Journal of Cleaner Production 234 (2019) 423–435

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

Understanding uncertainty in the carbon footprint of beef production

Alasdair J. Sykes*, Cairistiona F.E. Topp, Robert M. Rees

Scotland's Rural College, King's Buildings, West Mains Road, Edinburgh, EH9 3JG, UK

ARTICLE INFO

Article history:
Received 11 January 2019
Received in revised form
16 May 2019
Accepted 15 June 2019
Available online 19 June 2019

Handling Editor: Giovanni Baiocchi

Keywords:
Carbon footprint
Beef production
Livestock
Greenhouse gas
Uncertainty
Monte Carlo

ABSTRACT

Greenhouse gas (GHG) accounting models facilitate mitigation of emissions from livestock systems. Such models are approximations, and uncertainties in their output may stem from a) uncertainty or variability in input data, b) uncertainty resulting from model scope and allocation methods, or c) uncertainty in modelling approach used. While sources a) and b) vary depending on the modelled scenario, c), referred to as epistemic uncertainty, relates to the modelling process, and as such is inherent in the methodology used rather than the specific scenario. This study combines a farm-level model comprised of widely used GHG accounting methodologies with a typical northern hemisphere suckler beef production system, and employs Monte Carlo simulation to assess the sensitivity of the modelled GHG footprint to epistemic uncertainty in the model. Following a cradle-to-gate approach, an emissions intensity of 19.20 ± 2.49 kg CO_2-eq kg live weight^{-1} was estimated for the modelled system. The study also highlights a discrepancy of 8.3% between deterministically and stochastically calculated emissions; this results from skewness in key modelling coefficients, primarily those relating to nitrous oxide emissions. Sensitivity analysis showed coefficients relating to emissions of nitrous oxide from land and methane from enteric fermentation were most influential in the modelled uncertainty, though coefficients relating to livestock feed production also contributed substantially. In conducting a root-cause analysis of uncertainty in GHG accounting from beef production, this study makes a novel contribution to the literature surrounding uncertainty in livestock emissions modelling. Developers of GHG accounting methodologies may use these insights to focus efforts on refining the most influential elements of these approaches, while researchers applying the models should be aware of the associated uncertainty. The latter should be quantified and effectively communicated where these models are used to support policy decisions.

1. Introduction

Global livestock production is faced with the twin challenges of increasing productivity to meet demand and reducing emissions to meet climate commitments (Opio et al., 2013; OECD/FAO, 2017). Cattle production systems (i.e. beef and dairy) contribute almost three quarters to total livestock emissions (Caro et al., 2014) and are therefore under considerable scrutiny in many national greenhouse gas budgets (e.g. Moran et al., 2011; Schulte et al., 2012; Pellerin et al., 2013). Greenhouse gas (GHG) accounting models are important for understanding and quantifying emissions from complex livestock production systems (Opio et al., 2013). These tools provide a better understanding of emissions hotspots, and opportunities for mitigation. The models used differ in goal and scope; system-level life cycle assessments (e.g. Beauchemin et al., 2010), farm-level GHG accounting tools (e.g. Sykes et al., 2017), and national inventory assessments (e.g. Milne et al., 2014) are common implementations. While such models draw on common methodologies (e.g. IPCC, 2006), there is recognition that broad-brush approaches necessary in national-level assessments are often insufficient to facilitate detailed policy analysis of the heterogeneous livestock sector (Moran et al., 2011). As such, a requirement is growing for system-level assessments of GHG emissions from livestock systems, and scalable GHG accounting tools are increasingly sought to facilitate this on an ongoing basis (Hall et al., 2010; Macleod et al., 2017; CSA Wales, 2017).

However, livestock production systems are fundamentally complex, and limitations in the methodological ability of extant modelling approaches to accurately capture these intricacies represent a major challenge both to modellers (Röös and Nylinder, 2013) and those seeking to utilise such approaches for decision making (Milne et al., 2015). Accordingly, emissions models of livestock systems carry considerable uncertainty (e.g. Gibbons

* Corresponding author.
E-mail address: alasdair.sykes@sruc.ac.uk (A.J. Sykes).

https://doi.org/10.1016/j.jclepro.2019.06.171

et al., 2006; Lovett et al., 2008; Dudley et al., 2014; Zehetmeier et al., 2014), and (whether or not it is quantified) this has important implications for their use in decision-making.

Röös and Nylinder (2013) identify several areas which may contribute to uncertainty in the carbon footprint of a livestock system. Namely;

a) uncertainty or variability in input data,
b) uncertainty resulting from scenario choices such as scope and allocation method, and
c) uncertainty in modelling approach used to assess emissions from biological systems

Considering this range of sources, narrowing the focus to a specific category of uncertainty allows for more insightful analysis. Uncertainty in input data is likely to be considerably lower for a farm-level assessment than for a dataset which is intended to be nationally representative. It is also difficult to assess in a general sense, given variability in the source and provenance of input data between different assessments. Decisions relating to scope and allocation method are important at farm-level, and need to be highly transparent. The effects of inclusion/omission of emissions sinks and sources are also relatively well documented (e.g. Flysjö et al., 2012) and hence easy to assess, as are the impacts of different allocation methods (Nguyen et al., 2012). However, the modelling approach used to capture and quantify emissions from different sources remains a considerable challenge and source of uncertainty in both farm- and national-level GHG and LCA assessments (Röös and Nylinder, 2013). This is further exacerbated by the complexity of livestock systems, both biologically and in terms of interactivity between system components. Milne et al. (2014) provided considerable insight into this at a national level; however, the necessarily broad scope of national-level assessments means that results are not focused on a particular livestock product or system.

System-level GHG assessments have a demonstrable role, then, in understanding and mitigating greenhouse gas (GHG) emissions from livestock systems globally (e.g. Gerber et al., 2013). The extent to which these approaches differ from national-level assessments, and the role of livestock production systems in present and future food production and climate change mitigation means the requirement is present for a comprehensive analysis of the causes and impacts of uncertainty in farm-level GHG modelling of livestock production systems. As complex systems (Janzen et al., 2006) and major GHG contributors (Caro et al., 2014), cattle production systems are a useful case study.

Monte Carlo simulation has been identified as a highly appropriate technique for uncertainty assessment in livestock systems (Groen et al., 2017). Some previous approaches have used Monte Carlo to assess system-level uncertainty in beef production (Gibbons et al., 2006; Dudley et al., 2014) and dairy production (Lovett et al., 2008; Henriksson et al., 2011; Zehetmeier et al., 2014). This approach has also been the basis of national inventory-level uncertainty assessments (Karimi-Zindashty et al., 2012; Milne et al., 2014). The focus is typically on the final result, meaning limited interrogation of the data to determine the root causes of uncertainty is possible. However, these assays serve to highlight the wide uncertainty in the GHG intensity of beef production and the range of sources which contribute to uncertainty in the footprint. Milne et al. (2014) conducted a Monte Carlo-based uncertainty and sensitivity analysis of N_2O and CH_4 emissions modelled for the United Kingdom national GHG inventory. Based on the results of the sensitivity analysis, the authors showed that emission factors relating to N_2O land and CH_4 from enteric fermentation were key sources of uncertainty.

National-level assessments of agricultural emissions (e.g. Milne et al., 2014) also differ from farm-level footprints in the range of emissions sources they consider; indirect emissions from production in other sectors (e.g. agrochemicals) are not considered as agricultural emissions in national-level assessments, but are typically important in estimates of GHG emissions made with a production system focus. Given the impacts of uncertainty when interpreting model output, and the importance of beef production to GHG budgets at both national (Committee on Climate Change, 2010) and global scales (Caro et al., 2016), this study identifies the causes and impacts of uncertainty in the modelling process for a farm-level GHG footprint of UK beef production. Propagation of uncertainty in a complex modelled system can be convoluted and counter-intuitive; recognising this, this study employs Monte Carlo simulation to trace uncertainty propagation throughout a the GHG footprint of a beef system modelled at farm-level. The most sensitive parameters are identified, providing the basis for a discussion of a) improvement of farm-level GHG footprint modelling, and b) interpretation of model output by researchers and decision makers.

2. Methods

2.1. Study set-up

The model was designed as a system-focused carbon footprint of a beef production system, with a cradle-to-farmgate scope. In addition to production stock, all replacements and breeding stock, together with their respective feed, bedding and energy requirements, were accounted for. On-farm GHG sources were modelled: N_2O emissions from crop residues, fertiliser application and manure application and deposition; CH_4 from enteric fermentation and manure; CO_2 from diesel use. In addition, off-farm (embedded) GHG emissions were modelled from production of livestock feed, bedding, fertiliser, pesticide and electricity used as part of the modelled production system. The functional unit of the analysis was defined as one kg beef live weight (LW) at the farm gate (Fig. 1).

2.2. Modelled beef suckler system

The system chosen to form the basis of this study was designed as a spring calving, lowland 'rear-finish' suckler beef system producing 18–20 month finished cattle. Whilst suckler beef production systems in the United Kingdom are highly heterogeneous, such a system can nevertheless be deemed relatively typical (SAC, 2017). This system was selected from the array of such 'typical' systems because a) it is a fully integrated system, meaning that production of replacement stock and finishing of production stock takes place on the same enterprise, and b) it provides the opportunity to finish both heifers and steers. Both of these aspects allow the carbon footprint to focus entirely on one enterprise. This system was not intended to encompass the full breadth of production practices, but rather to provide a representative example with which to explore the study objectives.

Collated activity data from the 2016 Scottish Cattle and Sheep Enterprise Profitability Report (QMS, 2016) provided the basis for estimation of the herd parameters, whilst data from SAC (2017) was employed to estimate cattle live weights for the systems (Table 1).

The system was modelled as an annual snapshot, with all necessary replacement breeding animals produced within the modelled system. A common approach is to model an arbitrary herd size, often 100 suckler cows (e.g. Pelletier et al., 2010; Beauchemin et al., 2011), however, this study takes the approach of scaling the herd size to yield exactly one finishing animal at the farm gate. This renders the total footprint directly relatable to the

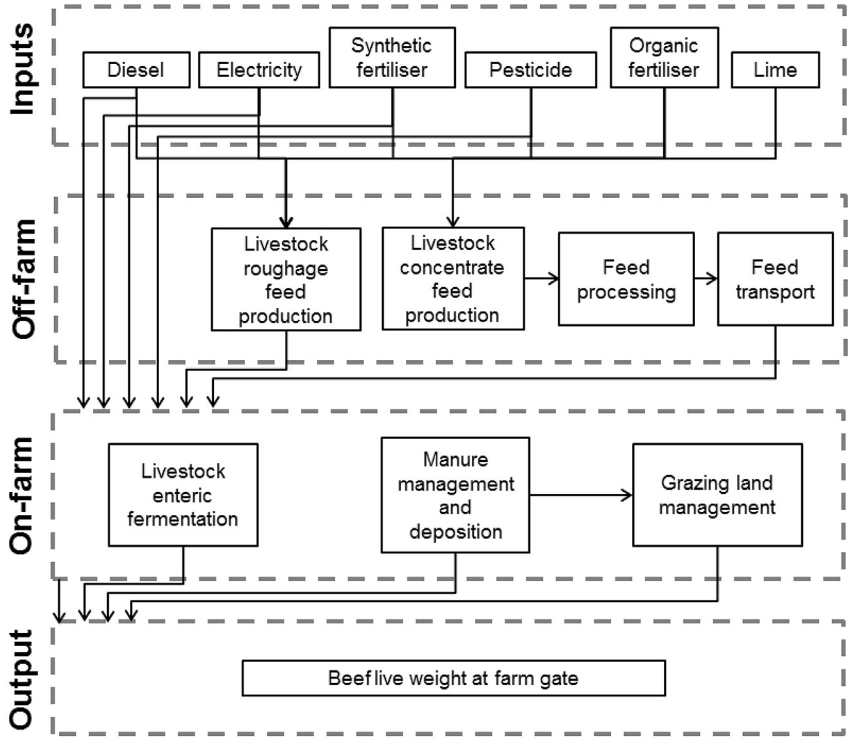

Fig. 1. System boundaries, emissions sources and process flows defined in the modelling approach.

Table 1
Activity data for the modelled beef suckler system.

Parameter	Units	Value	Source
Bulls per cow	n/a	0.0380	QMS (2016)
Calving percentage	% $year^{-1}$	88.5	QMS (2016)
Calf mortality	% $year^{-1}$	2.30	QMS (2016)
Cow repl. rate	% $year^{-1}$	12.0	QMS (2016)
Cow mortality	% $year^{-1}$	1.70	QMS (2016)
Other cattle mortality	% $year^{-1}$	0.70	SAC (2017)
Milk production	litres hd^{-1} $year^{-1}$	2200	SAC (2017)
Suckler cow adult live weight	kg	670	SAC (2017)
Bull adult live weight	kg	1250	SAC (2017)

production output. Table 2 details the numbers and class categories for animals in the modelled system.

Diets for production and replacement animals were defined in the model according to sample data from Morgan and Vickers (2016), HCC Wales (2006) and SAC Consulting (Karen Stewart, pers. comm.). Daily ration quantities were adjusted to reflect class-specific energy requirements, calculated using equations from Dong et al. (2006). Fed rations, in kg hd^{-1} day^{-1}, are presented in Table 3. Based on system descriptions from SAC (2017), animals were assumed to spend 7 months at grass vs. five months housed, with manure in solid storage for the housed period. Dietary digestible energy (DE%) and crude protein content (CP%) were calculated based on data from INRA (2012) to reflect the individual dietary composition. Emissions from the total feed requirements of the beef system were included within the modelled scenario (see 2.3.6).

The modelled pasture area received 150 kg N ha^{-1} $year^{-1}$ and

Table 2
Numbers, weights and performance for animal classes in the modelled system. Numbers are scaled to produce one finishing animal at the farm gate, accounting for mortality and replacement of breeding stock.

	Class	Age (months)	Number (head)	Period duration (days)	Weights (kg)			Daily live weight gain (kg)
					Start	End	Av.	
Breeding stock	**Heifer calf (suckling)**	0–7	0.171	212	40	240	140	0.94
	Heifer calf (weaned)	8–12	0.167	153	240	367	304	0.83
	Replacement heifer	13–24	0.166	365	367	670	519	0.83
	Suckler cow without calf	Mature	0.159	365	670	670	670	0.00
	Suckler cow with calf	Mature	1.222	365	670	670	670	0.00
	Bull calf	0–12	0.014	365	40	444	242	1.10
	Young bull	13–24	0.013	365	444	847	645	1.10
	Young bull	25–36	0.013	365	847	1250	1048	1.10
	Mature bull	Mature	0.052	365	1250	1250	1250	0.00
Production stock	**Finishing calf (suckling)**	0–7	1.038	212	40	260	150	1.04
	Finishing calf (weaned)	8–12	1.014	153	260	390	325	0.85
	Finisher	13–19	1.007	212	390	600	495	0.99

Table 3
Fed rations (in kg FW hd^{-1} day^{-1}) for the different livestock classes. The system was spring calving, meaning suckling calves and finishing animals from 13 to 19 months were at pasture and did not require fed rations. All other classes spent 5 months (153 days) housed.

	Age (months)	Straw	Hay	Grass silage	Barley	Rape meal	Distillers' pellets	Maize gluten	Beef concentrate feed	Sugar beet pulp
		kg fresh weight $head^{-1}$ day^{-1}								
Heifer calf (weaned)	8–12	2.2	–	10.1	–	–	–	2.0	1.1	0.8
Replacement heifer	13–24	2.7	–	12.4	–	–	–	2.5	1.3	1.0
Suckler cow w/o calf	Mature	1.6	2.1	5.0	0.2	0.3	0.5	0.6	–	0.4
Suckler cow with calf	Mature	2.1	2.7	6.6	0.3	0.4	0.7	0.8	–	0.6
Bull calf	0–12	1.8	–	8.3	–	–	–	1.6	0.9	0.7
Young bull	13–24	3.4	–	15.7	–	–	–	3.1	1.6	1.3
Young bull	25–36	–	6.5	25.6	–	–	4.7	–	1.3	–
Manure bull	Mature	–	3.8	15.1	–	–	2.8	–	0.8	–
Finishing calf (weaned)	8–12	2.1	–	9.8	–	–	–	1.9	1.0	0.8

was assigned a 7-year renovation period; whilst rates of fertiliser application and pasture renovation vary, these represent typical median values for lowland pasture in the United Kingdom (SAC, 2017). Based on this application rate and data from SAC (2017), pasture was estimated to produce 8740 kg DM ha^{-1}. Calculated grazing energy requirements (based on Dong et al., 2006), were used deterministically to define pasture dry matter (DM) requirements and allocation between classes; 0.65 ha was required to support production of one finished animal, with associated breeding stock. As a spring calving system, calves were suckled entirely at pasture; calculated energy provision from lactating cows was used to scale additional grazing requirements for suckling calves.

The quantity of manure produced by the cattle during the housed period was calculated according to energy calculations from Dong et al. (2006). Typical values of 25% and 0.012% (Defra, 2010) were employed for manure dry matter content and available N respectively, which resulted in an estimated 5.53 kg of available manure N per year. For a fixed pasture area of 0.65 ha, this equated to an application rate of 8.55 kg N ha^{-1} to the grazing land. The remaining nitrogen requirements of the land (141.45 kg ha^{-1}) were supplied by the application of 91.59 kg of synthetic NPK fertiliser, also supplying the phosphorus and potassium requirements of the grassland. Herbicide was modelled as being applied to pasture at a national average rate of 1.08 kg active substance ha^{-1} (Garthwaite et al., 2013). Electricity and diesel use by the enterprise was estimated at 30 kWh hd^{-1} $year^{-1}$ and 10 L hd^{-1} $year^{-1}$ respectively (SAC, 2017).

Allocation of emissions between cull and finishing animals was handled economically, as in PAS2050 (BSI, 2011), using market data from SAC (2017). The functional unit of the simulation was defined as 1 kg of live weight (LW) at the farm gate.

2.3. Modelling approach and uncertainty analyses

The farm-level footprinting model AgRE Calc (SRUC, 2014) was used to provide a footprint estimate for the modelled beef system. The base model is PAS 2050 certified (BSI, 2011); full details of model functionality are given in Sykes et al. (2017), and details specific to this study (related to characterisation of uncertainty in the modelled system) are summarised here. It was first necessary, however, to make a distinction between the sources of uncertainty in the model.

Uncertainty can stem from variability (e.g. temporal, spatial) in natural and managed systems; this may to some extent be mitigatable through management practices, but (once scope is defined) cannot be reduced by the modelling approach. The remaining uncertainty can be classified as epistemic (Groen et al., 2017), and is fundamentally derived from lack of understanding of, or ability to capture the intricacies of complex biological systems.

This study was designed to assess epistemic uncertainty relating to the beef production system as modelled at farm level. In this sense, a great deal of uncertainty derived from natural variability is represented as epistemic uncertainty, given that the emission factors used to calculate the footprint do not account for spatially or temporally variable factors (such as climate). As such, uncertainties in modelling coefficients are designed to encompass geographical and temporal variation in emissions.

Aside from natural variability, and depending on the scope of the assessment, variation in production practices means that input data for any modelled real-world production system is likely to exhibit some uncertainty. This may be of considerable importance in the overall model (e.g. Dudley et al., 2014), but its nature and magnitude is likely to be relatively situation-specific, and hence non-generalisable. Accordingly, input data for the modelled system is treated as certain; in doing this, the remaining uncertainty, which represents the epistemic uncertainty in a greenhouse gas model of a suckler beef production system, is isolated. Thus defined, this category of uncertainty forms the basis of this assessment. The following sections describe the characterisation of this modelling uncertainty within the AgRE Calc model.

ModelRisk (Vose Software) was incorporated into the AgRE Calc model to provide Monte Carlo functionality. Utilising the input data described above, the model was calculated for one annual timestep. The model was run both deterministically, using best estimate values for the coefficients, and a MCS of 10,000 repeats (Mersenne seed = 2605) was conducted, which formed the basis for the uncertainty assessment.

The following sections describe the rationale used in the derivation of uncertainty estimates for modelling parameters. To minimise the impact of additive uncertainty reduction (Röös and Nylinder, 2013), this study followed the approach of aggregation where possible; only one iteration of each stochastic coefficient is used in the simulation The full set of coefficients, uncertainties and sources is presented in the supplementary information (Table S1).

2.3.1. CH_4 from livestock and manure

Data characterising uncertainty relating to the IPCC Tier 2 methodology (Dong et al., 2006) was used to quantify uncertainty in CH_4 emissions from livestock. These data typically took the form of best, minimum and maximum estimates. Where these distributions were not skewed around the mean, it was deemed appropriate to employ a normal (Gaussian) distribution to characterise these coefficients. Milne et al. (2014) also followed this approach using data from Penman et al. (2000); the authors chose to interpret the min-max range as a 95% CI to allow the use of an unbounded distribution, and the same approach was followed here.

2.3.2. N_2O and CO_2 from managed soils

Emissions of N_2O and CO_2 from soils were calculated using an IPCC (2006) Tier 1 approach. Uncertainties for these emissions were characterised using data from de Klein et al. (2006).[1] All Tier 1 N_2O emission factors (designated $EF_{1,\ 2,\ etc.}$) show a positive (right-tailed) skew. This reflects the pattern typically observed in measurement of N_2O emissions (e.g. Rees et al., 2012). Previously, some authors (e.g. Milne et al., 2014) have chosen to characterise this using a lognormal distribution, whilst others (e.g. Gibbons et al., 2006) have used triangular distributions.

Uncertainty statistics were presented for N_2O in the form of a best estimate with minimum and maximum bounds (de Klein et al., 2006; Dong et al., 2006). Whilst the triangular distribution is more straightforward to parameterise with these data, the increased weight this type of probability density function (PDF) puts on the distribution 'tails' can lead to under-representation of the best estimate in the Monte Carlo analysis, and subsequently to systematic bias where the distributions are skewed. It was therefore decided to follow the approach of Milne et al. (2014) and to utilise a lognormal distribution to represent uncertainty associated with N_2O emission factors.

The IPCC methodology for the calculation of N_2O emissions from soils and manure systems also include other coefficients, in addition to direct emission factors ($EF_{1,\ 2,\ etc.}$). These coefficients are associated with the processes leading to the indirect emission of N_2O (namely volatilisation and leaching) and denote the fractions of N from a particular pool which are transported by these processes (Dong et al., 2006; de Klein et al., 2006).

Uncertainty statistics are presented for these coefficients in the form of a best estimate and range, as above. However, given that these coefficients do not represent the emission of N_2O (but rather the processes which lead to this), there is no theoretical justification for reconciling these values to a lognormal distribution. The given minimum and maximum values also exhibit highly variable skew between coefficients, suggesting that an unskewed distribution would not be appropriate. Milne et al. (2014) applied a Beta distribution to these coefficients, and a similar approach was chosen here.

The PERT distribution (also called Beta PERT) is a derivative of the Beta distribution, and is designed specifically for the purpose of modelling expert estimates (Clark, 1962). As such, it follows the basic format of a Beta distribution, but employs a best, minimum and maximum estimate as distribution parameters. It was chosen as it represents an advantage over the simpler triangular distribution through lower weighting of the distribution 'tails', and hence lower likelihood of systematic error where distributions are skewed. A PERT distribution was also deemed most appropriate for EFs denoting CO_2 emissions as a fraction of applied lime and urea.

2.3.3. Crude protein and digestible energy

Dietary digestible energy (DE%) and crude protein content (CP%) are required inputs for the IPCC Tier 2 calculation of enteric CH_4, manure CH_4 and manure N_2O (Dong et al., 2006). Digestible energy directly impacts enteric CH_4 emissions and manure production quantity (which in turn impacts emissions of manure CH_4 and N_2O); dietary CP% scales manure nitrogen content, which directly scales N_2O emissions.

Feedipedia (INRA, 2012) was used to supply estimates of the standard deviation for the DE% and CP% of fed rations by individual ration component. There was no evidence to suggest that skew existed in any of the dietary parameters, and so a normal distribution was employed to characterise these. The DE, CP and DM parameters are employed in the modelling process as percentages (DE as a % of GE, CP as a % of DM, DM as a % of fresh weight) and so the distributions were bounded at 0 and 100% to ensure stochastically sampled values would remain within this boundary.

2.3.4. Production of agrochemicals

Emissions from production of fertilisers were characterised in the model using emission factors, specific to western Europe (Kool et al., 2012). The authors also supplied an estimated minimum and maximum value for each EF; given variable direction of skew, a Beta PERT distribution was chosen to characterise these. Pasture in the modelled system was treated with NPK fertiliser with an embedded emission factor of parameters $min = 3.05$, $B.E. = 5.62$, $max = 7.27$ kg CO_2-eq kg N^{-1}.

For the production of herbicides, AgRE Calc utilises mean emission factors calculated from data provided by Audsley et al. (2014). To estimate uncertainty in the emission factor for herbicide applied to pasture, the range of the Audsley et al. (2014) dataset for herbicides was used to provide a minimum and maximum emission factor estimate. Given the relatively small size of the dataset ($N = 37$), a limited amount could be inferred about the shape of the distribution; as such, a uniform distribution of parameters $min = 7.38$, $max = 47.68$ kg CO_2-eq (kg active ingredient)$^{-1}$ was defined for herbicide production.

2.3.5. Emissions from fuel and electricity

For emissions from electricity production, AgRE Calc makes use of emission factors provided by GHG Protocol (2012). This database does not provide a *de facto* estimate of uncertainty in the emission factors provided, so the range of values given for emission factors from 2000–2012 was employed to provide an estimate of variability. A Beta PERT distribution of parameters $min = 0.44$, $B.E. = 0.48$, $max = 0.51$ was therefore employed to characterise uncertainty in electricity production, with the best estimate (B. E.) corresponding to the most recent (2012) emission factor.

For emissions from diesel use, a similar approach was followed, utilising EFs from the DEFRA/DECC (2015) Conversion Factors for Company Reporting. For the best estimate, the 2015 EF was utilised, with uncertainty stemming from the range 2012–2015. This resulted in a Beta PERT distribution of parameters $min = 3.14$, $B.E. = 3.17$, $max = 3.25$ kg CO_2-eq litre^{-1}.

2.3.6. Production of livestock feeds

All of the fed ration was modelled as being produced off-farm; whilst some feeds, particularly roughage, would typically be produced on-farm, this approach ensured the use of nationally representative production practices while avoiding biasing the estimate through adherence to a farm-specific production strategy, and allowed uncertainty in feed production practices to be accounted for. To reflect the fact that roughage would typically be produced on-farm, transport emissions for roughage feeds were excluded from the footprinting process. As discussed in the introduction to this section, where variability in production practices takes place outside the modelled system (i.e. in the production of imported livestock feed), this would be treated as an epistemic uncertainty with respect to the production system in question.

Nitrous oxide emissions from crop residues, fertiliser application, and manure application were modelled, as in AgRE Calc, using emission factors and uncertainties from de Klein et al. (2006).

[1] The United Kingdom has recently developed a Tier 2-level methodology for this emissions source (Chadwick et al., 2016), reducing epistemic uncertainty associated with this variable. However, this was not available during the development of this modelling approach.

Carbon dioxide emissions from lime and urea were calculated according to the same methodology (see 2.3.2). Emissions from electricity, fuel and agrochemical use were calculated using the same sources as AgRE Calc (see 2.3.4, 2.3.5). Note that for electricity and agrochemicals, the country of production impacts the choice of emission factor; this is of more consequence for imported feeds, which may be produced outside of the UK.

Activity data was sourced for cereal production (Marinussen et al., 2012b), production of oil seeds (Marinussen et al., 2012d), and production of roughages (Marinussen et al., 2012c). Activity data from this source was also used for estimation of emissions from feed processing (Marinussen et al., 2012a; Marinussen et al., 2012e; Marinussen et al., 2012f). This includes estimates of uncertainty for cultivation parameters (primarily yield, agrochemical application rates, and processing inputs), which were incorporated into the Monte Carlo simulation. The components of some feeds, particularly concentrates, were produced outside of the UK. Where country of production or processing was variable, this was accounted for, and was modelled as a stochastic element in the simulation.

3. Results

3.1. Simulation results and uncertainty analysis

The simulated system produced a total of 12.2 (10.0–15.1) tonnes CO_2-eq annually.[2] Total production output was 1 finished steer sold for slaughter, at an average live weight of 600 kg, and cull beef at 0.07 head of cull cows and 0.013 head of cull bulls, equating to 64 kg of LW. Of the total live weight produced by the system, 90.4% was finished beef and 9.6% was cull beef.

Calculated deterministically, the emissions intensity of the beef production system as a whole was estimated at 17.7 kg CO_2-eq kg LW^{-1}. Calculated stochastically, the mean production emissions intensity was higher at 19.2 (15.7–23.7) kg CO_2-eq kg LW^{-1}, as the distribution of the stochastically calculated results was positively skewed (*skew* = 0.95) (Fig. 2).

Breaking down the system emissions into source categories (Fig. 3), the emissions intensity of production for the system was found to be dominated by CH_4 emissions from enteric fermentation, which accounted for 48.3% of the deterministic total and 44.9% of the stochastic total. The three largest categories (enteric fermentation, feed production and manure deposition) between them accounted for 84% of the total footprint. Methane (from manure and enteric fermentation) accounted for just under half of total emissions (in CO_2-eq), whilst N_2O accounted for approximately one third (Fig. 3).

Contribution to the overall uncertainty in the emissions total varied considerably by emissions type (Fig. 4). Nitrous oxide emissions were most variable despite being lower in magnitude than CH_4 emissions. Embedded emissions showed similar uncertainty to CH_4 emissions, though both N_2O and embedded emissions showed a strong positive skew. Methane emissions were relatively unskewed.

A breakdown of the components of the footprint highlights the discrepancies between the deterministically and stochastically calculated estimates (Table 4). Emissions from the system as a whole demonstrate considerable positive skew, meaning that the modelled mean emissions are 8.3% higher than the deterministically calculated estimate. The breakdown of this value into component emission sources shows that this positive skew stems from emissions of N_2O; emission factors for these components of the footprint were modelled to follow a lognormal distribution. Mean emissions of N_2O are 20–40% higher for the stochastically modelled system in comparison to the deterministic estimate.

By contrast, CH_4 emissions from enteric fermentation and manure storage are unskewed, and the stochastically calculated mean did not differ systematically from the deterministic estimate. Uncertainties as a fraction of the mean were lower for CH_4 emissions in comparison to N_2O, but greater quantities of CH_4 meant that overall these uncertainties were of a similar absolute magnitude. Emissions from production of feed showed significant uncertainty and a positive skew, whilst fertiliser production emissions were negatively skewed, rendering the calculated mean lower than the deterministic estimate. Uncertainty in fertiliser production emissions was low in comparison to other sources, however. Emissions from fuel and electricity use made relatively small contributions to the overall EI and uncertainty, and were not skewed.

3.2. Sensitivity analysis of system emissions intensity

A sensitivity analysis identified a total of 76 coefficients and emissions factors (with associated probability distributions) which impacted the result of the stochastic model calculations. These coefficients, together with their distributions, descriptions and sources, are presented in the supplementary information (Table S1).

Providing an initial assessment of the propagation of uncertainty through the model as a whole, Fig. 5 shows the influence on conditional mean emissions intensity of coefficients ranked in order of influence. The variation in sensitivity of the conditional mean to a coefficient derives jointly from a) the role of the coefficient in the model, and b) the uncertainty surrounding it. The vast majority of the uncertainty in the modelled emissions intensity is derived from uncertainty in 10–15 coefficients (Fig. 5); for coefficients ranked lower than this, the impact on the conditional mean levels off at < 0.5 kg CO_2-eq kg LW^{-1}. As such, these coefficients represent the 'low-hanging fruit' in terms of improving the ability of the model to accurately and precisely predict emissions from livestock production.

Based on this initial assessment, the impact of the fifteen most important coefficients in terms of contribution to modelled uncertainty were analysed in greater detail. Coefficients were aggregated where necessary to avoid multiple iterations of a similar parameter in the analyses, and the conditional mean for the aggregated coefficients plotted over a 90% confidence interval. Accordingly, the resulting 'tornado plot' shows the impact of each of the 15 highest ranked coefficients on the calculated conditional mean emissions intensity (Fig. 6 and Table 5). Together, these coefficients explained 77.9% of the variability in the stochastically calculated emissions intensity for the modelled system.

A significant proportion of the coefficients to which the modelled scenario was most sensitive were direct emission factors for N_2O (Fig. 6, Table 5). Nitrous oxide made up only 29.8% of the footprint; less than CH_4 and only slightly more than embedded emissions (Fig. 3), though it is also worth noting that a significant proportion of embedded emissions in feed and bedding was N_2O. The positive skew observed in the final result, and to a large extent the discrepancy between the deterministically and stochastically modelled emissions intensities, can be explained by the strong influence of these variables.

Uncertainties in the IPCC Tier 2 energy calculations for livestock

[2] Note that due to the nature of the modelled system, some systematic discrepancy was evident between deterministically and stochastically calculated values. In the following section, unless otherwise specified, quoted values refer to stochastically calculated results. Where distributions are skewed, the uncertainty ranges, reported in parentheses, represent the 5–95% confidence interval. Unskewed distributions are reported ±1 standard deviation.

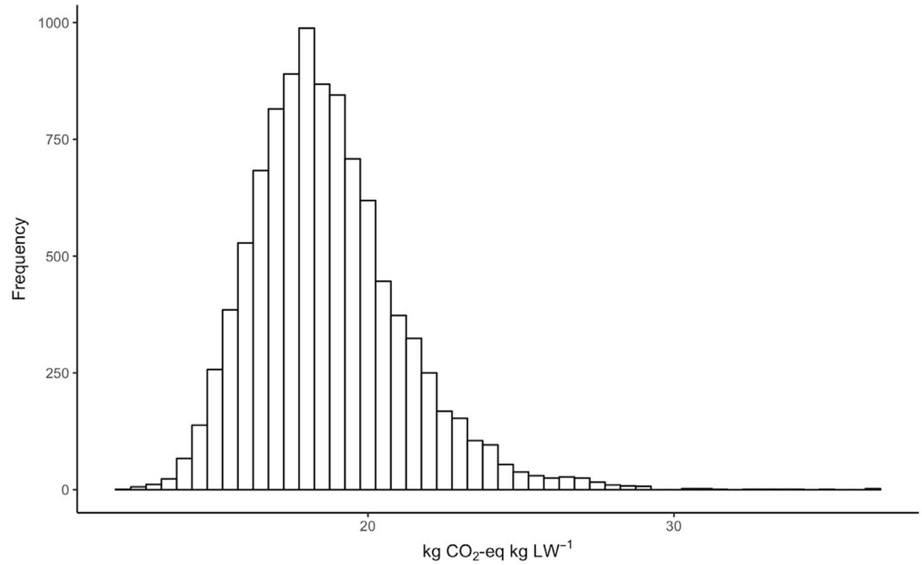

Fig. 2. Histogram showing distribution of stochastically calculated emissions intensity for the modelled system. Total frequency = 10,000. Note that the distribution exhibits a positive skew (*skewness* = 0.95), leading to the difference between the deterministically estimated E.I. (17.73) and stochastically calculated mean (19.20).

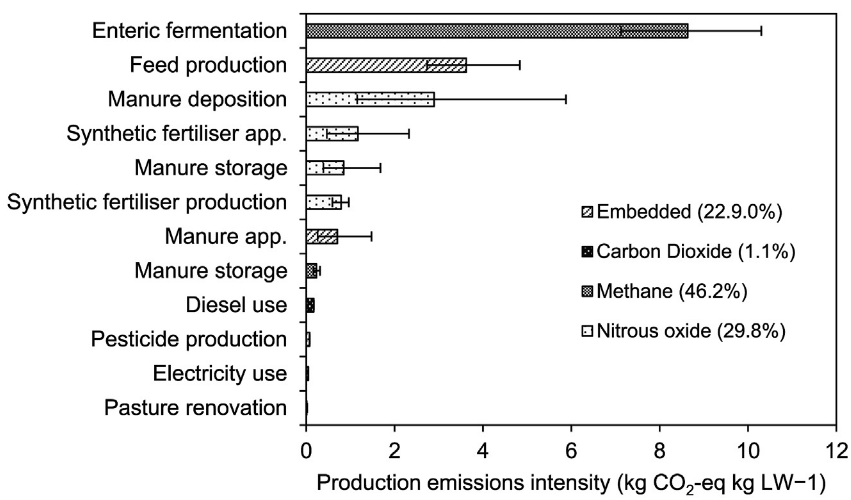

Fig. 3. Breakdown of the total emissions intensity estimate (calculated stochastically) to the level of individual emissions sources. Error bars indicate 5–95% *CI* for each source, calculated via Monte Carlo simulation. Asymmetry in the 5–95% *CI* results from skewness in the modelled uncertainties, primarily for N_2O emissions. Total % breakdown by gas (for mean values) is given in parentheses in the legend.

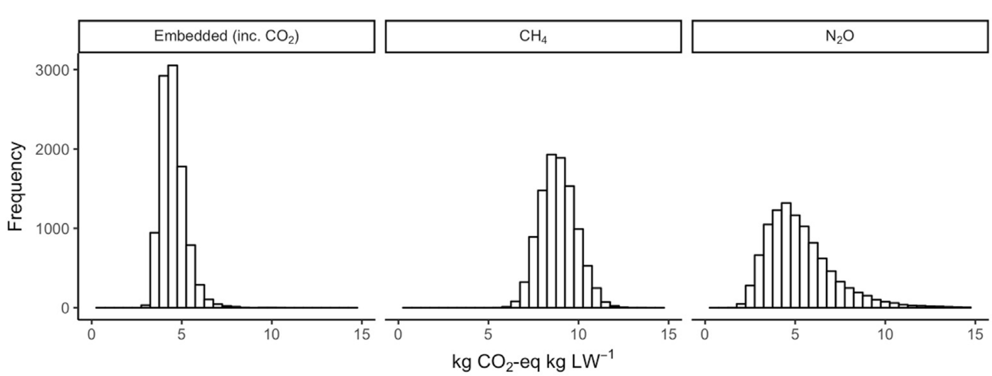

Fig. 4. Histograms showing uncertainty and distribution for different emissions types. Total frequency = 10,000. Note that CO_2 emission factors for diesel use are incorporated into the embedded emissions estimate due to their small overall magnitude and variability.

Table 4
Breakdown of emissions estimates into source categories based on deterministic and stochastic calculation approaches.

		Deterministic model output (kg CO_2-eq kg LW^{-1})	Stochastic model output (kg CO_2-eq kg LW^{-1})				% discrepancy (deterministic -stochastic)
					Confidence interval		
			Mean	St. dev.	5%	95%	
Pasture renovation	N_2O	0.01	0.01	0.01	0.00	0.02	−32.1%
Fertiliser application	N_2O	0.88	1.17	0.66	0.47	2.33	−33.4%
Manure application	N_2O	0.49	0.70	0.41	0.26	1.48	−43.6%
Manure storage	N_2O	0.69	0.85	0.48	0.39	1.68	−23.0%
Manure deposition	N_2O	2.23	2.90	1.55	1.15	5.88	−30.1%
Enteric fermentation	CH_4	8.56	8.63	0.97	7.13	10.30	−0.8%
Manure storage	CH_4	0.23	0.23	0.05	0.16	0.31	−2.3%
Diesel use	CO_2	0.08	0.08	0.00	0.07	0.08	0.4%
Electricity use	CO_2	0.17	0.17	0.00	0.17	0.17	−0.4%
Fertiliser embedded	CO_2-eq	0.81	0.79	0.11	0.59	0.96	2.7%
Feed/bedding embedded	CO_2-eq	3.54	3.62	0.68	2.74	4.84	−2.3%
Pesticides embedded	CO_2-eq	0.05	0.05	0.00	0.05	0.05	0.0%
Total system emissions intensity	CO_2-eq	17.73	19.20	2.49	15.69	23.70	−8.3%

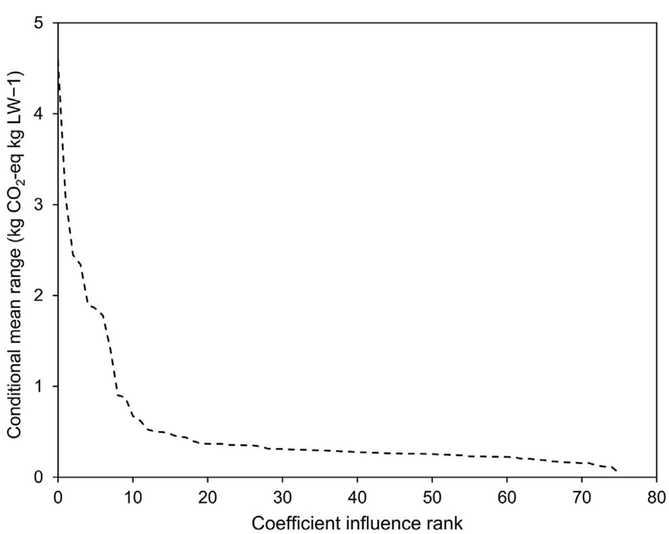

Fig. 5. Scree-type plot showing conditional mean range (production emissions intensity, in kg CO_2-eq kg LW^{-1}) plotted against sensitivity ranking for disaggregated coefficients.

(Dong et al., 2006) also contributed significantly to the footprint uncertainty. The calculated energy requirements of livestock are used in the calculations to estimate the gross energy intake of each class, which impacts the resulting enteric CH_4 emissions and manure production. The parameter in this calculation to which the model was most sensitive was Cf_i, a coefficient denoting the estimated maintenance net energy (NE_m) requirements of different livestock classes. A number of additional components of this calculation (NE_p, NE_a) are scaled by the calculated NE_m, which contributes to the influence of this coefficient. The coefficient C_a, which scales the calculation of net energy for activity (NE_a), is also influential in the modelled uncertainty (Fig. 6).

The coefficient Y_m also forms part of this calculation, and represents the percentage of gross energy which will be converted to enteric CH_4. Given the relatively high uncertainty in this coefficient, and the direct relationship it has with enteric CH_4 emissions, it is unsurprisingly important in its contribution to modelling uncertainty.

Coefficients relating to manure production, such as the CP% (crude protein %) and GE (gross energy) of grazing also showed an important impact on the footprint (Fig. 6). CP% directly scales the modelled nitrogen content of manure, which itself impacts N_2O emissions from manure storage, spread and deposition on grazing land. The gross energy content of the diet is a coefficient which permits calculation of the dry matter (DM) intake from calculated gross energy requirements; this in turn impacts modelled manure production and resulting CH_4 and N_2O emissions.

Emissions from off-farm feed production formed the second largest emissions source and the fifth largest source of uncertainty of the carbon footprint of beef production for the modelled system. Assessment of the drivers behind uncertainty in this component of the footprint is complex, as the embedded emissions of production were modelled separately. To simplify the sensitivity analysis, separate emission factors were aggregated into a weighted average for assessment in Fig. 6. Calculated stochastically, the average emission factor per kg of feed fresh weight (FW), weighted to reflect the overall ration composition, was 360.9 ± 114.5 g CO_2-eq kg FW^{-1}.

The modelling approach assumed fixed quantities of feed, but accounted for uncertainty in modelled emissions and cultivation practices. Further analysis of the drivers behind the uncertainty in the average EF shows that emissions from production of concentrate feeds (e.g. maize gluten, concentrates) were among the largest per kg of feed, and also showed some of the highest uncertainties (Fig. 7). Given the high proportion of silage in the diet, however, emissions from off-farm silage production represented the largest source of feed-production emissions, and the largest uncertainty. Silage has a low DM fraction in respect of other feedstuffs, meaning the water content and emission factor per kg FW is lower, but its inclusion as FW in the diet is higher in comparison to drier roughages.

Of the non-roughage feeds, lowest emission factors and uncertainties were shown by byproduct-based feeds such as sugar beet pulp and distillers' pellets (Fig. 7). In these cases, cultivation emissions were allocated to the primary co-products (sugar and alcohol respectively), meaning that remaining emissions (and accompanying uncertainty) stemmed solely from the processing and transport sectors. This is the approach employed by Vellinga et al. (2013), and is justified by economic allocation; the

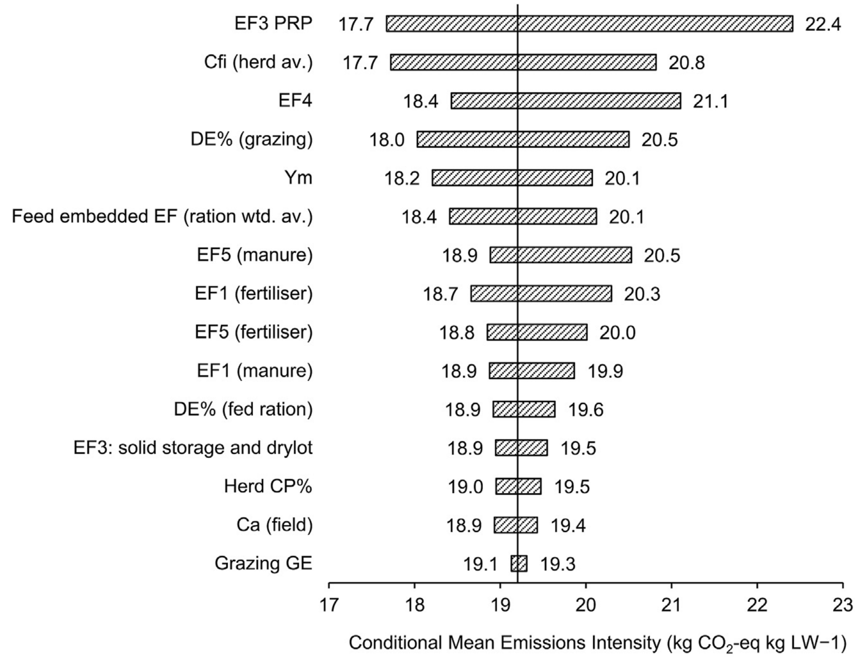

Fig. 6. Tornado plot presenting the impact of the 15 most influential modelling uncertainties on the calculated mean emissions intensity. Conditional mean is given to 90% confidence interval (i.e. 5–95%). The y-axis intersects at the calculated mean emissions intensity (19.2 kg CO_2-eq kg LW−1). See Table 5 for coefficient definitions.

Table 5
Values and descriptions for most influential modelling uncertainties in the calculated production emissions intensity for the modelled beef system.

Emission type(s)	Parameter	Distribution type	Mean ± std. dev.	Description
N_2O	EF_{3PRP}	Lognormal	0.0236 ± 0.0143	Fraction of nitrogen in manure deposited by livestock on grazing ground which is directly emitted as N_2O
CH_4/N_2O	Cf_i (herd mean)[a]	Normal	0.322 ± 0.050	Net energy for maintenance (NE_m) required by livestock, in MJ kg LW^{-1} day^{-1}
N_2O	EF_4	Lognormal	0.0140 ± 0.0136	Fraction of volatilised nitrogen from manure deposited/spread on grazing land emitted as N_2O
CH_4/N_2O	DE% (grazing)	Calculated	71.0 ± 4.0	Digestible energy content of the grazed diet, as a % of GE
Embedded	Feed embedded EF (ration mean)	Calculated	707 ± 274	Weighted average embedded emission factor for purchased livestock feed, in g CO_2-eq kg FW^{-1}
N_2O	EF_5 (manure)	Lognormal	0.0123 ± 0.0162	Fraction of leached nitrogen from manure deposited/spread on grazing land emitted as N_2O
CH_4	Y_m	Normal	6.50 ± 0.51	Enteric CH_4 emission factor for all cattle, % of gross energy intake released as CH_4
N_2O	EF_1 (fertiliser)	Lognormal	0.0121 ± 0.0077	Fraction of nitrogen in applied synthetic fertiliser which is directly emitted as N_2O
N_2O	EF_1 (manure)	Lognormal	0.0121 ± 0.0077	Fraction of nitrogen in spread manure which is directly emitted as N_2O
N_2O	EF_5 (fertiliser)	Lognormal	0.0123 ± 0.0162	Fraction of leached nitrogen from synthetic fertiliser applied to grazing land emitted as N_2O
CH_4/N_2O	DE% (fed ration)	Calculated	63.0 ± 1.3	Digestible energy content of the housed diet, as a % of GE
N_2O	EF_3 (solid storage & drylot)	Lognormal	0.00528 ± 0.00189	Fraction of nitrogen in manure stored in solid storage which is directly emitted as N_2O
CH_4/N_2O	C_a (field)	Normal	0.170 ± 0.026	Ratio of net energy for activity (NE_a) to net energy for maintenance (NE_m) (all cattle)
N_2O	Grazing CP%	Calculated	15.9 ± 0.5	Crude protein in the grazed diet, as a % of DM
CH_4/N_2O	Grazing GE	Normal	18.3 ± 0.4	Gross energy in the grazed diet, in MJ kg DM^{-1}

[a] The given Cf_i value of 0.322 is raised by 20% for lactating females and by 15% for intact males (Dong et al., 2006).

economic value of the co-products in these cases is deemed to be negligible or zero prior to transport and processing.

4. Discussion

This study is unique in identifying and quantifying the root causes and impacts of uncertainty in an IPCC Guidelines-based carbon footprint of suckler beef production. Whilst the narrative developed here is, to some extent, specific to the modelled system, it can be generalised many respects to the majority of pasture-based northern hemisphere suckler beef systems, including major GHG contributors such as western Europe, the US and Canada. The mean emissions intensity calculated here (19.2 kg CO_2-eq kg LW^{-1}) is also comparable to ranges obtained by deterministic carbon footprint analyses of these systems; for example, Beauchemin et al. (2010) estimated 13.0 kg CO_2-eq kg LW^{-1} for Canadian systems, and Pelletier et al. (2010), in the US Midwest, estimate 14.8 and 19.2 kg CO_2-eq kg LW^{-1} for feedlot- and pasture-finished beef respectively. Irish beef (Casey and Holden, 2006) has been estimated to produce 11.3 kg CO_2-eq kg LW^{-1}. These systems vary somewhat in structure, but retain the core components of the cow-calf system, finishing system, and balance between summer grazing and winter housing.

IPCC N_2O and CH_4 emission factor uncertainties have been identified as important in national inventory calculations for agriculture in the United Kingdom (Milne et al., 2014) and Canada (Karimi-Zindashty et al., 2012), but as national-level assays, these

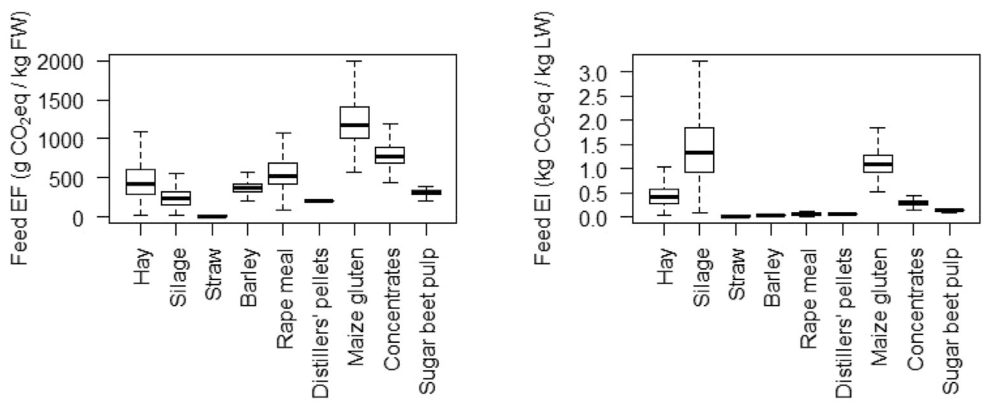

Fig. 7. Uncertainty in calculated emission factors (left) and emissions intensity (right) for off-farm feed production in the modelled beef system (FW = fresh weight of feed, LW = live weight of beef produced).

calculations are differently scoped, and crucially differ from the present assessment in that they do not permit the calculation of an emissions intensity of production for a particular commodity. This study found that uncertainties in N_2O emission factors (relating primarily to emissions stemming from manure and fertiliser application) are of greatest importance in a suckler beef system, and any effort to refine these which reduces uncertainty in field-based N_2O emissions would significantly improve confidence in modelled estimates of emissions intensity for beef production. Recent improvements in methodology used by the UK government for reporting agricultural N_2O (Chadwick et al., 2016) reflect the importance of uncertainty in this variable to many aspects of agricultural emissions.

Of all N_2O emissions in the modelled system, emissions stemming from manure were of greatest importance to the overall footprint, and hence the emission factors associated with this variable were of greatest consequence to uncertainty in the modelled system. Secondarily to direct N_2O emission factors, decreased uncertainty in coefficients which impact modelled manure production volume (livestock GE requirements, GE of diet, CP% of diet) would also greatly increase confidence in calculations of emissions from this source.

In particular, grazing gross energy, which scales the calculation of manure production volume for this period, was an influential factor. For the modelled scenario, this coefficient for grazed grass was taken from measurements made by Stergiadis et al. (2015) with a relatively low standard deviation of around 2.1%. The IPCC guidelines (Dong et al., 2006) provide a generalised GE estimate for all feed types which has a much higher uncertainty of 8.0% (Monni et al., 2007); given the influence of this variable in the modelled system even with lower uncertainty, the argument can made for a further refinement of this estimate where possible.

Enteric CH_4 emissions formed a significant proportion (47.5%) of the overall system emissions. Uncertainty relative to the overall magnitude of this emissions source was lower in comparison to N_2O emissions, but remains of considerable importance given the relative contribution of CH_4 to the footprint. The coefficient Cf_i (animal maintenance energy, in MJ kg body weight^{-1}) was found to be the most influential coefficient in this calculation chain, and second most important uncertainty overall. For simplicity in the broader sensitivity analysis (Fig. 6, Table 5), this coefficient was calculated as a herd average; disaggregation of this showed that the Cf_i for lactating suckler cows was the most influential iteration of this coefficient. This is likely to be due to both the maintenance energy requirements per head for this class and the large number of animals in this class required in the overall herd structure (see Table 2). Adding to the influence of this coefficient, calculations of net and gross energy are used to scale not only enteric CH_4 emissions, but also manure production volume, which in turn scales emissions of N_2O and CH_4 from manure. This finding backs those of Karimi-Zindashty et al. (2012) and Milne et al. (2014) at national level.

The coefficient Y_m was also found to have significant impact on the uncertainty in emissions (Fig. 6, Table 5). Y_m is an emission factor for enteric CH_4, denoting the percentage of calculated animal gross energy intake which is released as CH_4. The use of a fixed value for Y_m has come under criticism by some authors (e.g. Smith et al., 2015), and the IPCC acknowledge some limitations (Dong et al., 2006); GE intake affects the Y_m percentage (partly accounted for by the revision of Y_m to 4% for feedlot cattle on >90% concentrate feed), as do factors such as heat or cold stress and variations in rumen fauna (Röös and Nylinder, 2013). Refinement of this approach such that uncertainty in Y_m is reduced would serve to reduce uncertainty in the calculated emissions from the production system; however, this study shows that uncertainties in the calculation of gross energy requirements must also be addressed.

The system-focused nature of the approach means that these epistemic uncertainties were considered alongside uncertainty in embedded emission factors for commodities used in the production process; this substantially differentiates this approach from national-level inventory uncertainty assessments (e.g. Karimi-Zindashty et al., 2012; Milne et al., 2014). This uncertainty differs in that it encompasses both epistemic uncertainty, as considered for the modelled production system, and uncertainty resulting from variability in production practices. This study finds that emissions from the production of livestock feed form both a substantial component of the footprint (the 2nd largest category after enteric emissions), and a large contributor to uncertainty within the calculated overall emissions from the production system.

Epistemic uncertainty in the emissions from feed production is composed to a large extent of uncertainties in N_2O emission factors. Refinement of N_2O EFs, as suggested with respect to direct emissions from the modelled system, would therefore reduce this uncertainty considerably. However, variability in production practices and yields is also a major contributor to the uncertainty in emissions for off-farm feed production, and this is harder to mitigate. Improvement in crop production activity databases would reduce uncertainty, though particularly in the context of climate change, production practices are not fixed (Olesen et al., 2011), and this rate of change may represent a barrier to improvement of activity data. On-farm production of livestock feed is not uncommon, and would reduce this uncertainty; however, incorporation of this into a footprint reduces the general applicability of those results, since practices are likely to be to some extent farm-specific.

Dietary digestibility (DE%) was also shown to represent an important uncertainty in the footprint. This study distinguished between grazing and fed rations; both were influential, though the grazing period showed the greater effect (Fig. 6), likely due to being slightly longer (seven vs. five months) and with greater uncertainty surrounding the final value. Milne et al. (2014) estimated $65\% \pm 4.98$ for beef cattle ration digestibility; the scope of this assessment differed in that a) the scenario modelled by Milne et al. (2014) scenario covered the full range of UK beef production strategies, and b) the uncertainty utilised by these authors represented uncertainty in ration composition as well as epistemic uncertainty in measured DE% for ration components. For the present study, the fed ration DE% was lower (62.99 ± 1.34) and the grazed DE% was higher (70.95 ± 4.07). Both uncertainties were lower than that utilised by Milne et al. (2014), suggesting that where ration composition is known (i.e. in a farm-level assessment), epistemic uncertainty can be reduced via utilisation of a modelling approach to estimate digestibility, especially in the case of the fed ration.

This has a number of implications for beef system carbon footprinting; foremost, is the recognition that the emissions intensity of production is highly sensitive to the chosen DE% value. For many studies (e.g. Pelletier et al., 2010; Cardoso et al., 2016), DE% is modelled based on a deterministically estimated value; whilst these are typically expert estimates and may be highly accurate, their adoption nonetheless means that the calculated GHG footprint is potentially subject to arbitrary influence in this respect. Often, these studies seek to compare intensive vs. extensive production systems, and it is important to recognise the impact that variations in the magnitude of estimates for this variable can make. Uncertainty in this variable therefore represents a driving factor in uncertainty in the emissions intensity of production; an improved modelling approach could reduce this, and provide insight into how this influential variable might be manipulated to reduce emissions in real-world production systems.

Correlation between coefficient uncertainties has been identified as a potentially important factor in the assessment of national level emissions (Milne et al., 2014). Where emissions sources are aggregated in a calculation, this can serve to increase uncertainty as estimated in a Monte Carlo simulation; where calculations are disaggregated, additive combination of uncertainties in different iterations of the same coefficient will serve to reduce modelled uncertainty (Röös and Nylinder, 2013). This study followed the approach of aggregation where possible; only one iteration of each coefficient was used for the simulation. Logically, this is justifiable in that much of the uncertainty in emission factors and other coefficients is likely to stem from spatial and temporal variability in the modelled system, which will be limited at farm level. Milne et al. (2014) suggest that IPCC publish clear guidance on how this issue should be treated in uncertainty analyses; this study backs this conclusion. In addition, given the widespread application of these national-level guidelines for smaller-scale assessments (Sykes et al., 2017), it is suggested that the IPCC should additionally clarify this issue for application of these calculations at farm level.

More broadly, Monte Carlo simulation has been identified as a highly appropriate tool to investigate uncertainty propagation in complex agricultural system models (Groen et al., 2014). As computational demand becomes a less limiting factor, use of Monte Carlo in this context has increased (e.g. Gibbons et al., 2006; Lovett et al., 2008; Dudley et al., 2014; Zehetmeier et al., 2014), and assessment of uncertainty in national inventory calculations for agriculture has also successfully utilised this approach (Karimi-Zindashty et al., 2012; Milne et al., 2014). This study demonstrates that characterisation of uncertainties given in the IPCC Guidelines (Dong et al., 2006; de Klein et al., 2006) for Monte Carlo simulation requires a large degree of interpretation, and some decisions required here can significantly affect results. A key example is the choice of triangular vs. lighter-tailed distributions (e.g. normal, lognormal, Beta) for skewed coefficients; different practitioners have followed different approaches here (e.g. Gibbons et al., 2006 vs. Milne et al., 2014), and given the influence of these coefficients, decisions made here may affect results considerably. It is therefore suggested that future iterations of the guidelines contain recommendations for parameterisation of coefficient uncertainty in Monte Carlo simulation. Furthermore, where assessments include upstream emissions, this study demonstrates that epistemic uncertainty from emissions sources not specified in the IPCC guidelines (e.g. embedded feed production emissions) may be significant. There is no standardised approach for the necessary combination of data sources and uncertainty, and so it is important for future research to take into account the issues raised in this respect by this study.

Whilst quantification of uncertainty in farm-level GHG modelling is a relatively technical issue, it impacts the application of such approaches as a decision aid, and hence has important implications for users and policy makers. Studies have previously concluded that uncertainties in modelled GHG emissions do not greatly impact comparisons between scenarios, as similarity between scenarios and sources mean that uncertainties are likely to be highly correlated (Gibbons et al., 2006; Dudley et al., 2014). However, these studies have tended to focus on relatively similar systems; this study therefore supports this conclusion in certain circumstances, but also highlights that uncertainty in results can fundamentally affect confidence in comparisons based on trade-offs between different emissions sources; a key example would be the intensification of beef systems, where excessive enteric CH_4 from an extensive system is substituted for N_2O from feed production to supply the requirements of an intensive one (Hünerberg et al., 2014). In such a scenario, the emissions from one system are not equivalent to emissions from the other, and as such uncertainties are unlikely to be correlated. Higher uncertainties, coupled with a positively skewed distribution for N_2O emissions means that a stochastic model of this option may provide a different picture to a deterministic approach.

Finally, given the varying scale and scope of assessments for which these methods are applied, it is suggested that it may be appropriate to define ‘layers’ of uncertainty for certain influential coefficients. For example, Y_m, identified by this study and others (Karimi-Zindashty et al., 2012; Milne et al., 2014) as an important factor in the calculation of enteric CH_4 production by ruminants, has been shown to be affected by a number of management-related and biological factors such as GE intake, heat and cold stress, and rumen microbiota (Röös and Nylinder, 2013). Each of these factors is either uncertain or has an uncertain impact on the value of Y_m, or both; division of the coefficient uncertainty into categories related to each factor would, if possible, enable researchers to make an informed choice about the scope and nature of uncertainty in a particular modelling scenario.

5. Conclusion

This simulation demonstrated that epistemic uncertainty in modelling coefficients relating to a) N_2O emissions from manure and fertiliser, b) enteric emissions, c) embedded emissions from feed production and d) nutritional quality of the ration (especially digestibility) are highly influential in the derivation of uncertainty for a modelled suckler beef production system. These results are likely to be applicable to northern hemisphere beef production in general, and provide a novel quantification of epistemic uncertainty for systems and models of this type.

With this in mind, researchers have a responsibility to account for and effectively communicate uncertainties in modelled results. It is particularly important that issues such as systematic discrepancy between stochastically and deterministically calculated estimates (e.g. Table 4) be communicated, and their implications made clear. Whilst the more technical aspects of the derivation of these are likely to be less accessible to non-specialist users, it is important that the implications of this are communicated effectively; in recognition of this necessity Milne et al. (2015) identify a number of methods by which this may be approached. It is equally important that the end-user of the results of such studies should be aware of the implications of this uncertainty in decision-making.

To facilitate this, it is suggested that the IPCC, in the next iteration of the guidelines for national-level GHG reporting, provide guidance on the scale and scope at which uncertainties should be applied. Additionally, it is suggested that this update recognise the widespread use and proven efficacy of Monte Carlo simulation as a tool for uncertainty and sensitivity analysis in this field. The availability of this base methodology would go some way towards informing and standardising approaches to IPCC guidelines-based uncertainty and sensitivity analyses, and would greatly improve the confidence with which these models and assessments can be employed as decision-support tools in the definition of agricultural GHG mitigation policy.

Funding

Funding for this project was provided primarily by Innovate UK through J Sainsbury PLC [TS/K003895/1].

Acknowledgements

The authors would like to thank J Sainsbury PLC for funding this work as part of a PhD studentship. Additional contributions to this research project were funded by the Scottish Government and Innovate UK [TS/K003895/1]. The authors would also like to thank Gillian Inman and Karen Stewart of SAC Consulting for contributions to the data used in this analysis, and David Styles and Gareth Hughes for their input.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.06.171.

References

Audsley, E., Stacey, K., Parsons, D.J., Williams, A.G., 2014. Estimation of the Greenhouse Gas Emissions from Agricultural Pesticide Manufacture and Use. Cranfield University.

Beauchemin, K.A., Henry Janzen, H., Little, S.M., McAllister, T.A., McGinn, S.M., 2010. Life cycle assessment of greenhouse gas emissions from beef production in western Canada: a case study. Agric. Syst. 103 (6), 371–379. Available at: https://doi.org/10.1016/j.agsy.2010.03.008.

Beauchemin, K.A., Janzen, H.H., Little, S.M., McAllister, T. a., McGinn, S.M., 2011. Mitigation of greenhouse gas emissions from beef production in western Canada – evaluation using farm-based life cycle assessment. Anim. Feed Sci. Technol. 166 (167), 663–677. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0377840111001660. (Accessed 4 December 2014).

BSI, 2011. PAS 2050:2011 Specification for the Assessment of the Life Cycle Greenhouse Gas Emissions of Goods and Services. British Standards Institute, UK.

Cardoso, A.S., Berndt, A., Leytem, A., Alves, B.J.R., de Carvalho, I.D.N.O., de Barros Soares, L.H., Urquiaga, S., Boddey, R.M., 2016. Impact of the intensification of beef production in Brazil on greenhouse gas emissions and land use. Agric. Syst. 143, 86–96. Available at: https://doi.org/10.1016/j.agsy.2015.12.007.

Caro, D., Davis, S.J., Bastianoni, S., Caldeira, K., 2014. Global and regional trends in greenhouse gas emissions from livestock. Clim. Change 126, 203–216.

Caro, D., Davis, S.J., Bastianoni, S., Caldeira, K., 2016. Chapter 2: greenhouse gas emissions due to meat production in the last fifty years. In: Quantification of Climate Variability, Adaptation and Mitigation for Agricultural Sustainability, pp. 27–37.

Casey, J.W., Holden, N.M., 2006. Quantification of GHG emissions from sucker-beef production in Ireland. Agric. Syst. 90 (1–3), 79–98. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0308521X0500257X. (Accessed 18 July 2014).

Chadwick, D., Rees, B., Bell, M., Cardenas, L., Williams, J., Nicholson, F., Watson, C., McGeough, K., Hiscock, K., Smith, P., Top, K., Fitton, N., Skiba, U., Cowan, N., Manning, A., Misselbrook, T., 2016. Final Report - AC0116: Improvements to the National Agricultural Inventory - Nitrous Oxide. The InveN2Ory Project (2010-2016). Report to Defra. DARDNI, Scottish Government and Welsh Government.

Clark, C.E., 1962. The PERT model for the distribution of an activity. Oper. Res. 10, 405–406.

Committee on Climate Change, 2010. The Fourth Carbon Budget - Reducing Emissions through the 2020s.

CSA Wales, 2017. Climate Smart Agriculture Wales. Welsh Government. [Online]. Available at: https://www.aber.ac.uk/en/ibers/research/major_research_projects/csa-wales/.

de Klein, C., Novoa, R.S.A., Ogle, S., Smith, K.A., Rochette, P., Worth, T.C., 2006. Volume 4, chapter 11 - N2O emissions from managed soils, and CO2 emissions from lime and urea application. In: IPCC Guidelines for National Greenhouse Gas Inventories.

Defra, 2010. Fertiliser Manual. (June), p. 257.

DEFRA/DECC, 2015. GHG Conversion Factors for Company Reporting.

Dong, H., Mangino, J., McAllister, T.A., 2006. Volume 4, chapter 10 - emissions from livestock and manure management. In: IPCC Guidelines for National Greenhouse Gas Inventories. IPCC.

Dudley, Q.M., Liska, A.J., Watson, A.K., Erickson, G.E., 2014. Uncertainties in life cycle greenhouse gas emissions from U.S. beef cattle. J. Clean. Prod. 75, 31–39. Available at: https://doi.org/10.1016/j.jclepro.2014.03.087.

Flysjö, A., Cederberg, C., Henriksson, M., Ledgard, S., 2012. The interaction between milk and beef production and emissions from land use change - critical considerations in life cycle assessment and carbon footprint studies of milk. J. Clean. Prod. 28, 134–142. Available at: https://doi.org/10.1016/j.jclepro.2011.11.046.

Garthwaite, D., Hudson, S., Barker, I., Parrish, G., Smith, L., Pietravalle, S., 2013. Pesticide Usage Survey Report 255: Grassland & Fodder Crops 2013. DEFRA, ONS.

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G., 2013. Tackling Climate Change through Livestock – A Global Assessment of Emissions and Mitigation Opportunities. Food and Agriculture Organization of the United Nations (FAO), Rome.

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, 347–355. Available at: http://linkinghub.elsevier.com/retrieve/pii/S016788090500424X.

Groen, E.A., Heijungs, R., Bokkers, E.A.M., de Boer, I.J.M., 2014. Methods for uncertainty propagation in life cycle assessment. Environ. Model. Softw. 62, 316–325. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1364815214002953.

Groen, E. a., Bokkers, E. a. M., Heijungs, R., de Boer, I.J.M., 2017. Methods for global sensitivity analysis in life cycle assessment. Int. J. Life Cycle Assess. 22, 1125–1137. Available at: http://link.springer.com/10.1007/s11367-016-1217-3.

Hall, P., Holmes-Ling, P., Stewart, K., Sheane, R., 2010. A Scottish Farm-Based Greenhouse Gas Accounting Tool for Scotland. Laurence Gould Partnership Ltd. & Best Foot Forward Ltd, Scottish Government.

HCC Wales, 2006. Practical Beef Cattle Nutrition.

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 (09), 1474–1484.

Hünerberg, M., Little, S.M., Beauchemin, K.A., McGinn, S.M., O'Connor, D., Okine, E.K., Harstad, O.M., Kröbel, R., McAllister, T.A., 2014. Feeding high concentrations of corn dried distillers' grains decreases methane, but increases nitrous oxide emissions from beef cattle production. Agric. Syst. 127, 19–27.

INRA, 2012. Feedipedia Animal Feed Resources Information System | an On-Line Encyclopedia of Animal Feeds. INRA, CIRAD, AFZ & FAO [Online]. Available at: http://www.feedipedia.org/. (Accessed 15 April 2015).

IPCC, 2006. In: Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), 2006 IPCC Guidelines for National Greenhouse Gas Inventories. IGES, Japan.

Janzen, H.H., Angers, D. a, Boehm, M., Bolinder, M., Desjardins, R.L., Dyer, J., Ellert, B.H., Gibb, D.J., Gregorich, E.G., Helgason, B.L., Lemke, R., Massé, D., McGinn, S.M., McAllister, T. a, Newlands, N., Pattey, E., Rochette, P., Smith, W., VandenBygaart, a J., Wang, H., 2006. A proposed approach to estimate and reduce net greenhouse gas emissions from whole farms. Can. J. Soil Sci. 86, 401–418.

Karimi-Zindashty, Y., Macdonald, J.D., Desjardins, R.L., Worth, D.E., Hutchinson, J.J., Vergé, X.P.C., 2012. Sources of uncertainty in the IPCC Tier 2 Canadian livestock model. J. Agric. Sci. 150, 556–569, 2012.

Kool, A., Marinussen, M., Blonk, H., 2012. LCI Data for the Calculation Tool Feedprint for Greenhouse Gas Emissions of Feed Production and Utilization: GHG Emissions of N, P and K Fertilizer Production (Wageningen).

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. Livest. Sci. 116, 260–274.

Macleod, M., Sykes, A., Leinonen, I., Eory, V., 2017. Quantifying the Greenhouse Gas

Emission Intensity of Scottish Agricultural Commodities: Technical Report. CxC, Edinburgh.
Marinussen, M., Kernebeek, H. van, Broekema, R., Groen, E., Kool, A., Zeist, W.J. van, Dolman, M., Blonk, H., 2012a. LCI Data for the Calculation Tool Feedprint for Greenhouse Gas Emissions of Feed Production and Utilization. Bioethanol industry, Wageningen.
Marinussen, M., Kernebeek, H. van, Broekema, R., Groen, E., Kool, A., Zeist, W.J. van, Dolman, M., Blonk, H., 2012b. LCI Data for the Calculation Tool Feedprint for Greenhouse Gas Emissions of Feed Production and Utilization: Cultivation of Cereal Grains. Wageningen.
Marinussen, M., Kernebeek, H. van, Broekema, R., Groen, E., Kool, A., Zeist, W.J. van, Dolman, M., Blonk, H., 2012c. LCI Data for the Calculation Tool Feedprint for Greenhouse Gas Emissions of Feed Production and Utilization: Cultivation of Forage and Roughage. Wageningen.
Marinussen, M., Kernebeek, H. van, Broekema, R., Groen, E., Kool, A., Zeist, W.J. van, Dolman, M., Blonk, H., 2012d. LCI Data for the Calculation Tool Feedprint for Greenhouse Gas Emissions of Feed Production and Utilization: Cultivation of Oil Seeds and Oil Fruits. Wageningen.
Marinussen, M., Kernebeek, H. van, Broekema, R., Groen, E., Kool, A., Zeist, W.J. van, Dolman, M., Blonk, H., 2012e. LCI Data for the Calculation Tool Feedprint for Greenhouse Gas Emissions of Feed Production and Utilization: Dry Milling Industry. Wageningen.
Marinussen, M., Kernebeek, H. van, Broekema, R., Groen, E., Kool, A., Zeist, W.J. van, Dolman, M., Blonk, H., 2012f. LCI Data for the Calculation Tool Feedprint for Greenhouse Gas Emissions of Feed Production and Utilization: Sugar Industry. Wageningen.
Milne, A.E., Glendining, M.J., Bellamy, P., Misselbrook, T., Gilhespy, S., Rivas Casado, M., Hulin, A., van Oijen, M., Whitmore, A.P., 2014. Analysis of uncertainties in the estimates of nitrous oxide and methane emissions in the UK's greenhouse gas inventory for agriculture. Atmos. Environ. 82, 94–105. Available at: https://doi.org/10.1016/j.atmosenv.2013.10.012.
Milne, A.E., Glendining, M.J., Lark, R.M., Perryman, S. a. M., Gordon, T., Whitmore, A.P., 2015. Communicating the uncertainty in estimated greenhouse gas emissions from agriculture. J. Environ. Manag. 160, 139–153. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0301479715300839.
Monni, S., Perälä, P., Regina, K., 2007. Uncertainty in Agricultural CH4 and N2O Emissions from Finland - Possibilities to Increase Accuracy in Emission Estimates. Mitigation and Adaptation Strategies for Global Change, vol. 12, pp. 545–571. Available at: http://search.proquest.com/docview/745972658?accountid=10297%5Cnhttp://sfx.cranfield.ac.uk/cranfield?url_ver=Z39.88-2004&rft_val_fmt=info:ofi/fmt:kev:mtx:journal&genre=article&sid=ProQ:ProQ:abiglobal&atitle=Uncertainty+in+Agricultural+CH4+AND+N2O+Emissions+.
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, C., Vickers, M., 2016. Feeding suckler cows and calves for Better Returns. AHDB Beef BRP Manual 5.
Nguyen, T.T.H., van der Werf, H.M.G., Eugène, M., Veysset, P., Devun, J., Chesneau, G., Doreau, M., 2012. Effects of type of ration and allocation methods on the environmental impacts of beef-production systems. Livest. Sci. 145 (1–3), 239–251. Available at: https://doi.org/10.1016/j.livsci.2012.02.010.
OECD/FAO, 2017. OECD-FAO Agricultural Outlook 2017-2026. OECD Publishing.
Olesen, J.E., Trnka, M., Kersebaum, K.C., Skjelvåg, a. O., Seguin, B., Peltonen-Sainio, P., Rossi, F., Kozyra, J., Micale, F., 2011. Impacts and adaptation of European crop production systems to climate change. Eur. J. Agron. 34 (2), 96–112. Available at: https://doi.org/10.1016/j.eja.2010.11.003.
Opio, C., Gerber, P., Vellinga, T., Falcucci, A., Tempio, G., Gianni, G., Henderson, B., Macleod, M., Makkar, H., Mottet, A., Robinson, T., Weiler, V., 2013. Greenhouse Gas Emissions from Ruminant Supply Chains - a Global Life Cycle Assessment.
Pellerin, S., Bamière, L., Angers, D., Béline, F., Benoît, M., Butault, J.P., Chenu, C., Colnenne-David, C., De Cara, S., Delame, N., Doreau, M., Dupraz, P., Faverdin, P., Garcia-Launay, F., Hassouna, M., Hénault, C., Jeuffroy, M., Klumpp, K., Metay, A., Moran, D., Recous, S., Samson, E., Savini, I., Pardon, L., 2013. How Can French Agriculture Contribute to Reducing Greenhouse Gas Emissions? Abatement Potential and Cost of Ten Technical Measures. Synopsis of the Study Report, INRA, Paris (France). (July 2013), p. 92.
Pelletier, N., Pirog, R., Rasmussen, R., 2010. Comparative life cycle environmental impacts of three beef production strategies in the Upper Midwestern United States. Agric. Syst. 103 (6), 380–389. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0308521X10000399. (Accessed 18 July 2014).
Penman, J., Kruger, D., Galabally, I., Hiraishi, T., Nyenzi, B., Emmanuel, S., Buendia, L., Hoppaus, R., Martinsen, T., Meijer, J., Miwa, K., Tanabe, K., 2000. Good Practice Guidance and Uncertainty Management in National Greenhouse Gas in- Ventories. Intergovernmental Panel on Climate Change. (IPCC). IPCC/OECD/IEA/IGES, Hayama, Japan.
GHG Protocol, 2012. GHG emissions from purchased electricity [Online]. Available at: http://www.ghgprotocol.org/calculation-tools/all-tools. (Accessed 3 August 2016).
QMS, 2016. Cattle and Sheep Enterprise Profitability in Scotland.
Rees, R.M., Augustin, J., Alberti, G., Ball, B.C., Boeckx, P., Cantarel, a., Castaldi, S., Chirinda, N., Chojnicki, B., Giebels, M., Gordon, H., Grosz, B., Horvath, L., Juszczak, R., Klemedtsson, Å.K., Klemedtsson, L., Medinets, S., Machon, a., Mapanda, F., Nyamangara, J., Olesen, J., Reay, D., Sanchez, L., Sanz Cobena, a., Smith, K. a., Sowerby, a., Sommer, M., Soussana, J.F., Stenberg, M., Topp, C.F.E., van Cleemput, O., Vallejo, a., Watson, C. a., Wuta, M., 2012. Nitrous oxide emissions from European agriculture; an analysis of variability and drivers of emissions from field experiments. Biogeosci. Discuss. 9 (7), 9259–9288. Available at: http://www.biogeosciences-discuss.net/9/9259/2012/. (Accessed 27 October 2014).
Röös, E., Nylinder, J., 2013. Uncertainties and Variations in the Carbon Footprint of Livestock Products.
SAC, 2017. In: Craig, K. (Ed.), Farm Management Handbook 2017/18, 37th ed. SAC Consulting.
Schulte, R., Crosson, P., Donnellan, T., Farrelly, N., Finnan, J., Lalor, S., Lanigan, G., Brien, D.O., Shalloo, L., Thorne, F., 2012. A Marginal Abatement Cost Curve for Irish Agriculture. (April), p. 32.
Smith, F.A., Lyons, S.K., Wagner, P., Elliott, S.M., 2015. The importance of considering animal body mass in IPCC greenhouse inventories and the underappreciated role of wild herbivores. Glob. Chang. Biol. 21 (10), 3880–3888 p. n/a-n/a. Available at: http://doi.wiley.com/10.1111/gcb.12973.
SRUC, 2014. AgRE Calc [online]. Available at: http://www.sruc.ac.uk/info/120355/carbon_and_climate/1333/agricultural_resource_efficiency_calculator_agre_calc.
Stergiadis, S., Allen, M., Chen, X.J., Wills, D., Yan, T., 2015. Prediction of nutrient digestibility and energy concentrations in fresh grass using nutrient composition. J. Dairy Sci. 98 (5), 3257–3273. Available at: http://www.sciencedirect.com/science/article/pii/S0022030215001502.
Sykes, A.J., Topp, C.F.E., Wilson, R.M., Reid, G., Rees, R.M., 2017. A comparison of farm-level greenhouse gas calculators in their application on beef production systems. J. Clean. Prod. 164, 398–409.
Vellinga, T.V., Blonk, H., Marinussen, M., Zeist, W.J. Van, Boer, I.J.M. De, Starmans, D., 2013. Methodology Used in Feedprint: a Tool Quantifying Greenhouse Gas Emissions of Feed Production and Utilization, p. 121 (March).
Zehetmeier, M., Gandorfer, M., Hoffmann, H., Müller, U.K., de Boer, I.J.M., Heißenhuber, a., 2014. The impact of uncertainties on predicted greenhouse gas emissions of dairy cow production systems. J. Clean. Prod. 73, 116–124. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0959652613006860.