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Uncertainties and Variations in the Carbon Footprint of Livestock Products

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Foreword

The first life cycle assessments (LCA) were conducted in the late 1960s and early 1970s, in the field of packaging. Since then, there has been a huge expansion in the practice of estimating the environmental impact from a product perspective, accounting for a broad array of environmental impacts and taking into account emissions and resource use in all stages of the product's life cycle, including extraction of raw materials, production, transport, use and waste disposal. LCA is now used in both industry and research, and is applied to a wide variety of products and services, e.g. waste management, metals and other materials, transport modes, electronics, electricity and heat generation, biofuels and foods. LCA has proven to be a very useful tool for holistically assessing the environmental impact of products to avoid pollution swapping and sub-optimisation when trying to improve the environmental performance of products. However, even though the methodology in the field of LCA has improved enormously during the last 20-30 years, modelling a complex reality is highly challenging and LCA results remain uncertain. This uncertainty needs to be minimised, but can never be reduced to zero, so illustrating the uncertainty in results is crucial to enable good decision making.

LCA of foods is especially uncertain, since most emissions arise from biological processes that are difficult to control and model, and there is high variability in management practices, climate conditions and soil characteristics. Due to the focus on climate change in recent years, several studies have assessed the carbon footprint (CF) of livestock products, a LCA restricted to the impact category of global warming. These studies have provided valuable knowledge on the greenhouse gas (GHG) emissions associated with producing meat, milk and eggs, but the results are uncertain and comprehensive uncertainty assessments are generally lacking, so care must be taken when interpreting the results.

The Federation of Swedish Farmers (LRF) commissioned and funded this report, spurred by curiosity about the magnitude of uncertainty in livestock LCA, when uncertainty is important and how uncertainty analysis can be conducted. The work was carried out at the Department of Energy and Technology, Swedish University of Agricultural Sciences (SLU) during spring 2013 by Elin Röös, a PhD student who has published studies on uncertainty in CF calculations, and Dr. Josefine Nylinder, a specialist in the field of modelling nitrous oxide emissions. The authors wish to greatly thank the following researchers who provided valuable input on parts of the report: Cecilia Sundberg (sections 4.2, 4.4 and 5), Per-Anders Hansson (sections 4.4, 5 and 6), Niclas Ericsson, Serina Ahlgren, Ingrid Strid, Gunnar Larsson (section 4.4), Jan Bertilsson (section 4.3) and Åsa Kasimir Klemedtsson (section 4.1). Thanks also to Jan Eksvärd and Helena Elmquist at LRF for comments on the report. Finally, great thanks to Mary McAfee for helping to improve the language.

Uppsala, Sweden, 25th of April 2013

Elin Röös & Josefine Nylinder

Abstract

Livestock production is a major contributor to anthropogenic climate change, being responsible for 18% of global greenhouse gas (GHG) emissions. In the quest to reduce emissions, the amount of GHG released during the production of livestock products is commonly quantified by calculating the carbon footprint (CF), which includes all GHG emitted during the life cycle of the product. Quantification of the CF is challenging for several reasons. The majority of GHG emissions from agricultural systems arise from complex microbial processes that are difficult to fully understand and highly variable in time and space. Changes in carbon pools above and below ground can have huge impacts on GHG emissions from agricultural systems. The increasing demand for food, feed and biofuel on the global market is leading to deforestation and thus increased emissions of GHG. In addition, there is great diversity between livestock systems, e.g. in feeding strategies, animal growth and production, housing systems and manure handling.

This report describes uncertainties and variations in input data and models used to calculate the CF of livestock products. It discusses when uncertainty assessments are important and how uncertainty can be included in CF calculations.

Uncertainty in the CF of livestock products arises from: 1) uncertain input data; 2) the choice of model used for calculating emissions of e.g. N_2O from soil, CH_4 from enteric fermentation in ruminants, CO_2 emissions or sequestration in soils and emissions as a result of land use change, as well as uncertainties in these models; and 3) uncertainty due to scenario choices in modelling the livestock system, e.g. how system boundaries are drawn and how allocation between co-products is handled. It is important to account for uncertainty when comparing different production systems where emissions arise from different sources. However, when similar production systems are compared, e.g. when they only differ in the amount of feed used, it is possible to draw solid conclusions without comprehensive uncertainty assessments. Uncertainty in input data and model parameters can be propagated through the CF model using stochastic simulation, which gives an uncertainty range for the resulting CF. Sensitivity analysis can be used to test how different modelling choices affect the results, thus providing a measure of their robustness. In a full sustainability assessment, it is important not to focus solely on the CF, but to include other environmental impact categories and social and economic aspects.

Sammanfattning

Animalieproduktion är en viktig bidragande orsak till de klimatförändringar som orsakas av människan och står för 18% av de globala växthusgasutsläppen. I arbetet med att minska utsläppen, kvantifieras ofta animalieprodukters klimatpåverkan genom att beräkna produktens klimatavtryck (‘carbon footprint’ på engelska), d.v.s. den totala mängden växthusgaser som släpps ut under produktens livscykel. Att beräkna klimatavtrycket är en utmaning av flera skäl. Merparten av växthusgasutsläppen från jordbrukssystem uppstår via komplexa mikrobiella processer som varierar mycket i tid och rum. Dessutom kan förändringar i kolbalansen ovan och under jord ha stor effekt på utsläppen av växthusgaser från jordbrukssystem. Den ökande efterfrågan av livsmedel, foder och biobränsle på den globala marknaden leder till skövling av skog och därmed ökade växthusgasutsläpp. Dessutom finns det stora skillnader mellan olika djurhållningssystem t.ex. i utfodringsstrategier, tillväxttakt och produktionsnivåer, inhysningssystem och gödselhantering.

Denna rapport beskriver osäkerheter och variationer i de indata och modeller som används för att beräkna klimatavtrycket av animalieprodukter. Det diskuteras när bedömningar av osäkerhet är viktiga och hur osäkerhet kan ingå i beräkningar av klimatavtryck.

Osäkerheten i klimatavtrycket av animalieprodukter uppstår vid 1) osäkra indata, 2) val av modeller som används för beräkning av utsläpp av t.ex. lustgas från mark, metan från matsmältning hos idisslare, koldioxidutsläpp och upptag i mark och till följd av förändrad markanvändning, samt osäkerheten i dessa modeller, och 3) osäkerhet som beror på val vid modellering av produktionssystemet, t.ex. hur systemgränserna sätts och hur fördelningen av utsläpp mellan olika biprodukter hanteras.

Det är viktigt att ta hänsyn till osäkerhet när man jämför olika produktionssystem där utsläppen uppstår från olika källor. Däremot när liknande produktionssystem jämförs t.ex. när de bara skiljer sig i mängden foder som använts är det möjligt att dra slutsatser utan omfattande osäkerhetsanalys. Osäkerhet i indata och parametrar kan fortplantas i klimatavtrycksmodeller med stokastiska simuleringstekniker, vilket ger ett osäkerhetsintervall för klimatavtrycket. Känslighetsanalys kan användas för att testa hur olika val av data och modeller påverkar resultatet och således ge ett mått på resultatets robusthet. I en fullständig hållbarhetsbedömning är det viktigt att inte enbart fokusera på klimatavtrycket utan också inkludera andra miljöeffekter så väl som sociala och ekonomiska aspekter.

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1 Introduction

1.1 Background

Combating climate change is one of the most pressing challenges for humanity. Emissions of greenhouse gases arise mainly from the combustion of fossil fuels in the energy and transport sectors (*Figure 1*). However, the livestock sector has been identified as a major contributor to anthropogenic climate change, as it is responsible for 18% of global greenhouse gas (GHG) emissions when the emissions in the agriculture, transport and energy sectors that relate to livestock production are included (Steinfeld et al., 2006). Due to the estimated global population growth to approximately 9 billion in 2050 and growing income levels, FAO suggests that an 70% increase in food production will be necessary (FAO, 2009). This is obviously an enormous challenge at a time when climate change, biodiversity loss, land, water and energy shortage, soil erosion and chemical pollution are placing serious stress on global food production systems. It is apparent that there is a huge need to improve production systems and lower the environmental burden per kg of product produced, but also to look into other measures such as reducing food losses and changing diets (SBA, 2012). The improvement of production systems and the development of more sustainable consumption patterns will require solid evaluation methods.

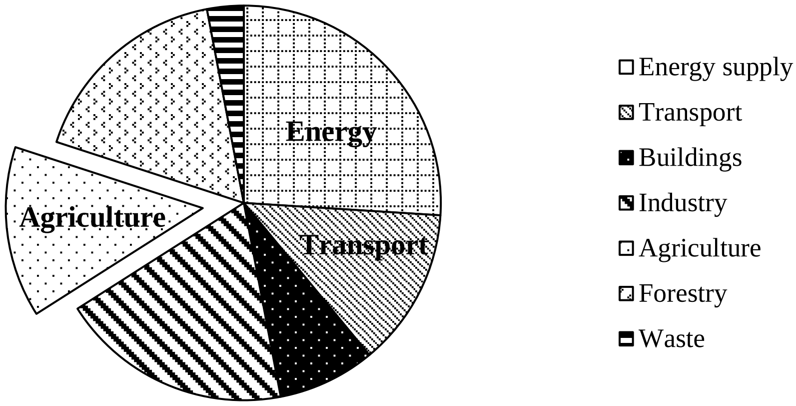

Figure 1. Contribution to global greenhouse gas emissions from different sectors in 2004 (IPCC, 2007a). The agricultural sector does not include energy use and transport, as these are reported in the energy and transport sectors.

When considering the environmental impact from livestock, the focus has commonly been on the release of GHG (Steinfeld et al., 2006; Gerber et al., 2010; Leip et al., 2010). However, quantification of the carbon footprint (CF), the total amount of GHG emitted during a product's lifetime, is difficult for agricultural products for several reasons. The majority of GHG emissions from agricultural systems arise from complex microbial processes that are difficult to fully understand, and to measure and model. The emissions are strongly affected by climate conditions and features in the agricultural system such as soil conditions. Hence, the emissions from one farm can greatly vary between years and fields, and variations within a region or country can be substantial. Furthermore, changes in carbon pools above and below ground can have huge impacts on the GHG emissions from agricultural systems. On-farm emissions arise from energy use, animals, soil and manure. Upstream processes such as animal feed production and production of capital goods are also emitters of GHG. The increasing demand for food, feed and biofuel on the global market is leading to deforestation in the quest for more agricultural land, and thus emissions of GHG. Emissions from all these phases and processes need to be included in the total assessment of the impact from livestock production. In addition, the diversity in livestock systems is great. Livestock can be produced in close linkage with crop (feed) production or as land-less systems where feed is bought on the global feed market. Different feeding strategies, animal growth and production rates, housing systems and manure handling give varying amounts of GHG emissions released from different systems.

Several studies have been conducted on livestock systems to quantify the GHG emissions or CF for different livestock products (see summaries in de Vries & de Boer, 2010; Nijdam et al., 2012; Röös et al., 2013). CF can be calculated for a multitude of purposes. Some studies aim at identifying ‘hot-spots’ in production (processes which give rise to the majority of emissions) and effective mitigation options and some at comparing different production systems with different feeding strategies, manure handling etc. Other studies aim to quantify the emissions from the entire livestock sector in a region or a specific livestock sector, e.g. the dairy sector (Gerber et al., 2010). The purpose of a study determines how the work is carried out and how the results are presented and interpreted. Due to the great complexity of livestock systems, uncertainty analysis is often needed to draw solid conclusions but such an analysis is often lacking. In addition, it is not sufficient to assess the total sustainability of a livestock system using only the CF, as other environmental aspects, aspects of resource use efficiency and social and economic factors need to be included for a full sustainability assessment.

1.2 Goal and scope of the report

The overall goal of this report was to describe uncertainties and variations in input data and models used to calculate the CF of agricultural products. A further goal was to discuss when uncertainty assessments can be included in CF calculations and how this can be performed.

The report does not claim to be comprehensive and to cover all aspects and models. Rather, it presents examples of different ways of quantifying GHG emissions from agricultural systems in order to highlight that uncertainties are substantial and that different modelling choices can give varying and in some cases contradictory results. The report is limited to studying the climate impact from a product life cycle perspective.

1.3 Structure of the report

The remainder of the report is structured as follows:

Chapter 2 describes the methodology behind calculating the CF of livestock systems by first describing the underlying methodology used, namely life cycle assessment (LCA). In section 2.1 basic concepts in LCA are explained and exemplified using examples from the field of livestock production. The concept of CF is described generally in section 2.2 and specifically for livestock systems in section 2.3.

Chapter 3 deals with general concepts of uncertainty and variation. Section 3.1 describes the difference between uncertainty and variation. Sources of uncertainty are described in section 3.2, while ways to handle and present uncertainties in LCA are presented in section 3.3 and 3.4.

Critical methodological choices for livestock CF calculations are described in Chapter 4. Section 4.1 describes the difficulties in measuring and modelling N_2O emissions from agricultural soils used for feed production, while section 4.2 discusses CO_2 emissions from soil and carbon sequestration in soils. Section 4.3 deals with methane emissions from enteric fermentation in animals and section 4.4 describes emissions from manure handling. In section 4.5 emissions due to land use change (LUC), which includes the transformation of forests, scrubland, grassland and other non-crop land into crop producing land, are discussed. Section 4.6 gives a brief overview of CO_2 emissions from energy use, while section 4.7 highlights some of the production parameters which influence the CF of livestock products.

Chapter 5 deals with the uncertainties in the final CF of livestock products. Section 5.1 describes how different types of uncertainties are aggregated in the CF. Section 5.2 discusses and gives examples of when it is important to include uncertainty in comparisons. How uncertainties can be illustrated is described in section 5.3, while the wider concept of sustainable livestock production systems is discussed in section 5.4. Chapter 6 ends the report with a summary.

2 Calculating carbon footprint

2.1 Life cycle assessment

Life cycle assessment (LCA) is a well-established quantitative method for assessing the environmental impact of a product or service from a life cycle perspective. Inflows of natural resources (e.g. raw materials, energy, land and water) to the system and outputs in form of products, by-products, emissions and waste are quantified for all steps in the life cycle, starting at raw material extraction and continuing through to manufacturing, use and finally ending with the disposal of the product. LCA is a generic method that is not limited to the study of livestock products or food. It has been used extensively in many different fields, e.g. in energy production and in waste management.

LCA aims at being a comprehensive methodology for assessing the complete environmental impact of a product, hence avoiding sub-optimisation and problem shifting. LCA was originally limited to describing the *environmental* damage of a product, but on-going research has suggested ways of including social issues (Kruse, 2010). LCA can be combined with other tools to provide a more comprehensive evaluation of a product, e.g. life cycle costing (LCC). See section 5.4 for a more extended discussion of the role of LCA in sustainability assessments.

LCA is standardised by ISO (ISO, 2006a, b). The standard can be regarded as a framework that encapsulates the different types of LCA variants (section 2.1.1), defines basic concepts and describes how a LCA study should be structured and what it should contain, i.e. it gives guidance on a general level. In a standard such as that for LCA, which has to be applicable in disparate sectors such as energy, transport, manufacturing and agriculture and be valid for a wide range of different types of LCA and for evaluating different types of environmental aspects, it is very difficult to set up very detailed requirements. Instead, using the ISO standard as the basic framework, different organisations have developed more specific specifications targeting a specific issue. For example, PAS 2050 (BSI, 2011) and the Greenhouse Gas Protocol Reporting Standard (WRI & WBSCD, 2011) treat calculation of CF for products in general, while PAS 2050-1 contains additional specifications specifically for the production of horticultural products (BSI, 2012). The European Food Sustainable Consumption and Production Round Table, an initiative co-chaired by the European Commission and food supply chain partners, is developing the ENVIFOOD Protocol, which aims at providing a harmonised environmental assessment methodology for food and drink products (Food SCP, 2012). In addition, through the International Dairy Federation (IDF) the global dairy industry has developed a common approach for calculating the CF of milk and dairy products (IDF, 2010). The international Environmental Product Declaration (EPD) system contains a framework for developing specific rules for specific products, Product Category Rules (PCR). Within that system, PCR have been developed for meat from mammals, with specific methods for the assessment of such production systems (EPD, 2013).

Although standards are highly valuable for ensuring more consistent assessments, due to the diversity in the purposes of conducting LCA studies, it is very difficult to create a standard that fulfils all purposes in an optimal way. Therefore, there are still occasions when deviations from the more detailed standards are justified. In addition, there is a risk of the results being biased by the selection of methods and data collection strategies specified in the standard.

2.1.1 Uses and types of LCA

LCA can be used for different purposes, e.g. for decision making, learning about the environmental impact of the system, identifying mitigation options and communication. Decision making in product development has been a prime use of LCA since the formulation of the methodology and is still one of the most common uses. Other important decisions that are based on LCA are purchasing decisions and the development of environmental policies (Tillman, 2010).

There are also different types of LCA. First, a division can be made between process-based LCA and input-output LCA (IO LCA). Process-based LCA uses a ‘bottom-up’ approach in which the resource use and emissions from every process stage (raw material extraction, manufacturing, use, disposal) for every component (e.g. in the case of a bicycle: steel, rubber, electricity, machinery etc.) are surveyed individually. In IO LCA, economic input-output models that describe the monetary transactions between different economic sectors, such as the electricity sector, the steel sector etc., are extended with information on emissions to the environment. Hence, IO LCA models provide a way of studying ‘transactions’ of emissions between sectors and can be used to assess the environmental impact of products using a ‘top-down’ approach (Hendrickson et al., 2006). Although IO LCA has been used in LCA of livestock systems (Weidema et al., 2008), use of process-based LCA is most common. Therefore, when LCA are referred to hereafter in this report, process-based LCA is what is meant.

LCA can be performed as either attributional LCA (ALCA) or consequential LCA (CLCA). Nguyen et al. (2010) provide a good description of the two:

"The former [ALCA] seeks to cut the portion of the global environmental impact related to a particular product, and the later [CLCA] seeks to capture change in environmental impact as a consequence of a certain activity and thereby provides information on consequences of actions."

In ALCA average data are used while in CLCA marginal data are used, since it is the marginal processes that will be affected by change (Weidema et al., 1999). Such data choices can lead to very different results, as is further discussed in section 4.6. Allocation of emissions between co-products is most often based on economic or physical relationships in ALCA, while in CLCA the system is expanded to include processes that are affected by the by-products entering the market (section 2.1.4). It could be argued that all LCA studies should be performed as CLCA studies, since the results are used as a basis for decisions that will inevitably lead to change. However, some authors argue that the ALCA approach can be more appropriate when the interest lies in evaluating how the new product would perform in a future steady state rather than the dynamic impact when the product is introduced or expanded on the market (Sonesson & Berlin, 2010).

2.1.2 The structure of LCA

The ISO standard for LCA stipulates that a LCA study should be structured into four different phases; goal and scope definition, inventory analysis, impact assessment and interpretation (ISO, 2006a, b). A short description of the different phases as described in the ISO standard is provided below, together with some illustrative examples from LCA studies on livestock products. Although LCA is divided into four consecutive phases, conducting an LCA is very much an iterative process. For example, the goal and scope of the study defined in the first phase might need to be revised as more knowledge is gathered about the system in later phases, and sensitivity analysis performed in the last phase might call for more careful data collection in the inventory phase.

Goal and scope definition

When formulating the goal definition of the study the reasons for carrying out the LCA should be stated, as well as how the study is to be used and by whom. A few examples of how objectives in previous studies on livestock products have been formulated are given below.

- *"The objective of this study…. was to assess the environmental profile of four different EU beef production systems, three based on dairy bull calves and one on suckler herds"* (Nguyen et al., 2010)
- *"Our objective was to assess regional differences in GHG emissions associated with production of dairy, beef, pork and poultry and eggs in the EU-27"* (Lesschen et al., 2011)
- *"The goal was to identify the processes in the product chain of pork with the largest environmental impacts…"* (Dalgaard, 2007)

When defining the scope of a study, several crucial decisions need to be taken and consistently complied with in the following phases of the LCA. These include choosing the system to study and the system boundaries, formulating a functional unit, deciding how to handle allocation of impact across co-products, and determining data quality requirements and methods to use for evaluating the environmental damage. Some of these critical choices are discussed in further detail in sections 2.1.3 and 2.1.4. Subjective choices are inevitable in this phase of an LCA study, but choices must be carefully justified and consistent with the aim and intended use of the LCA study as defined in the goal definition.

Inventory analysis

The inventory analysis phase is the phase in which data is collected. Often a 'cradle-to-grave' flow model is constructed for the system under study in accordance with the goal and scope definition. An example of a flow model corresponding to the objectives stated by Nguyen et al. (2010) in the section above on goal and scope definition is shown in *Figure 2*.

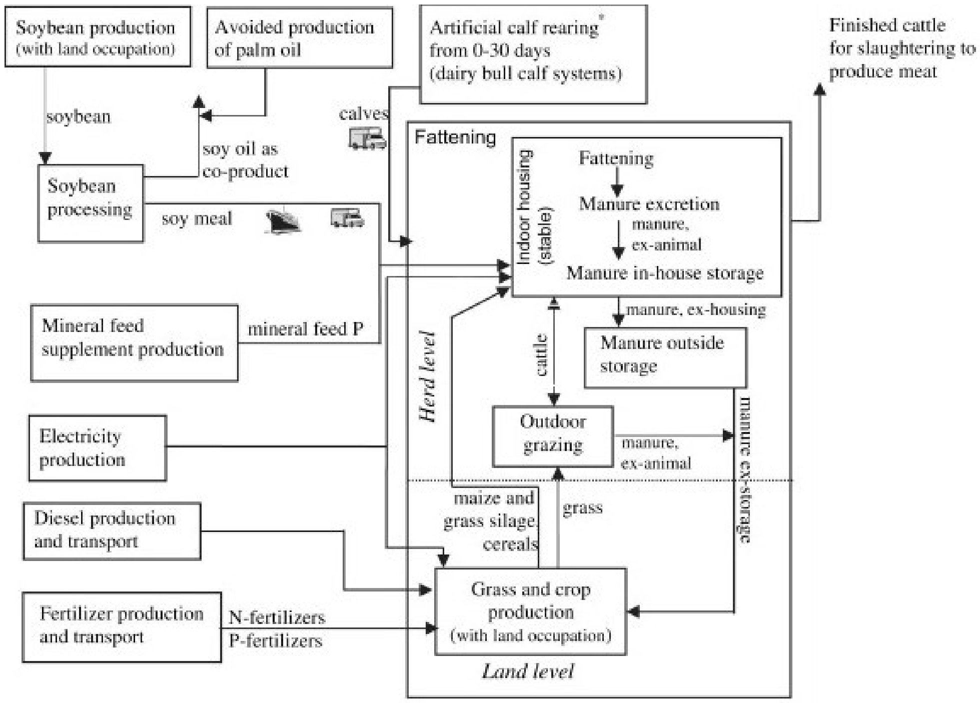

Figure 2. Flow model for studying beef fattening from Nguyen et al. (2010).

Data on the flows that are relevant for environmental impact assessment, e.g. use of resources, amount of environmentally damaging emissions and the production of waste and by-products, are collected for every step in the product life cycle. These data are aggregated over the life cycle and related to the functional unit (see section 2.1.3).

The inventory analysis is often the most time-consuming phase of an LCA study, as the processes included are often many and complex. Life cycle inventory (LCI) databases (e.g. ecoinvent; Ecoinvent Centre, 2012) provide generic data, but depending on the purpose of the LCA, large amounts of more specific data are generally needed. For example, if the purpose of the study is to quantify the environmental impact from a specific farm, farm-specific data is needed, while if the purpose is to compare the impact of a product from two different countries, country-specific average data from those two countries are needed. However, data collection from a large number of farms is very time-consuming, so most studies use data from a few farms that are considered representative, or average data on yields, fertiliser use etc. from national statistics. These parameters are used to estimate emissions of GHG based on emission factors and simplified models, since emissions from agricultural systems cannot be measured directly (see Chapter 4).

Impact assessment

The result of the inventory analysis is typically a long list of amounts of natural resources used (e.g. oil, coal, natural gas, different types of metals, land, water etc.) and substances emitted (e.g. CO_2, N_2O, CH_4, SO_2, NO_x, HCl, NH_3, P, CFCs etc.) to the environment during the life cycle of the product. In the impact assessment phase (also called life cycle impact assessment, LCIA), the physical flows identified in the inventory analysis are used to estimate how the product affects the environment. The substances are first *classified* (sorted) in accordance with the environmental impact category to which they contribute; CO_2, N_2O and CH_4 cause climate change, while SO_2, NO_x, HCl and NH_3 cause acidification and so on. In the *characterisation* step, the different substances are aggregated into one indicator for each impact category depending on their relative damage contribution according to some documented characterisation model. The model commonly used to calculate the global warming potential (GWP) expressed in CO_2-equivalents (CO_2e) and relevant for the CF is described in more detail in section 2.2.2.

Results from an LCA study can be presented as individual impact categories. The most commonly used categories in LCA studies on livestock products are global warming potential, eutrophication potential, acidification potential, land use and energy use (Röös et al., 2013). An example of how results are commonly presented in LCA studies on livestock is shown in *Figure 3,* which is also taken from the study on different beef fattening systems by Nguyen et al. (2010).

Impact category	Unit	Suckler cow–calf SCC	Dairy bull calf/age at slaughter		
			A/12 months	B/16 months	C (Steers)/ 24 months
Global warming (without land use consideration)	kg CO_2e	27.3	16.0	17.9	19.9
Acidification	g SO_2e	210	101	131	173
Eutrophication	g NO_3e	1651	622	737	1140
Non-renewable energy	MJ primary	59.2	41.3	41.7	48.2
Land occupation	m^2year	42.9	16.5	16.7	22.7
Grassland		36.9	0	2.0	18.2
Highly productive		6.81	0	1.97	8.34
Moderately productive		0	0	0	9.82
Low productive		30.07	0	0	0
Cropland		6.0	16.5	14.7	4.5
Cereals		5.94	12.39	11.48	4.50
Soy meal		0.05	4.11	3.25	0.04

Figure 3. Example of how results from LCA studies on livestock systems are typically reported (from Nguyen et al., 2010).

The results for the individual impact categories can also be normalised and weighted using pre-defined methods so that the results from the LCA study can be given as only one or a few ‘environmental scores’ (e.g. Goedkoop et al., 2009). This way of presenting results from LCA studies on livestock is rather uncommon, since most studies aim not only to determine which system has the smaller or larger impact, but also to learn about the systems and how the impacts arise.

Interpretation

In the interpretation phase, significant issues in the results should be highlighted and discussed in relation to the purpose of the study, e.g. identification of impact categories contributing considerably to the environmental impact or the contribution from different life cycle stages. According to the ISO standard the interpretation phase must also include an evaluation of results that considers completeness, sensitivity and consistency. Finally in this phase, conclusions are drawn, limitations discussed and recommendations given.

2.1.3 The functional unit

In LCA the environmental impact is measured relative to the ‘functional unit’, which describes the function of the product or the service in a quantitative manner. The most commonly used functional unit for food products is simply the production of one kg of the food being studied, often also with a specification regarding system boundaries (section 2.1.4), e.g. *“the production of 1 kg of potatoes at the farm gate”*. In the case of meat it is important to specify whether the functional unit is 1 kg of live weight, carcass weight or edible meat (without bones). This is particularly important when comparing meat from different animal species, since the meat yield per animal carcass varies substantially between species (Hallström & Börjesson, 2012; Nijdam et al., 2012). The yield can also vary considerably between breeds and production systems, so it is very important to clearly state the type of meat yield used in calculation of the CF, as this could heavily influence the results.

In LCA studies comparing different alternatives for the same ‘function’, it is crucial that the functional unit is chosen so that the products can be compared fairly. As an example, in LCA studies comparing milk production systems the functional unit should account for differences in nutrient content in the milk, so measures that include e.g. the fat and protein content of the milk are commonly used as the functional unit. One common measure is ECM (Energy Corrected Milk), which is defined as follows:

$$ECM = 0.25*M + 12.2*F + 7.7*P$$

where M is the mass of milk in kg, F is the fat content in kg and P is the protein content in kg (Sjaunja et al., 1990). Hence, the functional unit in LCA studies of milk is often stated as *"the production of 1 kg of ECM (at the farm gate)"*.

In the Western diet, livestock products are major sources of protein and it can be argued that the function of meat is to provide protein. Hence for LCA studies comparing different meat products and especially when comparing these to alternative protein sources, use of 1 kg of the food product as the functional unit might not be the most appropriate one, since different foods can have very different protein contents, e.g. eggs contain 12% protein and most meats approximately 20%. In that case, it might be wiser to use *"the production of 1 kg of protein"* as the functional unit. Livestock products not only provide proteins but are also important sources of several micronutrients such as iron and zinc (Hallström et al., 2013). To include several nutritional aspects, foods can be evaluated based on their 'nutritional density' in which their content of different nutrients such as proteins, carbohydrates, fats, vitamins and minerals is taken into account and weighted according to the recommended daily intake (Kernebeek et al., 2012; Saarinen, 2012).

It is important that the functional unit represents the *function* of the product being studied. In most developed countries average protein intake is far beyond recommendations, so it could be argued that the function of livestock products in these countries is to supply pleasure rather than protein, which could motivate the use of mass as the functional unit. In addition, livestock not only provide food, but also other important functions, e.g. they help preserve biodiversity by grazing semi-natural grasslands, which might be relevant to include in the functional unit.

2.1.4 System boundaries and allocation

The system boundaries specify which processes to include in the product system under study. The ISO standard requires that all life cycle stages, processes, inputs or outputs that affect the conclusions of the study must be included. Typically, a product system for the production of livestock products should include the following processes; cultivation, processing and transport of feed and for this the manufacturing of all necessary inputs such as seed, fertilisers, pesticides, fuel, electricity and capital goods, the on-farm activities and post-farm processes such as slaughtering, processing, packaging, storage, distribution, preparation and waste disposal. However, since post-farm emissions are small in comparison with the emissions on the farm and from the production of inputs, the study often ends at the farm gate, called a 'cradle-to-farm-gate' study.

The system boundaries used need to delineate the product system under study from the 1) natural system and 2) the surrounding technical system. Drawing the line between the natural system and agriculture can be challenging, e.g. there are different opinions on whether sequestration of carbon in soils and hence removal of CO_2 from the atmosphere should be included within the system boundaries (section 4.2). Isolating the studied product system from the surrounding technical system is often associated with several challenges too, since agricultural systems are generally highly complex in several ways. One classical LCA topic that arises in most studies is how to handle the fact that most processes produce more than one product. This 'allocation problem' can be handled in several ways. In CLCA, the system is always expanded to include processes affected by the by-products reaching the market (system expansion), while in ALCA emissions from the product systems are split between the main products and the co-products according to physical (e.g. energy or mass) or economic relationships.

A typical allocation problem in LCA on livestock products arises in the joint production of milk and meat. In an ALCA study on milk, emissions from the joint production can be divided (allocated) between the milk and the meat based on either the price of milk and meat (economic allocation) or some physical relationship, e.g. the energy and/or protein content of the milk and meat. A 'biological' relationship based on the proportion of a dairy cow's feed that is needed for milk production can also be used to allocate emissions. Such an allocation resulted in 85% of the total emissions being allocated to milk and 15% to the meat and the surplus calves in a study by Cederberg & Stadig (2003). The production system can also be expanded to include the production of pure meat, i.e. from suckler herds. Hence, the emissions from a corresponding amount of meat coming from joint milk-meat production, but produced from the suckler herd system, can be subtracted from the total emissions from the joint production of milk and meat. The remaining emissions are attributed to the milk. The reasoning behind system expansion is that when meat from the milk-meat system enters the market, 'pure beef meat' from suckler herds is no longer needed and its production is avoided.

Results can show large variations depending on the way in which by-products are handled. *Figure 4* shows the CF of milk using three different allocation methods and system expansion. In the first method (No all), all emissions are allocated to the milk, in the second (Ec all 92%) economic allocation is used and 92% of emissions are allocated to the milk, and in the third (Bi all 85%) "biological" allocation as described above is used and finally system expansion is used. Since existing LCA studies show that GHG emissions from meat from suckler herds are generally larger than those from milk-meat systems, the CF of milk is substantially lower when system expansion is applied, since large emissions can be subtracted from the joint milk-meat production system.

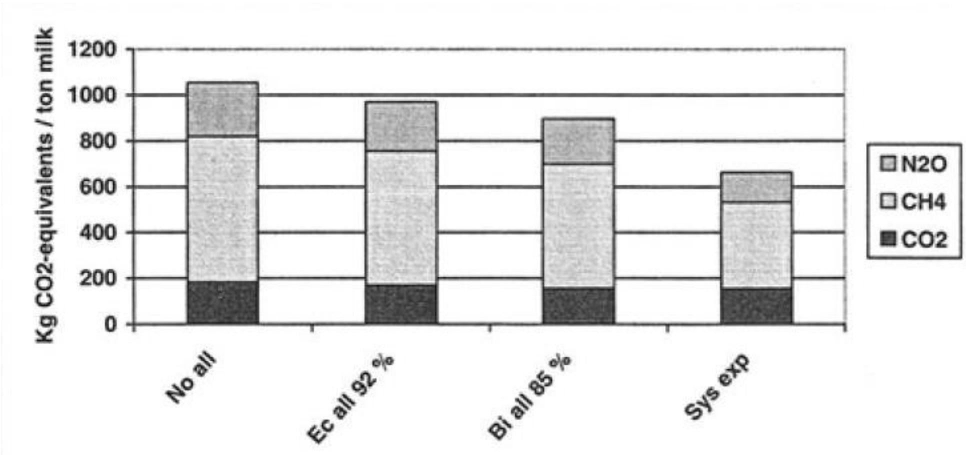

Figure 4. Carbon footprint of milk with different ways of handling allocation of emissions between meat and milk (from Cederberg & Stadig, 2003).

Examples of other allocation issues that arise in livestock systems are: allocation between the food products produced in the livestock system and other outputs such as manure, wool and leather, as well as allocation of emissions across different types of meat, e.g. higher value cuts such as fillet steak, other lower value parts and offal. In addition, in feed production, emissions from cultivation need to be allocated to the part of the crop used for human food and feed to animals, e.g. in production of oilseeds, the oil is used for human consumption and the meal for animal feed.

2.2 Carbon footprint

2.2.1 Overview of carbon footprint

The global focus on the issue of climate change increased after the presentation of the fourth IPCC assessment report in 2007 and was further spurred by media events such as the launch of the movie *The Inconvenient Truth* by former US senator Al Gore in 2008. This new focus on climate change was accompanied by increased interest among researchers, industries and authorities in calculating the CF of e.g. products, services, companies and sectors.

The CF is the total amount of GHG emitted from a life cycle perspective from the system under study, thus giving an estimate of the contribution to climate change from the products produced or services provided. The different GHG are summarised taking their different global warming potential (GWP) into account, arriving at a unit for the CF of kg CO_2-equivalents (CO_2e). For a product or service, the CF is therefore exactly the same as an LCA that only takes the impact category of climate change into account, and all methodological aspects as discussed in section 2.1 apply to estimation of the CF too (apart from aspects related to LCIA other than the climate change impact category).

2.2.2 Global warming potential (GWP)

The CF is expressed as the total GWP from all GHG released. The GWP is defined as the integrated global mean radiative forcing out to a chosen time of an emission pulse of 1 kg of a compound relative to that for 1 kg of CO_2 (IPCC, 2007b). The GWP value for a specific gas depends on how efficiently and in which wavelength span the gas absorbs the infra-red radiation and the life span of the gas in the atmosphere. As a result of efficient absorption of infra-red radiation and long life span in the atmosphere, the greenhouse gas GWP value will be high. The GWP of a gas depends on the time perspective considered. The climate impact during 100 years is usually used, but this is an arbitrarily chosen time period. The GWP of different GHG is expressed as CO_2e and can be added together in order to arrive at one measure of the climate impact, including all gases. Hence, the total GWP or CF is calculated as:

Carbon footprint or GWP_{tot} (kg CO_2e) =
= Amount of CO_2 * 1 + Amount of CH_4 * GWP_{CH4} + Amount of N_2O * GWP_{N2O}

where GWP_{CH4} is the characterisation factor for CH_4 and GWP_{N2O} is the characterisation factor for N_2O. *Table* 1 shows the characterisation factors for different time intervals. The uncertainty in these factors is estimated to be ±35% (90% confidence range) (IPCC, 2007b).

Table 1. *Characterisation factors for the GWP of methane and nitrous oxide for different time perspectives (IPCC, 2007b).*

Gas	20 years	100 years	500 years
CH_4	72	25	7.6
N_2O	289	298	153

Indirect climate effects due to emissions are not included in the GWP concept. By including gas-aerosol interactions, Shindell et al. (2009) found that the GWP value for CH_4 was substantially larger when this indirect effect was included. Changes to the climate system as a consequence of livestock production might also be caused by phenomena other than emissions of GHG, e.g. decreased evapotranspiration, aerosol formation and changes in albedo, which can have both cooling and warming effects (Höglund et al., 2013). Quantifying these effects is highly uncertain and has so far not been included in CF of livestock products.

Some haloalkanes, previously commonly used as e.g. refrigerants, are very powerful GHG, but their emissions are rare in livestock systems and they are not further discussed here.

2.3 Carbon footprint of livestock products

2.3.1 Contributing processes

The main processes that are directly associated with livestock production and which contribute to emissions of GHG are the following (see also Figure 5):

Pre-farm processes:

- Production and transport of inputs to the farm; feed, fertilisers, fuels, pesticides, pharmaceuticals, machinery, buildings and other capital goods etc.

On-farm processes:

- Soil emissions
- Emissions from enteric fermentation in animals
- Emissions from manure handling
- Emissions from energy use on fields and in animal houses

Post-farm processes:

- Slaughtering
- Processing and packaging
- Storage and refrigeration
- Transport and distribution
- Retail and wholesale
- Preparation
- Digestion and waste disposal

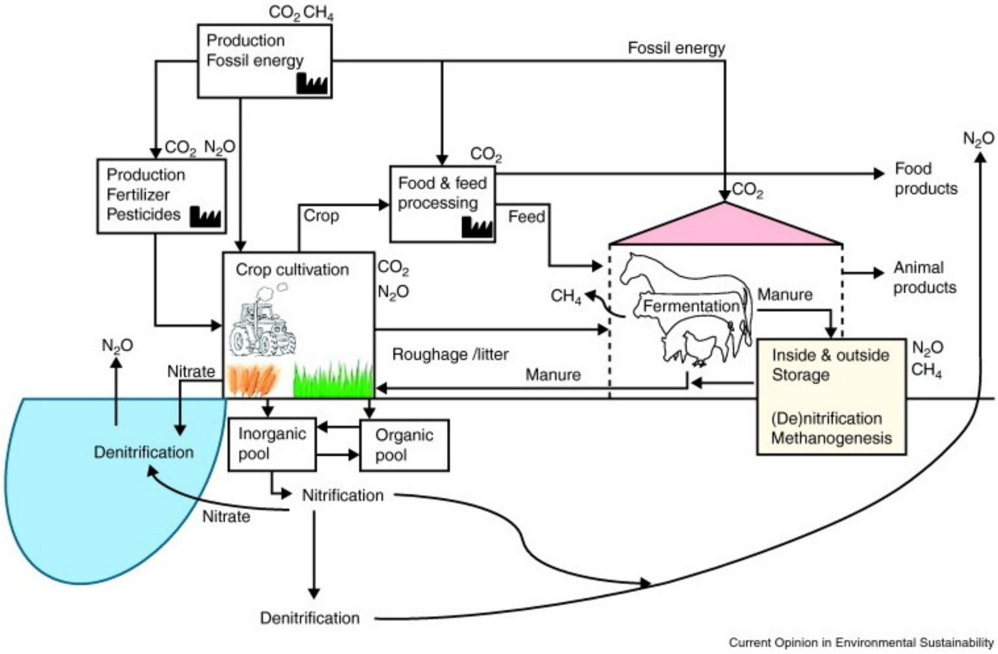

Figure 5. Processes contributing to the emissions of GHG from livestock systems (from de Boer et al., 2011).

Apart from these direct emissions, indirect emissions also arise from eventual land use change, which is further discussed in section 4.5. CO_2 can also be removed from the atmosphere through carbon sequestration in soils, hence contributing 'negative emissions' to the CF (section 4.2).

Direct emissions from livestock production are dominated by on-farm emissions, while post-farm emissions are often considerably smaller (*Figure 6*). However, transport from retail to the home can make a large contribution to GHG emissions if it is done by private car (Davis et al., 2006). Looking at the food sector as a whole, post-farm emissions are substantial in developed countries. Garnett (2011) estimated that post-farm emissions make up 50% of the emissions from the food sector in the UK.

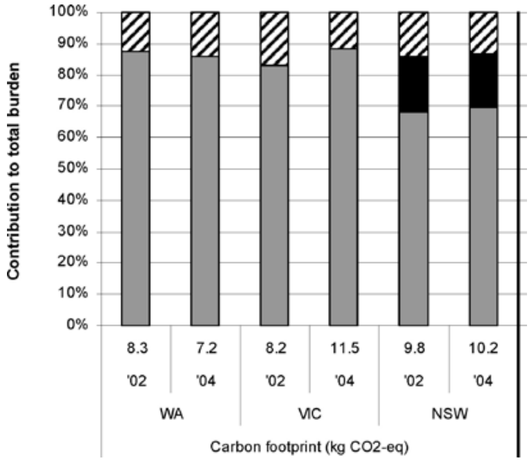

Figure 6. Processes contributing to the carbon footprint of sheep meat (WA) and beef meat (VIC and NSW) in Australia. The processing stage (striped) contributes less than 20% to the CF. The processing stage does not include transport to the consumer, preparation and waste handling (from Peters et al., 2010).

For beef meat, direct pre- and on-farm emissions are dominated by emissions from enteric fermentation, with 50% or more of the emissions coming from this process, while emissions from feed production and emissions from manure (including a small part from energy use) make up approximately equal shares of the rest (*Figure 7*). For monogastric animals emissions from feed production dominate the CF (Cederberg et al., 2009; Nijdam et al., 2012).

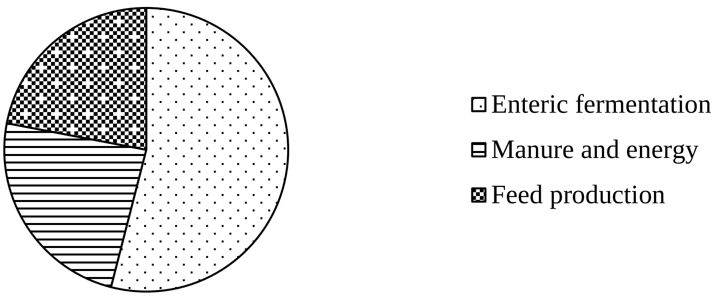

Figure 7. Direct emissions of greenhouse gases from beef production (data from Cederberg et al., 2009)

2.3.2 Results of carbon footprint of different livestock systems

Nijdam et al. (2012) reviewed 52 LCA studies of animal and vegetal sources of protein and found great variation in the CF of livestock products due to diversity in production systems. The results for pork and poultry were more homogeneous than those for beef, as monogastric production systems are more streamlined. *Figure 8* shows a summary of results from the 52 studies surveyed.

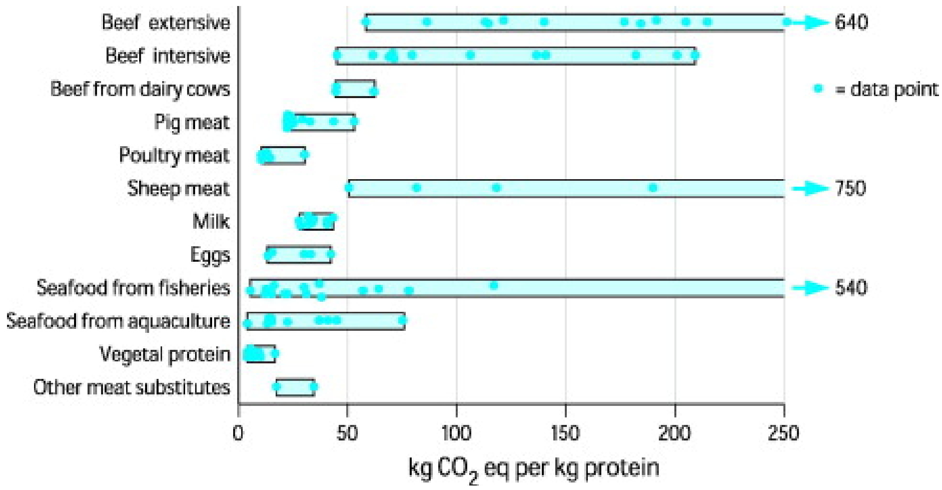

Figure 8. Carbon footprint per kg of protein for different protein sources (from Nijdam et al., 2012).

2.3.3 Challenges with CF of food

Assessing the CF of livestock systems, or other agricultural products, introduces additional complexities compared with calculating the CF of industrial products. The difficulties in measuring and modelling GHG emissions from the biological processes involved in agriculture, and uncertainties arising from modelling emissions from LUC and energy use are discussed in Chapter 4. Other complexities include the following (based on a summary by McLaren, 2010):

Agriculture uses and affects large areas of land. When comparing two agricultural systems, they may produce the same products, but use different amounts of land. It could be argued that alternative uses of the land ‘saved’ should be included in the assessment. One such use could be to grow bioenergy crops on the surplus land, which would lower GHG emissions from society by substituting for fossil fuels. Hence, the more land-efficient production system could then be seen as having a lower climate impact when this substitution effect is included.

Large amounts of carbon are stored in agricultural soils. Depending on soil characteristics, climate and management practices, soil cultivation can lead to either loss of soil carbon to the atmosphere or carbon sequestration in soils, hence removing CO_2 from the atmosphere. Conceptually, it is easy to argue for the inclusion of soil CO_2 emissions in the CF of agricultural products. However, these changes in soil carbon are very difficult to model. When it comes to carbon sequestered in soils, this uptake of carbon is also uncertain and highly variable. In addition, it can be debated whether the climate advantage of this temporary storage of carbon should be attributed to the products being produced on this soil. This is further elaborated upon in section 4.2.

Due to the practice of growing crops in rotation, it can be difficult to separate the processes belonging to different products in agricultural production. For example, if green manure is grown in one year, the fertiliser effect from this activity will be beneficial for several crops to follow.

Weather conditions, outbreaks of pests, soil characteristics and other uncontrollable factors give rise to great variability in yield between years and places, even with similar management practices. Differences in on-farm practices give rise to additional variability.

3 Uncertainties and variations

This chapter describes basic concepts of uncertainty and variation in relation to LCA and CF calculations. Chapter 5 further elaborates on these issues in specific relation to livestock production.

3.1 Difference between uncertainty and variation

Uncertainty arises due to lack of knowledge about the true value of a quantity. All measurements contain some uncertainty generated through systematic error and/or random error. Systematic error is an inherent flaw or bias in measurement where the mean of many separate measurements differs significantly from the actual value, while random error in measurements leads to the measured value being inconsistent when repeated measures of a constant or quantity are taken. Careful methodology can reduce uncertainty by correcting for systematic error and minimising random error. However, uncertainty can never be reduced to zero.

Uncertainty should be distinguished from variability, which is attributable to the natural heterogeneity of values. Variability cannot be reduced by further measurement or improved measuring methods, but better sampling can improve knowledge about the processes causing the variability.

In model estimations uncertainties arise from the input values, but also since models are an approximation of reality. In this regard, quality rather than quantity of measurements is more important for model development and more accurate answers, and could give an indication of what issues need further investigation (Juston, 2012).

Acknowledging the uncertainty of data (both for models and measurements) is an important component of reporting the results of scientific investigations. Uncertainty specifies the degree to which scientists are confident with their data and models.

3.2 Sources of uncertainty in carbon footprint and life cycle assessment

Uncertainty in LCA is challenging to address, but in most cases crucial to manage in order to understand LCA results. Uncertainty can be systematically divided in many different ways. One illustrative way of dividing uncertainty is into dependency of parameters, models and scenarios (*Figure 9*) (Baker & Lepech, 2007). Parameter uncertainty arises from incomplete knowledge about the true value of a parameter and it is generally due to measurement error in input data. Model uncertainty arises e.g. when temporal and spatial characteristics are lost by aggregation, or when non-linear phenomena are simplified into linear models (Huijbregts, 1998). Uncertainty in model scenarios is due to choices made regarding e.g. functional units, system boundaries, allocation procedures and how to access future scenarios (Huijbregts, 1998).

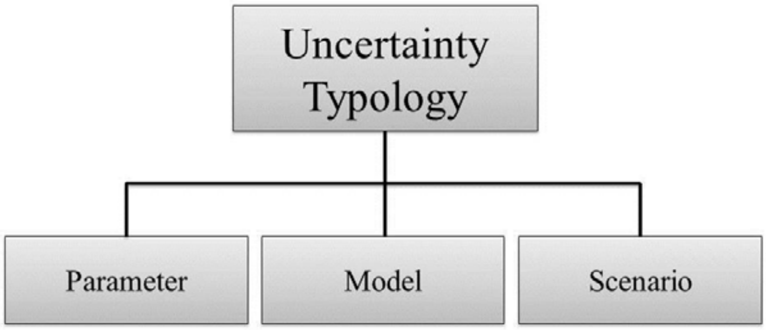

Figure 9. Uncertainty divided into three categories; parameter, model and scenario (from Baker & Lepech, 2007).

Parameters can be divided into emission factors and activity data (Röös et al., 2010). Activity data, or production data, are directly measurable parameters that describe the production system, e.g. the amounts of inputs spent, such as the amount of fuels, fertilisers and chemicals, and descriptive parameters such as the soil humus content and the transport distance. The emission factors describe the emissions caused by the production and transport of e.g. inputs or emissions from soil emissions per unit of activity data.

Table *2* shows a way of summarising and structuring different types of uncertainty in LCA proposed by Björklund (2002).

Table 2. *Examples of types of uncertainty and variability in life cycle assessment. Based on Björklund (2002).*

Type	Description
Data inaccuracy	Inaccurate emission measurements
Data gaps	Lack of inventory data
Unrepresentative data	Lack of representative inventory data
Model uncertainty	Static instead of dynamic modelling. Linear instead of non-linear modelling
Uncertainty due to choices of functional units, system Boundaries	Choice of allocation methods, technology level, marginal/average data
Spatial variability	Regional differences in emission inventories
Temporal variability	Differences in yearly emission inventories
Variability between objects/sources	Differences in performance between equivalent processes
Epistemological uncertainty; ignorance about relevant aspects of studied systems	Ignorance about modelled processes
Mistakes	Any
Estimation of uncertainty	Estimation of uncertainty of inventory parameters

3.3 Handling uncertainties in life cycle assessment

Uncertainty in LCA can be reduced by following standards, most importantly the ISO LCA standard (ISO, 2006a, b), but since this standard only provides guidance on a high level, more targeted standard documents can be used to ensure consistency in calculation methods. Uncertainty in input data can be reduced by e.g. improving data collection and measurements, using data from well-regarded databases and validating data. Uncertainty due to choices can be reduced using critical reviewing and model uncertainties can be reduced by using a higher resolution model with higher precision (Björklund, 2002; Heijungs & Huijbregts, 2004).

Uncertainty in LCA can only be reduced to a certain extent. The remaining uncertainty needs to be illustrated and presented as part of the results. The ISO LCA standard has a requirement for the inclusion of uncertainty assessment: "*An analysis of results for sensitivity and uncertainty shall be conducted for studies intended to be used in comparative assertions intended to be disclosed to the public.*" Uncertainty is defined in the ISO LCA standard as:

*“**Uncertainty analysis** is a systematic procedure to quantify the uncertainty introduced in the results of a life cycle inventory analysis due to the cumulative effects of model imprecision, input uncertainty and data variability”*

and sensitivity analysis as:

*“**Sensitivity analyses** are systematic procedures for estimating the effects of the choices made regarding methods and data on the outcome of a study.”*

Uncertainty and sensitivity analyses are further described in the next two sections. It should be noted that uncertainty and sensitivity analyses are used not only when presenting and interpreting LCA results but, since LCA is an iterative process, also for improving the study. For example, if uncertainty is too large in the final results it might be possible to improve the certainty with better data, while if sensitivity analysis shows that some scenario choices are crucial to the results, it might be possible to improve the reliability of the results through a more refined analysis (Curran, 2013).

3.3.1 Uncertainty analysis

Uncertainty analysis involves quantification and propagation of uncertainty. When uncertainty in input data is described using probability distributions, it is possible to use stochastic stimulation to propagate the uncertainty in the input data though to the end results. Several such techniques have been employed in LCA and in calculating the CF, most commonly Monte Carlo (MC) simulation (Rubinstein and Kroese, 2007; Röös et al., 2010, 2011).

In MC simulation, parameters are described by a probability distribution rather than a single deterministic value, and the calculation of the CF is repeated for a large number of times, for each of which a random parameter value from the probability distribution is used. The results of a MC simulation consist of a number of possible outcomes of the calculation, hence giving a representation of the probability of different results depending on the uncertainty and variation in the input data (*Figure 10*).

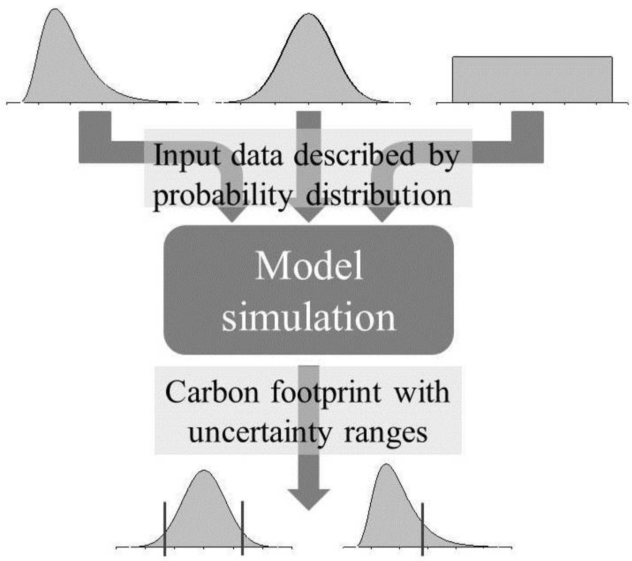

Figure 10. Schematically view of Monte Carlo simulation.

Although MC simulation is technically easy to perform, finding probability distributions that describe input data can be time-consuming and difficult. It is also highly important to take correlations between parameters into account when performing MC simulations, since failing to do so could lead to uncertainty in the end results being heavily overestimated (Bojacá & Schrevens, 2010).

Other ways of performing uncertainty analysis, using e.g. classical or Bayesian statistics or fuzzy logic, have been used to a limited extent in LCA. It is often complicated to use traditional statistical methods in LCA due to limited abundance of data, complex models and several correlations between parameters. Hence it has proven easier to use stochastic simulation techniques. Uncertainty analysis in the CF of livestock products is further discussed in section 5.3.

3.3.2 Sensitivity analysis

Sensitivity analysis aims at illustrating how choices in models and data affect the end results. It is useful for testing the robustness of models and results. It can give knowledge about the relationship between input and output variables in a model and thereby identify input parameters causing strong effects on the outputs. Sensitivity analysis can be carried out in several different ways in LCA. Some are exemplified here and the subject is further discussed in section 5.3.

Sensitivity analysis can be performed by allowing one input parameter value to change by a certain predefined percentage while all other parameters are kept constant. The change in the end result shows how sensitive the results are to uncertainties or variability in this specific parameter. By using actual min and max values, or e.g. a 95% confidence interval, for input parameters instead of an arbitrarily chosen percentage value, a better picture of the sensibility of the model is provided. This is called uncertainty importance analysis and one example of results from such an analysis is shown in *Table 3*.

Table 3. *Uncertainty importance analysis when calculating the carbon footprint of Swedish wheat (from Röös et al., 2011), testing how boundary values for different input parameters affect the final carbon footprint of wheat.*

	Boundary values		Change in wheat CF (%)	
Humus content (%)	2.4	11	−3	+23
Yield (kg/ha)	3,700	11,000	+37	−20
Amount of N (kg/ha)	49	357	−38	+7
EF production of mineral fertilisers (kg CO_2e/kg N)	5.2	9.0	−7	+9
EF N_2O from mineral fertilisers (kg N_2O-N/kg applied N)	0.003	0.03	−14	+41
EF N_2O crop residuals (kg N_2O-N/kg applied N)	0.003	0.03	−4	+11
EF N_2O leakage (kg N_2O-N/kg applied N)	0.0005	0.025	−2	+5

Scenario analysis is a type of sensitivity analysis in which different modelling assumptions such as system boundaries, allocation methods, data choices etc. are tested in order to see how these choices affect the results. Scenario analysis can also be used to investigate future scenarios or alternative production strategies. Sensitivity analysis also includes testing different methods for calculating the emission sources (Chapter 4).

3.4 Presenting results from uncertainty and sensitivity analysis

The results from uncertainty and sensitivity analysis can be presented in several ways depending on the purpose of the study and the type of results. One common way of presenting the outcome of an uncertainty analysis is to use bar diagrams with error bars. The error bars usually represent a 95% confidence interval, i.e. 95% of the expected results lie within this range. However, error bars can also represent other intervals or minimum and maximum values, so it is important to state in the figure legend what the error bars represent.

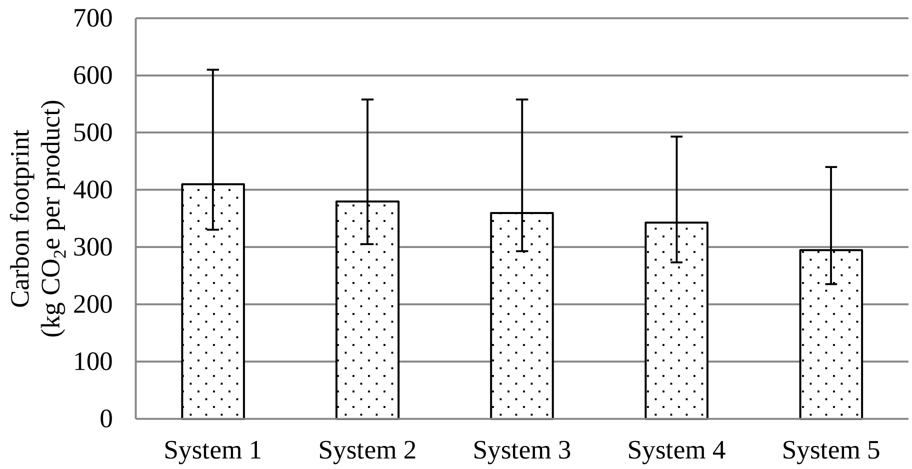

Figure 11. Example of results shown in a bar diagram with error bars illustrating the uncertainty in results. The possibility of drawing robust conclusions about the difference in CF depends on the correlations between systems.

The results from uncertainty analysis can also be presented as a histogram, which gives additional information compared with a bar diagram with error bars as it shows the probability of different outcomes and not just an uncertainty range. A histogram shows the occurrence (commonly called frequency or density) of outcomes from the uncertainty analysis in different intervals. For example, the following outcomes {1,1,2,2,3,3,3,3,3,4,4,4,5,5,6} could be illustrated in a histogram according to *Figure 12*.

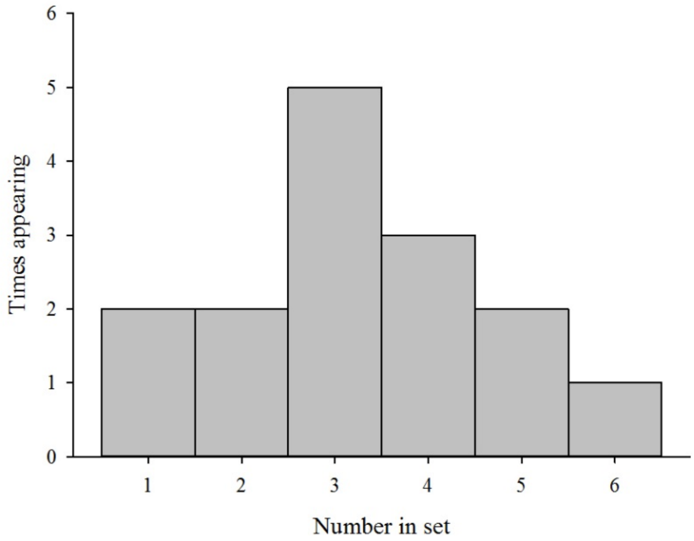

Figure 12. Example of simple histogram showing the series {1,1,2,2,3,3,3,3,3,4,4,4,5,5,6}.

When results from several systems are plotted together in one diagram, using either error bars in bar diagrams or histograms, and the uncertainty intervals overlap, it may appear difficult to distinguish between alternatives. However, if there are correlations between the systems, e.g. if they use the same uncertain input data for fertiliser production, it might be possible to differentiate between alternatives despite high uncertainty in the end results (section 5.2). Hence, when correlated systems are compared, it is wiser to show the outcome of the pair-wise difference in CF between the systems under comparison from e.g. MC simulation (*Figure 13*).

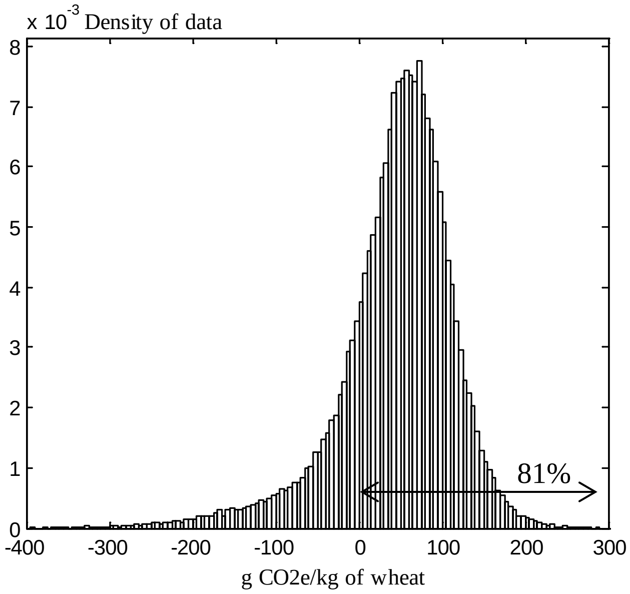

Figure 13. Difference in carbon footprint between two types of wheat mixes. The histogram shows the pair-wise difference from Monte Carlo simulation of the two wheat mixes in which correlations are considered. For example, the same value is used for fertiliser production for the two systems in ne iteration in the simulation, since the same fertiliser is used in both systems. The histogram shows that in the majority of cases (81%), the carbon footprint of one wheat mix was higher (positive numbers) than that of the other wheat mix (from Röös et al., 2011).

The results from uncertainty analysis can also be presented using a cumulative distribution function (CDF), which describes the probability that the result will be found at a value equal to or less than a value on the x-axis (*Figure 14*).

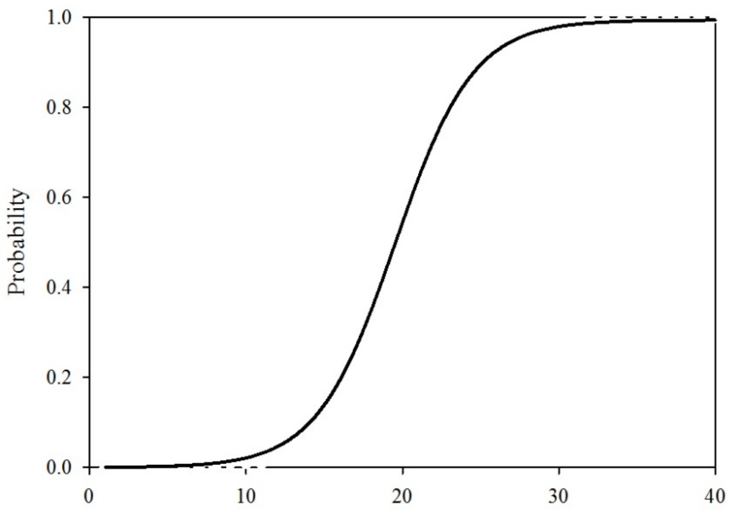

Figure 14. Example showing results as a cumulative distribution function. Values on the y-axis represent the probability of the parameter measured/calculated being less than or equal to the value on the x-axis. For example, if the numbers on the x-axis represent the carbon footprint of beef meat in kg CO_2e per kg meat, there is an 80% probability that the carbon footprint is 22 or less.

The results from sensitivity analysis can also be presented in several different ways. One common way is to show in a table how the end result is affected by a change in input data or other assumptions (*Table 4*).

Table 4. *Example of presenting results from a sensitivity analysis in which the influence on the end result from changing input parameter values is evaluated. In this example parameters 1 and 2 have considerably larger influence on the end result than parameters 3-5.*

	Change in end result as a change in input parameter value	
Input parameter	+ 20%	-20%
Parameter 1	+15%	-12%
Parameter 2	+12%	-10%
Parameter 3	-2%	+2%
Parameter 4	+1%	-1%
Parameter 5	+0.5%	-0.5%

Other common ways include showing results from different scenarios in bar diagrams (see for example *Figure 4*, *23*, *26* and *27)* in this report, which are all examples of results from sensitivity analysis testing different modelling assumptions or production scenarios). Another way of showing results from sensitivity analysis is using tornado diagrams.

4 Critical method and data choices

4.1 Nitrous oxide from soil

Nitrous oxide (N_2O) is naturally formed in soil when nitrogen is released from organic matter and is further converted to ammonium (NH_4), nitrate (NO_3) and with nitrogen gas as the end product (*Figure 15*). The formation of N_2O occurs both during an aerobic process called nitrification and an anaerobic process called denitrification. During nitrification, ammonium is converted to nitrate with N_2O as a by-product depending on the nitrification rate (the pressure through the pipe, *Figure 15*) and the maximum fraction of N_2O that can be emitted (the size of the hole in the pipe, *Figure 15*). During dentrification, nitrate forms N_2O with nitrogen gas (N_2) as the end product in the reaction chain ($NO_3^- \rightarrow NO_2$- $\rightarrow NO \rightarrow N_2O \rightarrow N_2$). Small amounts of N_2O will always be emitted to the atmosphere since the production of N_2O cannot fully be avoided.

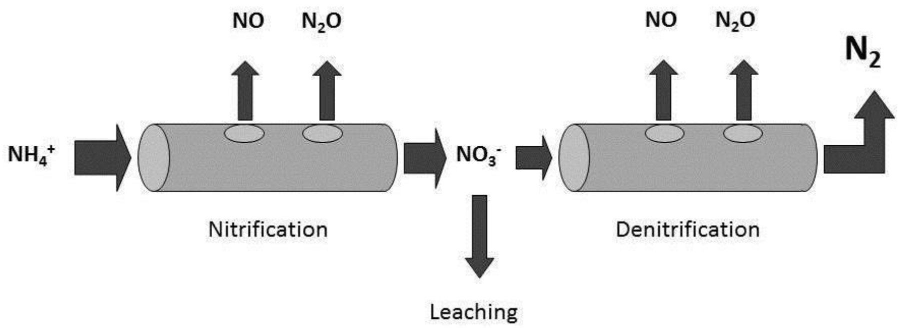

Figure 15. Schematic view of the 'hole in the pipe' concept (after Firestone & Davidson, 1989).

The amount of N_2O emitted is mainly regulated by available nitrogen and carbon supply, water content, pH and temperature in soil (Schindlbacher et al., 2004), which are the factors governing the size of the holes (*Figure 15*). The complex connections between the factors in the soil system contribute to large oscillations in N_2O emissions. Since N_2O is a very powerful GHG, with 1 kg N_2O corresponding to 298 kg CO_2 in a 100 year perspective, small amounts (often less than 1 kg per hectare) are highly important. Apart from direct N_2O emissions, indirect N_2O emissions originate from nitrogen that is removed from the soil via volatilisation, e.g. as ammonia or nitrogen oxide, or from leaching and runoff, e.g. nitrate (IPCC, 2006). Part of this nitrogen is later converted to N_2O in other parts of the ecosystem.

4.1.1 Measuring N_2O emissions from field soils

Measurements of N_2O emissions from soils provide an indication of the magnitude of these emissions and their variations in space and time. The most common way of measuring N_2O emissions from soil is by a manual chamber technique. Chambers are placed on the ground and caps close the chambers regularly so that samples of gas are taken (Klemedtsson et al., 1997). The concentration of N_2O is measured and the rate of N_2O emission can be estimated. By using automatic chambers, measurements with higher resolution are possible. Such measurements, with samples collected hourly, have shown that the temporal variation in N_2O emission is large, 2-3 orders of magnitude (Zhu et al., 2012). Using the chamber technique, measurements are restricted to small areas (often <1 m^2) and even with replicates of chambers, the uncertainty of these techniques is high. Errors have been detected when the concentration of N_2O in the chamber builds up to such a high level that chamber capacity inhibits the normal emission rate (Rochette, 2011). Differences in rainfall, temperature and moisture between the chamber and the field can further contribute to the uncertainty.

The best, but most expensive, measuring method available at present is the automatic micro-metrological technique, which measures emissions of N_2O from an entire field, without disturbing plants or soil (Wagner-Riddle et al., 2007). The atmospheric concentration of the gas and meteorological measurements such as wind speed, wet- and dry-bulb air temperature, net radiation and heat flux are continually measured by sensors on a mast. The frequency of measurement is typically 10 samples per second of vertical wind speed and N_2O concentration and the sampling periods are long enough to encompass all the significant transporting eddies. This technique is reliable for determining field-scale fluxes, includes eddy correlation, energy balance, aerodynamic and mass balance and can capture the variability in both time and space. However, the wind direction can cause uncertainties in the results, particularly if the experimental field plot is square or rectangular rather than circular. If the plot is circular and the mast is placed in the middle, the wind will always blow towards the centre regardless of wind direction and error is minimised (FAO, 2001). *Figure 16* shows an example of the temporal and spatial variation in measured N_2O emissions.

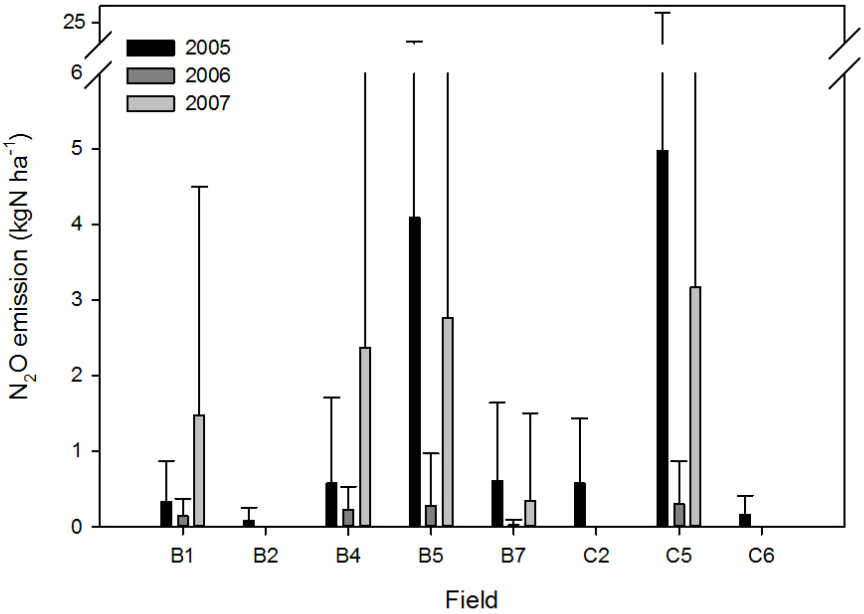

Figure 16. Measured annual N_2O emissions from five organic (B) and three integrated (C) fields during three years at Logården research station.

These measurements were made in manual chambers on eight fields (B1-2, 4-5, 7 and C2, 5-6) at the Logården research station in south-west Sweden (see Nylinder et al. (2011) for data on B2 and B4; data on other fields not published). The measurements were made in a crop sequence (field beans – spring wheat and green manure – winter rye) for organic (B) and integrated (C) systems. The bars in *Figure 16* represent mean annual emissions from each field. In addition, the error bars include the spatial variation within the fields between six chambers and the temporal variation during one year. The large N_2O emissions, with a high error bar, in field B4 2005 were governed by one occasion with a very large peak in emissions (*Figure 17*). The soil generally emits larger amounts and higher peaks of N_2O during freezing-thawing periods. On an annual basis, these occasional emissions can be responsible for 66% of total emissions (Johnson et al., 2010). Thus freezing-thawing periods could be an explanation for the high peaks in *Figure 17*. N_2O emissions depend on many factors, as mentioned earlier, so it is difficult to assess exactly the causes of variations between and within fields. To increase existing knowledge, accurate qualitative measurements of N_2O emissions and the processes involved are important.

4.1.2 Modelling N_2O emissions from field soils

The most frequently used method to estimate N_2O emissions in LCA is to use the IPCC emission factors, which only takes the amount of applied nitrogen into account (IPCC, 2006). More advanced empirical models are available, e.g. Crutzen et al. (2008), Stehfest & Bouwman (2006) and Novoa & Tejeda (2006), however, to use these models, information is needed about more parameters and site-specific characteristics and, depending on the type of study, these are not always available. For example, in a case study on crops from a specific field during a certain year, it would be possible to collect these data, while in a study investigating the CF of a livestock product from a specific region it would be very expensive to collect such data for all fields on which the feed is grown.

Empirical models for predicting N_2O emissions

IPCC (2006): The emission factor is 1% of nitrogen applied to the field as mineral fertiliser, manure and crop residues with an uncertainty span of 0.3-3%. Indirect N_2O emissions are estimated as 1% of nitrogen from volatilisation and 0.75% of leached nitrogen. The emission factors are based on the models developed by Bouwman et al. (2002), Stehfest & Bouwman (2006) and Novoa & Tejeda (2006), the latter two being described below.

Stehfest & Bouwman (2006): This empirical model was developed based on statistical analyses of over 1000 measurements of N_2O emissions, nitrogen application rate, crop type, fertiliser type, soil organic carbon content (SOC), soil pH and texture in agricultural fields. The relationship can be formulated as:

$$\text{Log}(N_2O\text{-}N) = -1.5 + 0.0038\ \text{fertN} + k_{orgC} + k_{pH} + k_{textue} + k_{clim} + k_{crop} + k_{experiment}$$

where fertN is the nitrogen amount in the fertiliser and k are constants, where k_{orgC} for different soil organic carbon content, k_{pH} for different soil pH, k_{textue} for different texture, k_{clim} for different climate zones, k_{crop} for different crop types and $k_{experiment}$ differ depending on experiment length. This statistical model is useful to estimate seasonal or annual N_2O emissions based on site-specific environmental and management parameters and the authors suggest that it can serve as a guideline for process-based models applied at larger spatial scales.

Novoa & Tejeda (2006): Two linear models were developed from a data set of 45 observations from literature reviews considering variable N_2O emission rates, nitrogen (kg/ha) applied in plant residues (NPR), whether the residues were incorporated into the soil or not (ApM), rain (mm) and temperature (ºC):

Eq.1 $N_2O\text{-}N = -4.154 + 0.00955\ NPR + 1.7278\ ApM + 0.003996\ Rain + 0.6242\ Tem - 0.0230\ Tem^2$

and

Eq.2 $N_2O\text{-}N = 0.6535 + (-0.0404 + 0.0078\ ApM + 0.000044\ Rain + 0.00567\ Tem - 0.0001975\ Tem^2)\ NPR$

Both models explained 83% of the observed variation in N_2O emissions. Novoa & Tejeda (2006) also suggested a general overall emissions factor of 1.055% of nitrogen applied in plant residues, which explained 60% of the observed variation in emissions.

Crutzen et al. (2008): The method was developed by considering the historical change in the atmospheric concentration of N_2O and relating this to the total amount of nitrogen that has been added to the agricultural system using either mineral fertilisers or nitrogen-fixing crops. Only 75% of the total N_2O emitted has decayed to date and, according to Crutzen et al. (2008), 80% is derived from agriculture. It was found that 3-5% of the nitrogen added to agriculture has been emitted as N_2O.

Mechanistic models for predicting N_2O emissions

Li et al. (1992): DNDC (DeNitrification-DeComposition) is a mechanistic model of carbon and nitrogen biogeochemistry in agro-ecosystems. Apart from N_2O emissions, the model can be used for predicting crop growth, soil temperature and moisture regimes, soil carbon dynamics, nitrogen leaching and trace gas emissions (NO, N_2, NH_3, CH_4 and CO_2).

Jansson & Karlberg (2004): The CoupModel considers base processes of heat and water flow in a deep soil profile with plant and atmospheric exchange and interactions between different components. The model allows for simulation of different spatial and temporal scales, and is well adapted to consider winter conditions with snow and frost. The heat and water processes form a core framework to which it is possible to connect modules of interest linked with feedbacks to the core framework. It has been used to describe N_2O emissions from a clay soil at Logården research station in south-west Sweden (Nylinder et al., 2011). Temporal and spatial variations in N_2O emissions from two fields in that crop sequence experiment are shown in *Figure 17*.

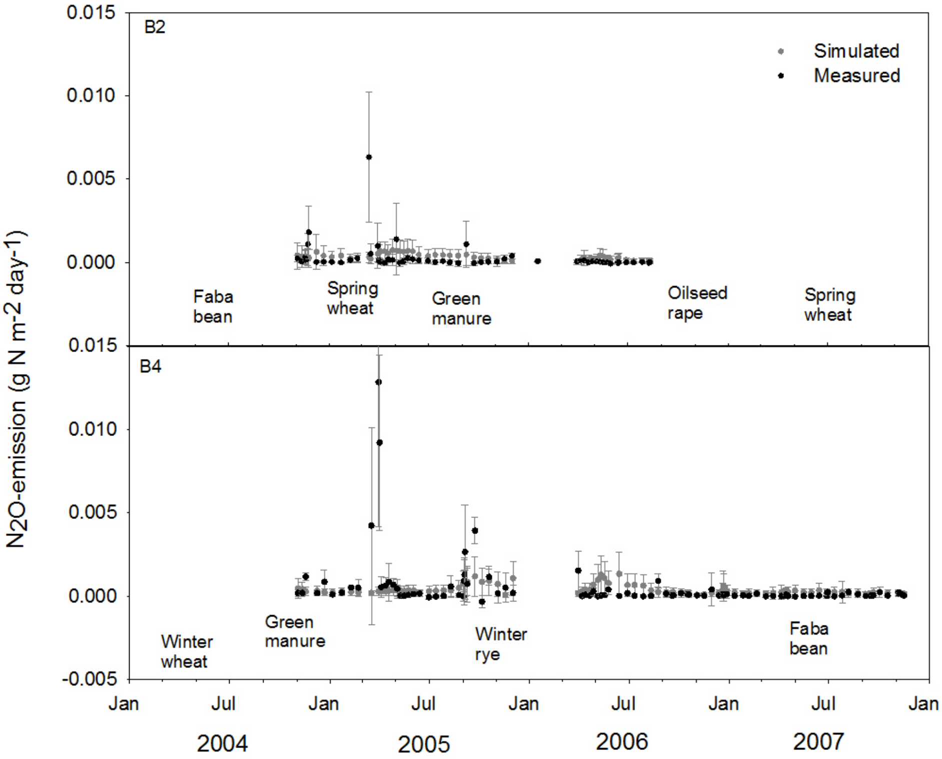

Figure 17. Simulated (grey) and measured (black) N_2O emission rates from two organic crop fields from Oct. 2004 to Oct. 2006 for B2 and Oct. 2004 to Nov. 2007 for B4 (recreated from Figure 3 in Nylinder et al., 2011).

Figure 17 shows simulated and measured N_2O emission rates with six parallel chambers with error bars representing the standard deviation (SD) from the mean value. Both simulations were calibrated with a method called GLUE (Generalised Likelihood Uncertainty Estimation, Beven & Binley, 1992), where the model results are expressed as probability distributions of possible outcomes, using Monte Carlo simulations. The GLUE method was used by Nylinder et al. (2011) because many parameter sets within the CoupModel could give similar model responses due to the complex interactions of parameters. The GLUE method aims to quantify the uncertainties associated with the model predictions within predefined limits for the parameters. In the simulations carried out by Nylinder et al. (2011) the uncertainty of a number of predefined parameters was tested by 20000 model runs. Values were randomly picked between a maximum and a minimum for each parameter simultaneously. Thereafter, a number of runs were selected with respect to measured values of N_2O emissions from the six chambers, nitrate leaching, mineral nitrogen in soil at three depths, nitrogen in grain, biologically fixed nitrogen from air, nitrogen in harvested crops, discharge and soil temperature at three depths. This example shows the difficulty in simulating the exact oscillation of the measured N_2O emissions.

A comparison of measured emissions and emissions simulated using the CoupModel on an annual basis is shown in *Table 5*. The measured annual emissions were markedly higher than the simulated emissions. A probable reason is that field measurements are performed more frequently when emission peaks are expected, which could cause the estimated annual mean of measurements to be higher than expected on a yearly basis and expand the SD. It is not possible to determine whether the measured or simulated values of annual emissions is closest to reality.

The United States Environmental Protection Agency (US EPA) is in the front line of research using the process-based model DNDC instead of emissions factors in LCA (Salas & Li, 2013). In an ongoing LCA project on swine, the objective is to use a livestock farm design of the DNDC model to create region and practice emission factors, validate mitigation options from a LCA-LCC model and scale up GHG reductions. The capacity to perform this kind of investigation is a great opportunity and it might be applicable for other process-based models, but is still very time-consuming and expensive (a lot of data and modelling time are needed).

Table 5. *Measured and simulated annual N_2O emissions with standard deviation (SD) in 2005 from two fields at Logården, Sweden. B2 measured on 30 occasions and B4 measured on 33 occasions.*

N_2O-N emission 2005 (kg ha^{-1})	B2		B4	
	Mean	SD	Mean	SD
Measured	3.06	8.83	4.86	9.93
Simulated	1.61	0.70	1.68	1.05

4.1.3 Discussion

To illustrate how results can vary based on calculation method, three different methods (the IPCC emission factors (IPCC, 2006), Stehfest & Bouwman (2006) and Novoa & Tejeda (2006)) were used to calculate N_2O emission from cereals, grass and legumes (*Table 6* and *Table 7*). The results from the three methods differed, with the lowest emissions given by the Stehfest & Bouwman method, higher emissions from IPCC factor estimations and the highest by the Novoa & Tejeda method. The low N_2O emissions calculated using the Stehfest & Bouwman method would have been considerably higher if it had been assumed that measurements of N_2O emissions covered >300 occasions per year (where $k_{experiment}$ >300 is 1.9910 instead of zero for $k_{experiment}$ <=300 in the equation by Stehfest & Bouwman described above). The N_2O emissions would then have been 7.5, 6.2 and 10.2 kg N_2O-N/ha for cereals, grass and legumes, respectively. This strong influence of one specific parameter has also been identified as a weak point by

Kasimir-Klemedtsson & Smith (2011), who estimated N_2O emissions from bioenergy crops.

Table 6. *Data used for estimations of N_2O emissions in* Table 7

	Cereals	Ley	Soy
Yield (kg/ha)	4100	7000	2544
Fertilisers (kg N/ha)			
- Mineral nitrogen	80	55	9
- Organic nitrogen	24	93	0
Crop residues above ground (kg N/ha)	28	26	28
Crop residues below ground (kg N/ha)	17	45	48
Total nitrogen	**150**	**219**	**85**

Table 7. *Direct N_2O emissions calculated using three different approaches (IPCC (2006), Stehfest & Bouwman (2006) and Novoa & Tejeda (2006)) from cereals, grass and legumes with data from Flysjö et al. (2008), Berglund et al. (2009) and IPCC (2006).*

Method	Emissions of N_2O-N (kg/ha)		
	Cereals	Grass	Legumes
IPCC, 2006	1.50	2.19	0.85
IPCC, 2006 (confidence interval 95%)	0.45 - 4.49	0.66 - 6.58	0.26- 2.59
Stehfest & Bouwman, 2006	0.08	0.06	0.10
Stehfest & Bouwman, 2006 (95% confidence interval, -51-107%)	0.04 - 0.16	0.03 - 0.13	0.05 - 0.22
Novoa & Tejeda, 2006. Eq.1	1.63	1.87	1.92
Novoa & Tejeda, 2006. Eq.2	1.29	1.64	1.71

A benefit with using the IPCC default emissions factors in LCA is that it is simple. The disadvantage is that it is coarse and gives a far from accurate description of the cause-effect chain of N_2O emissions from soils, which are highly dependent on several other parameters in addition to yearly application of nitrogen. Hence, it is not possible to suggest mitigation options for reduced emissions using this method. Kasimir-Klemedtsson & Smith (2011) also point out that the IPCC factors are not always an accurate method for estimating N_2O emissions, since it can underestimate the actual emissions, e.g. when the soil contains large amounts of organic matter, which contribute to the emissions by releasing nitrogen accumulated into the ecosystem long ago. Using the uncertainty range provided by IPCC (0.3-3%), a rough estimation of the uncertainty in emissions is obtained. The uncertainty interval can potentially include the large variation in N_2O emissions. With the IPCC approach it is very important to state uncertainty ranges with the results.

The many dependent parameters and feedbacks in the formation of N_2O emissions leave large uncertainties and difficulties in choosing methods for LCA. Use of the IPCC factors is convenient and not as time-consuming as the use of mechanistic models. Furthermore, it does not demand from the user in-depth information about all contributing factors in the formation of N_2O emissions. Process-based models can be a significant help for creating specific emission factors and will probably become important as tools in LCA for estimating N_2O emissions from local ecosystems or for supporting up-scaling in modelling.

4.2 Carbon dioxide from and to soil

Large amounts of carbon are stored in agricultural soils. The carbon content in soils varies considerably; from sandy soils with very low carbon content (<1%) to very humus-rich soils that may contain up to 50% carbon. Agricultural soils can be either carbon sources or carbon sinks. When the soil acts as a carbon sink, this is positive from a climate perspective, as CO_2 is removed from the atmosphere and carbon stored in more stable forms in the soil. Much has been written regarding the possibility of slowing climate change though carbon uptake in soils (e.g. Freibauer et al., 2004; Smith et al., 2007).

Management practices, input of biomass, climate conditions and soil characteristics determine whether a soil loses or sequesters carbon. Tillage speeds up the oxidation of carbon compounds into CO_2, while the addition of carbon to soils in the form of roots, crop residues, animal manure and other organic material is a prerequisite for carbon storage. For example, permanent pastures that are not ploughed and have large growth of biomass below and above ground can store more carbon than soils that are tilled and have low input of biomass. Soils very rich in carbon, so-called organic soils as opposed to mineral soils, lose large amounts of carbon annually as it is rapidly oxidised into CO_2 in these soils.

Since the stock of carbon in agricultural soils is large, small changes in soil carbon are of great importance for the overall GHG balance. It was only recently that changes in soil carbon began to be included in LCA and CF calculations of livestock products (Halberg et al., 2010; Pelletier et al., 2010; Veysset et al., 2011). Quantifying CO_2 emissions from soils and sequestration in soils is difficult and highly uncertain. There is also a lack of consensus regarding whether removal of CO_2 from the atmosphere through carbon sequestration should be included in the CF or not. This is further discussed in section 4.2.3.

This chapter discusses emission/sequestration of CO_2 from/in *existing* agricultural soils. GHG emissions due to land use change, most importantly the transformation of forests to agricultural land, are discussed in section 4.5. Carbon can also be temporarily stored in trees and other standing biomass in e.g. pastures.

However, the CO_2 captured by living biomass will eventually be released back to the atmosphere as the biomass either decays or is burnt, although this could take a considerable time, potentially hundreds of years, if e.g. a tree is used to build houses, bridges and other infrastructure. Hence, such temporary storage, or the positive substitution effect of biomass replacing fossil fuels as an energy source, should not necessarily be included in the CF of the livestock products produced on the farm. This is further discussed in section 5.4.2.

4.2.1 Measuring carbon dioxide from and to soils.

It is possible to measure changes in carbon stored in soils by soil sampling. Accurate determination of changes in carbon stocks requires long time series (decades). It is also possible to use flux measurements in which fluxes of CO_2 to and from fields are measured and carbon sequestration is calculated as the difference (Soussana et al., 2007). To allow certain estimates to be made of the long-term trend, long time series are needed for flux measurements too, as fluxes can vary considerably between years.

4.2.2 Modelling carbon dioxide from and to soils

Methods for including emissions and sequestration of CO_2 to and from soils in LCA and CF are still highly immature and there is no consensus on how this issue should be handled. A common approach so far in studies on livestock production has been to use rough estimates of the annual carbon sequestration potential of grassland based on literature data, instead of actually modelling the carbon stock changes in the system under study. Some examples are given below (Leip et al., 2010; Veysset et al. 2011).

A few studies have modelled the changes in soil carbon stock using models calibrated against long-term trials that can be used to predict changes in soil carbon depending on management practices and soil characteristics. One such model is described below (Sundberg et al., 2012).

Methods based on using literature data as rough estimates

Veysset et al. (2011): who studied organic and conventional suckler cattle farming systems, used an estimate from Arrouays et al. (2002) that pastures older than 20 years store 200 kg carbon per ha and year and pastures younger than 20 years store 500 kg carbon per ha and year. Veysset et al. (2011) used an average of 350 kg carbon per ha and year to account for carbon sequestration in all permanent pastures and found that 13-21% of gross GHG emissions were offset by carbon sequestration. This result is of course heavily affected by the choice of carbon sequestration potential.

Leip et al. (2010) also used carbon sequestration potential data from the literature (Soussana et al., 2007; 2009) to include CO_2 removal from the atmosphere in the calculation of CF for different livestock systems. However, Leip et al. (2010) included changes in both arable land and managed pasture in relation to natural grassland, which was assumed as the ‘natural’ land cover. Arable land was assigned the ‘lost carbon storage potential of natural grasslands’, while from a climate perspective managed grassland benefited from increased carbon sequestration compared with natural grassland. Hence, all use of arable land was burdened by emissions of 2.16 tons CO_2 per ha and year, while managed grass/legume pasture was assumed to sequester 0.87/0.46 tons CO_2 per hectare and year.

Methods based on modelling soil carbon changes

Sundberg et al. (2012): who studied organic milk production, used the ICBM model (Kätterer & Andrén, 1999) to assess emissions and sequestration of carbon in soils and included these sources/sinks in the CF of milk. ICBM is the most widely used model to calculate changes in carbon storage in agricultural land for Swedish conditions. The model calculates how much carbon is emitted or sequestered depending on the initial carbon content in the soil, carbon input, climate conditions and management practices.

There are several other soil models which could be used in LCA, if not directly, as a tool for creating specific emission factors for regions and/or agricultural practices, e.g. the Roth C model (Coleman & Jenkinson, 1996), the CENTURY model (Parton et al., 1987) and the DNDC model (Li et al., 1992).

4.2.3 Discussion

To use models for assessing the carbon balance of soils, e.g. the ICBM model, detailed data on soil characteristics at field level is necessary. In many LCA/CF studies on livestock products it is not possible to track all the fields used for feed production, as feed is also commonly imported from other farms and other countries and bought from feed companies. Even when feed is produced on the farm, data on soil parameters are not always available to feed into models. In addition, since crops used for feed are commonly produced in a crop rotation, it is not obvious how changes in the soil carbon content, which depends on the design of the complete crop rotation, should be allocated between crops. Despite uncertainties and difficulties in assessing emissions/sequestration, it is important to try to assess the magnitude of emissions/sequestration of CO_2 from/in soils, since its contribution to the CF can be substantial.

Due to the difficulty in modelling soil carbon balance, several studies on livestock production that include uptake of CO_2 as carbon sequestration in grassland use values of carbon sequestration potential from other studies that specifically studied this. For example, results from the study by Soussana et al. (2007), which measured carbon fluxes during two years at nine different grassland sites in Europe, have been used in this way (Leip et al., 2010). Their study showed great potential for carbon sequestration in European grassland, of up to several tons of carbon sequestered per hectare and year. However, the variation was very large both between sites and between years for the same site. In addition, drawing firm conclusions from soil measurements performed during only a few years requires some caution, since variations between years are large. For example, measurements and model estimates of carbon sequestration rates in Swedish permanent semi-natural grassland showed much lower potential, only 30-60 kg carbon per hectare and year (SBA, 2010). More research is needed in this area to investigate the potential of different types of grasslands to sequester carbon and methodology regarding the inclusion of carbon sequestration in CF calculations needs to be established.

Including carbon sequestration in the CF of livestock products can heavily influence the results. For large carbon sequestration rates, the uptake of CO_2 in soils can cancel out the emissions from enteric fermentation, manure and feed production, as illustrated in *Figure 18*.

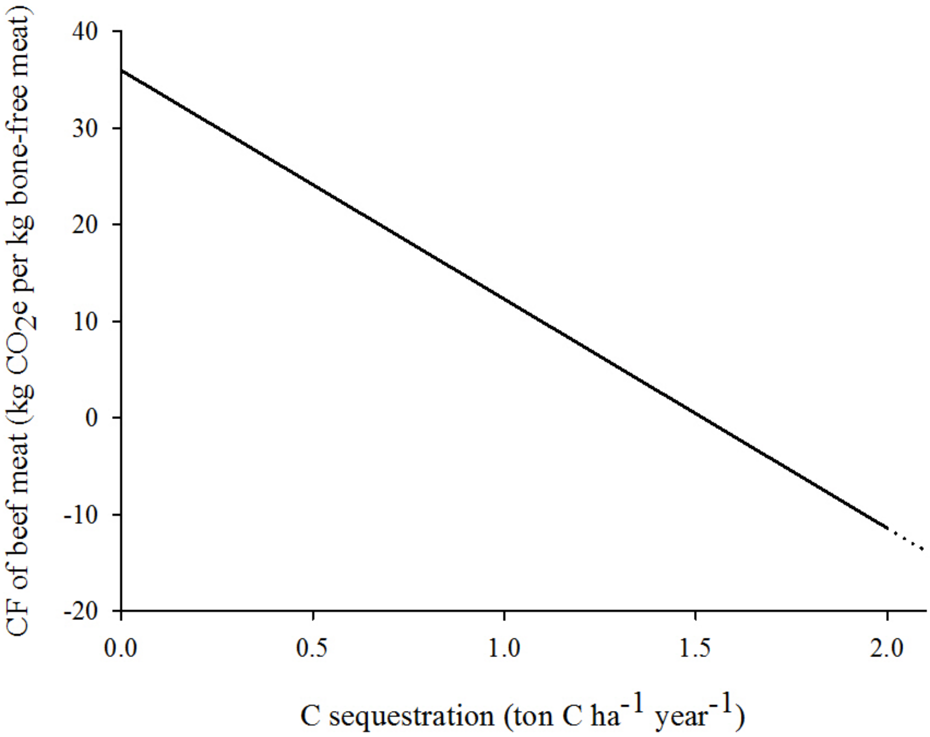

Figure 18. Carbon footprint (CF) of beef meat for different levels of assumed carbon sequestration in soils. Carbon footprint without any sequestration is assumed to be 36 kg CO_2e per kg bone-free meat, corresponding to extensive beef production in Sweden with grazing during summer and mainly roughage feed during winter and a slaughter age of 22 months (based on data from Cederberg *et al*., 2009b).

Apart from estimates of carbon sequestration potential being highly variable and uncertain, there are also other methodological challenges in including sequestration in the CF of livestock products. One very important aspect is that the process of storing carbon is reversible, i.e. carbon stored in soils is slowly released to the atmosphere as CO_2 again if management practices change, e.g. if grassland is later ploughed under to be used for growing crops. While this risk is small for some types of semi-natural grassland unsuitable for annual cropping, the carbon sequestration potential is also sensitive to heat and drought, which affect biomass growth and ecosystem respiration (Soussana et al., 2007). In addition, although the study by Soussana et al. (2007) indicated that carbon sequestration can take place even in old grassland, conventional soil science builds on an assumption of soil saturation. That means that in the absence of changes in management and environmental factors, soils will reach equilibrium in terms of carbon. Thus, although carbon sequestration can continue for many years, the potential to store carbon in the soil will diminish with time (Powlson et al., 2011; Smith, 2012). This is illustrated in *Figure 19*.

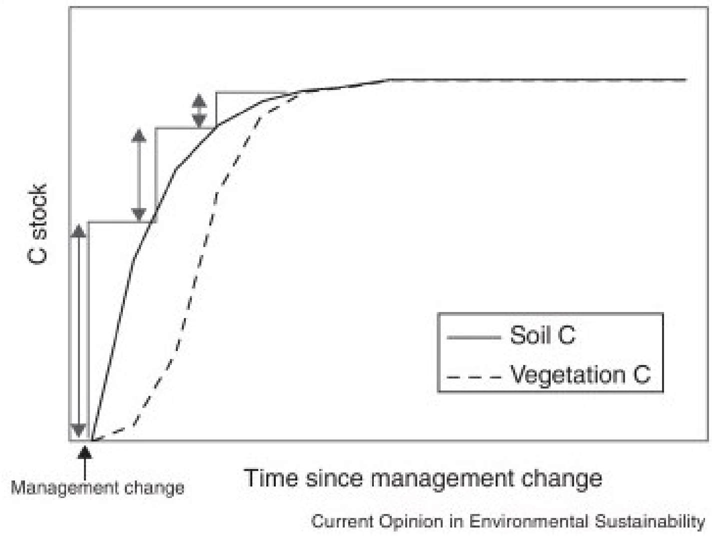

Figure 19. Decline in carbon sink strength over time. Change in soil and vegetation carbon sequestration, with large atmospheric carbon removals (sink strength) soon after management change (large vertical arrow on left-hand side of the diagram), but smaller removals over the subsequent equivalent time periods, as the soil approaches a new equilibrium (smaller arrows as soil gains in carbon) (from Smith, 2012).

Due to these factors, it is not a foregone conclusion that carbon sequestration should be included when calculating the CF of livestock products, as one could argue that from a precautionary point of view it should not. If it is, care should be taken when forming decisions based on CF that include large potential carbon sequestration since: 1) the effect is reversible; and 2) the effect might not last forever. In addition, it is wise when presenting results to clearly distinguish 'negative' emissions from carbon sequestration in soils from other emission sources, so that potentially exaggerated hopes for carbon sequestration do not eclipse other sources of emissions (Powlson et al., 2011). In addition, some management practices that increase carbon sequestration might lead to an increase in other GHG, e.g. increased fertilisation might lead to an increase in N_2O emissions. This risk of pollution swapping is captured by the life cycle methodology used when calculating CF.

4.3 Methane from enteric fermentation

Emissions of methane (CH_4) from enteric fermentation in ruminants are a major source of GHG emissions from livestock production. Monogastric animals such as pigs also emit CH_4, but in much lower amounts (IPCC, 2006) and are not further discussed here.

Through a highly specialised digestive system, ruminants have the ability to digest cellulose and thereby utilise roughage feed such as grass for growth and milk production. In the process in which microorganisms in the rumen digest fibre-rich feed material, CH_4 is formed as a by-product. The CH_4 is released to the atmosphere mainly with the exhaled breath. The formation of CH_4 means a considerable loss of dietary energy. As an average, 6.5% of the gross energy intake is lost as CH_4, but the variation is large (Johnson & Johnson, 1995; IPCC, 2006).

It is well recognised that diet composition and the total amount of feed consumed affects CH_4 emissions from ruminants (Beauchemin et al., 2008; Eckard et al., 2010; Shibata & Terada, 2010). Feed with high digestibility and low fibre content is known to reduce CH_4 emissions from enteric fermentation, e.g. introducing grains, legumes and/or high-quality forage to roughage-based diets can lead to reduced CH_4 emissions. Fat is another feed component known to decrease CH_4 formation.

4.3.1 Measuring methane emissions from enteric fermentation

CH_4 emissions from enteric fermentation can be measured directly from the animals. This can be done either by measuring the CH_4 concentration in the exhaled and excreted air directly using a chamber that can fit the whole animal or a face mask, or by using tracer techniques in which a tube of tracer gas is added to the rumen. It is also possible to measure CH_4 production from enteric fermentation by analysing concentrations in stable air or by in vitro techniques using artificial rumens (Johnson & Johnson, 1995). A newly developed technique in which CH_4 emissions are measured while the animal is eating concentrates opens the way for less expensive measurements (Garnsworthy et al., 2012).

4.3.2 Modelling CH_4 emissions from enteric fermentation

When calculating the CF from livestock production, emissions of CH_4 from enteric fermentation need to be modelled to better understand the relationships behind CH_4 formation in the rumen, since measurements are expensive and can only be used in specialist research projects. Several different models for estimating the CH_4 emissions from cattle have been developed. Empirical models based on observed CH_4 production use feed characteristics such as total dry matter intake (DMI), different types of energy measurements, fibre and fat content etc. and/or animal production data such as body weight, weight gain or milk production to predict emissions (Ellis et al., 2007, 2009, 2010). There are also mechanistic methane models in which the functioning of the rumen is modelled mathematically. Typically, these models build on hydrogen gas balance models from which CH_4 production can be predicted (Ellis et al., 2008). So far empirical models have been most commonly used in LCA and CF calculations, since the input data needed for these models are more commonly available and mechanistic models are often too complex to be used on farm level (Gibbons et al., 2006).

A few empirical models are briefly summarised below. These methods use measures of the energy content in feed in different ways, as well as other feed characteristics, to calculate yearly emission factors per animal (kg CH_4 per animal and year).

IPCC (2006) Tier 2: This method is commonly used both in national inventories and in LCA of livestock products. Emissions are calculated as a percentage of the gross energy intake. An average value of 6.5% is used to estimate the proportion of the gross energy in the feed that is converted to methane (Y_m). The gross energy intake is calculated by adding net energy requirements for maintenance, animal activity, lactation, pregnancy and growth, and taking into account the digestibility of the feed ingredients. Parameters needed to calculate net energy requirements are amount of milk produced, fat content in milk, body weight and weight gain.

Kirchgessner et al. (1991, 1995): In this method emissions from dairy cows are calculated based on milk yield and body weight. The model is based on data from 67 milking cows. For other cattle, an equation using the amounts of crude fibre, protein, fat and NFE (Nitrogen Free Extract, an estimate of crude starch and sugar content) in the feed is used.

Lindgren (1980): This is the model used in Swedish reporting for the national inventories and it has also been used in many LCA studies of Swedish livestock production systems. CH_4 emissions are calculated based on the amount of feed and digestible energy in the feed.

Mills et al. (2003): This model is based on data from lactating cows in the UK. Four linear models and one non-linear model have been developed. Two of the linear models are very simple to use; the first one includes the DMI as the only variable and the second one MEI (metabolisable energy intake), while the third includes several nutrients in the equation and the fourth the proportion of forage in the feed.

Moe & Tyrrell (1979): These authors developed a model based on an experiment with Holstein dairy cattle in North America. Emissions of CH_4 were found to be most influenced by the soluble residue, hemicellulose, and cellulose and a regression equation was set up to describe this relationship.

4.3.3 Discussion

Since emissions from enteric fermentation dominate the CF of dairy and ruminant meat, large uncertainty in estimates of these CH_4 emissions results in large uncertainty in the CF of the products. The choice of model used for calculating the emissions from enteric fermentation introduces uncertainty, as models give very different results. Table *8* shows emissions from dairy cows with different milk yields, calculated using three different models.

Table 8. *Estimated production of CH_4 from enteric fermentation in dairy cows at different milk yields and using different models to calculate the emissions (from Berglund et al., 2009)*

	Methane production (kg CH_4 per cow and year)		
Milk yield (kg ECM)	IPCC Tier 2, 2006	Kirchgessner et al., 1991, 1995	Lindgren, 1980.
6000	109	100	123
9000	138	114	135
10000	148	118	136
11000	158	123	137
12000	172	127	136

The IPCC model has a linear relationship between milk yield and CH_4 production. However, there is reason to suspect that the emissions are not linearly correlated to milk yield, since at a high feed intake the feed passes through the rumen faster and the methane-producing bacteria do not have time to process the feed to the same extent (Berglund et al., 2009). This phenomenon is better described by the model by Lindgren (1980). The model suggested by Kirchgessner et al. (1991, 1995) gives considerably lower emissions than the IPCC model and the model by Lindgren (1980).

Several studies have evaluated models for estimating enteric fermentation from ruminants by comparing observed (measured) values with values calculated (predicted) by the model (Wilkerson & Casper, 1995; Mills et al., 2003; Kebreab et al., 2006; Ellis et al., 2007; Ellis et al., 2010). *Figure 20* shows the results from such a comparison, where observed values are plotted on the x-axis and predicted values on the y-axis. For a good fit the symbols should be aligned along the diagonal line. The IPCC Tier 1 model, which uses a default value per animal type, performed very badly of course, but the IPCC Tier 2 model was only slightly better. The Moe & Tyrrell (1979) and Kirchgesser et al. (1995) models were the best predictors for this dataset, but even for these the RMSPE (square root of mean square prediction error) was approximately 24%. For another dataset evaluated in the same study, the IPCC Tier 2 model (using the old Y_m value of 6% instead of 6.5%) performed as well as the Moe & Tyrrell model, with an RMSPE of approximately 20%. RMSPE values of between 20-40% were the common outcome of all studies evaluating models for estimating emissions from enteric fermentation included here (Wilkerson & Casper, 1995; Mills et al., 2003; Kebreab et al., 2006; Ellis et al., 2007, 2010).

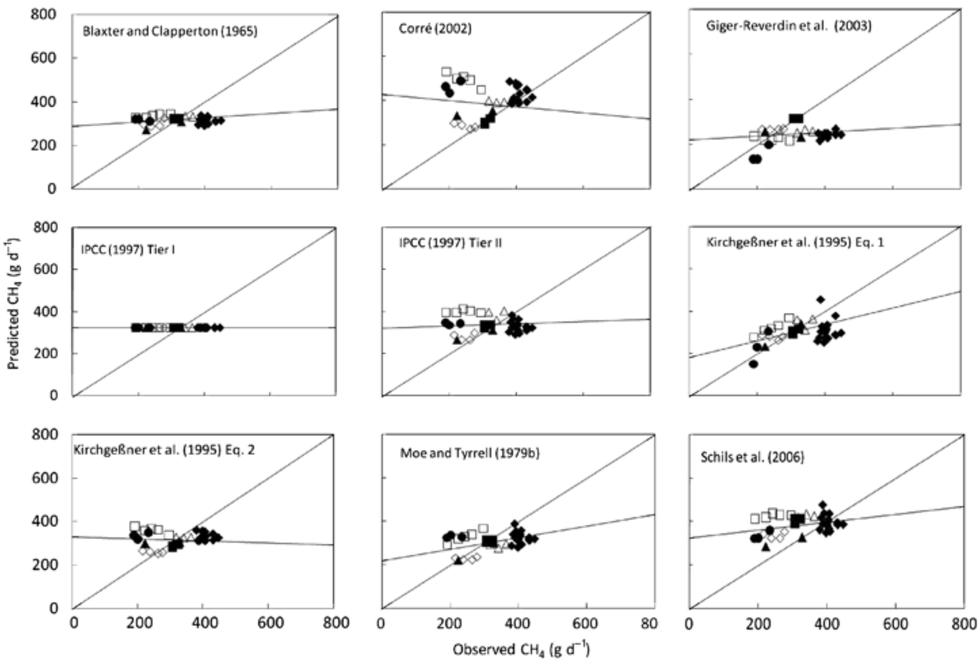

Figure 20. Predicted versus observed CH_4 production (g/day) using different models to predict emissions (from Ellis et al., 2010).

How different models perform in evaluations depends to a large extent on the dataset used in the evaluation and how well data in the dataset match the data used to develop the model. For example, if the model was developed based on data from lactating cows it might perform well for such animals, but not for heifers or dry cows (Kebreab et al., 2006). Mills et al. (2003), who also compared different models for calculating CH_4 emissions from enteric fermentation, concluded that statistical models usually fail to give reliable predictions outside the range of intake used in their development. Mills et al. (2003) also found that the model developed by Moe & Tyrrell (1979) and their own non-linear model performed best. However, the Moe & Tyrrell (1979) model requires the content of cellulose and hemicellulose in the feed to be known, which is seldom the case, which makes it difficult to use this model in practice.

Therefore the IPCC Tier 2 method is commonly used in LCA and CF calculations due to its simplicity. IPCC estimates that the uncertainty range of Y_m, the proportion of the gross energy (GE) in the feed that is converted to CH_4, is 6.5% ± 1%. However, it is well established that as intake increases, the percentage of GE lost as CH_4 decreases and that Y_m should vary with GE intake (Kebreab et al., 2006). This limitation is acknowledged by IPCC, which also lists additional factors influencing CH_4 emissions that are not included in the model, e.g. heat and cold stress, effect of feed intake and variations in microbial populations within the digestive system. How accurately GE intake can be estimated also affects the uncertainty in the end result (IPCC, 2006).

Most model development to date has been based on measurements of emissions from dairy cattle, so estimating CH_4 emissions from other types of cattle, e.g. heifers, bulls and suckler cows, and other ruminants is more uncertain than estimating emissions from dairy cows. The variation in emissions from this group is also large, since feeding strategies can differ considerably (Ellis et al., 2007).

Ellis et al. (2007, 2009, 2010) found in their studies that variations in observed emissions were higher than variations in predicted values, which shows that current models cannot fully explain the variation in emissions due to several different factors, most importantly as a result of different feeding strategies. Ellis et al. (2010) highlight the risk of designing sub-optimal mitigation options if the model used to predict the CH_4 emissions does not reflect the underlying cause-effect chain. For example, the IPCC Tier 2 model only takes into consideration the total GE intake and not the feed composition. It is known that the proportion of CH_4 that is lost (Y_m) can vary between 2-12% (Johnson & Johnson, 1995), but this variation as a result of diet composition would not be captured by the IPCC model. Hence, if the purpose of the study is to evaluate mitigation options or compare systems with very different feeding strategies, it is important to use a model that describes the effect of the different strategies studied on emissions, e.g. a diet high in concentrates or a diet high in fat (Ellis et al., 2009). As most empirical models show low prediction accuracy and none covers all aspects, Ellis et al. (2010) suggest that when designing mitigation options it might be wiser to use mechanistic models which have the capacity to describe several of the fermentative and digestive processes not included in simple regression analysis. It is also very important to consider mitigation options from a life cycle perspective. For example, healthy animals that produce and grow well are important for reduced emissions per kg of product. When it comes to different feeding strategies for reduced emissions, emissions from production of the feed need to be included. This is because some feedstuffs can contribute to lower CH_4 emissions from enteric fermentation, but cause higher emissions from production, especially if these feed products are associated with LUC effects (section 4.5). Ley cultivation could also lead to carbon uptake and sequestration (section 4.1), which could potentially balance out increased CH_4 emissions from enteric fermentation.

4.4 Emissions from manure

This section discusses emissions of GHG from managing, storing and spreading manure from the point that the manure leaves the animal until it is applied to the field. Emissions of N_2O from microbial processes in the soil due to manure application are discussed in section 4.1.

N_2O is produced in manure in storage or on pasture by the same processes as N_2O formation in soil. The type of manure system and the amount of nitrogen and carbon in the manure, as well as temperature and water content, mainly determine the amount of N_2O produced (IPCC, 2006). Solid manure systems promote N_2O formation, since they provide an opportunity for both nitrification and denitrification (see section 4.1). Emissions of N_2O can be especially large in deep litter systems due to the good oxygen supply. Ammonia emissions can be substantial in manure management, giving rise to indirect emissions of N_2O. Emissions of ammonia can be reduced by covering stored manure and lowering the temperature or pH of the manure. The technique used to apply the manure in the field also affects the ammonia emissions.

In anoxic environments such as slurry systems, there is a significant risk of CH_4 release. Some important factors that affect the amount of CH_4 produced during the storage period are temperature and the carbon content and pH of the manure (IPCC, 2006). At low temperature the microbial activity is reduced, giving rise to less CH_4 formation. How the manure is stored also affects emissions, e.g. covering slurry during storage can reduce CH_4 emissions (although covering it with a floating crust can give rise to N_2O emissions). By feeding the manure to a biogas reactor, the CH_4 from the manure can be captured and used as bioenergy. Concentrated manure on pasture or feedlots and manure stored as solid manure that is not well aired also give rise to CH_4 emissions.

4.4.1 Methods for estimating emissions from manure

Most LCA studies use IPCC Tier 2 methodology for calculating the GHG emissions from manure management (IPCC, 2006). The Tier 2 method takes into account the type of manure storage and the amount of nitrogen (causing N_2O emissions) or volatile solids (causing CH_4 emissions) in the manure, while the Tier 1 method provides default emissions factors for CH_4 and N_2O only based on animal species and climatic region. Other more complex and targeted methods for estimating emissions from manure storage are also available, e.g. Sommer et al. (2004) presented a model for estimating CH_4 emissions from manure storage in slurry systems. However, these models require sophisticated input data that are not readily available on farms, and hence they are used for increasing the understanding of the underlying chemistry and biology in GHG formation from manure handling rather than in LCA studies. Only the IPCC methodology is discussed in detail here.

CH_4 from manure management

IPCC (2006): When calculating the CH_4 emissions using the IPCC Tier 2 methodology, the manure characteristics are described by the daily amount of volatile solids (VS) excreted and the theoretical ability of the manure to form CH_4 (B_o). The VS can be measured or calculated based on feed intake and digestibility (same parameters as needed when calculating CH_4 emissions from enteric fermentation, see section 4.3). To differentiate between different manure management systems a factor called methane conversion factor, MCF, is used. MCF describes the fraction of the theoretical CH_4 formation ability of the manure (B_o) that is realised for a specific manure management system.

The emission factor for CH_4 from manure management up until application in the field is hence calculated as follows (0.67 is a conversion factor for converting 1 m^3 of CH_4 to 1 kg of CH_4):

$$EF_{CH4} = VS * B_o * 0.67 * MCF \qquad [\text{kg } CH_4 \text{ per animal and year}]$$

The IPCC guidelines provide default values for B_o and MCF that can be used, but it is recommended that country-specific values based on measurements be used. IPCC provides default values for average annual temperatures starting at 10 ºC and going up to 28 ºC with 1 ºC increments, giving 19 different MCF values ranging from 10% to 50% for covered slurry systems. The MCF for uncovered slurry storage is higher (17-80%), while it is considerably lower for solids storage, feed lots and pasture (1-5%). For B_o, values for different animal species and continents are given in the IPCC guidelines. The uncertainty range for the default values is estimated to be ±15%.

The IPCC estimates that the uncertainty in the Tier 2 emission factors for calculating the CH_4 emissions from manure management is in the range ±20%.

IPCC (2006): In the IPCC guidelines, direct N_2O emissions from manure handling are calculated by multiplying the amount of nitrogen in the manure on an annual basis by an emissions factor (in kg N_2O-N per kg nitrogen in the manure) that varies for different manure management systems. The IPCC guidelines provide default excretion rates for different animal species in different regions (Tier 1), but in most LCA studies the excretion rate is calculated using the feed intake and the retention rate. The nitrogen content in manure can be accurately determined by analysing the manure for different nutrients. The uncertainty in the IPCC emissions factors for N_2O emissions is estimated to be a factor of 2 (IPCC, 2006).

For indirect N_2O emissions, the amount of nitrogen volatised as ammonia is multiplied by the same emissions factor used for calculating indirect N_2O emissions from soils (0.01 kg N_2O-N per kg NH_3-N volatised). The uncertainty range is 0.002-0.05. Emissions of ammonia from manure, especially urine, on pasture can be substantial, especially in warm climates. Leakage of nitrogen into soils from manure storage directly on the ground also causes indirect N_2O emissions. However, very few measurements of such leakage have been conducted, so calculations of these emissions using the default values in the IPCC guidelines are highly uncertain. The emission factor is the same as for N_2O leakage from soils, 0.0075 kg N_2O-N per kg nitrogen leaked, with an uncertainty interval of 0.005-0.025 (IPCC, 2006).

4.4.2 Discussion

Manure is a highly heterogeneous substance and the content of nitrogen and VS (parameters needed for calculating emissions from manure handling using the IPCC methodology) varies with animal species, feed composition, bedding material used and manure handling system. On farm level the amount of nitrogen and VS in the manure can be established with reasonable precision through analysis of the actual manure. However, the IPCC emission factors are associated with large uncertainties, resulting in large uncertainties in the emissions of GHG from manure handling even in cases when input parameters can be established with good precision.

The IPCC MCF values, determining the fraction of CH_4 released from different manure handling systems, are in most cases not based on solid measurements due to lack of data, but on the judgment of the IPCC expert group. IPCC estimates that the uncertainty in the CH_4 emissions factor calculated using the Tier 2 approach is ±20%. Rodhe et al. (2012) compiled results from studies measuring CH_4 emissions from different types of manure handling systems, animal species and regions and found large variations both within and between studies (*Figure 21*).

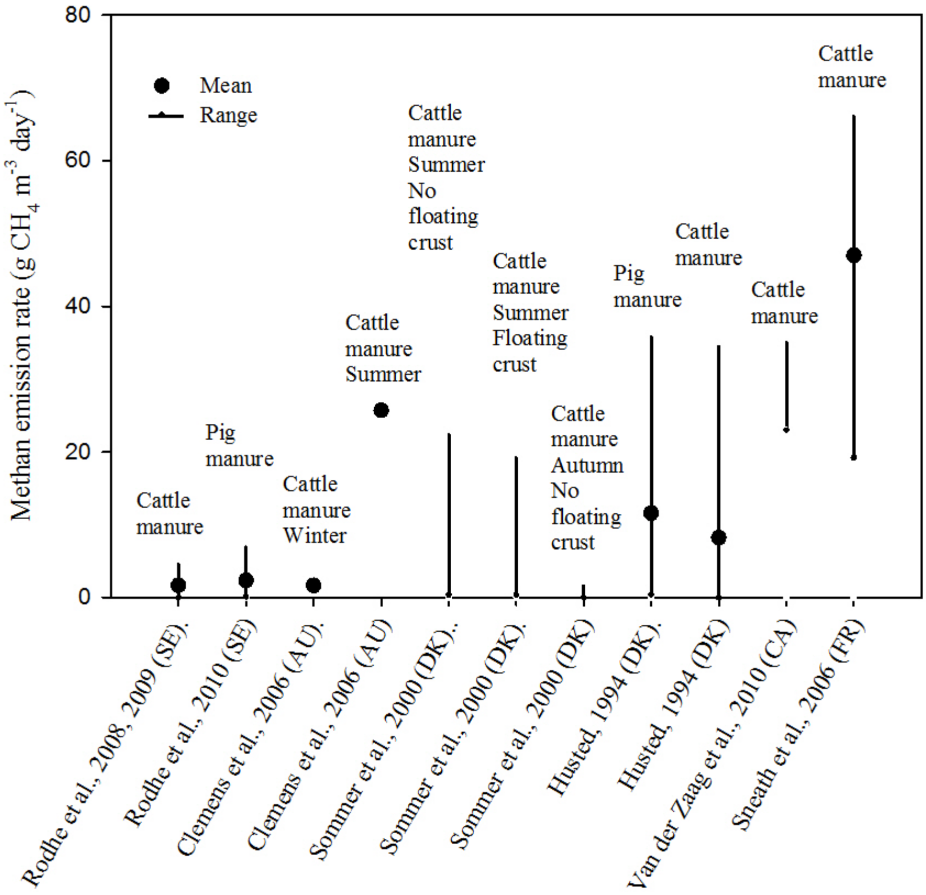

Figure 21. Results from studies measuring CH_4 emissions from different types of manure handling systems, animal species and regions (from Rodhe et al., 2012).

Data from warmer regions showed considerably higher emissions than in colder regions, as is expected due to higher microbial activity, and hence greater CH_4 production at higher temperatures, as reflected in the default MCF suggested by IPCC (2006). In the IPCC guidelines, all regions with a mean annual temperature below 10 ºC are given the same default MCF factor of 10%. However, MCF measurements at a site in Sweden with mean annual temperature of 5 ºC showed a mean MCF value of 2.7% (Rodhe et al., 2009). Hence, using the default MCF value of 10% in cold climates could overestimate the CH_4 emissions from manure storage.

The emission factor for direct N_2O emissions from manure management is associated with an uncertainty of -50% and +100% according to the IPCC guidelines. Hence, even if the nitrogen content in the manure is established through measurements, the uncertainty in the calculated N_2O emissions is large. This is due to the complex and highly variable processes driving N_2O formation (see section 4.1), as well as the varying characteristics of manure, particularly solid manure, which can contain very different amounts and types of bedding material and be stored under more or less aired conditions. During solid manure storage composting can occur, increasing the temperature and the risk of N_2O emissions. Webb et al. (2010) compiled literature data on N_2O measurements from solid manure storage for different animal species and found high variability, with CV 40-110%. Furthermore, the amount of nitrogen volatised as ammonia in animal houses, pastures and manure storage can be substantial, giving rise to indirect N_2O emissions. The variation in ammonia losses is large, owing to differences in manure management and climate conditions, and can be difficult to establish. In addition, the uncertainty range for indirect N_2O emissions due to volatilisation is 0.2-5%, making estimations of indirect N_2O emissions from manure management highly uncertain.

It is only in case studies analysing GHG emissions from a certain farm that the nitrogen and VS content in the manure can be established through measurement. For studies covering a certain agricultural sector in a country or region or for hypothetical scenario studies, the content of nitrogen and VS needs to be established using modelling, introducing further uncertainty.

Estimating emissions of N_2O from manure dropped on pasture is associated with particularly high uncertainty. Apart from the emission factor being highly uncertain (0.3-3% of deposited nitrogen, see section 4.1), establishing the amount of nitrogen in the manure is uncertain for several reasons. It is difficult to know how much grass is consumed by the animals and the nitrogen content in the grass also varies throughout the year. In addition, the amount of nitrogen that is volatilised as ammonia, causing indirect emissions, is highly uncertain (Cederberg et al., 2009).

Figure 22 presents a simplified example illustrating how emissions from different manure handling systems can vary. In the example, the same amount of manure from a fattening bull during one year is handled as either slurry without cover (bull kept indoors on a slatted floor) or as deep litter (bull kept indoors with bedding material).

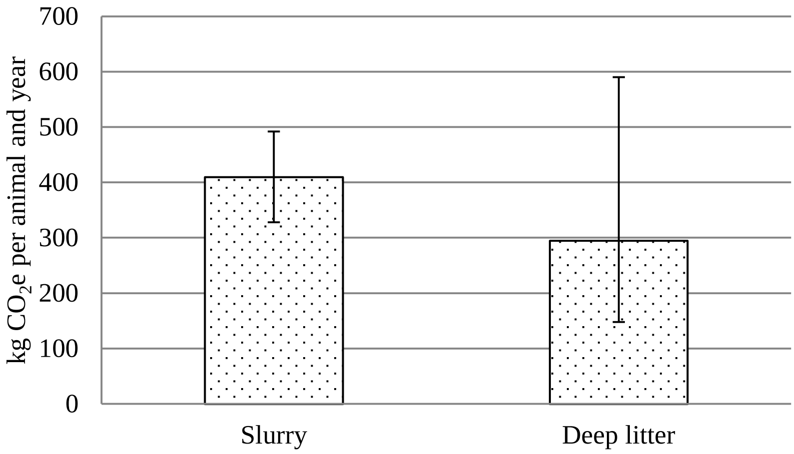

Figure 22. Emissions of greenhouse gases from manure storage from one animal during one year in two different types of storage system; slurry without cover (assuming only CH_4 and no N_2O emissions) and deep litter (assuming only N_2O and no CH_4 emissions). Emissions and uncertainty ranges calculated using the IPCC emission factors and uncertainty ranges (IPCC, 2006).

4.5 Land use change

According to the IPCC: *"land use change occurs whenever land is transformed from one use to another, for example, from forest to agricultural land or to urban areas"* (Verbruggen et al., 2011). Deforestation and other land use changes (LUC) are responsible for approximately 10% of global total CO_2 emissions. Numbers of total emissions from LUC are highly uncertain, 0.9±0.5 PgC in 2011 (Global Carbon Project, 2013). Emissions from LUC arise from burning of biomass above ground and soil carbon losses when forests and scrubland are turned into agricultural land. Conversion of grassland into arable land results in considerable amounts of carbon bound in soils being lost to the atmosphere as CO_2. Changes in soil carbon can also lead to increased N_2O emissions and burning of biomass leads to smaller amounts of CH_4 and N_2O being released. The most serious deforestation is currently taking place in Southeast Asia driven by oil palm plantations, in South America driven by the demand for soy and beef meat and in Africa driven by subsistence agriculture (UCS, 2011).

Demand for agricultural land has been identified as the major driver of deforestation (UCS, 2011; Houghton, 2012). Discussions about attributing emissions from LUC to agricultural products started with the increased demand for biofuels, which initiated an intense debate and numerous research projects on the risk of bioenergy feedstock driving deforestation. Although the results obtained are highly variable, several studies have since indicated that the contribution from LUC emissions to total emissions from biofuels can be considerable and in some cases outweigh carbon savings from using biofuels (e.g. Fargione et al., 2008; Searchinger, 2008). Emissions from LUC are relevant not only for bioenergy crops, but also for all agricultural products, especially those requiring large land areas as is the case for livestock products. Therefore, to make fair judgments of the climate impact of different food products it is necessary to include emissions from LUC in the CF of food. Later studies quantifying the GHG emissions from livestock production are also increasingly taking LUC into account (e.g. Nguyen et al., 2010; Cederberg et al., 2011; Meul et al., 2012).

LUC can be divided into direct land use change, dLUC, and indirect land use change, iLUC. Meul et al. (2012) give a good description of the two:

"dLUC relates to the conversion of land attributed directly to one or more feed ingredients, for example, the conversion of natural forest into cropland for cultivation of soybeans in Brazil. Therefore, dLUC emissions can be avoided by growing feed crops on already existing cropland. However, it is possible that in that case former agricultural production on that cropland is displaced to other areas, some of which will be converted from other land use types, causing indirect land use change. Therefore, iLUC is the conversion of land that is induced by changes in production of or demand for one or more feed ingredients, which is indirectly associated with these ingredients."

As an indirect consequence, the demand for agricultural products, apart from resulting in LUC, can also lead to intensification of land use (Kløverpris et al., 2010; Schmidt et al., 2011). Through e.g. increased fertilisation and irrigation, crop yields can be increased on land in other regions or countries. The emissions caused by the additional inputs can then be allocated to the crop driving the demand.

LUC is most commonly discussed in terms of emissions of GHG, but some LUC can lead to decreased climate impact due to carbon sequestration. One example would be the sequestration of carbon in perennial crops, e.g. fruit trees, grown on arable land which was previously used for annual crops. This type of LUC would lead to the sequestration of carbon in biomass and soil. A part from carbon sequestration in soils which is discussed in section 4.3, such LUC is of minor importance in relation to livestock production at present and is not further discussed here. However, systems integrating livestock production with e.g. bioenergy production or perennial food crops are interesting future systems that deserve more attention (SBA, 2011), but more research and methodological development is needed to estimate the CF of livestock products from such systems.

LUC can also affect the climate system in other ways than through emissions of GHG. Decreased evapotranspiration, aerosol formation and changes in albedo can have both cooling and warming effects. Quantifying these effects is highly uncertain and has so far not been included in CF of livestock products.

4.5.1 Methods for estimating emissions from land use change

Determining emissions from LUC for inclusion in the LCA of agricultural products requires modelling, which is associated with particularly large uncertainties, especially for iLUC. Models for iLUC cannot be verified by measurements or observation, and need to take into account the complexity of the global food and fibre market driving demand for land. Several methods for calculating LUC have been proposed during recent years, but there is as yet no consensus on a Best Practice approach.

Methods used to quantify emissions from LUC must include: 1) a way of estimating emissions per hectare of LUC, i.e. a way of determining the amount of GHG released as a consequence of e.g. converting forest land to arable land; and 2) a way of allocating these emissions to specific crops and other drivers of deforestation (e.g. demand for timber), i.e. a way of determining which crops are responsible for the LUC and should thus bear the burden of the LUC emissions (van Middelaar et al., 2013). For emissions per hectare of LUC, the guidelines provided by the IPCC for national accounting can be used to determine the emissions caused by one hectare of LUC for different land types (IPCC, 2006).

LUC can be calculated as dLUC only, or by using methods that include both dLUC and iLUC. In theory iLUC can also be handled separately but this is not commonly done. Some of the methods that have been used in the field of livestock production lately are summarised below.

Method for calculating direct LUC

Cederberg et al. (2011): This study calculates emissions from LUC in the LAR area of Brazil as a result of an expanding beef meat sector. Emissions from deforestation are calculated based on net difference in the carbon stock between the original land cover and the land cover after clearing. Emissions from decay of biomass that can continue for decades are included. The method takes into account that due to the dynamic nature of deforestation in Brazil (land being afforested again after some years or turned into pasture), more than one hectare of deforestation is needed to provide one hectare of arable land. Part of the emissions (6% of above and below ground biomass) is allocated to timber products based on the carbon content in the timber.

Using this approach, Cederberg et al. (2011) found that emissions from deforestation in LAR, Brazil corresponding to 572±198 kg CO_2e per ha should be attributed to the agricultural products being produced on the cleared land. When the emissions were attributed to beef meat produced on the deforested land only (42 kg carcass weight per hectare) using an amortisation period of 20 years, the CF of beef meat was found to be 726± 252 kg CO_2e per kg carcass weight. This is approximately 25 times greater than the CF of beef meat without considering LUC. The CF is heavily dependent on the amortisation period used, as is illustrated in *Figure 23*.

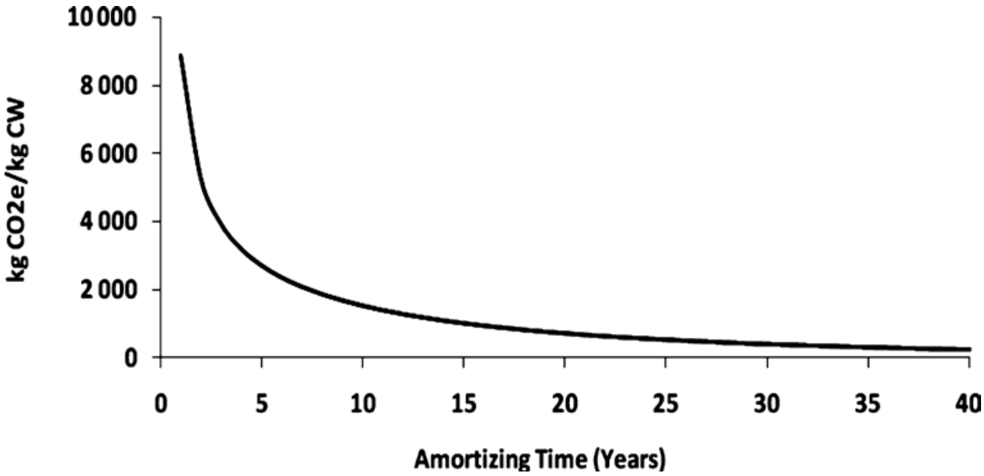

Figure 23. Example of the influence of amortisation on greenhouse gas emissions from land use change (Cederberg et al., 2011).

This study is illustrative in several ways. It shows the large uncertainties in determining the GHG emissions caused by deforestation of a piece of land. Although the geographical area is fixed, emissions from clearing one hectare of land are associated with an uncertainty of ±35%. The study also illustrates very clearly how the results greatly depend on the arbitrary choice of amortisation period.

The study also presents results of the beef CF when the emissions LUC were allocated on all beef meat produced in the LAR area (and using a 20-year amortisation period). The CF was then reduced considerably, to approximately 180 kg CO_2e per kg carcass weight, while allocating emissions on all beef produced in Brazil resulted in a CF of approximately 44 kg CO_2e. This way of allocating emissions is not dLUC in its strictest sense, since dLUC emissions should be directly associated with the product being produced on the newly deforested land, which is not the case for the beef from other regions. However, assigning all LUC emissions to the products being produced on the newly deforested land gives a very high CF for these products, while the same product produced in the same area but on available arable land goes free from the LUC burden. Hence, a more reasonable way of allocating LUC emissions to livestock products and feed ingredients might then be to use this ‘semi-direct’ approach, s-dLUC, since it can be argued that it is really the total demand for any such crops, regardless of where they are grown, that drives deforestation.

Methods for calculating emissions from semi-direct LUC

Meul et al. (2012): In this approach emissions due to s-dLUC (see above for explanation of s-dLUC) are calculated for soybean meal only, because soybean cultivation is recognised as a major driver of tropical deforestation. All other feed ingredients are assumed free from LUC burden. It is assumed that 3.2% of total soybean area in Brazil originates from tropical forests and 5.2% from scrubland. Default values from IPCC are used to calculate the carbon stock in above and below ground biomass from this deforested land. Emissions are amortised over 20 years and assigned to all soybean produced in Brazil. An s-dLUC factor for soybean meal of 0.63 kg CO_2e/kg was the result from using this method. (In the study total LUC was also calculated according to the methodology in Audsley et al., 2009, which is described below.).

van Middelaar et al. (2013): In this approach emissions due to s-dLUC (see above for explanation of s-dLUC) are calculated for feed ingredients directly associated with deforestation (soybean meal and palm kernel expeller) in a similar way as in Meul et al. (2012), but using slightly different assumptions regarding deforestation (1% of the soy produced in central west Brazil is assumed to come from former tropical forest land and 3.4% from scrubland, while soy produced in southern Brazil is assumed not be associated with LUC). Calculations of emissions from converting land into cropland are based on IPCC methods and default values. Two different ways of estimating emissions from s-dLUC during the 20-year amortisation period are considered; one including carbon sequestration from afforestation taking place during the period and delay in biomass decay (as in the Cederberg et al. 2011 method), and the other approach not taking this into account and just including emissions occurring at the point in time of deforestation. The s-dLUC factor for soybean meal was found to be 0.18 kg CO_2e per kg soybean meal using the method that included changes in land use after deforestation, and 0.17 kg CO_2e per kg soybean for the method that did not take this into account. (Total LUC was calculated in this study according to the methodologies in Leip et al., 2010 and Audsley et al., 2009, which are described below.).

Methods for calculating emissions from total LUC based on the viewpoint that expanding crops only are responsible for LUC

Leip et al. (2010): This method takes both dLUC and iLUC into account and uses historical land use changes to assign the responsibility for LUC between different crops. Data on the change in total arable area between 1999-2008, as well as the change in area for individual crops per EU country, were taken from FAO statistics. For those countries where the total arable area had increased, the new arable area was assigned to the individual crops based on their expansion compared with the total expansion in arable land. The expanded area assigned to a specific crop was then divided over the total production of the crop during the same time period, arriving at a measurement of ‘expanded area in hectares per kg of crop X produced’.

To establish the amount of emissions caused by the expansion of 1 ha of cropland, three different scenarios were used. In Scenario I it was assumed that all expansion was on former grassland and savannah, while in Scenarios II and III expansion was assumed to be on a mix of grassland and forest, with a higher percentage of forest in Scenario III, hence representing a ‘maximum emissions scenario’. Emission due to changes in above and below ground biomass carbon stocks, carbon stocks in dead organic matter and soils and emissions from biomass burning were calculated according to the IPCC 2006 Tier 1 approach.

The Leip et al. (2010) method resulted in low emissions from LUC for feed crops from Europe due to small expansion of agricultural land, while emissions from LUC for imported feed stuffs were considerable, especially for soybean and rapeseed. The LUC factor for imported soybean meal from non-EU countries was 1.5, 3.1 and 10 kg CO_2e per kg soybean meal in Scenario I, II and III, respectively.

In this method no emissions were allocated to other causes of LUC, e.g. timber. The arbitrary choice of amortisation period was avoided by allocating the LUC based on historical LUC and allocating these to the actual production of a certain crop. However, the historical time period of 10 years was a choice that affected the results.

Gerber et al. (2010): This method also uses historical changes in arable land expansion to quantify the emissions from LUC (total LUC, i.e. both dLUC and iLUC). The only crop that is assigned emissions due to LUC is soybean. From the average annual LUC rates in Argentina, Brazil and the US (countries that together with China, in which LUC is small, dominate the soybean market) and the expansion of soybean area in these countries, the amount and types of LUC to be attributed to soybean cultivation are determined. The default annual LUC value for forests and grasslands for these countries (e.g. deforestation in Brazil causes emissions of 37 ton CO_2e per hectare and in Argentina 17 ton CO_2e per hectare) given in PAS 2050 (BSI, 2011) is used to calculate the emissions per hectare undergoing LUC due to soybean cultivation. Allocation between the soybean cake and oil is done using economic allocation. Using this methodology, the LUC factor was 7.7 kg CO_2e per kg for soybean meal originating from Brazil and 0.93 kg CO_2e per kg for soybean meal originating from Argentina. Soybean from other countries and other feed crops were assumed to cause no emissions from LUC.

Ponsioen & Blonk, (2012): This method is also based on historical LUC, but uses a trend analysis of land expansion for the period 1990-2009 rather than the actual emissions for a specific year or period. LUC emissions, which come from total LUC, are allocated between different crops according to the share of the total expansion for which a specific crop is responsible. The method uses a weighted average of existing land cover types (forests, steppe and scrubland) to estimate the type of land converted into agricultural land in different countries. The IPCC default values for above ground biomass of each forest type per continent and the IPCC soil organic carbon stocks are used to calculate the emissions caused by LUC. Emissions due to LUC are allocated between timber harvest and cleared land based on timber prices and the agricultural return from cultivating the cleared land (resulting in an allocation factor of 0.65 for the use of agricultural land in Brazil). This method produces a LUC factor of 3.7 kg CO_2e per kg for soybean meal from Brazil and 4.8 kg CO_2e per kg for soybean meal from Argentina (calculated from values per hectare in Ponsioen & Blonk, 2012 using a soybean yield of 2500 kg/ha, an allocation factor of 0.72/0.28 between soybean meal and soy oil and 80% yield of soybean meal from soybean).

Methods for calculating emissions from total LUC based on the viewpoint that all land use drives LUC

Audsley et al. (2009): This method is based on the assumption that all demand for agricultural land contributes to commodity and land prices and therefore to LUC (total LUC). It uses a simple top-down approach in which all global emissions from LUC (according to IPCC) that can be attributed to the expansion of commercial agriculture (58%) are evenly divided over the total area of land used for commercial agriculture, which gives an LUC factor of 1.4 t CO_2e per ha. Examples of LUC factors per kg of feed product based on this values are: 0.50 kg CO_2e per kg soybean meal (soybean yield of 2500 kg/ha, an allocation factor of 0.72/0.28 between soybean meal and soy oil and 80% yield of soybean meal from soybean) and 0.23 kg CO_2e per kg wheat (yield 6000 kg/ha).

Schmidt et al. (2011): This method also covers both dLUC and iLUC and uses emissions from total globally observed LUC (from FAO data) and distributes these emissions on all activities occupying land, based on the viewpoint that all use of land is responsible for land use, irrespective of where occupation is taking place. In contrast to most other methods, when distributing emissions the ability of land to produce biomass is taken into account using the measure Net Primary Production (NPP). Hence, using land with a high capacity to produce biomass inefficiently (low yields) will result in higher LUC emissions per kg crop than using the same land and obtaining high yields. The method also accounts for emissions due to intensification (increased fertiliser use on existing arable land) as a result of demand for land. Two ways of distributing emissions from global LUC on the land used are provided. One is suited for use in attributional LCA and divides emissions from LUC over all land, i.e. land already in use and expanded land, as well as land under intensified production. The other allocates emissions only to expanded and intensified land and is aimed at consequential LCA modelling. The two approaches give very different results. The consequential approach gives emissions due to LUC of 145 tons of CO_2e per hectare and year, while the attributional approach results in 5.7 tons CO_2e per hectare and year as a global average. Applying these numbers gives an iLUC factor of 52 or 2 kg CO_2e per kg soybean meal for the consequential and attributional approach (calculated using a soybean yield of 2500 kg/ha, an allocation factor of 0.72/0.28 between soybean meal and soy oil and 80% yield of soybean meal from soybean).

Method based on 'missed potential carbon sink'

Schmidinger & Stehfest (2012): This method is fundamentally different from the other methods presented above as it does not aim to calculate the emissions caused by deforestation, but is based on the approach that all agricultural production on land prevents the land from regrowing its natural vegetation cover and in that way sequestering carbon. This 'missed carbon sink' is attributed to the products being produced on the land and in this way the CO_2 implications of using land are quantified. The potential carbon sink for different world regions is calculated using an integrated assessment model for global environmental change (IMAGE). For example, cultivation of land in South America during a 30-year timeframe prevents the sequestration of 0.95 kg CO_2 per m^2 and year. The corresponding figure for Europe is 0.53 kg CO_2 per m^2 and year, which is close to the world average of 0.54 kg CO_2 per m^2 and year. This method does not differentiate between the different types of demand, and hence different rates of arable land expansion for different crops, e.g. the recent increased demand for soybean. Rather, it views all land occupation as equally contributing to the missed opportunity to sequester carbon, with a differentiation based on the ability of the land to regrow different amounts of biomass. The missed potential carbon sink for soybean from South America using this method is 4.8 kg CO_2 per kg soybean meal (soybean yield of 2500 kg/ha, an allocation factor of 0.72/0.28 between soybean meal and soy oil and 80% yield of soybean meal from soybean). Note, however, that all crops are assigned emissions of this magnitude, and not only soy, using this method.

Economic modelling for determining LUC

Economic equilibrium models are complex models that use actual economic data to estimate how an economy reacts to changes in policy. Such models have been used extensively to predict possible LUC due to different biofuel policies. These models cannot distinguish between dLUC and iLUC, as they model the complete economic system on a global or regional level and study the increased demand for certain crops on the market, rather than cultivation of a crop at a specific site. Many of the crops used as feedstock for biofuels are the same as the crops used for feed, so the results from some of these studies could be used to calculate LUC factors for feed ingredients. However, the results from these economic models are highly variable, as illustrated in *Figure 24*. The variation is to some extent expected, as the models describe very complex and varying future scenarios which are inherently uncertain. Furthermore, there is variation due to different modelling approaches, e.g. modelling of the entire world economy or only the agricultural sector, geographical resolution in crop trading and whether land expansion is allowed on pasture and/or forest land. In addition, parameters such as yield levels and amount of by-products differ between studies (Höglund et al., 2013). Although results from different studies that use economic equilibrium models to determine LUC cannot be directly compared due to different policies being studied and different scopes and purposes of the studies, the great variation in results illustrates the uncertainty associated with predicting future land use development.

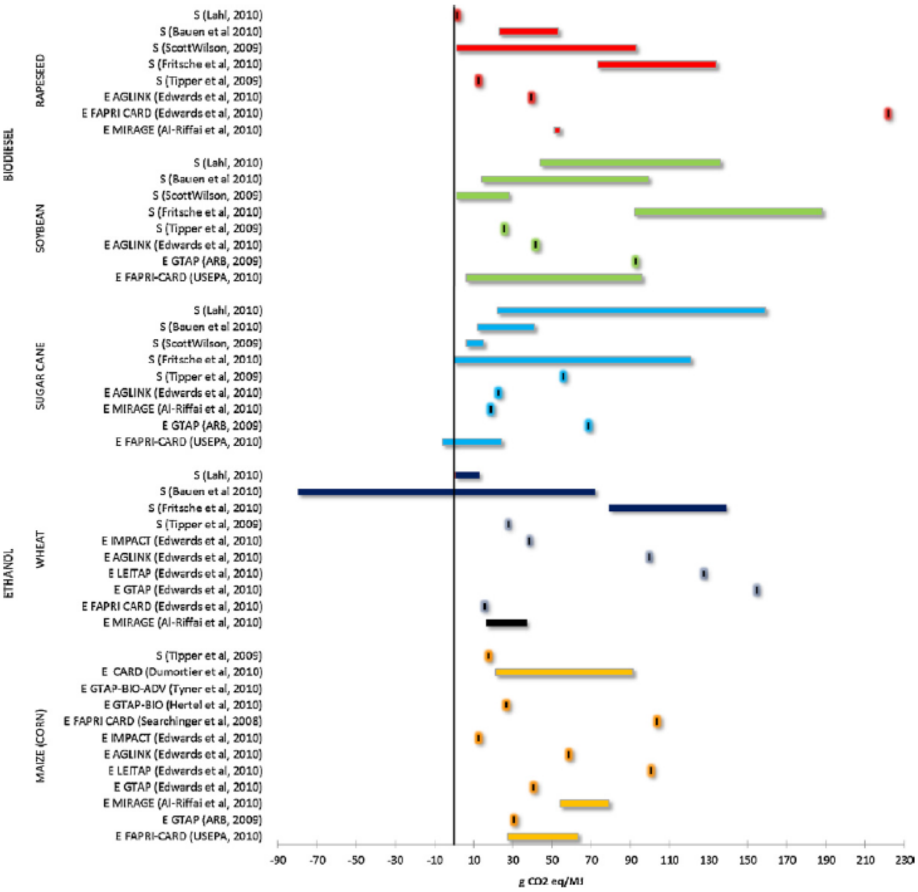

Figure 24. Land use change factors for biofuels (g CO_2e/MJ) calculated using different economic equilibrium models (from Di Lucia et al., 2012).

In some of the studies using economic equilibrium modelling to determine emissions due to LUC, uncertainty analysis using Monte Carlo simulation (section 3.3.1) has been used but the uncertainty ranges in the end results are large, ±30% or more and in some cases more than +100% (Plevin et al., 2010; IFPRI, 2011). It should be noted that Monte Carlo analysis only caters for uncertainties in parameter input and not in model uncertainties.

4.5.2 Discussion and recommendations

Crucial methodological choices

Estimating emissions due to LUC, and especially iLUC, is highly complex. Some of the major modelling choices/challenges that are revealed from the models described above are summarised below:

- **Amount of emissions per hectare of LUC.** The amount of CO_2 released when an area is cleared varies greatly with the type of land deforested, since different land types hold different initial carbon stocks, e.g. Amazon forest compared with cerrado (DG Energy, 2010). LUC are in some places also highly dynamic with cropping following deforestation, to be replaced later with pasture and later regeneration of forests again when land is depleted or overgrazed (Foley et al., 2007), so emissions also depend on the subsequent land management.

- **Allocation of emissions to crops.** Emissions from LUC can be allocated to crops grown on the deforested land only, or on all crops in that country or region (or globally) of a specific type especially associated with deforestation, e.g. soy, or allocation of emissions from LUC on crops grown on all agricultural land.
- **Amortisation period**. The LUC emissions can be amortised over an arbitrary period of e.g. 20, 30, 50 or 100 years after deforestation, or an arbitrary historical period can be used to predict future LUC.
- **Type of land affected.** The amount and type of land globally that is affected by iLUC due to increased demand of feed crops can be determined using e.g. economic equilibrium modelling of trade with agricultural goods or more descriptive methods, e.g. using historical crop production statistics to identify trends.
- **Allocation between crops and other drivers of LUC.** The emissions from LUC have to be allocated between timber/fuel wood (or other drivers of deforestation) and the large number of agricultural products that will be produced on the deforested land, e.g. on a mass basis or economic basis.

Apart from the methodological choices described above, finding correct, relevant and up-to-date data from e.g. FAO statistics to feed into the models can be difficult and introduces more uncertainty into the LUC calculations.

Comparing LUC factors and results obtained using different methods

The LUC factors for soybean meal according to the methods described in the paragraphs above are summarised in *Table 9*. The variation is large, ranging from 0.5 to 52 kg CO_2e/kg soybean meal. However, all values are not directly comparable, since they come from conceptually different methods and their use in a full life cycle assessment needs to be taken into account when determining the full impact due to LUC for a specific livestock product. What can be concluded, however, is that the contribution from deforestation to the total CF of soybean is considerable in all cases, and in most cases greatly overshadows other life cycle emissions, such as N_2O from soil and energy-related emissions estimated at approximately 0.7 kg CO_2e/kg of soybean meal (Dalgaard et al., 2008).

Table 9. *Land use change (LUC) factors for soybean meal using different LUC methods. Life cycle emissions from soybean meal without LUC are approximately 0.7 kg CO_2e/kg (Dalgaard et al., 2008). Note that for methods distributing emissions from LUC on all crops, this means all feed crops and not only soybean.*

Method	Distribution of emissions to crops	LUC factor (kg CO_2e per kg soybean meal)
Meul et al., 2012 (dLUC only)	Soy only	0.63
van Middelaar et al., 2013 (dLUC only)	Soy (and palm)	0.17-0.18[1]
Leip et al., 2010	Expanding crops[2]	1.5, 3.1 or 10.5[3]
Gerber et al., 2010	Soy only	7.7 Brazil
		0.93 Argentina
Ponsioen & Blonk, 2012	Expanding crops[2]	3.7 Brazil
		4.8 Argentina
Schmidinger & Stehfest, 2012	All crops	4.8 Missed carbon sink[4]
Audsley et al., 2009	All crops	0.50
Schmidt et al., 2011	All crops	52 Consequential LCA
		2 Attributional LCA

1 Method 1 in the study, variation is due to whether afforestation and delayed decay of biomass is included (0.18) or not (0.17)
2 Crops that are expanding in a region where the total cropland is expanding bears the burden of LUC
3 Three scenarios are used to describe the type of land converted: only grassland (1.5), only forest (10.5) or a mix (3.1)
4 This is not an LUC factor but describes the missed carbon sink when land is occupied by agriculture which prevents the natural vegetation from regrowing.

van Middelaar et al. (2013) calculated the CF including LUC for six different feed ingredients. LUC emissions were calculated in three different ways; 1) By the dLUC method described above for van Middelaar et al. (2013), 2) by the method by Leip et al. (2010) allocating emissions to expanding crops, and 3) by the method by Audsley et al. (2009) assigning emissions to all crops grown on agricultural land. Soybean meal and palm kernel expeller were the only feedstuffs that were assigned dLUC emissions using method (1), while all feed ingredients were assigned iLUC emissions using methods (2) and (3). Method (1) increased the CF of soybean meal by 35-38%, method (2) increased emissions by 632%, and method (3) increased emissions by 82%. The lower increase from using method (1) is explained by it only accounting for dLUC, i.e. only LUC directly associated with the crops under study, while methods (2) and (3) include both dLUC and iLUC. However, these two methods differ in principle, since Leip et al. (2010) assign LUC emissions based on the expansion rates of different crops, while Audsley et al. (2009) assign LUC emissions to all crops grown on agricultural land globally. This difference is illustrated by a simplified example in the next section.

A simplified example

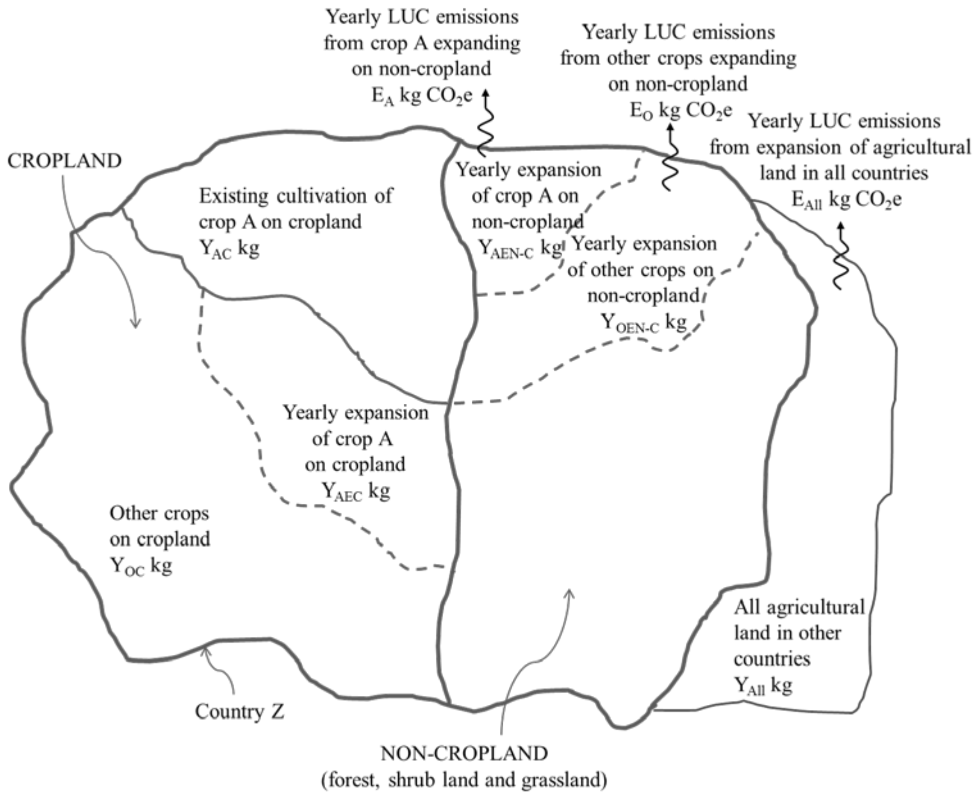

Figure 25. A simplified example of accounting for greenhouse gas emissions from land use change (LUC). Y is the yield of crops from the different land areas. E are the emissions of greenhouse gases from LUC.

Figure 25 shows LUC in country Z. Every year, an area of non-cropland is converted into cropland on which crop A, a crop in large expansion, e.g. soy, is grown (yielding $Y_{AEN\text{-}C}$ kg per year) as well as other crops (Y_{OEN-C} kg), giving rise to emissions from LUC (E_A kg CO_2e from the area with expanding crop A on non-cropland and E_O kg CO_2e from the area with other crops expanding into non-cropland). When calculating dLUC emissions, only LUC emissions directly associated the crop expansion are considered, i.e. only Y_A emissions in *Figure 25* are included in the dLUC factor for crop A. In the strictest sense, these dLUC emissions, $Y_{A,}$ should only be assigned to the products produced on the newly deforested land as:

dLUC factor crop A [kg CO_2e per kg crop A] = E_A/ $Y_{AEN\text{-}C}$

However, it might be more reasonable to assign the E_A emissions to all crops A as:

$$\text{s-dLUC factor crop A [kg CO}_2\text{e per kg crop A]} = E_A / (Y_{AEN\text{-}C} + Y_{AEC} + Y_{AC})$$

This semi-direct LUC approach (s-dLUC) is used in the studies by Meul et al. (2012) and van Middelaar et al. (2013).

When calculating iLUC emissions, it is the displacement effects that are taken into account. Since crop A is also expanding on existing cropland, this pushes other crops out onto non-cropland, causing iLUC. Emissions from iLUC can be calculated as:

$$\text{iLUC factor crop A [kg CO}_2\text{e per kg crop A]} =$$
$$= E_O / Y_{AEN\text{-}C} \quad \text{or} \quad = E_O / (Y_{AEN\text{-}C} + Y_{AEC} + Y_{AC})$$

However, this is seldom done in practice and rather total LUC, including both dLUC and iLUC, is considered. Some methods (Gerber et al., 2010; Leip et al., 2010; Ponsioen & Blonk, 2012) assign total emissions caused by LUC (E_A and E_O) to the expanding crop A on the basis that it is the demand for crop A that is driving the increased need for land.

$$\text{Total LUC factor crop A [kg CO}_2\text{e per kg crop A]} =$$
$$= (E_A + E_O) / (Y_{AEN\text{-}C} + Y_{AEC} + Y_{AC})$$

Other methods (Audsley et al., 2009; Schmidt et al., 2011) assign total global LUC emissions (E_A and E_O, as well as LUC emissions in other countries E_{All}) to all agricultural land, generally justifying this strategy by the viewpoint that all use of land occupies land and is responsible for the need to expand agricultural land onto non-cropland:

$$\text{Total LUC factor crop A [kg CO}_2\text{e per kg crop A]} =$$
$$= (E_A + E_O + E_{All}) / (Y_{AEN\text{-}C} + Y_{AEC} + Y_{AC} + Y_{OC} + Y_{OEN\text{-}C} + Y_{All})$$

This difference in viewpoint and the consequences it has for comparing the CF of livestock products are further elaborated upon in the following section.

Comparing methods assigning emissions to expanding crops only or to crops from all agricultural land

For methods assigning emissions to all crops (Audsley et al., 2009; Schmidt et al., 2011; Schmidinger & Stehfest, 2012), low total land use is important for lowering the LUC emissions, while for methods distributing emissions to crops that are expanding in area (Gerber et al., 2010; Leip et al., 2010; Ponsioen & Blonk, 2012) using less of these crops, of which soy is the most common one, is more important. When comparing production systems that use more land but less concentrate feed with production systems that use less land but more concentrate feed, this difference in viewpoint, i.e. either all land use drives LUC or crops with a high demand drive LUC, can result in contradicting results.

To illustrate this, results from a study by Flysjö et al. (2012) in which the CF of conventional and organic milk was quantified using different methods for accounting for LUC are shown in *Figure 26*. Conventional milk production, which uses more soy as feed than the organic system (45 g soybean meal per kg milk compared with 12 g), produces milk with a higher CF if LUC is calculated using the Gerber et al. (2010) or the Leip et al. (2010) methods. These methods either allocate all LUC emissions to soybean (Gerber et al., 2010) or to expanding crops (Leip et al., 2010). However, since organic production requires more land in total (2.93 m^2 per kg of milk compared with 1.54 m^2), LUC methods assigning LUC emissions to all land give a higher CF for organic milk than for conventional milk (Audsley et al., 2009; Schmidt et al., 2011).

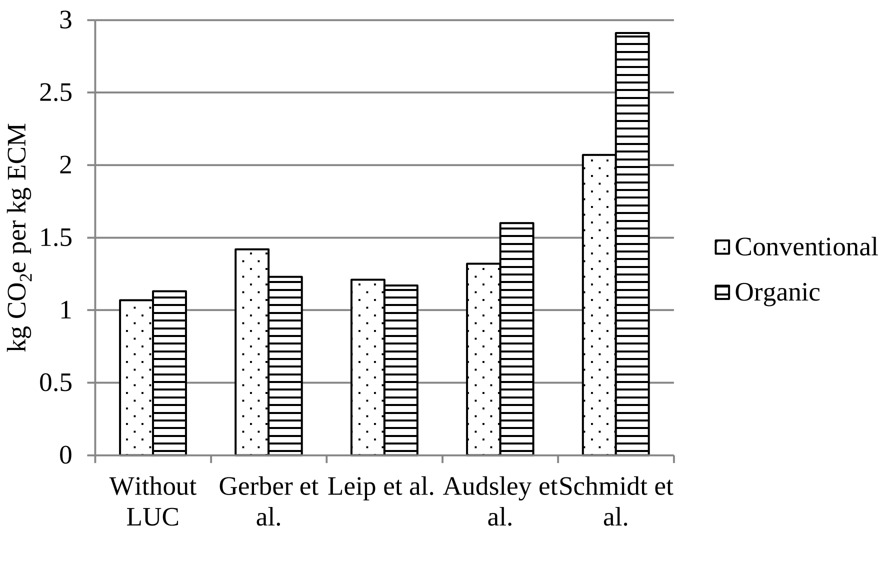

Figure 26. The carbon footprint of 1 kg of milk (ECM) without emissions from land use change (LUC) and including emissions of LUC using four different LUC methods. Data from Flysjö et al. 2012. (All emissions were allocated to milk and none to meat in this example.)

Another example of the same phenomenon that is highly relevant is in comparisons of the CF of poultry meat and pig meat. This can be illustrated by adding emissions from LUC to the CF values for Swedish chicken and pig meat without LUC, which were estimated to be 2.5 kg CO_2e per kg bone-free meat for chicken and 5.8 kg for pork in 2006 (Cederberg et al., 2009) using a meat yield from carcass weight to bone-free meat of 59% for pork and 77% for chicken (Hallström & Börjesson, 2012). In Swedish chicken production, 4.3 kg of feed, of which 0.72 kg is soybean meal, is consumed for every kg edible meat produced. The feed production results in a land use of approximately 6.4 m^2 per kg bone-free meat. In pig production, more feed is used per kg of meat produced, 7.0 kg, but less soybean meal per kg of bone-free meat, 0.32 kg. Thus feed production for Swedish pig production results in a land use of approximately 10.3 m^2 per kg meat. For most methods used to include LUC, chicken still has a lower CF than pork, but for two of the models chicken is approaching pork or even has a higher CF (*Figure 27*).

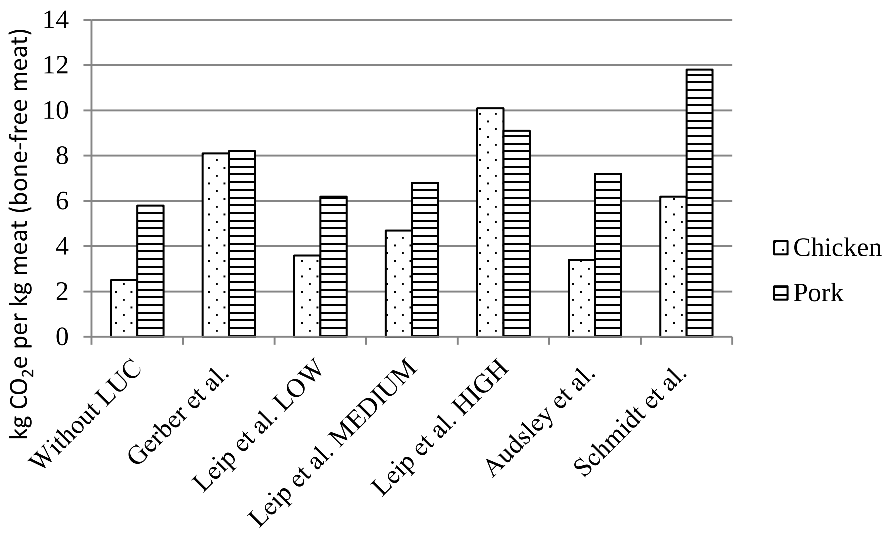

Figure 27. The carbon footprint of 1 kg of chicken and pork meat (bone-free weight) without emissions from land use change and including land use change emissions using four different LUC methods. Data on feed consumption from Cederberg et al. (2009).

The advantage in using methods that assign LUC emissions to crops that are expanding in area, e.g. those by Leip et al. (2010) and Gerber et al. (2010), is that they put the focus on currently ongoing deforestation by assigning high LUC factors to soybean in particular. This sends a clear signal to the actors in the soybean industry of the importance of halting deforestation. Ponsioen & Blonk

(2012) suggest an elaborated version of the same modelling approach, using trend analysis of crop data to avoid arbitrary amortisation periods.

However, these methods do not take into account more long-term development and displacement effects driven by demand for certain feed crops. If Brazilian soybean is abandoned due to its high emissions from LUC and replaced with soybean from other countries, the effect could be either dLUC effects in that country or iLUC effects in other parts of the world (Flysjö et al., 2012). This is not always the case, as there are areas in which agricultural land is being abandoned and afforested, e.g. in inland Sweden. If LUC from soybean production in South America can be avoided by using this land for either production of other protein crops or high-quality forage that could replace soybean in dairy feed, methods 'blaming' expanding crops are relevant and give logical results. Using methods which assign a LUC factor to all land (Audsley et al., 2009; Schmidt et al., 2011; Schmidinger & Stehfest, 2012), and hence result in higher emissions for production systems requiring more land, might discourage systems which use land that risks being abandoned for protein feed production, if the protein feed cannot be produced with the same yield as soybean meal. This is despite the fact that the alternative use of this land is for forest rather than producing feed or food for the global market, which makes these methods less useful for this specific case (Flysjö et al., 2012).

However, in most regions, agricultural production is either stable or expanding and the limited availability of agricultural land is in most cases highly relevant. The methods by Audsley et al. (2009), Schmidinger & Stehfest (2012) and Schmidt et al. (2011), which assign LUC emissions to all agricultural land, include the aspect of land scarcity, since products requiring more land are assigned higher LUC emissions. The method suggested by Schmidt et al. (2011) has an major advantage over that suggested by Audsley et al. (2009) as it takes into account different types of land and their suitability for different uses, thus assigning lower LUC emissions per ha to production on rangeland that is not suitable for arable cultivation. Assigning general LUC factors to all land use, regardless of what is produced (food or biofuels), is attractive in its simplicity and generalizability but may be too simplistic, since the amount of land taken into production and where this land is located vary depending on where the demand increases (Kløverpris et al., 2010). However, as long as the much more complex, and thus harder to grasp, methods used in economic equilibrium modelling show very disparate results when comparing GHG emissions from different livestock systems, simpler methods might be 'good enough' to give a very rough estimate of the magnitude of LUC emissions. In that instance, it is highly important that very uncertain results from LUC are not added together with life cycle emissions that are more certain, and that LUC results are presented just as very uncertain estimates.

Recommendations

Although studies quantifying LUC emissions and including these in the CF of livestock products show a great variation in results, they also show that the contribution of LUC emissions to the total CF of livestock products is considerable, sometimes totally overshadowing other life cycle emissions such as methane from enteric fermentation, soil emissions from feed production and emissions from manure and energy consumption. Hence, emissions due to LUC cannot be omitted when calculating the CF of livestock products.

Due to the great uncertainty in LUC estimates and the lack of consensus on the most appropriate method to use for quantifying LUC emissions and to avoid reducing the incentive to work with reduction measures from cultivation, several authors recommend that emissions arising from LUC be presented separately from the emissions caused during cultivation and production (Flysjö et al., 2012; Meul et al., 2012; van Middelaar et al., 2013). This is also the recommendation in the draft ISO standard for carbon footprints that is currently under development (ISO, 2010).

Meul et al. (2012) present emissions from dLUC and iLUC separately from the emissions from cultivation, transport and processing and denote iLUC emissions as “total LUC risk”. The “total LUC risk”, which they calculate using the Audsley et al. (2009) method, hence includes both dLUC and iLUC and can be interpreted as an estimated risk of causing emissions from LUC of this magnitude. When designing policy and taking action to decrease the CF from LUC, Meul et al. (2012) recommend that efforts be made above all to avoid dLUC and that production systems could be further optimised by decreased “total LUC risk”. van Middelaar et al. (2013) state that the appropriate choice of method depends on the purpose of the study. If the purpose is to stimulate companies and countries to invest in more sustainable products, LUC methods with a direct connection to deforestation should be used. If the purpose is to emphasise that due to globalisation all use of agricultural land is responsible for deforestation, then a method that assigns LUC emission to all crops should be used.

It is unlikely that emissions from iLUC can ever be quantified with a high degree of certainty due to the high complexity in the processes driving global deforestation and the fact that iLUC cannot be observed and therefore models cannot be verified. Emissions due to dLUC can be observed and are easier to measure, but using these measurements of GHG emissions in LCA studies is associated with several methodological challenges, e.g. the amortisation of the emissions over an period of time, which is an arbitrary choice. More research will help increase understanding of the processes and drivers behind deforestation and more standardised methods to include LUC in the CF of food will make it easier to compare results between studies. Future research also needs to address effects on the climate system from decreased evapotranspiration, aerosol formation and changes in albedo, which further increase the uncertainty regarding LUC. Since the climate effects from these phenomena can be substantial (Höglund et al., 2013), omitting their inclusion could lead to faulty CF of livestock products.

4.6 Carbon dioxide from energy use

Emissions of GHG from energy consumption in livestock arise mainly from: combustion of fuels used in field machinery, the use of fossil energy sources for the production of mineral fertilisers, feed, machinery and buildings, electricity use for lighting, ventilation and e.g. milking equipment in dairy units, combustion of fuels for heating animal houses and combustion of fossil fuels in vehicles used for transporting e.g. fertilisers, feed and animals.

Calculating emissions from the combustion of fossil fuels is straight-forward, since the emissions are governed by the chemical reaction of hydrocarbon compounds in the fossil fuel being converted to CO_2 and water. Emissions from combustion can vary somewhat, as some combustion conditions can lead to the production of N_2O and CH_4, but these variations are small (Eriksson & Ahlgren, 2013). Emissions from the extraction of oil and production and transport of the fuel need to be added to the emissions from combustion. The uncertainty in emissions from these process steps is small compared with the uncertainties from other processes in agriculture, at least as long as conventional fossil sources are considered and not oil shale, tar sands and other unconventional sources (Eriksson & Ahlgren, 2013). Hence, the major uncertainty in assessing emissions from fossil fuel use lies in correctly assessing the actual amount of fuel used. Still, the uncertainty in emissions from e.g. diesel use is usually much less than the uncertainty arising from soil emissions (*Figure 28*).

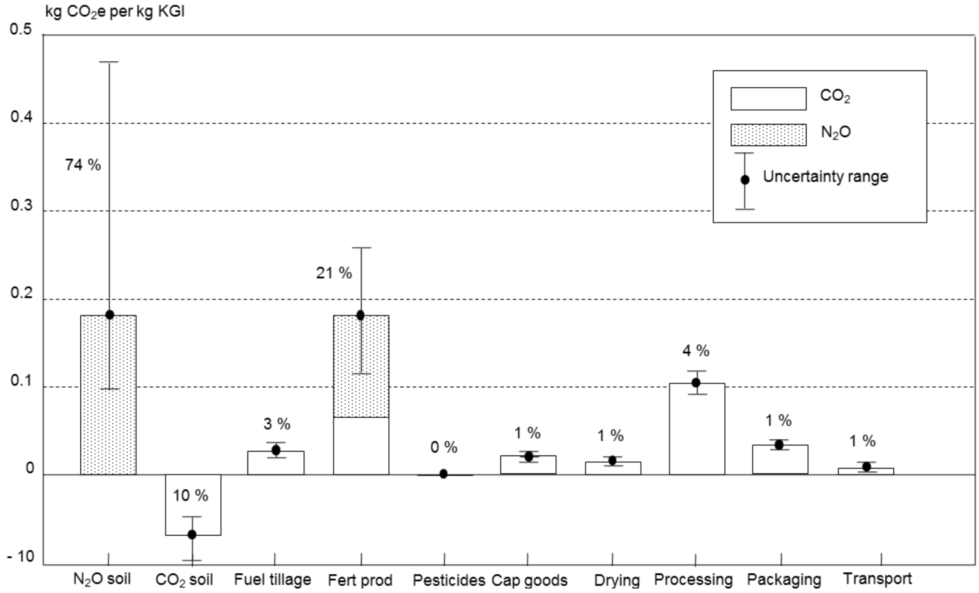

Figure 28. Contributing processes to the carbon footprint of Swedish wheat for pasta production (KGI). Error bars show uncertainty as the range between the 2.5 and 97.5 percentiles. Numbers are the relative contribution to uncertainty from an individual process as the range divided by the total mean carbon footprint. Soil emissions, especially emissions of N_2O from soils, give rise to large uncertainty. Emissions from production of mineral fertilisers are also uncertain, since it was unknown whether the fertilisers came from factories with or without N_2O cleaning equipment (Röös et al., 2011).

Estimating emissions from electricity consumption opens the way for several modelling choices. In ALCA the emissions from the average electricity mix are used and the challenge lies in determining the relevant mix to use, e.g. the national mix or whether electricity is traded on a market smaller or greater than the national borders, in which case this mix might be more relevant. In CLCA, the marginal electricity supply is used when modelling emissions from electricity, as this is the supply that will be affected when the demand for electricity increases. Determining the future marginal electricity source is far from simple (Finnveden, 2008; Lund et al., 2010). For products which demand large amounts of electricity during production or use, the choice of modelling approach for electricity can have a major influence on the results. In most livestock production, however, emissions from electricity use are minor in comparison with other GHG emissions sources and the electricity modelling choice therefore has less influence on the final results.

Manufacturing of mineral fertilisers is energy-demanding and also gives rise to emissions of N_2O. Depending on the N_2O cleaning technique used in production, total emissions of GHG from the production of mineral nitrogen fertiliser can vary greatly (*Figure 28*). If the origin of the fertiliser is known, the uncertainty in the emissions is small, ±30% for a 95% confidence interval (Röös et al., 2011), compared with e.g. the uncertainty in soil emissions or that due to modelling choices.

4.7 Collection of activity data

Uncertainties in methods used for calculating GHG emissions from various processes are discussed in sections 4.1-4.6. The present section briefly discusses the uncertainty in the activity data, or production data, used in these methods.

Substantial amounts of data are needed for calculating the CF of livestock production. It is important to get good data with regard to feeding and the production of feed, e.g. types and rations of feed used during the lifetime of the animal, and also for parent animals, crops yields and amounts of inputs used in cultivation (e.g. fertilisers and diesel), transport distances and means for imported feed, and energy use in feed industries, as well as feed losses in all stages. Production parameters such as milk, egg and meat yields, recruitment rates, number of off-spring per mother animal, age at first calving and slaughter age influence the results and need to be correctly described. In addition, information on grazing periods, manure management systems and energy consumption in animal houses is needed. Some models require information on soil characteristics and climate conditions. Generally, the variation in these parameters between farms, regions and nations is substantial.

In a case study studying one or a few farms, this information can be gathered with rather high precision by surveying the actual farms directly. However, some parameters can show high variability even within farms and some can be difficult to assess, e.g. those relating to the production of imported feed. For studies covering e.g. a whole livestock sector, data collection at farm level is not feasible and data found in national or global statistics databases or data recorded by e.g. trade organisations have to be used. However, data for all parameters can usually not be found at this high level, so data from case studies are often scaled up and used as an approximation in these kinds of studies, which can result in substantial uncertainty. Some studies use economic models that contain a large amount of aggregated agricultural data for data collection (e.g. Leip et al., 2010). Little is known about the precision and uncertainty in these data, since the complexity of the models makes it difficult to verify the data and the results.

5 Uncertainties in the carbon footprint of livestock products

5.1 Aggregating uncertainties

In LCA and CF calculations a very complex reality is modelled to estimate the product-related environmental impact. The climate impact from agriculture arises from the emissions of CO_2, N_2O and CH_4 coming from several different complex and highly variable biological processes. Emissions from these processes, which are mainly N_2O emissions from soils, direct and indirect emissions and sequestration of CO_2 in soils and biomass, CH_4 from enteric fermentation in animals as well as N_2O and CH_4 emissions from manure management, can be estimated using different more or less uncertain models which only include parts of the cause-effect chain. These are discussed in sections 4.1-4.4. These uncertain model results are aggregated in the LCA model, which in itself is an uncertain and limited representation of reality built on several choices regarding functional unit, system boundaries, allocation principles (see sections 2.1.3-2.1.4) and methods for calculating the emissions from the different processes. These choices are to some extent subjective, although the purpose of the study sets the framework. Added to this are the GHG emissions from energy use. For fossil fuel combustion, it is relatively straight-forward to calculate the GHG emissions, while for electricity and especially biofuels several methodological complexities are introduced (section 4.6). In addition, it is not only the models that are uncertain, but also the data that are fed into these models, e.g. yield levels, energy use and types and amounts of fertilisers and feed, which are characterised by a high degree of uncertainty, but more importantly, variability (section 4.7).

Figure 29 illustrates how the carbon footprint estimated is affected by several 'layers' of uncertainty.

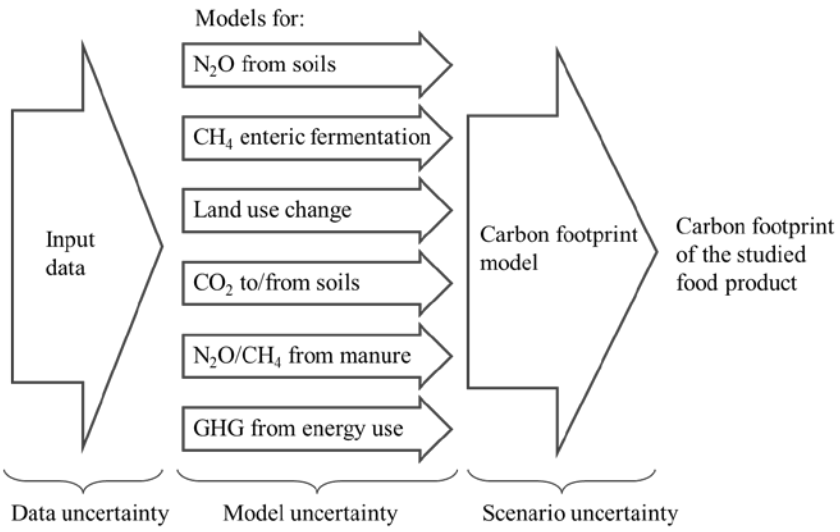

Figure 29. Many and different types of uncertainties contributing to the final uncertainty in the carbon footprint.

From *Figure 29* and the above discussion, it is easy to get the impression that LCA and CF calculations are so uncertain that they are verging on unusable. However, that is not true as these types of calculations have greatly increased our knowledge when it comes to the environmental impact of livestock products and other foods. Although CF are uncertain, without performing quantitative estimations of the GHG emissions from different types of livestock systems, it is highly likely that more intuitive beliefs and perceptions would govern decision making amongst consumers, industry and policy makers, e.g. that grazing animals are more ‘natural’ and hence less environmentally harmful than animals in more industrial systems, or that emissions of GHG from livestock are dominated by transport emissions rather than emissions from cultivation of feed and enteric fermentation. In addition, as will be discussed in section 5.2, there are several situations where solid conclusions can be drawn despite large uncertainties.

It must be stressed, however, that the CF of a food product is an *estimate of the magnitude of emissions under the conditions formulated in the study*. A CF value should not be presented as a single value and especially not to several significant digits. It should be presented together with results from relevant uncertainty and sensitivity analyses. The preferred way of presenting the results from CF studies is highly dependent on the purpose of the study, as further elaborated upon in sections 5.2 and 5.3. Although it is important to illustrate uncertainty in most cases, there are also cases when the uncertainty in the final CF is irrelevant. In addition, when evaluating the sustainability of livestock systems it is important to include other aspects than just the impact on global warming (see section 5.4).

5.2 When are uncertainties important?

The necessity to include uncertainty and sensitivity estimates for the CF of livestock systems and products varies depending on the purpose of the study and the type of systems being evaluated or compared. Large uncertainties can make it difficult or impossible to draw solid conclusions between different livestock products. Even though it is not possible to distinguish a clear ‘winner’ a CF study is still far from useless, however, since much knowledge of the systems being investigated is gained and the pros and cons of different systems are clearly revealed (Curran, 2013). On the other hand, caution must be taken so that uncertainties in LCA results are not deliberately used to slow down regulation or policy instruments that might limit growth in a specific sector, as has been the case in regulation of tobacco and GHG emissions (Mattila et al., 2012). There are situations where uncertainties have little importance and decisions can be taken on solid grounds despite large uncertainties in the CF.

Some examples of when uncertainty analysis is and is not important when studying livestock systems are given below.

Comparing similar productions systems. There are several situations in which solid conclusions can be drawn from a comparison between different production systems despite large uncertainties. Such situations arise when the cause-effect chain between an activity and its emissions is known with certainty and only the activity data, and no other circumstances, differ between the systems being compared. This can be explained by the following simplified example: Imagine two bicycles, functionally the same, being produced in the same factory, but one bicycle is made from 10 kg of steel while the other is made from 11 kg of the same steel. Assume further that the emissions from steel production are highly uncertain. Despite these uncertainties, however large, it can be concluded that the bicycle made of 10 kg steel is environmentally preferable, since the cause of the emissions from the steel production depends on the amount of steel with absolute certainty.

A simplified example from the livestock sector is when comparing two beef production systems with the same feeding regime, housing, manure handling system etc. and the only difference being slower growth and hence higher slaughter age in one system (due to e.g. bad health). In such a comparison it is possible to conclude with certainty that the system with a shorter fattening period causes less GHG on average despite all uncertainties in the CF calculations, since the causes of emissions are enteric fermentation, feed production and manure handling, all of which will be larger with a longer animal lifetime.

For livestock systems, however, comparisons are seldom this simple. Consider for example a comparison of different diets fed to animals on the same farm. If all crops are grown on the farm itself and land area required to grow the different diets is the same in both diets, emissions from iLUC (and its uncertainties) do not need to be included in the comparison. Since the same land is used for the feed cultivation in both alternatives, the soil conditions are the same and hence uncertainty in N_2O emissions from soil is less than indicated by the IPCC uncertainty range. However, emissions of N_2O vary between different crops (Bouwman et al., 2002) as well as soil carbon balances and the uncertainty in these processes needs to be considered when comparing the two different diets.

Comparing different production systems. When comparing systems for which emissions arise from very different sources, emissions from different processes might cancel each other out. It is then crucial to include uncertainty and sensitivity analyses to establish solid comparisons. For example, in a comparison between an intensive ruminant production system with an extensive system, methods for estimating CH_4 emissions from enteric fermentation (section 4.3) show that feed with a higher digestibility results in less emissions. More grain and concentrate in the feed will also result in faster growth, which causes less CH_4 emissions from enteric fermentation per animal. These two aspects would put the intensive system ahead of the extensive system. However, production of grain and concentrates can lead to less or no carbon sequestration or carbon loss from soils (section 4.2) compared with production of roughage and could in addition lead to major emissions from iLUC (section 4.5). Hence, since all estimations of emissions from these processes are highly uncertain, in order to draw any firm conclusions on which system has the lowest CF per kg of product, it is necessary to perform uncertainty and sensitivity analyses. Uncertainty analysis is necessary to establish the probability that decreased emissions from enteric fermentation due to a more digestible diet and shorter lifetime will lead to lower emissions when effects on soil balances and emissions from iLUC are included. Sensitivity analysis, including testing different methods, is necessary to evaluate how model uncertainties affect the result, e.g. by testing different methods for calculating iLUC.

Comparing different foods. Many studies have highlighted the need in the Western world for changed food consumption patterns away from foodstuffs with high CF values (most importantly meat and dairy). A need to compare different types of protein sources arises from such conclusions, i.e. a need to compare the CF of products such as meat from beef, pork, chicken, fish and other animals, as well as egg, dairy products and different types of legumes, nuts and novel foods which could replace meat in the diet. In such comparisons of products from very different production systems that cause GHG emissions from different sources and with varying uncertainties, it is very important to use both uncertainty analysis and sensitivity analysis in order to draw solid conclusions. For example, chicken are known with certainty to be much better feed converters than pigs. As a result, most LCA studies on chicken meat show considerably lower CF than pork meat (see e.g. summary in Röös et al., 2013 and Nijdam et al., 2012). Although the results of different LCA studies should not be compared in detail due to methodological differences, a clear trend of chicken meat having lower CF than pork is evitable from existing studies. However, these have not included emissions from LUC. *Figure 27* in section 4.5.2 shows the CF of Swedish chicken and pork including the emissions from LUC according to different methods and makes clear that when emissions from LUC are included, the difference in the CF between chicken and pork meat is less pronounced.

Hot-spot identification for determining mitigation options. Not infrequently, LCA studies are performed on just one production system, e.g. as a case study on a specific farm, with the purpose of identifying mitigation options on farm level. Using a LCA perspective, it is possible to identify which mitigation options offer most reductions in GHG. The uncertainty in the end result is of less importance in such studies, while it is crucial to perform sensitivity analysis to determine which parameters have a large influence on the results.

Total impact from a sector. Several studies have estimated the CF of either the total livestock sector or a specific sector, e.g. the dairy or poultry sector in either the world, a country or a region (Steinfeld et al., 2006; Gerber et al., 2010). The outcomes from these studies can be used to compare the total impact from livestock production with that from other sectors, such as energy or transport (Steinfeld et al., 2006). In such comparisons it is necessary to include an uncertainty estimate, since emissions from agriculture are highly uncertain while emissions from energy and transport, which are dominated by emissions from fossil fuel combustion, are easier to calculate with high precision. It is also necessary in such comparisons to ensure that system boundaries and other assumptions in the different studies are the same. In the study by Steinfeld et al. (2006), the life cycle emissions of GHG from the livestock sector were wrongly compared to the emissions from the transport sector calculated according to the UNFCCC accounting methodology, which is not done using a life cycle perspective and hence only includes combustion from fuels and not emissions from infrastructure or production of fuels (Place & Mitloehner, 2012).

5.3 How to illustrate uncertainties

In a paper by Björklund (2002), an array of ways to address uncertainty in LCA in general are outlined. The most commonly used methods are summarised in section 3.3 of this report. In the present section, ways to illustrate uncertainties specifically in the CF of livestock products are outlined, assuming that measures to reduce uncertainty, such as following standards, filling data gaps where possible and validating data, have been taken.

Basically, two types of uncertainties need to be illustrated:

- Input data/parameter uncertainty and variability, which is handled with uncertainty analysis, most commonly using probabilistic simulation (section 5.3.1).
- Modelling uncertainty, which is handled with sensitivity analysis (section 5.3.2). Modelling uncertainty in calculating the CF of livestock products can be divided into:
    - Different choices related to LCA modelling
    - Choices of models to calculate emissions from different processes, e.g. N_2O from soil, CH_4 from enteric fermentation and LUC, including uncertainties in these models

5.3.1 Input data/parameter uncertainty and variability

To establish how uncertainty and variability in input data are propagated though the CF model and affect the uncertainty in the final results, probabilistic or stochastic simulation can be used. Monte Carlo simulation (described in section 3.3.1) is the most commonly used method in LCA, although other stochastic simulation methods have been proposed (Imbeault-T´etreault et al., 2013).

Using MC simulation or similar techniques, it is possible to provide results as uncertainty intervals rather than just one highly uncertain deterministic value (for examples see section 5.3.3), which is advantageous for several reasons. Obviously the result is more correctly described with an uncertainty interval than with just one value, but an additional advantage is that an uncertainty interval also indicates that the result is uncertain and that conclusions and policy implication drawn from the result must take the uncertainty analysis into consideration.

Although MC simulation is technically easy to perform, establishing relevant uncertainty representations for the input data in the form of probability distributions is often difficult and time-consuming. Available data are seldom in the abundance and form needed for classical statistical analysis and expert judgment is often needed to establish probability distributions and its parameters.

For example, although IPCC provides uncertainty intervals for its emission factors for N_2O, it is not clear which distribution they relate to.

Correlations are many in livestock systems and can sometimes be difficult to establish. For example, the yield of feed ingredients depends on the amount of nitrogen supplied, but also on several other parameters and it is not easy to establish a yield dependency based on the multitude of parameters involved in livestock production systems. Failing to take correlations into account can heavily overestimate the uncertainty in the end result.

It must be stressed that MC simulation only provides an estimate of uncertainty due to uncertainty and variability in input data. It can give a false sense of certainty, as it is not uncommon for model uncertainties when calculating emissions from livestock systems, regarding e.g. the method chosen to calculate N_2O from soil, CH_4 from enteric fermentation and LUC or the allocation method used, to be much larger and to overshadow the uncertainties due to input data uncertainty and variations. In such cases the relevance of performing MC simulation must be questioned, especially considering the amount of time required to perform MC simulation. Whether or not it is sensible to perform stochastic simulations depends on the purpose of the study. In cases when model uncertainties affect the result more than input data uncertainty, sensitivity analysis (section 5.3.2) should be prioritised over stochastic simulation.

5.3.2 Model uncertainties

Model uncertainty in calculating of the CF of livestock products can be divided into: 1) Choices related to LCA/CF modelling; and 2) choices of models to calculate emissions from different processes, including uncertainties in these models. Different choices when it comes to CF modelling include choice of functional unit, system boundaries, allocation method and characterisation factors, as described in section 2.1 and 2.2.2. By using scenario analysis (section 3.3.2) and testing different alternatives of such choices, the robustness of the study results can be tested.

The way in which the choice of model to calculate e.g. emissions of N_2O from soil, CH_4 from enteric fermentation and LUC affects the result can be tested by applying different methods and comparing the results. A specific model of a biological system is also uncertain in itself. Environmental systems are complex with open boundaries, uncontrolled conditions and substantial feedbacks and interactions (Odum, 1983). These intrinsic complexities bring serious challenges to connecting model representations and predictions to field-collected data observations (Beven, 2009). For example, environmental models often require mathematical complexity beyond linear relationships, particularly process-based models that simulate time series data. To account for uncertainty in model parameters, stochastic simulation (section 3.3.1 and 5.3.1) can be used when employing these models in the CF calculation, e.g. IPCC provides uncertainty ranges for emission factors for N_2O and these can be used to establish a probability distribution that can be fed into a MC model.

Hence, model uncertainties should be illustrated using sensitivity analysis in which results from several model choices are presented both from choices related to LCA specific choices and methods used to quantify emissions from different processes. Model uncertainty in such methods can be illustrated using stochastic simulation.

5.3.3 Examples of handling uncertainties in LCA

This section provides a few examples of how uncertainties have been incorporated into LCA studies of livestock systems.

Henriksson et al. (2011) carried out a study to investigate how much the CF of milk varies between different Swedish dairy farms as a result of variation in the most important production parameters. The study used MC simulation to look at variation in milk yield, feed DMI (Dry Matter Intake), enteric CH_4 emissions, nitrogen content in DMI, nitrogen fertiliser rate and diesel use on the farm. The authors had access to a substantial amount of data regarding milk yields and feed intake and were able to perform statistical analysis to determine the probability distributions of the input data. The results were presented as a histogram or frequency distribution (*Figure 30*).

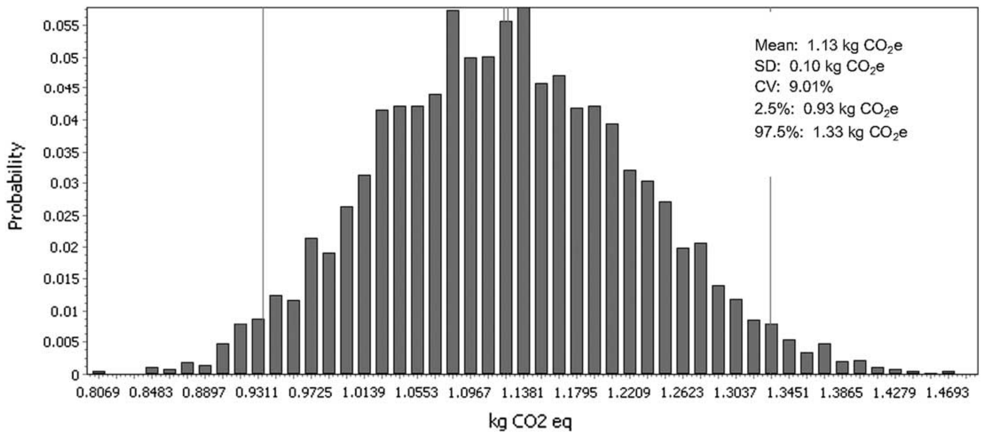

Figure 30. Frequency distribution of the carbon footprint of 1 kg milk (ECM) as a result of variation in production input data on farm level, based on Monte Carlo simulation. Right and left vertical lines indicate the predicted 95% confidence interval (from 2.5% to 97.5%) (from Henriksson et al., 2011).

The purpose of that study was to look at variation in the milk CF due to differences in management practices that the farmer could easily control, hence identifying mitigation options at farm level, and not to compare the milk CF between farms or assess the total uncertainty in the Swedish milk CF. Hence, it was not necessary to include uncertainties in emission factors for N_2O from soils.

Basset-Mens et al. (2009) studied how different sources of uncertainty and variation in input data and characterisation factors affected the CF of 1 kg of milk from New Zealand. MC simulation was performed to establish the uncertainty in the end result coming either from inherent 'variability' between farms represented by the standard deviation in data, or from 'uncertainty' in input data represented by the standard error of the mean. In the 'variability' analysis, the standard deviation (SD) was used in the MC simulation, giving a standard deviation of 38% in the resulting CF, representing the uncertainty in the CF due to variability in farming practices on dairy farms in New Zealand. The 'uncertainty' analysis instead used the standard error of the mean (SEM=SD/√n), which was much smaller than the SD due to the large number of farm data. The 'uncertainty analysis' gave a standard deviation of 7% in the CF, which gives a measure of the imprecision in the CF of average milk from New Zealand. The results were presented as two different frequency distributions which clearly illustrated the uncertainty in the results due to variability in parameters such as soil characteristics, climate and farming practices, as well as the uncertainty in the average CF of milk from New Zealand as a result of uncertainties in input data (*Figure 31*).

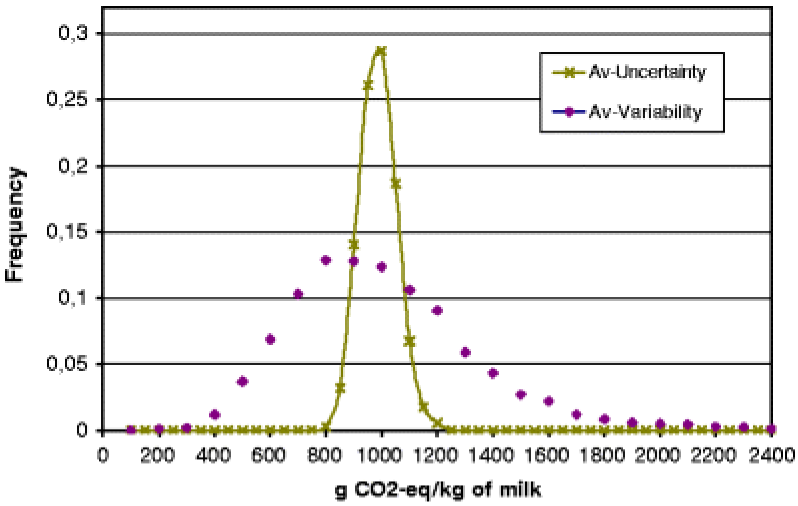

Figure 31. Frequency distributions of the carbon footprint of 1 kg of milk from an average farm in New Zealand. The "Uncertainty" and "Variability" analyses (from Basset-Mens et al., 2009).

Apart from the stochastic simulation performed, that study also used sensitivity analysis for assessing the uncertainty due to choice of time horizon for the GWP (20, 100 or 500 years) and for different scenarios for soil drainage. *Figure 32* shows how the results were presented, as three different cumulative probability distributions including the results from the uncertainty and the sensitivity analysis (three different drainage scenarios). Presenting results in this way provides far more information to the decision maker than just presenting a deterministic value that might look very certain, but in reality is highly uncertain.

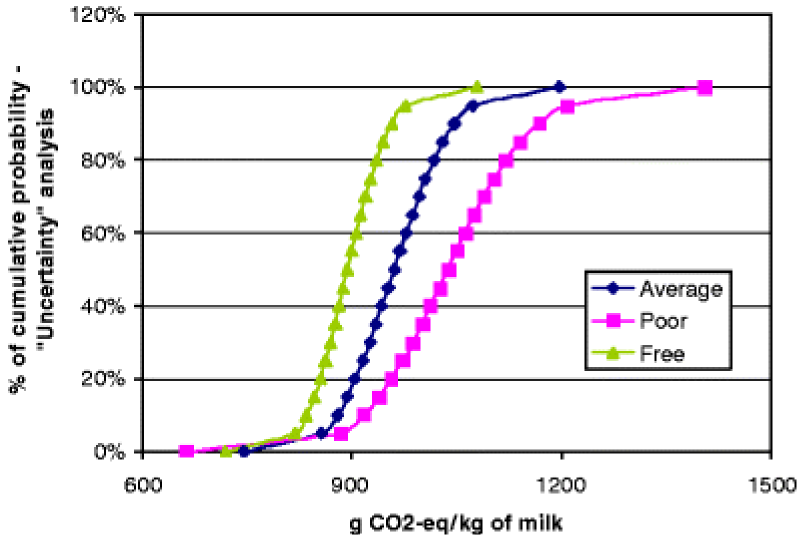

Figure 32. Cumulative probability distributions of the carbon footprint of milk from New Zealand (using “Uncertainty” analysis) for average, poorly drained soil and free-drained soil scenarios (from Basset-Mens et al., 2009).

Gerber et al. (2010) performed sensitivity analysis by varying several parameters one at a time by ±10% while monitoring the change in the CF of milk. They concluded from this analysis that the CF of milk was sensitive to variations in the feed digestibility and yield values, whereas it was relatively robust to uncertainties in the herd dynamics parameters and manure management practices. A limited MC simulation was performed in which a few key parameters were set to vary (feed digestibility by ±10%, the conversion for enteric fermentation by ±15%, emission factors regarding manure and nitrogen application by ±50% and the energy use for feed production by ±25%). The uncertainty analysis was performed using Swedish data but the same final uncertainty range, ±26% (95% confidence interval), was then used to communicate the uncertainty in the global average.

5.3.4 The use of uncertainty information in decision making

While the subject of uncertainty and sensitivity analysis in LCA is rather well documented in the literature and actual uncertainty and sensitivity analyses are beginning to appear in studies, the use of uncertainty information in decision making is a subject that is not well researched (Mattila et al., 2012; Curran, 2013).

Mattila et al. (2012) studied a consumer decision situation between beer and wine based on five decision criteria; carbon footprint, water footprint, energy content, price and taste. The uncertainty in the beer and wine CF, determined by MC simulation, was so large that even when correlations were accounted for it could not be determined which beverage was preferable from a CF point of view. However, depending on the weight given to the CF as decision criteria in comparison with the other criteria, the uncertainty had more or less of an impact. Hence, it is not possible to give an absolute acceptable level of uncertainty, as it depends on the type of decision at hand and other criteria upon which the decision is based.

5.4 Sustainable livestock systems

The sustainability of a livestock system cannot be determined solely based on the carbon footprint. Sustainable development is often considered as consisting of three pillars; environmental, social and economic sustainability (United Nations, 2005). Environmental sustainability is a necessity for all human development, while social and economic sustainability is necessary for systems to be equitable and viable.

5.4.1 Life cycle sustainability assessment (LCSA)

LCA can be used to assess many different types of environmental impact. For example, the ReCiPe LCIA method offers 18 mid-point indicators; ozone depletion, terrestrial acidification, freshwater eutrophication, marine eutrophication, human toxicity, photochemical oxidant formation, particulate matter formation, terrestrial ecotoxicity, freshwater ecotoxicity, marine ecotoxicity, ionising radiation, agricultural land occupation, urban land occupation, natural land transformation, water depletion, mineral resource depletion and fossil fuel depletion (Goedkoop et al., 2009).

Methods have also been suggested for assessing the impact on soils in terms of soil fertility (Garrigues et al., 2012), biodiversity due to land use (e.g. Milá i Canals et al., 2007; Schmidt, 2008; de Baan et al., 2012) and water use (e.g. Bayart et al., 2010; Berger and Finkbeiner, 2010; Ridoutt et al., 2012; Ridoutt & Pfister, 2013). It is especially important to include environmental indicators that risk being in conflict in a sustainability assessment. LCA studies on livestock production have shown that the CF can function reasonably well as a proxy for land use, eutrophication and acidification potential, but that there are risks of conflict when it comes to primary energy use, toxicity and biodiversity (Röös et al., 2013). However, local impact categories such as eutrophication and acidification are highly site-specific and the actual impact can differ substantially from the potential impact calculated in the LCA study.

A unique feature of livestock systems that distinguishes them from crop production and industrial production systems is that they involve living, sentient beings. Hence, the aspect of animal welfare cannot be omitted when designing sustainable livestock systems. Healthy animals which produce meat, eggs and milk efficiently are favourable both for low CF and for animal welfare, while access to pasture and outdoor runs can increase feed consumption and hence increase CF. Breeding for fast growth and high yield decreases the CF of livestock products, but leads to health implications, e.g. leg problems. Methods for incorporating animal welfare aspects into LCA are being discussed, but have not so far been used (Blonk et al., 2010).

Recent developments in LCA offer ways of assessing the social impacts of a product from a life cycle perspective, e.g. Social Life Cycle Assessment (SLCA), (Kruse, 2010), and economic performance can be assessed using tools such as Life Cycle Costing (LCC). A combination of these tools with the classic environmental LCA forms the concept of Life Cycle Sustainability Assessment (LCSA) (Heijungs et al., 2010).

Although it is important to cover many aspects in a full sustainability assessment, it is not necessary to cover all aspects in the same model or study, as the model can become too complex to verify and understand and the results too complex to interpret. Hence, isolating the aspect of climate change and studying the CF only in a study can be highly valuable as long as it is not used in isolation to make important policy decisions.

5.4.2 Limitations with LCA, SLCA and LCC

Although LCA offers methodology to assess the environmental and social impact of products, it does not offer a way of determining whether a product is sustainable. Unlike e.g. the Ecological Footprint methodology, LCA does not provide a reference value of sustainability (Acosta-Alba & van der Werf, 2011). The fact that a product has a low impact per product unit compared with other products does not mean that the product is sustainable, as that depends on the scale of usage of the product. Emission reductions per product from improvements in production will not lead to absolute reductions if consumption is increased.

Garnett (2009) outlines three limitations with using LCA in developing livestock policy strategies, namely the omission to include: 1) indirect second order effects; 2) the opportunity cost of using land; and 3) how much people need livestock products at all. Recent developments in LCA, and especially CLCA, have provided ways of including indirect effects in LCA, e.g. the effect of LUC on the CF as described in section 4.5, so the first criticism by Garnett (2009) is now less relevant. However, the other two points are still highly relevant. Few studies consider alternative uses of land, feed and by-products if not used for livestock production (opportunity cost), or to what extent society needs livestock products such as meat, eggs and milk, as well as e.g. manure and leather, or whether these functions can be provided by production systems that cause lower GHG emissions. By including such concerns into sustainability assessment of livestock, one might come to the conclusion that rearing animals on land and by-products not suitable production of crops for human consumption is the only sustainable way forward (Garnett, 2009).

de Boer et al. (2011) reviewed the main mitigation options from a life cycle perspective for reduced GHG emissions from livestock production and found several externalities that need to be considered. For example, animal welfare might suffer from breeding focused on increased production traits such as growth rate and milk production. Increased irrigation to increase biomass production, and hence yields and carbon sequestration in soils, might lead to freshwater depletion. Furthermore, de Boer et al. (2011) and Garnett (2009) mention that accounting for e.g. competition for land between grain for human consumption and animal feed might point towards producing beef on marginal land and feeding only by-products to monogastric animals. They also highlight the need for more interdisciplinary research that includes the cause-effect chain, i.e. consequential life cycle sustainability assessment in which traditional environmental CLCA is supplemented by social and economic aspects.

Depending on the decision at hand, other indicators than those provided within the current LCA framework can offer valuable additional insights when developing sustainable livestock systems. A few such indicators are briefly outlined below.

Human edible protein (or energy) out divided by human protein (or energy in). This indicator offers a way of assessing to what extent the feed production in livestock systems competes for land with human food. As competition for land and the demand for food increases, this is an important indicator of efficient land use. Efficient land use for food production is important for freeing up land that could be used for either bioenergy production and hence decreasing global warming, and/or for more extensive production or wildlife conservation, with benefits for biodiversity. Using this indicator, Wilkinson (2011) showed that milk production and upland beef production were more efficient systems for producing protein than pork and poultry, due to the large amount of grass in the diet of the ruminants. However, that study did not consider that some grassland might be suitable for bioenergy production. The grass as a resource for livestock feed is only truly ‘for free’ when there is no other competition for the grass.

Renewable energy to society per kg product. Agriculture has the unique possibility to mitigate global warming caused by the energy and transport sectors through the production of renewable energy, as has been proposed in several studies covering the GHG emissions reduction potential from the agricultural sector (e.g. SBA, 2012). Renewable energy can be produced in agriculture in the form of biogas from manure, crop residues and ley crops, solid bioenergy from short-rotation coppice and trees in pastures or on marginal land, liquid biofuels from grain, oil crops, by-products or solid biomass, as well as from wind and solar power. In a study commissioned by the Swedish Board of Agriculture, the GHG emissions reduction benefit of producing bioenergy in the form of trees on pasture was subtracted from the CF of lamb and beef meat and it was shown that the benefits of the bioenergy replacing fossil fuels could almost entirely compensate for the emissions from animal production (SBA, 2011). However, according to LCA methodology, different production systems should be kept separate, in this case the meat and the bioenergy production systems. Otherwise strange results might be obtained and the risk of double counting is great. In this case the bioenergy produced would ‘emit’ as much as fossil fuels when burned, since it is burdened with part (or all) of the emissions from animal production. Therefore, to reward farms which invest in renewable energy production, it could be wiser to use a separate indicator such as ‘renewable energy to society per kg of product’ to account for bioenergy production at farm level. Note, however, that this needs to be ‘new’ energy production and not existing bioenergy outtake of e.g. existing forest land. Defining what can be considered ‘new’ energy will be challenging.

‘New’ nitrogen per kg of product. Nitrogen losses from agricultural systems cause global warming and eutrophication. Hence, minimising nitrogen losses is crucial in sustainable agriculture. Nitrogen surpluses (added nitrogen minus removed nitrogen) per hectare or farm and nitrogen efficiency (added nitrogen divided by removed nitrogen) are important parameters that are commonly assessed. Another nitrogen-based indicator is the ‘new nitrogen per kg of product’, which is used in the Swedish Climate Certification for Food (Klimatcertifieringen, 2012). It measures ‘new’ nitrogen added to the system, through mineral fertilisers or using nitrogen-fixing crops per kg of product produced, and has been included under the assumption that parts of all new nitrogen added to the ecosystem will be lost to air or water. However, all use of nitrogen, old in the form of manure and new, will give rise to nitrogen losses, so it is important to keep track of all nitrogen used, not only that newly added.

Stocking density. The number of animals held per unit area of agricultural land, the stocking density, is important, since it determines the amount of manure that is generated in the area. High accumulation of nutrients on a restricted area of land increases the risk of eutrophication and water pollution due to nutrient run-off.

Grazing pressure on semi-natural grassland. Many of the endangered and red-listed species in Sweden and in Europe are found in the traditional mosaic agricultural landscape that is disappearing due to agricultural intensification and rationalisation, but also due the abandonment of agricultural land in less productive areas. Hence, keeping traditional semi-natural pastures grazed and conserving the traditional mosaic landscape has been identified as one of the most important measures for preserving biodiversity in Sweden and in many other parts of Europe (Henle et al., 2008). Hence, an indicator which shows e.g. the amount of land that will be grazed could be a relevant indicator, as could an indicator that shows the amount of landscape elements preserved that could act as refuges for different species.

Sustainable use of antibiotics. Antibiotics are the main drug used to treat bacterial infections in animals and humans. Through incorrect and generous use of antibiotics, problems with antibiotic-resistant bacteria have become one of the most serious threats to human and animal health world-wide. Resistant bacteria and resistance genes in the environment spread between animals and humans. In some countries, antibiotics are administered to animals routinely as a preventative measure or to increase growth. In some regions, e.g. in the EU, this is not permitted. There are large differences in the use of antibiotics in livestock production. Hence, including some measure of the sustainable use of antibiotics is important when assessing the sustainability of livestock systems. However, it is not straight-forward to compare the use of antibiotics across animal species and animals in different countries, since dosages and preparations differ across species and ways of treatment (Bondt et al., 2013), so careful thought is needed when designing an indicator for sustainable use of antibiotics in livestock production.

Animal welfare. Until methods for incorporating animal welfare into LCA have been fully developed, assessing the impact on animal welfare outside the LCA framework is necessary. Possible conflicts between CF and animal welfare exist, as discussed in section 5.4.1, making it particularly important to include considerations of animal welfare in a full sustainability assessment.

Additional indicators and ways of evaluating the sustainability of livestock systems can be beneficial for illuminating various aspects of different production systems. However, the recipient of the information is still left with the difficult task of weighing different aspects together. The LCA methodology provides various ways of doing this, so it could be preferable if possible to stick to the LCA framework. However, not everything can be quantified and/or put into categories that fit the LCA framework, so LCSA will need to include qualitative judgments of some aspects, as well as separate indicators that complement the LCA. Other frameworks for assessing the sustainability of livestock production have also been developed, e.g. the sustainability index for beef production within the REKS project, which includes a large number of aspects related to the sustainability of beef production and also a method for weighting these (REKS, 2013). However, these are often targeted at one type of livestock only and do not offer the possibility to compare products or systems across animal and plant species.

6 Summary and conclusions

6.1 The complexity of calculating the CF of livestock systems

Production of livestock products gives rise to emissions of GHG from a number of different complex processes (*Figure 33*).

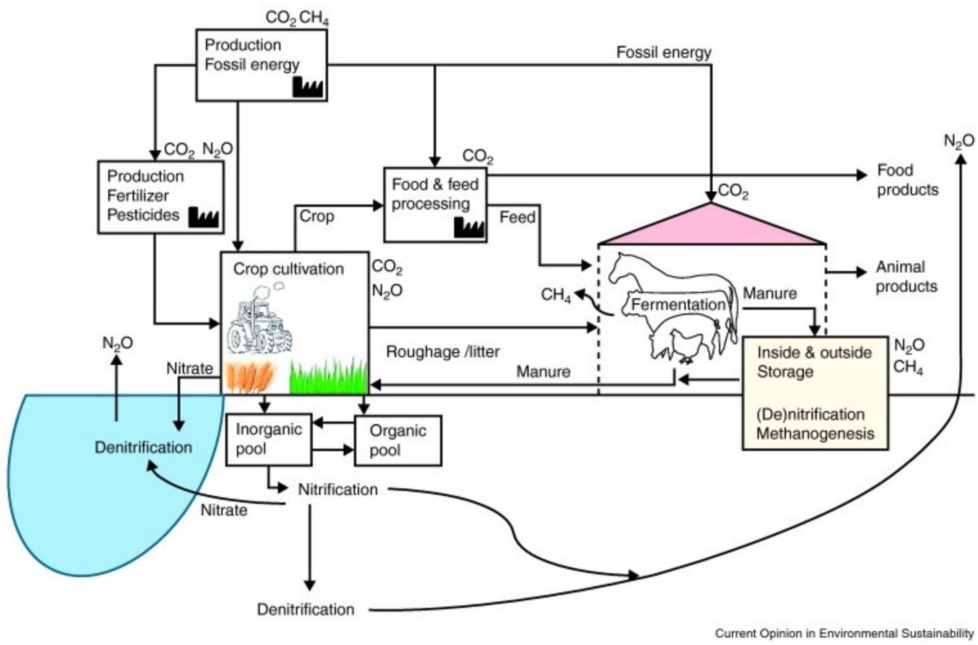

Figure 33. Direct sources of greenhouse gas emissions from a livestock system (de Boer et al., 2011).

Calculating the product CF of livestock products and other food is a valuable exercise for arriving at an estimate of the climate impact of different products and production systems. By including GHG emission sources from all stages in the life cycle of the product, including pre-farm, on-farm and post-farm processes, as well as in-direct effects, sub-optimisation and pollution swapping can be avoided when striving for lowered GHG emissions. By surveying different livestock systems in detail, knowledge about the environmental impact of the system is often greatly increased. By putting a value on the environmental impact, the sustainability of livestock systems becomes more tangible and concrete.

The complexity and diversity of livestock systems themselves are great. Emissions from processes directly associated with livestock production are mainly N_2O emissions from soils, emissions and sequestration of CO_2 in soils, CH_4 from enteric fermentation, N_2O and CH_4 emissions from manure management and CO_2 from energy consumption. Such emissions, except those from fossil energy consumption, arise from highly variable biological processes, which are difficult to measure and model. Methods used currently for quantifying GHG emissions only include parts of the cause-effect chain and have been developed using uncertain and variable input data. Methods for estimating indirect emissions, above all those from land use change, are also highly uncertain and there is lack of consensus as to how these changes should be modelled. With increased measurements of GHG and continued development of models, the capacity to produce increased robustness in estimations is high.

The diversity in management practices and in non-controllable parameters which influence emissions, e.g. climate conditions and soil characteristics, in agriculture is great. Hence, the variability in e.g. yields, fertiliser application in feed production, feeding strategies, manure management etc. is great. Scenario choices in modelling the livestock system introduce additional uncertainty in the calculation of the CF, e.g. how system boundaries are drawn and how allocation between different co-products is handled. Depending on the time perspective used for calculating GWP (e.g. 20, 100 or 500 years), the results can greatly vary. *Figure 34* illustrates how different types of uncertainty are aggregated in CF calculations.

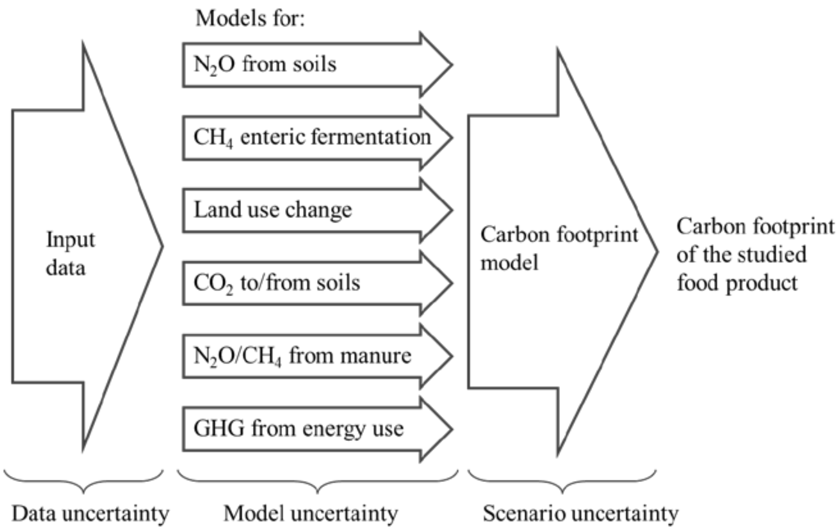

Figure 34. Many and different types of uncertainties contribute to the final uncertainty in the carbon footprint of livestock products.

Uncertainty can be reduced through improved models and data collection, while variation in e.g. yields and management principles is an inherent property of a system and cannot be reduced. In livestock systems, this variation can be larger than the measurement uncertainty, so uncertainty in the final CF can only be reduced to a certain limit. Therefore, it is in most cases important to illustrate and discuss uncertainty in the results. If uncertainties are handled in an appropriate manner and results used taking uncertainty and modelling assumptions into account, CF is a very valuable measurement of the climate impact of livestock products despite the high uncertainties associated with several of the processes.

Highly uncertain sources of emissions which arise from fundamentally different processes, such as emissions from land use change and ‘negative emissions’ due to carbon sequestration in soils, should be reported separately. However, it is important to include these highly uncertain sources, since they make a considerable contribution to overall emissions in many cases.

6.2 Input data uncertainties and variability

Uncertainty and variability in input data collected from farms directly, from agricultural statistics at local, regional or national scale, or chosen hypothetically in order to evaluate future scenarios can be propagated though the CF model using stochastic modelling, e.g. Monte Carlo simulation. By using stochastic modelling, an uncertainty range can be established for the CF showing the uncertainty in the end result due to uncertainty and variability in the input data.

The stochastic modelling process is straight-forward. The CF value is calculated a large number of times, each time randomly drawing different values for the input parameter from probability distributions describing the uncertain input data. However, finding probability distributions for different types of input data can be highly challenging and time-consuming. It is also very important to consider correlations between systems, since failing to do so will overestimate uncertainty. In particular, when systems are being compared it is important to account for correlations, e.g. if two systems using the same mineral fertilisers are being compared, the system using less fertiliser will cause less emissions from the production of fertiliser, regardless of how uncertain the estimate of emissions from fertiliser production happens to be. This illustrates that in some cases it is possible to draw solid conclusions despite large uncertainties and without performing uncertainty assessment.

6.3 Modelling choices and uncertainty

When calculating the CF of livestock products, emissions from agriculture need to be modelled, since it is very expensive and difficult to measure them directly. There are a number of methods available for estimating e.g. soil emissions, emissions from enteric fermentation and manure and emissions from LUC. Choosing a specific method to use introduces uncertainty due to model choice into the CF calculation. In addition, the method itself is an uncertain representation of reality.

Table *10* presents examples of the uncertainty in major sources of GHG from livestock production. A detailed description of these is given in Chapter 4. Except for emissions from energy use, the uncertainty in models and for different model choices is large for all processes. Uncertainty in model parameters can be propagated to the end CF result using stochastic simulation just as for input data uncertainty (section 6.2). By performing sensibility analysis and testing different models in comparisons of different systems or products, the robustness of the results can be investigated. For example, if one system performs better for all model choices, the result of identifying this system as better is robust. If the outcome depends on the method chosen for assessing emissions, the result has to be interpreted with great care.

Table 10. *Examples of uncertainty in major sources of greenhouse gases in the assessment of the carbon footprint of livestock products.*

Methodological choices related to emissions sources	Methods used in LCA	Example of uncertainty in commonly used emission factors
N_2O from soil	IPCC coarse method, several empirical and mechanistic models available but with limited use in LCA due to limited data availability and great variation in emissions	IPCC direct emissions: -70% - +200% IPCC indirect, volatilisation: -80% - +400% IPCC indirect leakage: -50% - +150%
CO_2 to/from soil	Several methods suggested, great variation, no consensus, differing opinions on if and how to include carbon sequestration on the CF	
CH_4 enteric fermentation	IPCC method for dairy, very coarse for other ruminants, several empirical and mechanistic models available but with limited use due to limited data availability	kg CH_4 per cow and year, milk yield 10,000 kg ECM/year: Lindgren, 1980: 136 IPCC Tier 2, 2006: 148 Kirchgessner et al., 1991: 118
N_2O and CH_4 from manure	IPCC method, empirical and mechanistic models available but with limited use due to limited data availability	Uncertainty range IPCC EF for: CH_4 from liquid storage: ±20% N_2O solid storage: -50%-+100%
Land use change	Several methods suggested, great variation, no consensus	LUC factor for Brazilian soybean, kg CO_2e per kg soybean meal: Leip et al., 2010: 1.5, 3.1 or 10.5[1] Gerber et al, 2010: 7.7 Ponsien & Blonk, 2012: 3.7
Energy use	Usually minor importance for ruminants, modelling electricity production (mix/marginal), biofuels associated with several of the uncertainty sources listed here	

1 Three scenarios are used to describe the type of land converted: only grassland (1.5), only forest (10.5) or a mix (3.1)

6.4 Scenario choices in LCA modelling

In addition to the uncertainty arising from input data uncertainty and variability and model uncertainty when calculating the CF, uncertainty is also introduced from choices associated with how the system is modelled. Although several standards for calculating the CF exist, which regulate some of the modelling choices, the application of these is still scarce. This is partly because several of the standards are new, but another reason behind the lack of widespread use is that it is very difficult to design a standard that fulfils the needs of all types of studies. How a livestock system is modelled, e.g. where system boundaries are drawn, how allocation between co-products is handled and whether the study is performed as an attributional LCA, ‘accounting’ emissions evenly on all the world’s products, or as an consequential LCA, looking at marginal changes and processes actually affected by an increased demand for the product, depends on the purpose of the study. Further examples of methodological choices when calculating the CF of livestock systems are given in *Table 11* and these choices were addressed in detail in Chapter 2.

How different modelling choices affect the end CF result can be assessed using sensitivity analysis, in which different model choices are tested and the results compared.

Table 11. *Examples of methodological choices when calculating the carbon footprint of livestock products*

Methodological choices LCA	Examples
Goal and scope of the study	Case study on one farm, national/global/regional average of the livestock sector, average milk/beef/pork/chicken/egg CF, comparison between different types of production systems/diets/manure handling systems
Functional unit	Per kg, per kg protein, nutritional index, live weight, carcass weight or bone-free meat
System boundaries	Indirect effects, opportunity cost from using land, boundaries with nature e.g. carbon sequestration and the surrounding technical system e.g. inclusion of capital goods
Allocation	System expansion, economic or physical allocation, e.g. between milk and meat, and between vegetable oil and oilseed meal
Data collection	Using farm level data or local, regional or national statistics, time period for data collection, use of databases for background data etc.
Type of LCA	Attributional (ALCA) or consequential (CLCA)
Time perspective GWP	20, 100 or 500 year perspective e.g. characterisation factor for methane: 20 years: 72, 100 years: 25, 500 years: 7.6

6.5 Presenting uncertainty and sensitivity analyses

Results from uncertainty and sensitivity analyses can be presented using bar diagrams with uncertainty ranges, histograms, cumulative distribution functions, tornado diagrams, text and tables (section 3.4). The results should be presented in such a way that the uncertainty in results is reflected, e.g. it is seldom possible to present the CF of livestock products to more than two significant digits.

6.6 Sustainable livestock systems

Climate change is one of the most severe challenges facing humanity. However, there are several other pressing environmental issues that need to be included in a full sustainability assessment of livestock production, as well as economic and social aspects, not least animal welfare and the sustainable use of antibiotics. Life cycle sustainability assessment (LCSA) shows promising progress in including both economic and social aspects as well as a wide array of environmental categories, including categories such as biodiversity impact and impacts on soil fertility, which have been challenging to quantify. However, to capture some aspects, especially related to the efficient use of land and other resources, other indicators (e.g. human edible protein out divided by human edible protein in, or renewable energy to society per kg of product produced), might provide additional information.

6.7 Conclusions

Despite the progress in research about GHG emissions in the past decade, the estimation of GHG emissions from livestock production systems is highly uncertain. The CF of a livestock product is an *estimate of the magnitude of GHG emissions under the conditions formulated in the study*. It is a great tool for preventing pollution swapping when identifying mitigation options and for identifying what is large and small. However, a CF value should not be presented as a single number and especially not to several significant digits. It should be presented together with results from relevant uncertainty and sensitivity analysis. Policy decisions and mitigation options should only be based on results that are robust and consistent under a wide range of scenarios.

The CF does not take into account the aspect of need or scale. Just because a livestock product has a lower CF than another livestock product does not mean that it is low enough. It is also important to take alternative ways of delivering the same function (nutrition, pleasure, tradition etc.) into account. Furthermore, in a full sustainability assessment of livestock production, the CF is only one part. Other environmental aspects, as well as economic and social sustainability, need to be considered.

Last, but not least, care must be taken to design studies that give answers to relevant questions and at the same time be aware of the limitations in science. The reductions in GHG emissions needed to reach global climate goals are enormous. Since environmental assessments and detailed analyses are time-consuming and costly, it is important that studies focus on solutions and approaches that could bring about the major changes necessary in food production and consumption to achieve a sustainable food supply system.

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