed intake and milk yield, came from different sources than the mean values of the parameters and were therefore not considered adequate. Therefore, we determined the effect of changing the correlation coefficient between the most important parameters, on the uncertainty propagation and the sensitivity index. The effect of changing the correlation coefficient on the output variance and the global sensitivity index is described in Section 3.5. Details of this method are described by Groen (2016), chapter 5. The measure of over- or underestimation of the correlation coefficient on the variance is given as follows:

$$\eta = \hat{\sigma}^2_U \big/ \hat{\sigma}^2_h \tag{8}$$

where $\hat{\sigma}^2_U$ is the variance from the LCA model that ignored correlations between input parameters and $\hat{\sigma}^2_h$ is the variance from the LCA model that included correlations between input parameters, as was given in Eq. 5. Furthermore, the sensitivity index from the LCA model that ignored correlations is equal to

$$\widehat{S}_{U;\rho=0}\left(h;p_j\right) = \widehat{\sigma}^2_{U;\rho=0}\left(h;p_j\right)/\widehat{\sigma}^2_U \tag{9}$$

where $\widehat{\sigma}^2_{U;\rho=0}\left(h;p_j\right)$ is the partial variance of parameter p_j, and $\rho = 0$ refers to an LCA model in which there is no correlation between any two pairs of input parameters (Groen 2016, chapter 5).

3 Results and discussion

3.1 Greenhouse gas emissions of milk production

The total GHG emissions for 1 kg ECM for the ZG diet were 1.08 kg CO_2 e. For the RG system, 1.12 kg CO_2 e was emitted and for the UG system, 1.11 kg CO_2 e was emitted per kg ECM.

These results are in line with figures found in the literature for comparable milk yields and grazing systems in Germany. The GHG emissions per kg ECM found in our study, for example, are 15 % higher than found by Zehetmeier et al. (2014) and 5 % higher than found by Zehetmeier et al. (2012). Compared to results from other European studies with similar milk yields and grazing systems, e.g. Ross et al. (2014), the results found in our study are similar when an average milk yield for one grazing system is assumed. The differences can be explained by several reasons. We used the new equivalency factors for the GWP as published by Myhre et al. (2013). When equivalency factors from IPCC (2007) were used, the GHG emissions were reduced by 1–6 %, depending on the grazing system (ZG 1.07 kg CO_2 e, RG 1.05 kg CO_2 e, 1.06 kg CO_2 e). In addition, our study is based on German average data for the crop yields and fertilizer rates, which include e.g. a wide range of soil types and efficiencies for the crop yields. Comparable studies are usually based on actual data from experimental farms, which can be assumed to be more efficient and developed than the average German farm.

The relative contribution of single parts of the production process to GHG emissions is shown in Fig. 3. Enteric fermentation of cows and replacement heifers is responsible for approximately 50 % of the total GHG emissions. This percentage is in line with results from other studies dealing with zero-grazing systems (Ross et al. 2014; Zehetmeier et al. 2012). All processes belonging to the production of feed add up to 23 % of the GHG emissions in our study. The auxiliary emissions mainly originated from the production of the crop inputs (production of CAN, P_2O_5 and K fertilizer) and on-farm electricity use.

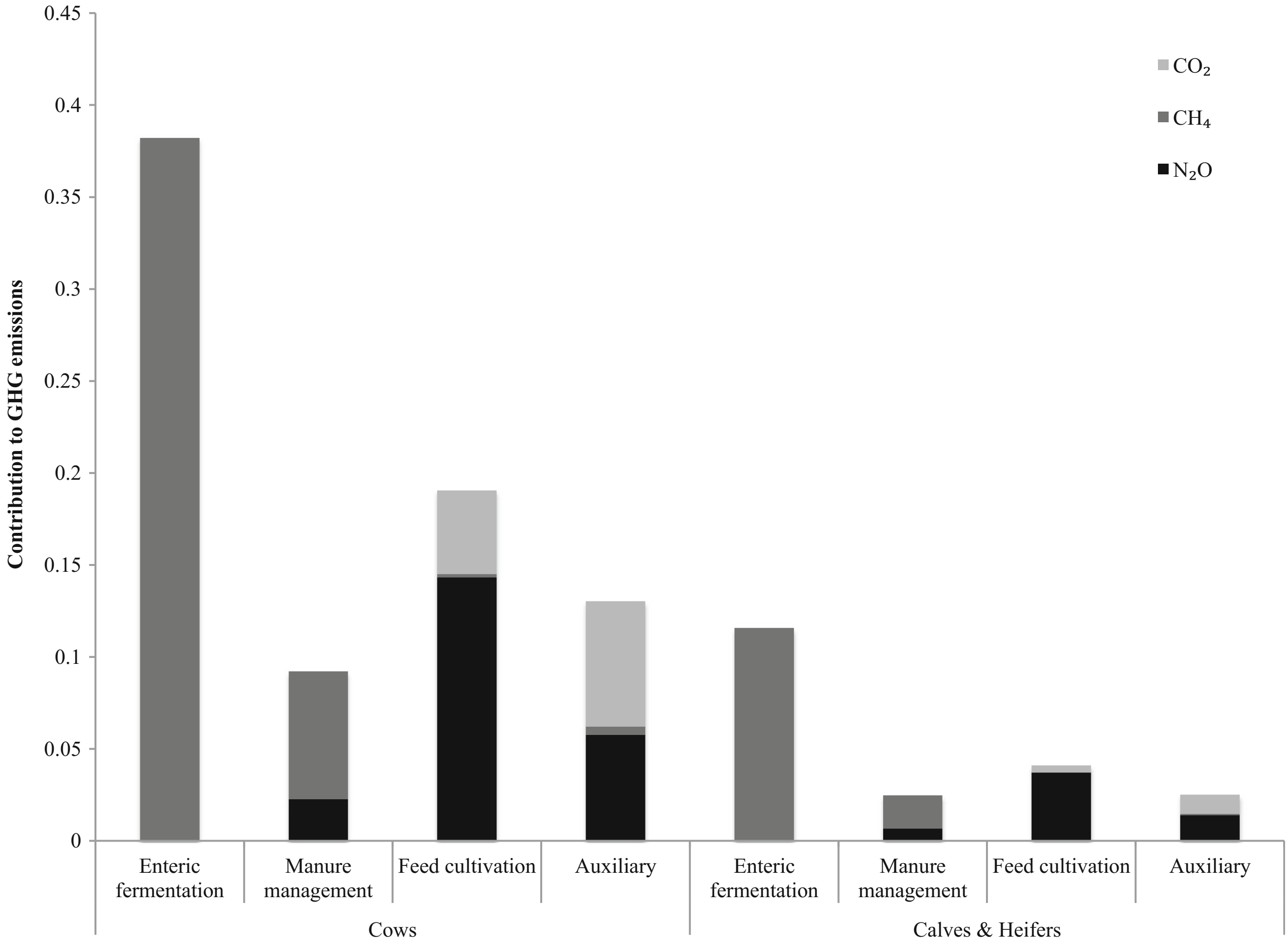

Fig. 3 Relative contribution of GHG sources to GHG emissions of 1 kg energy corrected milk in a zero-grazing system

Of the total GHG emissions, 59 % consists of CH_4 emissions, 28 % of N_2O emissions and 13 % of CO_2 emissions. These results reflect the figures found in the literature, accordingly, the contribution of CH_4 emissions varies from 46 to 63 % (Flysjo et al. 2011; Henriksson et al. 2011), the contribution of N_2O emissions varies from 19 to 35 % (Henriksson et al. 2011; Ross et al. 2014) and the share of CO_2 emissions from 10 to 24 % (Basset-Mens et al. 2009; Ross et al. 2014).

The relative contributions of the other two grazing systems (RG and UG) follow a similar pattern as the ZG system. Other studies also show relatively small differences between GHG emissions related to different grazing systems (Flysjo et al. 2011; Ross et al. 2014). The reason for the resemblance between our results is that the emissions from crop cultivation (higher in a ZG system) are interchanged for the direct N_2O emissions from excreta during grazing in RG and UG grazing systems. The similar milk yields allowed for not considering beef as a co-product, but at different milk yields it should be tested if allocation factors become relevant. It would also require further calculations to see if the conclusions are valid for more extensive grazing systems and different milk yields.

3.2 Local sensitivity analysis

Figure 4 shows the multipliers for the most influential parameters in the LCA model for a ZG system. Apart from milk yield, CH_4 emissions from enteric fermentation and dry matter feed intake of cows are the most influential parameter in the LCA model; increasing methane emissions due to enteric fermentation of the cows by 1 % will increase the GHG emissions by 0.39 %. The second most influential parameter is dry matter feed intake; increasing feed by 1 % (while keeping the same milk production) will increase the GHG emissions by 0.29 %. Crop yields also stand out as relative influential parameters. The N_2O emissions from crop cultivation, however, are less influential.

For the RG and UG system, the results were the same, apart from the components of the feed: especially for the UG system, the yield and the N_2O emissions from the pasture became more important. The results are shown in the Electronic Supplementary Material (Fig. S1 and Fig. S2).

The only study which is comparable to our approach of the local sensitivity analysis is the one-at-a-time approach of

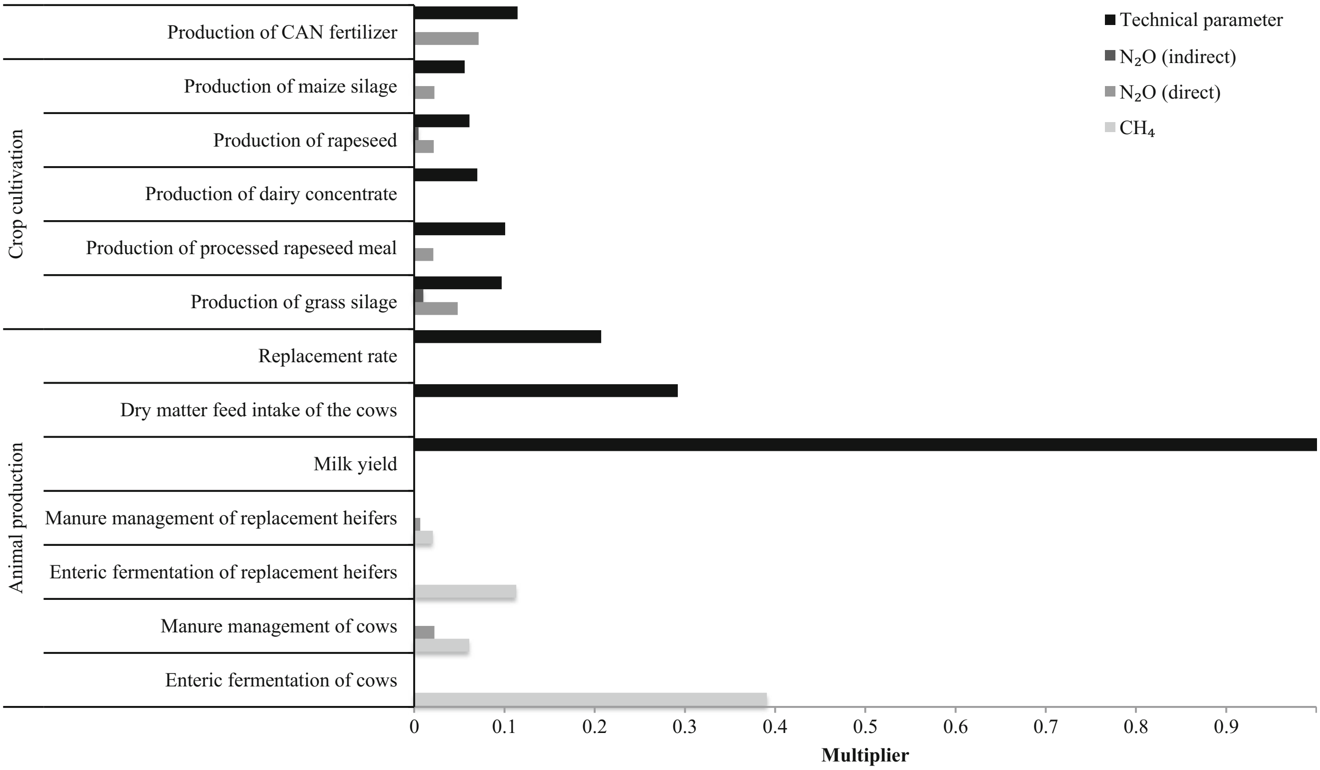

Fig. 4 Multipliers of the most influential parameters ($|\eta| > 0.05$) and their corresponding emissions, for cows in a zero-grazing system. For example, increasing methane emissions due to enteric fermentation of the cows by 1 % will increase the GHG emissions by 0.39 %

Flysjo et al. (2011). That study, however, only includes five technical parameters and four emission factors, which are varied within different ranges (e.g. an increase of 10, 20 and 100 %). To make their results comparable to ours, we recalculated their results to an increase of 10 %, assuming a linear behaviour of the parameters. In Flysjo et al. (2011), the most influential parameter is dry matter feed intake, followed by the emission factor of the enteric fermentation, and the emission factor for direct N_2O emissions from N in excreta deposited during grazing. The system reflects a UG system and is in line with our results for a UG system. However, since our study included all parameters in the local sensitivity analysis, also replacement rate and crop yields turned out to be influential. The MPM method, therefore, facilitated ranking and comparing the influence of all input parameters.

Based on the results of the local sensitivity analysis, combined with knowledge from literature, 25 technical parameters and eight (ten in the case of the grazing systems) emission factors were selected for the subsequent global sensitivity analysis. The technical parameters that were selected consisted of 11 N fertilizer rates and 11 crop yields; replacement rate, feed intake and milk yield. The emission factors that were selected consisted of the emission factor of direct and indirect N_2O emissions from cultivation, N_2O emissions from manure excretion during grazing, N_2O and CH_4 emissions of manure storage and CH_4 emission factor of enteric fermentation of the cows and replacement heifers. Details on the uncertainty around these input parameters are described in Section 2.5. Although not all emission factors showed up as influential in Fig. 4 (i.e. direct and indirect N_2O emissions from crop cultivation and the direct N_2O emissions from N excreted during grazing), based on literature (Basset-Mens et al. 2009; Chen and Corson 2014; Flysjo et al. 2011), these parameters were found important and therefore included.

3.3 Global sensitivity analysis

3.3.1 Uncertainty propagation

The mean and standard deviation of the GHG emissions per kg of ECM for the three grazing systems resulting from the Monte Carlo simulation can be found in Table 5.

To compare our results of the uncertainty analysis with other studies, we calculated the relative variation by dividing the standard deviation by the mean value. We found a CV between 12 % (RG) and 13 % (ZG and UG). This is in line with relative variations found by Flysjo et al. (2011) with 16 % (RG, Sweden) and Lovett et al. (2008) with 15–16 % (RG and UG, Ireland) but rather high when compared to the 7 % found by Basset-Mens et al. (2009), the 9 % found by Henriksson et al. (2011) and the 4–9 % found by Zehetmeier et al. (2014). However, as each study is based on a different set of

Table 5 Mean and standard deviation of the GHG emissions per kg ECM for zero-grazing, restricted grazing and unrestricted grazing

	ZG (N = 4875)[a]	RG (N = 4875)[a]	UG (N = 4875)[a]
Mean (kg CO_2 e per kg ECM)	1.08	1.12	1.11
Standard deviation (kg CO_2 e per kg ECM)	0.14	0.14	0.15

ECM energy corrected milk, *ZG* zero-grazing system, *RG* restricted grazing system, *UG* unrestricted grazing system

[a] The sample size was lower than 5000 because in 125 of the Monte Carlo runs, a value for the replacement rate higher than 0.5 was drawn and these runs were excluded from further analysis

parameters included in the uncertainty propagation the comparison should be treated with care.

3.3.2 Contribution to variance

Figure 5 shows the total sensitivity indices $(\hat{S}_T)$, of the parameters that contribute most to the output variance. The variance of emission factor of CH_4 emissions from enteric fermentation, followed by direct N_2O emission factor of crop cultivation, milk yield, dry matter feed intake, yield and N fertilizer rate of grass silage, and indirect N_2O emission factor of leaching, contributed most to the output variance. The replacement rate, CH_4 and N_2O emission factor from manure of the cows were less important. CH_4 from enteric fermentation of the replacement heifers were also less important.

For the RG and UG systems a similar result was found. Only the N_2O emissions from the pasture contributed more to the output uncertainty than the other feed components. The results are shown in the Electronic Supplementary Material (Fig. S3 and Fig. S4).

That only a couple parameters show up as important is in line with earlier work (Heijungs et al. 2005). We identified four studies that performed a (variant of a) global sensitivity analysis for dairy production systems. Basset-Mens et al. (2009) and Ross et al. (2014) calculated the (standardized) regression coefficients (not the *squared* standardized regression coefficients, which can be used to explain the output variance), so we could only compare their results based on the ranking of the parameters and not on how much the parameters explained. Basset-Mens et al. (2009) concluded that dry matter feed intake, excreta

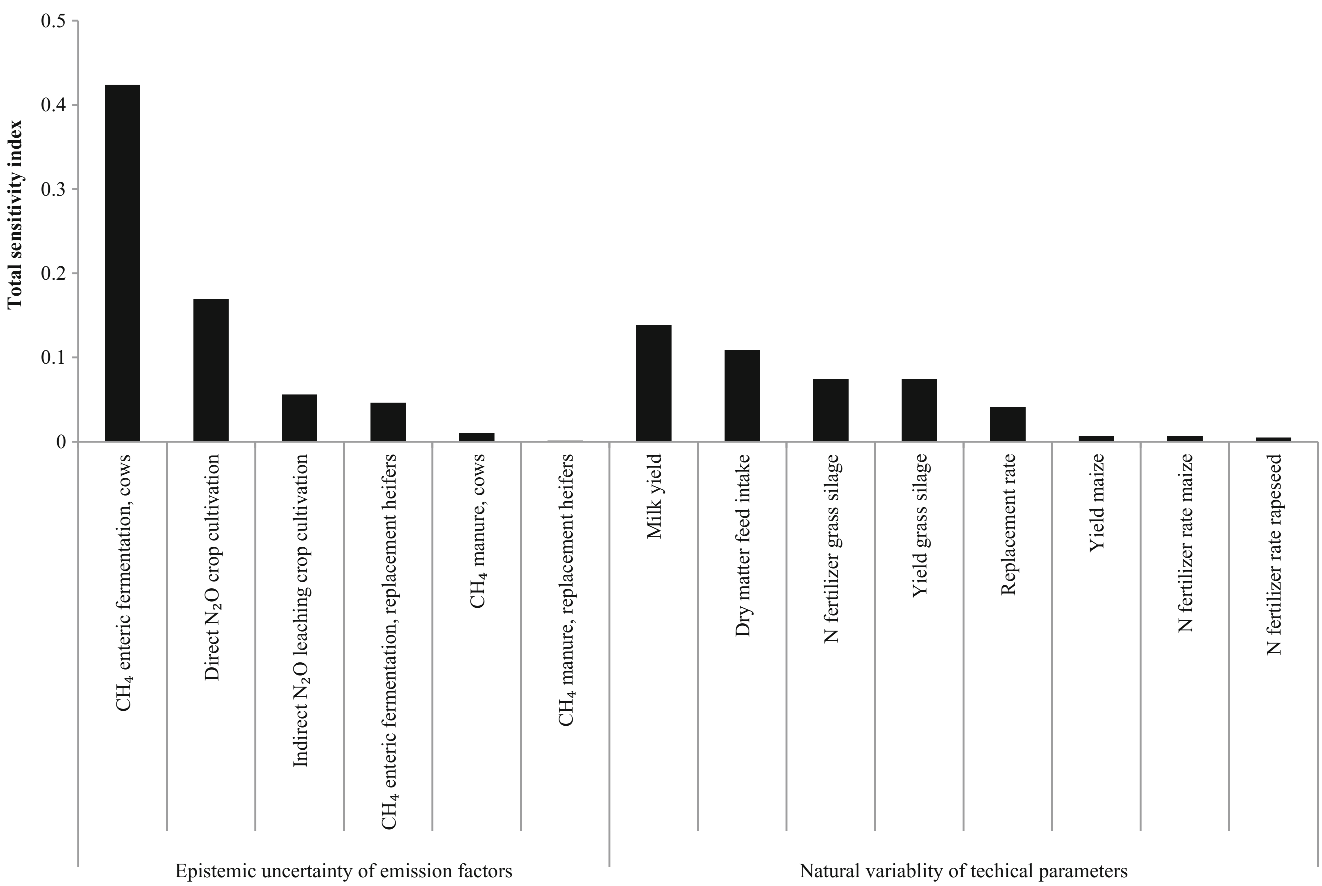

Fig. 5 Parameters that explain most of the output variance, given by the total sensitivity index $(\hat{S}_T)$, for cows in a zero-grazing system. Only parameters that explain more than 0.001 are shown, $(\hat{S}_T > 0.001)$

during grazing and CH_4 emissions of enteric fermentation were most important, while Ross et al. (2014) concluded that N_2O animal manure (management and application), CH_4 enteric fermentation and CH_4 animal manure were most important. Chen and Corson (2014) used the squared correlation coefficient to quantify how much a parameter contributes to the output variance. The squared correlation coefficient is equal to the squared standardized regression coefficient Groen (2016) chapter 4 and can also be used to explain the output variance. Chen and Corson (2014) only focused on the epistemic uncertainties of emission factors. For a conventional system (RG), they concluded that the emission factor of manure on pasture contributed approximately 70 %, followed by cattle housing and manure storage (~10 %), manure spreading (~10 %), mineral fertilization (~5 %), N_2O deposition and leaching (~5 %). The only study that used the same method for the global sensitivity analysis was Zehetmeier et al. (2014), but they considered only four parameters. They concluded that N_2O from N input into soil contributed 75 % to the output variance, followed by replacement rate (19 %) and CH_4 from enteric fermentation of dairy cows (6 %).

To summarize, our results were in line with the studies already performed but added insight by including more parameters (33, both technical parameters and emissions factors) and performing a global sensitivity analysis aiming at explaining the output variance and not just the regression coefficients, which overestimate the importance of the parameters. In addition, this study showed the importance of the emission factor of direct N_2O emissions, replacement rate, and the importance of the yield and fertilizer rate of the main crops.

3.4 Combining local and global sensitivity analysis

Figure 6 combines the most influential parameters from the local sensitivity analysis with the most important parameters from the global sensitivity analysis for all three grazing

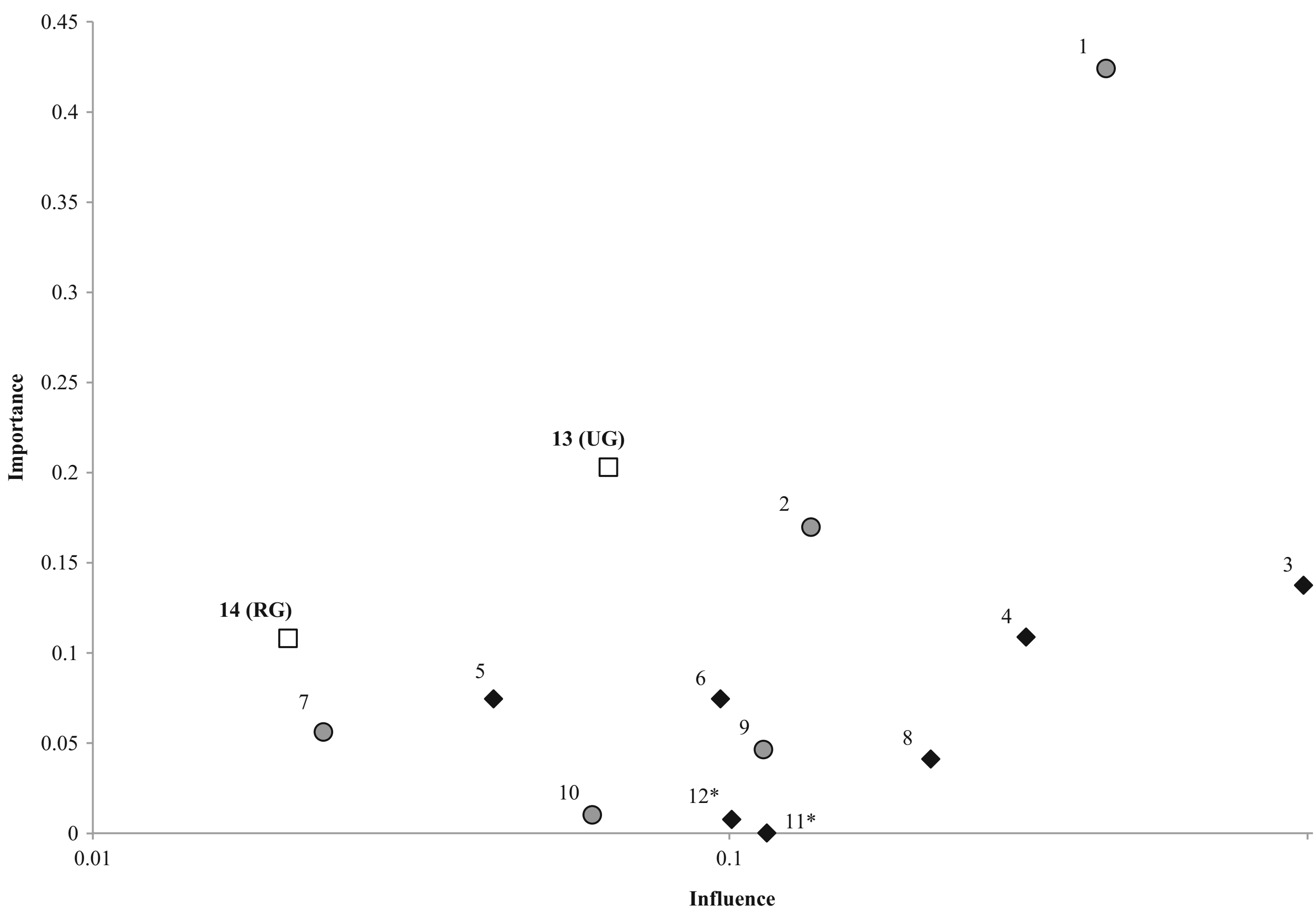

Fig. 6 Combination of the most influential parameters ($|\eta| > 0.1$) on the horizontal (log-) axis and the most important parameters ($S_T > 0.01$) on the vertical axis. *1* Emission factor (EF) enteric fermentation cows, *2* EF direct N_2O, crop cultivation, *3* milk yield, *4* dry matter feed intake, *5* N fertilizer rate grass silage, *6* yield grass silage, *7* EF indirect N_2O, leaching, *8* replacement rate, *9* EF enteric fermentation, replacement heifers, *10* EF CH_4 manure management cows, *11* production of CAN fertilizer, *12* production of processed rapeseed meal, *13* EF N_2O from grazing, unrestricted grazing system, *14* EF N_2O from grazing, restricted grazing system. The *asterisk* indicates parameters that were varied with a default variation of 10 %. *grey circle* parameters containing epistemic uncertainties, *black diamond* parameters containing variability, *white square* do not exist in zero grazing system

systems. Parameters that were selected from the local sensitivity analysis changed the outcome with more than 0.1 % when the input parameters were changed with 1 % (i.e. $|\eta| > 0.1$). Parameters that were selected from the global sensitivity analysis contributed more than 1 % to the output variance (i.e. $S_T > 0.01$). The only difference between the systems is the emission factor (EF) for N_2O from grazing. As the ZG system did not include grazing, the EF did not show up in the results. In contrast, the EF for N_2O from grazing is in the UG system the second most important parameter.

Figure 6 shows that when combining the two methods, the emission factor of CH_4 emissions from enteric fermentation, the emission factor of direct N_2O emission of crops, milk yield, and dry matter feed intake of the dairy cows are most essential. As the emission factor of direct N_2O emissions of the crops is independent from the single crop, number 2 in Fig. 6 (i.e. EF from direct N_2O from crop cultivation) represents the total direct N_2O emissions from all crops combined. Figure 4 shows, if looked at the direct N_2O emissions, on an individual crop level that direct N_2O emissions from crop cultivation per crop would have turned out only as important. Also, N fertilizer rate and yield of grass silage, the replacement rate of cows, the emissions factor of CH_4 emissions from enteric fermentation of the replacement heifers, and the indirect N_2O emission factor of leaching are an essential set of parameters. For parameters that did show up in the local sensitivity analysis (i.e. production of CAN fertilizer and rapeseed meal), but variability or uncertainty could not be included due to a lack of data, we applied a default uncertainty of 10 %. As can be seen in Fig. 6, the importance of those two parameters remained minor. Depending on the grazing system, the emission factor of N_2O for grazing become more essential with increasing grazing time (given by the s*quares* in Fig. 6), while emissions from crop cultivation become less essential.

Both reducing uncertainty and increasing data quality can improve reliability. The epistemic uncertainty of parameters (given by the *circles* in Fig. 6) can be reduced by gaining more knowledge of the parameters or improve measurements. Parameters containing natural variability (given by the *diamonds* in Fig. 6) that are essential should be of high quality before drawing conclusions. Parameters that were included in both the local and global sensitivity analysis but do not show up in Fig. 6 or appear in the left bottom corner can be of lower data quality. These parameters could be set to a fixed value in

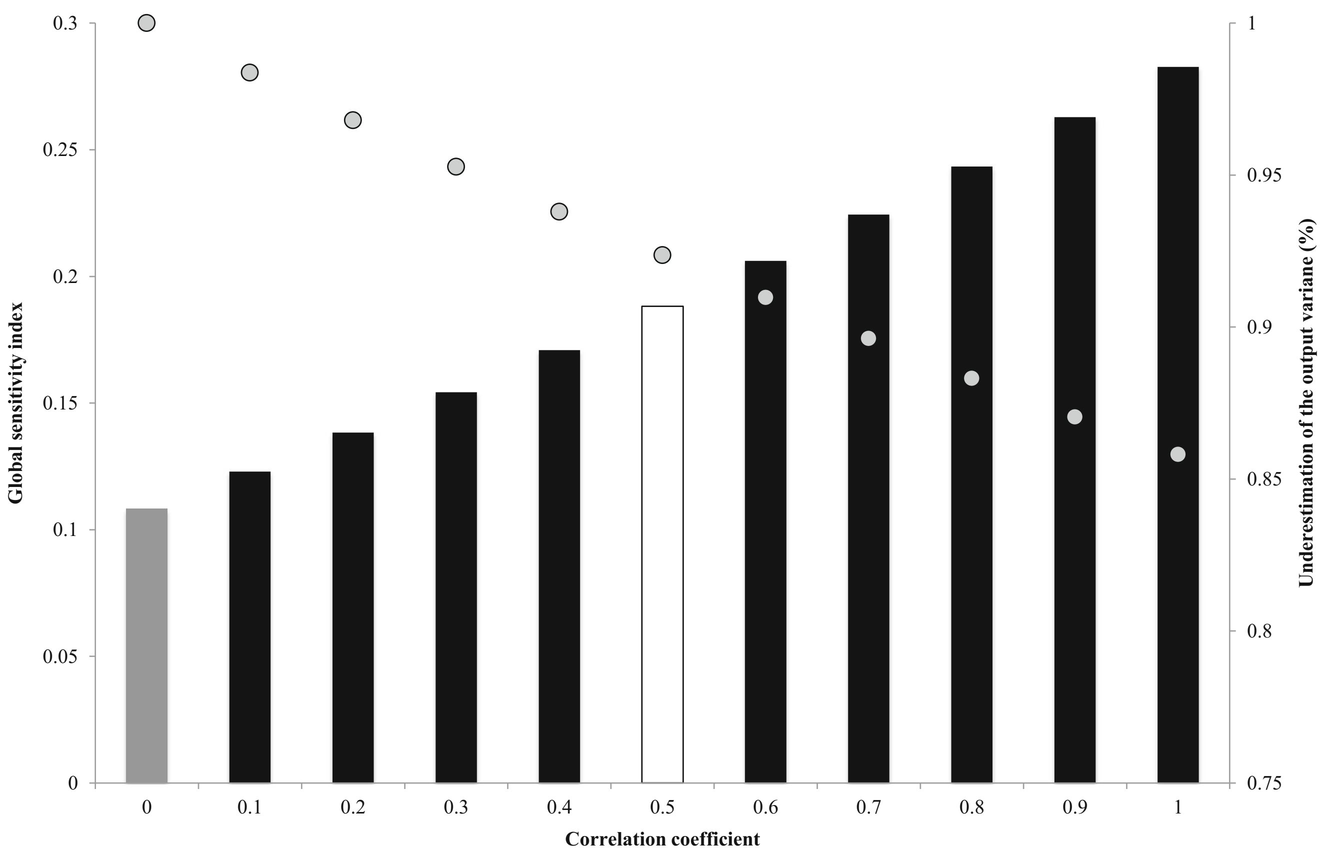

Fig. 7 On the left vertical axis, the effect of varying the correlation coefficient between dry matter feed intake and milk yield between ρ = 0 (i.e. ignoring correlation; *grey bar*) and ρ = 1 on the global sensitivity index of *milk yield* are shown. The *white bar* represents our current assumption. The effects of ignoring the correlation coefficients on the output variance are represented by the *grey dots* on the right vertical axis

future studies, as both their influence and contribution to the output variance is low.

3.5 The effect of the correlation coefficient on the results

The effect of the correlation coefficient is more or less independent from the grazing system because for each grazing system, dry matter feed intake and milk yield turned out to be important parameters. Therefore, the conclusions made with the following results are applicable for all three grazing systems.

The correlation coefficient between dry matter feed intake and milk yield is $\rho = 0.5$, based on Henriksson et al. (2011). However, we were not sure of the value for this correlation coefficient because the data source did not match with the data source we used for the yields and the feed intake. Therefore, we tested what the effect was of varying the correlation between $\rho = 0$ and $\rho = 1$ on the output variance and the global sensitivity index.

The effect of ignoring correlation between dry matter feed intake and milk yield on the output variance is shown in Fig. 7 by the grey dots. For example, if a correlation of 0.5 between dry matter feed intake and milk yield is ignored, the output variance is underestimated with approximately 8 % (1–0.92 = 0.08), if a correlation of 1 is ignored, the output variance is underestimated with approximately 14 % (1–0.86 = 0.14).

In addition, in Fig. 7, the results are given for the effect of changing the correlation coefficient on the global sensitivity index for milk yield. The grey bar on the left presents what happens if correlation between the two parameters was completely ignored (i.e. $\rho = 0$). The white bar represents the value that we have currently chosen (i.e. $\rho = 0.5$). Figure 7 shows that ignoring the correlation between dry matter feed intake and milk yield would lead to an underestimation of the importance of both parameters (dry matter feed intake and milk yield) and the output variance would be underestimated.

The effect of choosing the accurate correlation coefficient between dry matter feed intake and milk yield is clearly demonstrated to be important. Although the magnitude of the correlation between these two input parameters is unknown, they remain one of the most important parameters in the LCA model. A reasonable assumption of variation of the correlation coefficients between milk yield and dry matter feed intake is found in Veerkamp et al. (2000), where the lower limit is given as 0.34 for a high diversity in breed and a large number of animals, and an upper limit is given as 0.66 for a lower diversity in breed or animals specific for a certain region.

4 Conclusions

Parameters that are essential to assess the GHG emission of milk production are the emission factor of CH_4 emissions from enteric fermentation, milk yield, dry matter feed intake of the dairy cows and the emission factor of direct N_2O emission of crop cultivation. Depending on the grazing system, the emission factor of N_2O emissions from grazing becomes more important with increasing grazing time. To improve reliability, the epistemic uncertainty of the emissions factors could be reduced by gaining more knowledge of the parameters or improve measurements. Also, parameters of minor importance, such as the emission factors of CO_2 emissions from liming or other parameters that turned out low in the local and the global sensitivity analysis, could be set to a fixed value in future studies to reduce data collection efforts. In addition, data regarding variability of essential parameters should be of high quality before drawing conclusions, such as milk yield, dry matter feed intake, replacement rate and the N fertilizer rate and crop yield of the most important crops.

The correlation coefficient between feed intake and milk yield seemed to be important; however, better data are needed to determine the strength of the correlation coefficient. Future research should focus on reducing uncertainty and improving data quality of the most essential parameters.

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