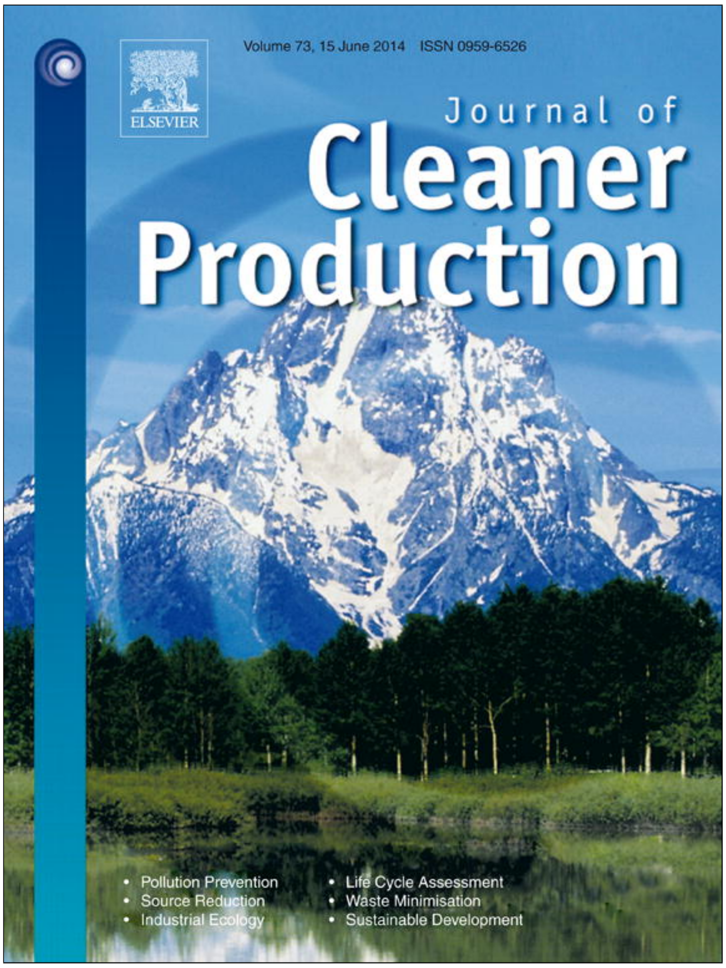
Volume 73, 15 June 2014 ISSN 0959-6526
ELSEVIER
Journal of
Cleaner
Production
• Pollution Prevention
• Source Reduction
• Industrial Ecology
• Life Cycle Assessment
• Waste Minimisation
• Sustainable Development

Journal of Cleaner Production 73 (2014) 116–124

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

The impact of uncertainties on predicted greenhouse gas emissions of dairy cow production systems

M. Zehetmeier [a,*], M. Gandorfer [b], H. Hoffmann [a], U.K. Müller [c], I.J.M. de Boer [d], A. Heißenhuber [a]

[a] Agricultural Production and Resource Economics, Technische Universität München, Alte Akademie 14, 85350 Freising, Bavaria, Germany
[b] Chair Group Economics of Horticulture and Landscaping, Technische Universität München, Alte Akademie 16, 85350 Freising, Bavaria, Germany
[c] Department of Biology, California State University Fresno, 2555 E San Ramon Avenue, Fresno, CA 93740, USA
[d] Animal Production Systems Group, Wageningen University, Wageningen, The Netherlands

A R T I C L E I N F O

Article history:
Received 27 March 2013
Received in revised form
21 July 2013
Accepted 12 September 2013
Available online 22 October 2013

Keywords:
GHG emissions
Uncertainty
Variability
Milk yield
System boundary
Beef

A B S T R A C T

Dairy farms produce significant greenhouse gas (GHG) emissions and are therefore a focal point for GHG-mitigation practices. To develop viable mitigation options, we need robust (insensitive to changes in model parameters and assumptions) predictions of GHG emissions. To this end, we developed a stochastic model to estimate the robustness of predictions based on input parameters (GHG emission factors and production traits) and their uncertainties.

In our study we explored how sensitive predictions of GHG emissions are to three factors: (1) system boundaries of the emission model (2) the uncertainty of input parameters due to quality of data or methodological choices (epistemic uncertainty) and (3) inherent variability in input parameters (variability uncertainty). To assess the effect of system boundaries, we compared two different boundaries: the "dairy farm gate" boundary (all GHG emissions are allocated to milk) and "system expansion" (the model gives a GHG credit to beef derived from culled cows and bull, heifer and calf fattening of surplus dairy calves outside the farm). Results using the farm-gate boundary provide guidance to dairy farmers to reduce GHG emissions of milk production. The results using system expansion are important for defining GHG abatement policies for milk and beef production. We found that the choice of system boundary had the strongest impact on the level and variation of predicted GHG emissions. Model predictions were least robust for lower-yielding dairy cow production systems and when we used system expansion.

We also explored which GHG-abatement strategies have the most leverage by assessing the influence of each input parameter on model predictions. Predicted GHG emissions were least sensitive to variability-related uncertainty in production traits (i.e. replacement rate, calving interval). Lower-yielding production systems had the highest variation, indicating the highest potential for GHG mitigation of all production systems studied. Variation in predicted GHG emissions increased substantially when both epistemic and variability uncertainty in emission factors and variability uncertainty in production traits were included in the model.

If the system boundary was set at the farm gate, the emission factor of N_2O from nitrogen input into the soil had the highest impact on variation in predicted GHG emissions. This variation stems from uncertainties in predicting N_2O emissions (epistemic uncertainty) but also from inherent variability of N_2O emissions over time and space. The uncertainty of predicted GHG emissions can be reduced by increasing the precision in predicting N_2O emissions. However, this additional information does not reduce GHG emissions itself. Knowing site specific variability of N_2O emissions can help reduce GHG emissions by specific management (e.g. reduce soil compaction, adopted manure management, choice of suitable crops).

In case of system expansion, uncertainty in GHG emission credit for dairy beef contributed the most to increasing the variation in predicted GHG emissions.

* Corresponding author. Tel.: +49 8161 71 3415; fax: +49 8161 71 4426.
E-mail addresses: monika.zehetmeier@tum.de (M. Zehetmeier), markus.gandorfer@tum.de (M. Gandorfer), hoffmann@wzw.tum.de (H. Hoffmann), umuller@csufresno.edu (U.K. Müller), Imke.deBoer@wur.nl (I.J.M. de Boer), heissenhuber@wzw.tum.de (A. Heißenhuber).

http://dx.doi.org/10.1016/j.jclepro.2013.09.054

The stochastic-model approach gave important insights into the robustness of model outcomes, which is crucial in the search for cost-effective GHG-abatement options. Despite the high degree of uncertainty when using system expansion, its results help identifying global GHG mitigation options of combined milk and beef production.

1. Introduction

In the search for greenhouse gas (GHG)-abatement options, agriculture has become a focal point as the livestock sector contributes greatly to its total GHG emissions (e.g. 10% of total European Union GHG emissions; Lesschen et al., 2011). In particular, milk and beef production emit high amounts of methane (CH_4) and nitrous oxide (N_2O). When trying to identify possible GHG-abatement options three main points need to be considered: (1) models of GHG emissions have a high degree of uncertainty (Flysjö et al., 2011b) (2) dairy farms have high variability related uncertainty (De Cara et al., 2005; Moran et al., 2011), further increasing the uncertainty of model outcomes, and (3) changes in one system can affect emissions elsewhere due to GHG emissions leakage. Leakage occurs e.g. in dairy cow production when GHG emissions are reduced on a farm or in a country by reducing beef output but replacing the production shortfall with beef from suckler cow production or imports from other countries emitting greater GHG emissions/unit of output (Franks and Hadingham, 2012; Lee et al., 2004).

(1–2) Epistemic uncertainties and variability-related uncertainty

Deterministic models of GHG emissions and life cycle assessment (LCA) of dairy cow production systems are well-established in the literature (Crosson et al., 2011; De Vries and de Boer, 2010; O'Brien et al., 2011; Thomassen et al., 2008). Many guidelines and scientific studies point out the importance of incorporating uncertainty in GHG modelling (IPCC, 2006; ISO, 2006; Pannell, 1997). Stochastic models use these uncertainties to predict a range of outcomes and their likelihood. A stochastic model predicting GHG emissions of dairy cow production systems needs to distinguish the nature of uncertainty: epistemic uncertainty due to data quality or methodological choices, and variability-related uncertainty ("variability uncertainty") due to inherent variability (e.g. of production traits among dairy farms) in the systems or processes under consideration (Walker et al., 2003). Several studies explored the impact of epistemic uncertainty (e.g. the choice of GHG emission factors) on predicted GHG emissions in dairy cow production (Basset-Mens et al., 2009; Flysjö et al., 2011b; Gibbons et al., 2006; van Middelaar et al., 2013). Other studies explored the impact of variability uncertainty on predicted GHG emissions (Henriksson et al., 2011; Lovett et al., 2006; Thomassen et al., 2009). Considering both types of uncertainties is important for developing GHG-abatement options because they have fundamentally different causes and need to be addressed in different ways (Morgan and Henrion, 2006). Consideration of uncertainties provides information for policy makers and farmers on robustness (sensitivity to changes in parameters) (Mußhoff and Hirschauer, 2011) and variation of model outcomes (Pannell, 1997). Furthermore, consideration of uncertainties helps identify "variables with the most influence on predictions" (Pannell, 1997).

(3) Possible GHG emission leakage

Many deterministic model approaches (Capper et al., 2009; Zehetmeier et al., 2012) have shown that GHG emissions per kg of milk can be reduced by increasing milk yield per cow. However, high-yielding dairy cow production systems with pure milk-oriented breeds produce relatively less beef than less intensified (lower milk yield) and less specialised (dual-purpose breed) dairy cow systems (Zehetmeier et al., 2012). If less beef is provided from dairy cow production systems, this decrease would have to be compensated by increases in suckler cow production systems to maintain the same level of beef production. The link between dairy and beef production illustrates the importance of developing models that go beyond the farm gate to include links between different GHG generating-processes (Franks and Hadingham, 2012). Incorporate these links should improve the understanding of GHG emissions derived from milk and beef production. Hence, previous studies developed "system expansion" to handle co-products from dairy cow production systems (i.e. beef from culled cows and fattening of surplus calves) (Flysjö et al., 2012). System expansion accounts for the observation that GHG emissions of beef from culled dairy cows and fattened surplus dairy calves are lower than those of beef from suckler cow production systems (Nguyen et al., 2010).

The main objectives of this study were twofold:

(1) include epistemic uncertainty and variability uncertainty of main model inputs to identify those with the largest effect on variation of predicted GHG emissions
(2) quantify the robustness of model predictions in response to varying input assumptions, such as type of dairy cow production system and method to account for milk and beef output.

2. Material and methods

This study is based on a deterministic model whose assumptions surrounding the livestock production systems and predictions of GHG emissions were described by Zehetmeier et al. (2012). In the following sections we present the main assumptions of the stochastic model.

2.1. Description of main model components

2.1.1. Livestock production systems

The stochastic model incorporated three dairy cow production systems with different breeds and milk yields: 6000 kg of milk/cow/year – dual-purpose Fleckvieh (6000 kg Fleckvieh-system); 8000 kg of milk/cow/year – dual-purpose Fleckvieh (8000 kg Fleckvieh-system); 10,000 kg of milk/cow/year – milk-oriented breed Holstein-Friesian (10,000 kg Holstein-Friesian–system).

Each system represents an average dairy cow of a typical dairy farm plus replacement heifer from birth to age of first calving plus surplus calves until sold. The number of breeding heifers was assumed to equal to the number of cows sold to culling and lost to natural mortality (= replacement rate of the herd). The annual number of calves born was derived from calving intervals and calf mortality. Production of milk, beef and calves was based on a time period of one year for investigated dairy systems. Surplus dairy calves were assumed to be sold to bull and heifer fattening systems at a weight of 50 kg (milk-oriented Holstein-Friesian breed) or at a weight of 85 kg (dual-purpose Fleckvieh breed) representing German production systems (Brüggemann, 2011). Bull and female calves from different dairy breeds were assumed to differ in fattening characteristics such as daily live weight gain and carcass conformation. A higher fattening performance, live weight and carcass kill-out for Fleckvieh compared to Holstein-Friesian animals was assumed (Zehetmeier et al., 2012).

We assumed a feeding regime of total mixed ration fed indoors all year round for all production systems considered in the model. Feed components were maize silage, grass silage, hay, and concentrates. Total dry matter intake and the proportion of concentrates and forage in dairy cows ration were calculated in order to satisfy metabolisable energy and crude protein requirements and considering limitation on dry matter intake (Zehetmeier et al., 2012).

2.1.2. Prediction of GHG emissions

Model predictions included on-farm GHG emissions (e.g. from crop cultivation, keeping of animals, and manure management) and off-farm emissions (e.g. from production of synthetic fertilisers, pesticides, diesel, and purchased feed) (Zehetmeier et al., 2012). The model included the GHGs CH_4, N_2O and carbon dioxide (CO_2). Global warming potentials of 1, 25, and 298 were used to convert CO_2, CH_4 and N_2O emissions into CO_2 equivalents (CO_{2eq}), respectively (IPCC, 2007).

2.1.3. Methods to handle co-products

We chose two methods to handle co-products from dairy cow production to show the impact of epistemic uncertainty and variability uncertainty on variation in predicted GHG emission intensity: "all GHGs to milk" and "system expansion" (Flysjö et al., 2011a). Both methods avoid the definition of an allocation factor to allocate GHG emissions between milk and beef, yet each arrives at a vastly different prediction of GHG emissions intensity expressed as kg CO_{2eq}/kg of milk.

For "all GHGs to milk" all GHG emissions from dairy cow production were allocated to milk. The system boundary is the dairy farm gate. As surplus calves were assumed to be sold to fattening systems beef output is confined to culled cows. This production system represents a specialised dairy farm. The "all GHGs to milk" provides a good metric for dairy farms to evaluate current and improved GHG emissions up to the dairy farm gate.

System expansion considers not only milk output but beef output from culled dairy cows and fattening of surplus dairy calves. Thus, system expansion goes beyond the system boundary of the dairy farm gate. In system expansion, also called the "avoided burden" method (Thomassen et al., 2008), beef from surplus dairy calves that were fattened in bull, heifer and calf fattening systems outside the farm gate was added to beef from culled dairy cows. Accordingly, GHG emissions occurring during the fattening of surplus dairy calves were added to GHG emissions of the dairy cow production system up to the farm gate. Dairy cow production systems received an avoided-burden GHG credit for beef output equal to the amount of GHGs that would have been emitted had the beef been produced in a sucklercow beef system (ISO, 2006). This GHG credit reduced the GHG emission intensity per kg of milk incurred by dairy cow production. Annual beef output was 322 kg/cow/year for the 6000 kg Fleckvieh-system, 315 kg/cow/year for the 8000 kg Fleckvieh-system and 218 kg/cow/year for the 10,000 kg Holstein-Friesian-system.

2.2. Classification of epistemic and variability uncertainties

We investigated three types of epistemic uncertainty (i.e. parameter uncertainty, model uncertainty and uncertainty due to methodological choices) and three types of variability uncertainty (i.e. temporal and spatial variability and variability within dairy cow production systems) (Table 1) (Huijbregts, 1998; Walker et al., 2003). Distinction between the nature of uncertainty i.e. epistemic uncertainty and variability uncertainty is important because they have fundamentally different causes and need to be addressed in different ways (Morgan and Henrion, 2006). Epistemic uncertainty is due to "imperfection of our knowledge, which may be reduced by more research and empirical efforts" (Walker et al., 2003). Variability uncertainty is due to the inherent variability of natural and human systems and thus natural heterogeneity of values (Walker et al., 2003); it may be reduced by disaggregation and points at possibilities for improving the system (Basset-Mens et al., 2009). Both types of uncertainty were included in the model to determine the robustness of predicted GHG emissions for different dairy cow production systems.

Model uncertainty: Model uncertainty arises from uncertainty due to simplifying assumptions implicit in mathematical expressions of relations between physical, biological or economic variables used to describe the production system (Walker et al., 2003). The prediction of emission factors for direct N_2O emissions from nitrogen (N) input into the soil (N_2O N_{input}) or CH_4 emissions from enteric fermentation (CH_{4ent}) based on measurements are examples of model uncertainty. *Parameter uncertainty.* "Empirical inaccuracy (inaccurate measurements), unrepresentativity (incomplete or outdated measurements) and lack of data (no measurements) are common sources of parameter uncertainty" (Huijbregts, 1998). In our model the lack of data on site specific N_2O N_{input} emissions is an example for parameter uncertainty (Table 1).

Table 1
Classification of uncertainty of main model inputs according to Huijbregts (1998) and Walker et al. (2003).

Model parameter	Sources of uncertainty				
	Epistemic uncertainty			Variability uncertainty	
	Model uncertainty	Parameter uncertainty	Uncertainty due to choices	Temporal/Spatial variability	Variability between sources
Production traits					
Calving interval/replacement rate					***X***
GHG emissions					
Emission factor nitrogen input into soil	***X***	***X***		***X***	
CH_4 enteric fermentation	***X***				
Emission factor beef from suckler cow production		***X***			
Methods to handle co-products[a]			***X***		

X: types of uncertainty considered in the model.
[a] Co-products in dairy farming (beef from culled cows and surplus calves sold to fattening systems).

Uncertainty due to methodological *choices*. Examples of choices leading to uncertainty in LCA modelling are the choice of functional unit or, as in our case study, method to handle co-products which affects the GHG intensity expressed in CO_{2eq}/kg of milk (Huijbregts, 1998).

Spatial and temporal variability. Spatial and temporal variability refers to natural variability between different geographical sites (Bjorklund, 2002) and variability that occurs over time. Examination of spatial and temporal variability can help to identify the most favourable regions for milk production (Basset-Mens et al., 2009). In many cases, uncertainties in N_2O N_{input} reported in literature are influenced by spatial and temporal variability.

Variability uncertainty. Dairy cow production systems with similar milk yields and breeds can differ in production traits due to differences in farm management. The production traits chosen in our study (replacement rate and calving interval) are mentioned in the literature as important for comparing dairy cow production systems with different milk yields and breed (Knaus, 2009).

2.3. Stochastic modelling using Monte Carlo simulations

To analyse the impact of epistemic uncertainty and variability uncertainty on predicted GHG emissions, we performed Monte Carlo simulations using @RISK (Palisade Corporation software, Ithaca NY USA) by varying parameters for GHG emissions factors and production traits (calving interval, replacement rate). For each dairy cow production system investigated, we ran 5000 iterations simultaneously to obtain a probability distribution of predicted GHG emissions.

2.3.1. Parameters estimating GHG emissions

We modelled uncertainty in GHGs emitted by enteric fermentation of dairy cows (CH_{4ent}), N input into the soil (N_2O N_{input}), and suckler cow beef production (for system expansion) (Table 2). Overall, emission sources included in the stochastic model accounted for more than 70% of total GHG emissions reported in several studies (Kristensen et al., 2011; Zehetmeier et al., 2012). To account for the considerable uncertainty in CH_{4ent} emissions from the dairy cows investigated (the model used different equations from the literature (Table 2). Uncertainty in N_2O N_{input} was represented by using the uncertainty range reported by IPCC (2006). The uncertainty model used a triangle distribution to describe the probability distribution of CH_{4ent} and emission factor for N_2O N_{input} based on their minimum, maximum and most likely values (Table 2) following previous studies (Lovett et al., 2008). These GHG emission factors were assumed to be independent because they do not interact.

Emission factors for GHG emissions from suckler cow beef production were taken from Crosson et al. (2011), who summarised GHG emissions from beef production systems from different countries and based on different models. From Crosson et al. (2011) we included 15 values for GHG emissions of beef from suckler cow production and assumed a uniform distribution. Emission factors per kg beef varied from 15.6 to 37.5 kg CO_{2eq} (Table 2).

Table 3
Mean and standard deviation (SD) to generate a normal distribution for stochastic modelling of production traits (calving interval and replacement rate).

System milk yield (kg milk/cow/yr)	Calving interval (days)		Replacement rate (%)	
	Mean	SD	Mean	SD
6000[a]	405	22	32.6	7.6
8000[a]	389	15	36.7	7.6
10,000[b]	416	17	30.3	6.4

Yr = year, normal distribution.
[a] Evaluation of data for 19,070 Fleckvieh dairy farms from LKV Bayern (unpublished data, 2004–2009).
[b] Evaluation of data for 3200 Holstein-Friesian dairy farms, from LKV Weser Ems (unpublished data, 2004–2010).

2.3.2. Production traits

Our study focused on two traits of dairy cow production systems that are closely linked to milk yield per cow (Knaus, 2009; Roemer, 2011): replacement rate and calving interval. We used data from 19,070 dairy farms breeding Fleckvieh cows and 3200 dairy farms breeding Holstein-Friesian cows for the time period 2004 to 2010 to identify variability in replacement rate and calving interval within dairy cow production systems of equal milk yield/cow/year and breed. Data were provided by LKV Bayern (unpublished data, 2004–2009) and LKV Weser Ems (unpublished data, 2004–2010). We fitted weighted linear regression models (weighted by farm size) with detrended milk yield/cow/farm as the dependent variable and replacement rate (%) per farm and average calving interval (days) as independent variables. We used quantile regression (Koenker, 2005) to calculate the standard deviation (SD) of replacement rate and calving interval for dairy cow production systems yielding 6000, 8000 and 10,000 kg of milk/cow/year. The resulting production trait values for these systems are shown in Table 3. We assumed that all production traits were normally distributed and we found no statistically significant correlations between production traits.

2.4. Impact of a single parameter on variation in predicted GHG emissions

We identified the impact of each parameter considered in the uncertainty modelling on variation in predicted GHG emissions within each modelled dairy cow production system (6000 kg Fleckvieh-system, 8000 kg Fleckvieh-system, 10,000 kg Holstein-Friesian-system). We used multivariate linear regression implemented in @Risk to calculate standardised regression coefficients.

Table 2
Minimum, maximum, most likely values and shape of distribution for greenhouse gases emissions and emission factors (EF) considered in the uncertainty modelling.

	Most likely	Minimum	Maximum	Probabilistic distribution
CH_4 enteric fermentation (kg CH_4/dairy cow) (6000/8000/10,000)[a]	128[b]/135[b]/138[b]	105[c]/116[c]/127[c]	140[d]/152[d]/157[d]	Triangle
EF N_2O N_{input}[e] (kg N_2O–N/kg N)	0.01[f]	0.003[f]	0.03[f]	Triangle
EF beef from suckler cow production (kg CO_{2eq}/kg beef)		15.6[g]	37.5[g]	Uniform

[a] kg milk/cow/year.
[b] Equation used to model CH4 emissions: Kirchgeβner et al. (1995);
[c] Equation used to model CH_4 emissions: Dämmgen et al. (2009).
[d] Equation used to model CH_4 emissions: Jentsch et al. (2009).
[e] Nitrogen input into the soil.
[f] IPCC (2006).
[g] Crosson et al. (2011).

Standardised regression coefficients were used to identify variable importance of multiple regression models. The coefficients predict "the standard deviation change in the dependent variable when the independent variable is changed by one standard deviation, holding all other variables constant" (Murray and Conner, 2009). If the input variables are independent, then the sum of all squared standardized regression coefficients is equal to the r-squared value of the whole model (Murray and Conner, 2009). This relation provides insight into the contribution of each input variable to the total variation in predicted GHG emissions (Bortz and Weber, 2005). When interpreting regression coefficients it is important to keep in mind that coefficients reflect both the uncertainty of the input variables and the sensitivity of the model to this particular parameter (Basset-Mens et al., 2009).

3. Results

3.1. Variation of predicted GHG emissions

3.1.1. Variability uncertainty in production traits

For all GHG to milk, mean predicted GHG emissions per kg of milk for all dairy cow production systems decreased with increasing milk yield. For system expansion, predicted GHG emissions per kg of milk were considerably lower due to crediting beef output with emissions from suckler cow production. Furthermore, dual-purpose lower-yielding dairy cow production systems (6000 and 8000 kg Fleckvieh-system, higher beef output per t of milk) resulted in lower predicted GHG emissions compared to the higher-yielding milk-oriented Holstein-Friesian breed dairy cow production system (10,000 kg Holstein-Friesian-system, lower beef output per t of milk) (Table 4). These results can be attributed largely to the high GHG credits for avoided beef production from suckler cows. Including only variability uncertainty in production traits in Monte Carlo simulations, resulted in a relatively low SD of predicted GHG emissions (SD = 0.068 to 0.016) (Table 4). For both methods of handling co-products, the SD of GHG emissions per kg of milk decreased with increasing milk yield of dairy systems. The fact that higher-yielding systems have a lower variation in predicted GHG emissions can be attributed largely to lower variability uncertainty in production traits in the high-yielding production systems (Table 3).

3.1.2. Epistemic and variability uncertainties

When both epistemic and variability uncertainties were included in the modelling, then variation of predicted GHG emissions increased considerably due to the high uncertainty of epistemic uncertainty model inputs. We observed the highest variation in predicted GHG emissions under system expansion. This high variation was mainly caused by the highly uncertain emission factor for beef derived from suckler cow production. Uncertainty of emission factor for suckler cow beef was classified as parameter uncertainty, which means that there is a lack of knowledge on GHG emissions of the replaced suckler cow production system. The Fleckvieh-system yielding 6000 kg of milk/cow/year had the highest variation in predicted GHG emissions (SD = 0.3 kg CO_{2eq}/kg of milk; Table 4). There is a high uncertainty in the credit for beef from suckler cow systems and relatively high beef output from the lowest yielding dairy cow system (ca. 55 and 22 kg of beef/t milk for the 6000 kg Fleckvieh-system and the 10,000 kg Holstein-Friesian-system, respectively). Differences in mean predicted GHG emissions between models that consider only variability uncertainty and those that consider epistemic and variability uncertainties can be attributed to the skewed triangle distributions of the epistemic uncertainties.

3.2. Impact on variation in predicted GHG emissions

For all GHGs to milk, the N_2O N_{input} contributed most to variation in predicted GHG emissions. 77% (10,000 kg Holstein-Friesian-system) to 65% (6000 kg Fleckvieh-system) of variation in predicted GHG emissions were explained by uncertainty of this emission factor. Variability uncertainty in replacement rate was the second greatest contributor (Fig. 1a). The effects of variability uncertainty in replacement rate were stronger in lower-yielding dairy cow production systems (30%) (Fig. 1a). In contrast, variability in calving interval did not influence variation in predicted GHG emissions for all GHGs to milk because calves are sold to fattening systems outside the dairy farm gate and are thus only marginal included in GHG emission modelling.

For system expansion, uncertainty in the emission factor for beef from suckler cow production systems had the highest impact on variation in predicted GHG emission outcome (i.e. from 79% of total variation in predicted GHG emissions in the 6000 kg Fleckvieh-system to 62% in the 10,000 kg Holstein-Friesian-system (Fig. 1b). The second biggest contributor was N_2O N_{input}, which explained 18%–35% of the total variation in predicted GHG emissions; Fig. 1b). The combined contribution of the remaining factors was less than 5%, with variability uncertainty in calving interval explaining 2.5% (6000 kg Fleckvieh-system) to 0.9% (10,000 kg Holstein-Friesian-system). Impact of calving interval was higher for dual-purpose dairy cow production systems (Fig. 1b) as surplus calves show better fattening characteristics resulting in a higher beef output/cow/year.

Table 4
Mean, standard deviation (SD), coefficient of variation (CV) and confidence interval of greenhouse gas (GHG) emissions (in kg CO_{2eq}/kg milk) for the dairy cow production systems investigated via uncertainty modelling.

Method to handle co-products		All GHGs to milk			System expansion		
Indicator		Dairy cow production system (kg milk/cow/year)					
		6000	8000	10,000	6000	8000	10,000
Considering only variability of production traits							
Mean (of which credit for beef output[a])		1.366	1.136	0.923	0.241 (1.406)	0.243 (1.102)	0.465 (0.880)
SD		0.068	0.051	0.035	0.051	0.030	0.016
CV		0.049	0.045	0.038	0.212	0.125	0.033
Confidence interval (95%)	Lower limit	1.255	1.053	0.867	0.154	0.194	0.440
	Upper limit	1.478	1.220	0.980	0.322	0.293	0.487
Considering both epistemic uncertainty of GHG modelling and variability in production traits							
Mean (of which credit for beef output[a])		1.432	1.201	0.986	0.323 (1.403)	0.321 (1.100)	0.534 (0.886)
SD		0.133	0.107	0.085	0.300	0.234	0.137
CV		0.093	0.089	0.086	0.929	0.731	0.257
Confidence interval (95%)	Lower limit	1.231	1.041	0.860	−0.237	−0.111	0.296
	Upper limit	1.670	1.388	1.138	0.786	0.684	0.755

[a] Value based on emission factor for suckler cow beef production.

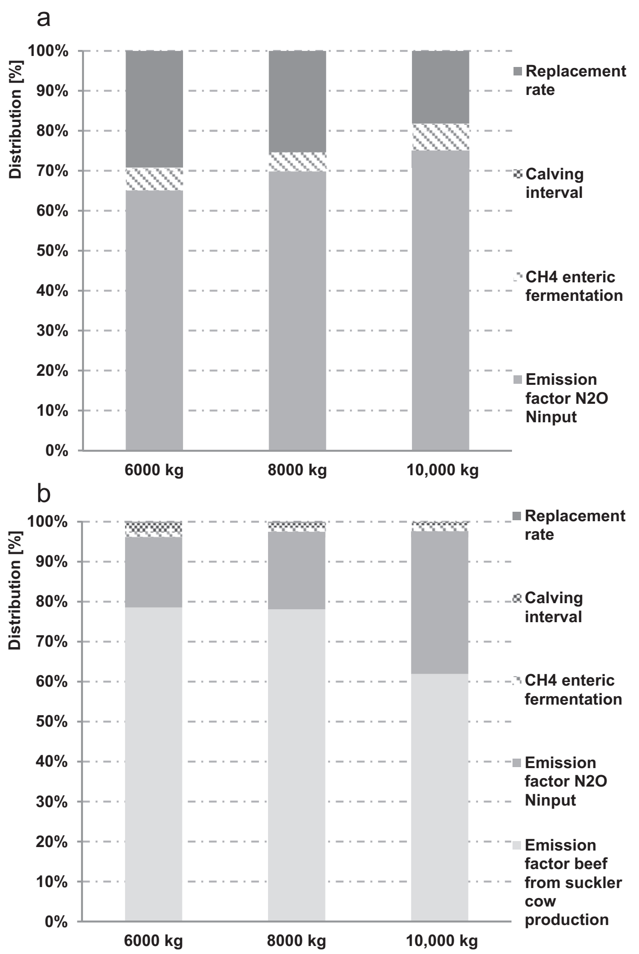

Fig. 1. Parameters influencing variation in predicted greenhouse gas (GHG) emissions under a) "all GHGs to milk" b) and "system expansion" methods to handle co-products.

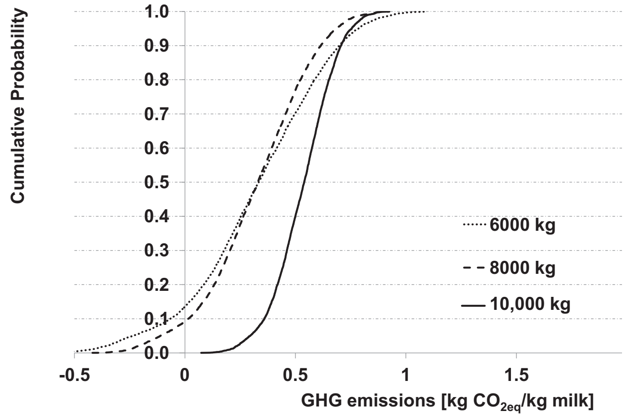

Fig. 2. Cumulative probability of greenhouse gas (GHG) emissions for dairy cow production systems differing in milk yield and breed based on Monte Carlo simulation in @Risk; System expansion was used to handle co-products.

3.3. Probability of predicted GHG emissions of dairy cow production systems

Cumulative distributions give insight into the probability of GHG emission outcomes as they display probabilities that emissions will be lower than a given amount. For all GHGs to milk lower-yielding systems resulted in higher GHG emissions per kg of milk at each level of probability. This indicates high probability that predicted GHG emissions of higher-yielding systems are lower compared to lower-yielding systems considering the system boundary of a typical dairy farm (dairy cow, heifers, selling of surplus calves).

For system expansion the model predicted a 49% probability that the 6000 kg Fleckvieh-system generates lower GHG emissions per kg of milk than the 8000 kg Fleckvieh-system (Fig. 2). The probability that the 6000 kg Fleckvieh-system has lower GHG emissions per kg of milk than the 10,000 kg Holstein-Friesian-system exceeds 91% (Fig. 2). In contrast, the 10,000 kg Holstein-Friesian-system had higher GHG emissions per kg of milk than the 8000 kg Fleckvieh-system at each stage of probability (first degree stochastic dominance) (Fig. 2).

We found negative GHG emissions per kg of milk in 9% (8000 kg Fleckvieh-system) and in 13% (6000 kg Fleckvieh-system) of model iterations. In these cases, the avoided GHG emissions from suckler cow beef production were higher than the GHG emissions incurred by the dairy cow production system.

4. Discussion

4.1. Methods to handle co-products

We applied two methods to investigate the variation of GHG emission outcomes within different dairy cow production systems, i.e. "all GHGs to milk" and "system expansion". In both cases a comprehensive interpretation of results needs to consider the main model assumptions and system boundaries. The "all GHG to milk" method appears suitable for dairy farms to quantify GHG emissions and their variations at the farm level. Its results provide guidance for dairy farmers to reduce GHG emissions at the farm. As system expansion accounts for milk and beef production beyond the boundary of the dairy farm gate, its results are important for politicians and decision makers to evaluate GHG emissions of regional or global milk and beef production. Results are also important for defining GHG-abatement policies for both food production systems.

Our study shows the stark contrast between predictions of a model allocating all GHG emissions to milk (all GHGs to milk) and one using system expansion. While the first method emphasises increasing milk yield as an abatement option on the dairy-farm level, the second indicates that any beneficial effects of increasing milk yield might be negated by GHG emission leakage due to increase in beef production from suckler cow systems. Franks and Hadingham (2012) emphasise that prediction of GHG emissions that are restricted to the dairy farm gate can lead farmers to adopt GHG mitigation options that inadvertently increase global GHG emissions despite lowering farm emissions. Our study showed that dairy cow production systems are such an example, because varying milk yield per cow affects beef production; hence, predicted GHG emissions of the two models differ. Flysjö et al. (2011a) also, found that these methods for handling co-products yield different results: GHG emissions per kg of milk dropped by ≤37% when system expansion was used compared to all GHGs to milk. Mean GHG emissions in our study decreased 46–77% for system expansion in comparison to all GHGs to milk (Table 4). System expansion assumes that beef from dairy cow production systems (culled cows, fattening of surplus calves) is needed on the market and will replace beef from suckler cows (Flysjö et al., 2011a; Zehetmeier et al., 2012). However, it could also be assumed that beef from dairy cow production replaces pork or poultry meat which would lead to lower credits for beef output increasing the net GHG emissions of lower-yielding dairy cow production systems (Flysjö et al., 2011a). Furthermore, we did not distinguish between different qualities of beef. Whether beef from culled cows can be considered equal to beef from suckler cow production should continue to be discussed.

4.2. Variation in predicted GHG emissions and identification of most important variables

We identified a relatively small impact of variability uncertainty in production traits on variation in predicted GHG emissions within the dairy cow production systems investigated. For all GHGs to milk, variability uncertainty in replacement rate showed an impact on variation in predicted GHG emission outcomes. Variability in number of replacement heifers caused comparatively high variations in GHG emission outcomes. The impact of replacement rate was higher for production systems with lower-yielding cows due to higher variability in replacement rate (Table 3). Thus, farmers, especially those with lower-yielding herds, have a certain potential to mitigate GHG emissions by increasing the longevity of dairy cows. This finding agrees with Garnsworthy (2004), who concluded that in the UK a decrease in the number of heifers needed for replacement could decrease CH_4 emissions by 11% per herd compared to 1995 levels.

The impact of replacement was small in case of system expansion since the impact on GHG emissions due to changing numbers of heifers was compensated by changes in beef output from culled cows (GHG emission credit for avoided suckler cow beef production). For system expansion, variability uncertainty in calving interval showed an impact on variation in predicted GHG emission outcomes. Calving interval affects the number of calves available for bull, heifer and calf fattening and thus beef output/cow/year. Lower calving intervals and thus more calves/cow/year can be an option to reduce GHG emissions considering both milk and beef production. The potential of improvement is again higher within lower-yielding dairy cow production systems as surplus calves of lower-yielding Fleckvieh systems were assumed to have better fattening characteristics resulting in a higher beef output/cow/year and due to higher variability uncertainty in calving interval.

Regardless of the method used to handle co-products, higher-yielding dairy cow production systems showed lower impact of production traits on variation in predicted GHG emissions and thus less potential for GHG mitigation. This may indicate that within higher-yielding dairy cow production systems more focus is given to management resulting in lower variability in production traits among farms. A more narrow focus on herd management might decrease variability in production traits among lower-yielding farms.

Considering both epistemic uncertainty and variability uncertainties variation in predicted GHG emissions increased for all dairy cow production system. The emission factor of N_2O from N_{input} had the highest impact for all GHGs to milk and the second highest impact for system expansion on variation in predicted GHG emissions. This result is consistent with Flysjö et al. (2011b) and Basset-Mens et al. (2009), who found that this emission factor was one of the highest contributors to uncertainty in GHG emissions from milk production. Uncertainty in the N_2O N_{input} emission factor in our study mainly stemmed from model uncertainty in finding a precise way to predict N_2O emissions but also from inherent variability of N_2O emissions over time and space. Model uncertainty of N_2O N_{input} emission factor could be reduced if the location of dairy farms was specified and measurements or models for single fields were available. One approach to identify field specific N_2O emission factors in Germany is discussed by Dechow and Freibauer (2001). Dechow and Freibauer (2011) emphasize that demand on amount and quality of data is high and thus not often available for more specified models. However, this additional information does not reduce GHG emissions itself.

Furthermore, variability uncertainty due to temporal and spatial variability within and between dairy farms would remain. There is a high range of N_2O emission factors caused by field differences (e.g. type of soil and climate) (Jungkunst et al., 2006). Knowing site specific variability of N_2O emissions can, however, help to reduce GHG emissions by specific management (e.g. reduce soil compaction, adopted manure management, choice of suitable crops) (Dechow and Freibauer, 2011; Van Groenigen et al., 2008).

For system expansion, the high uncertainty in the emission factor for beef from suckler cow production explained 60–80% of the total variation in predicted GHG emissions and thus dominated uncertainty compared to all other input uncertainties. This high parameter uncertainty resulted from a lack of data about which suckler cow beef production system should be chosen to credit beef production from dairy cow production systems. Epistemic uncertainty in our model could be reduced if the origin and production system of suckler cow beef used to credit dairy cow beef were known, which requires knowing where beef would come from if it was not produced as a co-product from dairy cow production. These data are difficult to determine at a regional or international level.

It has to be considered that the contribution of single model parameters to variation in predicted GHG emissions depends strongly on the parameters included in uncertainty modelling. Epistemic uncertainty in emission factors for soybean meal due to direct land use change had a large impact on variation in predicted GHG emissions in other studies (Flysjö et al., 2012; Zehetmeier et al., 2012), but this was not included in our study. The type and amount of land use and land use changes due to changes in dairy and beef production will be the focus of further studies. Furthermore, feed conversion efficiency can be considered as an important source of variability uncertainty between dairy cows and farms (Henriksson et al., 2011) but was not investigated in this study.

4.3. Probability of predicted GHG emissions for dairy cow production systems

Our model showed high probability of occurrence that lower-yielding dairy cow production systems have higher GHG emission per kg of milk compared to higher-yielding systems when all GHGs were allocated to milk (10,000 kg Holstein-Friesian-system compared to 8000 kg Fleckvieh-system; 8000 kg Fleckvieh-system compared to 6000 kg FV-system). This result is important for dairy farmers who want to decrease GHG emissions per kg of milk, e.g. if a carbon tax on GHG emissions were introduced.

For system expansion, the 10,000 kg Holstein-Friesian-system had higher predicted GHG emissions than the 8000 kg FV-system and the 6000 kg FV-systems, with a probability of 100 and 91%, respectively. Variation in predicted GHG emissions within the Fleckvieh systems was high. And switch from a 8000 kg Fleckvieh-system to a 6000 kg Fleckvieh-system has a roughly equal probability of increasing or decreasing GHG emissions. At regional and global levels, results of system expansion should help politicians and decision makers to find appropriate measures to mitigate GHG emissions from milk and beef production. This result also shows that GHG abatement-policies (e.g. carbon taxes, agri-environmental policies) need to consider both milk and beef production systems to avoid leakages. However, it is important to point out that the advantages of “system expansion” are countered by the high degree of variation it gives to results.

5. Conclusions

Comparing GHG emissions of dairy cow production systems and exploring their potential of GHG emission leakage is a three-step process. First, to identify "hot spots" (i.e. parameters that contribute most to GHG emissions), methods such as "all GHGs to milk" should be used to calculate GHG emissions based on the system boundary of the dairy farm gate (Moran et al., 2011). In the second step, system expansion can be used to ensure that production systems with lower farm-gate GHG emissions do not inadvertently increase overall GHG emissions due to shift of GHG emissions to other food production sectors or countries (GHG emission leakage). In the third step, stochastic models are particularly useful because they provide insight into the robustness of model predictions (Pannell, 1997). This study demonstrates the importance of taking into account epistemic and variability uncertainties and one possibility of GHG emission leakage (i.e. shift of GHG emissions from dairy beef production to suckler beef production systems).

However, differences in milk yield are likely to lead to leakage effects not only in beef production, but also e.g. in land use. Future studies should explore additional leakage effects and epistemic and variability uncertainties, e.g. of feed intake, cattle fattening systems and manure management.

There is a big interest in quantifying carbon footprints. However, our study shows that current LCA methods are not very precise because of large epistemic and variability uncertainties. The implementation of a single carbon footprint for different dairy cow production systems is problematic because of these uncertainties but also due to various other environmental impacts (e.g. biodiversity, nitrogen leaching).

Acknowledgements

The corresponding author was supported by the Association for Technology and Structures in Agriculture (KTBL). LKV Bayern and LKV Weser-Ems provided data from dairy farms, Javier Baudracco helped prepare the manuscript and Andreas Böck assisted in the statistical analysis. The comments from three anonymous reviewers greatly improved the manuscript.

References

Basset-Mens, C., Kelliher, F.M., Ledgard, S., Cox, N., 2009. Uncertainty of global warming potential for milk production on a New Zealand farm and implications for decision making. Int. J. Life Cycle Assess. 14 (7), 630–638.
Bjorklund, A.E., 2002. Survey of approaches to improve reliability in LCA. Int. J. Life Cycle Assess. 7 (2), 64–72.
Bortz, J., Weber, R., 2005. Statistik für Human- und Sozialwissenschaftler, sixth ed. Springer Medizin, Heidelberg.
Brüggemann, D.H., 2011. Anpassungsmöglichkeiten der deutschen Rindermast an die Liberalisierung der Agrarmärkte. Sonderheft 345. vTI, Braunschweig, DE.
Capper, J.L., Cady, R.A., de Bauman, D.E., 2009. The environmental impact of dairy production: 1944 compared with 2007. J. Anim. Sci. 87 (6), 2160–2167.
Crosson, P., Shalloo, L., O'Brien, D., Lanigan, G.J., Foley, P.A., Boland, T.M., Kenny, D.A., 2011. A review of whole farm systems models of greenhouse gas emissions from beef and dairy cattle production systems. Anim. Feed Sci. Technol. 166-67 (SI), 29–45.
Dämmgen, U., Haenel, H.-D., Rösemann, C., Hutchings, J., Brade, W., Lebzien, P., 2009. Improved national calculation procedures to assess requirements, nitrogen and VS excretions of dairy cows in the German emission model GAS-EM. Landbauforsch 59 (3), 233–252.
De Cara, S., Houze, M., Jayet, P.-A., 2005. Methane and nitrous oxide emissions from agriculture in the EU: a spatial assessment of sources and abatement costs. Environ. Resour. Econ. 32, 551–583.
De Vries, M., de Boer, I.J.M., 2010. Comparing environmental impacts for livestock products: a review of life cycle assessments. Livest. Sci. 128 (1–3), 1–11.
Dechow, R., Freibauer, A., 2011. Assessment of German nitrous oxide emissions using empirical modelling approaches. Nutr. Cycl. Agroecosyst. 91 (3), 235–254.
Flysjö, A., Cederberg, C., Henriksson, M., Ledgard, S., 2011a. How does co-product handling affect the carbon footprint of milk? Case study of milk production in New Zealand and Sweden. Int. J. Life Cycle Assess. 16 (5), 420–430.
Flysjö, A., Henriksson, M., Cederberg, C., Ledgard, S., Englund, J.-E., 2011b. The impact of various parameters on the carbon footprint of milk production in New Zealand and Sweden. Agric. Syst. 104 (6), 459–469.
Flysjö, A., Cederberg, C., Henriksson, M., Ledgard, S., 2012. The interaction between milk and beef production and emissions from land use change - critical consideration in life cycle assessment and carbon footprint studies of milk. J. Clean. Prod. 28, 134–142.
Franks, J.R., Hadingham, B., 2012. Reducing greenhouse gas emissions from agriculture: avoiding trivial solutions to a global problem. Land Use Policy 29 (4), 727–736.
Garnsworthy, P.C., 2004. The environmental impact of fertility in dairy cows: a modelling approach to predict methane and ammonia emissions. Anim. Feed Sci. Technol. 112 (1–4), 211–223.
Gibbons, J.M., Ramsden, S.J., Blake, A., 2006. Modelling uncertainty in greenhouse gas emissions from UK agriculture at the farm level. Agric. Ecosyst. Environ. 112 (4), 347–355.
Henriksson, M., Flysjö, A., Cederberg, C., Swensson, C., 2011. Variation in carbon footprint of milk due to management differences between Swedish dairy farms. Animal 5 (9), 1474–1484.
Huijbregts, M.A., 1998. Application of uncertainty and variability in LCA: part I: a general framework for the analysis of uncertainty and variability in life cycle assessment. Int. J. Life Cycle Assess. 5 (3), 273–280.
IPCC, 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. In: Agriculture, Forestry and Other Land Use, vol. 4. Intergovernmental Panel on Climate Change, Paris, France.
IPCC, 2007. Climate change 2007. The physical science basis. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L. (Eds.), Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, USA, pp. 20–91.
ISO, 2006. Environmental Management – Life Cycle Assessment – Requirements and Guidelines. ISO, Geneva. ISO14044:2006(E).
Jentsch, W., Piatkowski, B., Schweigel, M., Derno, M., 2009. Quantitative results for methane production of cattle in Germany. Arch. für Tierz. – Archiv. Anim. Breed 52 (6), 587–592.
Jungkunst, H.F., Freibauer, A., Neufeldt, H., Bareth, G., 2006. Nitrous oxide emissions from agricultural land use in Germany – a synthesis of available annual field data. J. Plant Nutr. Soil Sci. 169 (3), 341–351.
Kirchgeßner, M., Windisch, W., Müller, H.L., 1995. Nutritional factors for the quantification of methane production. In: van Engelhardt, W., Leonhard-Marek, S., Breves, G., Giesecke, D. (Eds.), Ruminant Physiology: Digestion, Metabolism, Growth and Reproduction. Proceedings of the Eighth International Sysmposim on Ruminant Physiology. Ferdinand Enke Verlag, Berlin, pp. 333–351.
Knaus, W., 2009. Dairy cows trapped between performance demands and adaptability. J. Sci. Food Agric. 89 (7), 1107–1114.
Koenker, R., 2005. Quantile Regression. Cambridge U. Press, New York.
Kristensen, T., Mogensen, L., Knudsen, M.T., Hermansen, J.E., 2011. Effect of production system and farming strategy on greenhouse gas emissions from commercial dairy farms in a life cycle approach. Livest. Sci. 140 (1–3), 136–148.
Lee, H.-C., McCarl, B.A., Schneider, U.A., Chen, C.-C., 2004. Leakage and Comparative Advantage Implications of Agricultural Participation in Greenhouse Gas Emission Mitigation. Research Report, Department of Economics. University of Western Ontario. No. 2004–1.
Lesschen, J.P., van den Berg, M., Westhoek, H.J., Witzke, H.P., Oenema, O., 2011. Greenhouse gas emission profiles of European livestock sectors. Anim. Feed Sci. Technol. 166-67 (SI), 16–28.
Lovett, D.K., Shalloo, L., Dillon, P., O'Mara, F.P., 2006. A systems approach to quantify greenhouse gas fluxes from pastoral dairy production as affected by management regime. Agric. Syst. 88 (2–3), 156–179.
Lovett, D.K., Shalloo, L., Dillon, P., O'Mara, F.P., 2008. Greenhouse gas emissions from pastoral based dairying systems: the effect of uncertainty and management change under two contrasting production systems. Livestock Sci. 116 (1–3), 260–274.
Moran, D., Macleod, M., Wall, E., Eory, V., McVittie, A., Barnes, A., Rees, R., Topp, C.F.E., Moxey, A., 2011. Marginal abatement cost curves for UK agricultural greenhouse gas emissions. J. Agric. Econ. 62 (1), 93–118.
Morgan, G., Henrion, M., 2006. Uncertainty, eighth ed. Cambridge University Press, Cambridge.
Murray, K., Conner, M.M., 2009. Methods to quantify variable importance: implications for the analysis of noisy ecological data. Ecol 90 (5), 1425.
Mußhoff, O., Hirschauer, N., 2011. Modernes Agrarmanagement: Betriebswirtschaftliche Analyse und Planungsverfahren. Vahlen, second ed. Franz. München.
Nguyen, T.L., Hermansen, J.E., Mogensen, L., 2010. Environmental consequences of different beef production systems in the EU. J. Clean. Prod. 18 (8), 756–766.
O'Brien, D., Shalloo, L., Buckley, F., Horan, B., Grainger, C., Wallace, M., 2011. The effect of methodology on estimates of greenhouse gas emissions from grass-based dairy systems. Agric. Ecosyst. Environ. 141 (1–2), 39–48.
Pannell, D.J., 1997. Sensitivity analysis of normative economic models: theoretical framework and practical strategies. Agric. Econ. 16 (2), 139–152.
Roemer, A., 2011. Investigations on longevity in German Holstein cows. Arch. Anim. Breed. 83 (1), 8–20.
Thomassen, M.A., van Calker, K.J., Smits, M.C.J., Iepema, G.L., de Boer, I.J.M., 2008. Life cycle assessment of conventional and organic milk production in the Netherlands. Agric. Syst. 96 (1–3), 95–107.
Thomassen, M.A., Dolman, M.A., van Calker, K.J., de Boer, I.J.M., 2009. Relating life cycle assessment indicators to gross value added for Dutch dairy farms. Ecol. Econ. 68 (8–9), 2278–2284.

Van Groenigen, J.W., Schils, R.L.M., Verlthof, G.L., Kuikman, P.J., Oudendag, D.A., Oenem, O., 2008. Mitigation strategies for greenhouse gas emissions from animal production systems: synergy between measuring and modeling at different scales. Aust. J. Exp. Agric. 45, 46–53.
Van Middelaar, C.E., Cederberg, C., Vellinga, Th.V., Werf, H.M.G., Boer, I.J.M. De, 2013. Exploring variability in methods and data sensitivity in carbon footprints of feed ingredients. Int. J. Life Cycle Assess. 18 (4), 768–782.
Walker, W., Harremoes, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P., von Krayer Krauss, M., 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integr. Assess. 4 (1), 5–17.
Zehetmeier, M., Baudracco, J., Hoffmann, H., Heißenhuber, A., 2012. Does increasing milk yield reduce greenhouse gas emissions? A system approach. Animal 6 (1), 154–166.