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Research article

Evaluation of allocation methods for calculation of carbon footprint of grass-based dairy production

P. Rice [a, b, *], D. O'Brien [a], L. Shalloo [a], N.M. Holden [b]

[a] Livestock Systems Department, Animal & Grassland Research and Innovation Centre, Teagasc, Moorepark, Fermoy, Co. Cork, Ireland
[b] UCD School of Biosystems and Food Engineering, University College Dublin, Belfield, Dublin 4, Ireland

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ABSTRACT

A major methodological issue for life cycle assessment, commonly used to quantify greenhouse gas emissions from livestock systems, is allocation from multifunctional processes. When a process produces more than one output, the environmental burden has to be assigned between the outputs, such as milk and meat from a dairy cow. In the absence of an objective function for choosing an allocation method, a decision must be made considering a range of factors, one of which is the availability and quality of necessary data. The objective of this study was to evaluate allocation methods to calculate the climate change impact of the economically average (€/ha) dairy farm in Ireland considering both milk and meat outputs, focusing specifically on the pedigree of the available data for each method. The methods were: economic, energy, protein, emergy, mass of liveweight, mass of carcass weight and physical causality. The data quality for each method was expressed using a pedigree score based on reliability of the source, completeness, temporal applicability, geographical alignment and technological appropriateness. Scenario analysis was used to compare the normalised impact per functional unit (FU) from the different allocation methods, between the best and worst third of farms (in economic terms, €/ha) in the national farm survey. For the average farm, the allocation factors for milk ranged from 75% (physical causality) to 89% (mass of carcass weight), which in turn resulted in an impact per FU, from 1.04 to 1.22 kg CO_2-eq/kg (fat and protein corrected milk). Pedigree scores ranged from 6.0 to 17.1 with protein and economic allocation having the best pedigree. It was concluded that when making the choice of allocation method, the quality of the data available (pedigree) should be given greater emphasis during the decision making process because the effect of allocation on the results. A range of allocation methods could be deployed to understand the uncertainty associated with the decision.

1. Introduction

With the global human population predicted to increase to over 9 billion by 2050 (Gerber et al., 2013), an increase in consumption of bovine milk and meat products is likely (FAO, 2009). Increasing primary production from large ruminant systems to meet demand will increase greenhouse gas (GHG) emissions. To tackle this problem, European Union (EU) nations have agreed measures to reduce GHG emissions from non-emission trading sectors, including agriculture. The EU aims to reduce these emissions by 10% by 2020 relative to 2005 levels, with Ireland required to achieve a 20% reduction as its contribution to this target (European and Council, 2009).

Life cycle assessment (LCA), an internationally excepted approach (ISO, 2006), is the preferred method to simulate GHG emissions from agricultural systems (IDF, 2010; Thomassen and De Boer, 2005). Many LCA studies focus on farm systems' impact to the point that the primary product is sold from the farm i.e., 'cradle to gate' (Cederberg and Mattsson, 2000; Haas et al., 2001; O'Brien et al., 2010). A single impact LCA considering GHG emissions interpreted in terms of climate change impact is commonly referred to as a carbon footprint. A major methodological issue for LCA is allocation of the environmental burden between multiple outputs of a process. To maintain relatively simple attributional models, when a system or process produces more than one output, the environmental burden has to be allocated between the outputs.

The British Standards Institute (BSI) and the International Dairy

* Corresponding author. Livestock Systems Department, Animal & Grassland Research and Innovation Centre, Teagasc, Moorepark, Fermoy, Co. Cork, Ireland. paul.rice@ucdconnect.ie

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Federation (IDF) advise that when considering the allocation of GHG emissions to co-products, the appropriate approach is to refer to the hierarchy as detailed within their specification (BSI, 2011; IDF, 2013), which is based on the ISO standard (ISO, 2006). Both suggest that allocation should be avoided if possible, but when it is not possible, allocation based on a physical relationship between both products is preferred to other relationships such as economic value (BSI, 2011; IDF, 2015).

As there is no accepted objective function that properly reflects allocation for dairy systems, studies have used different methods including physical causal relationships (Basset-Mens et al., 2009; Ledgard et al., 2009), protein content (Gerber et al., 2010) and economic value (Arsenault et al., 2009; Casey and Holden, 2005; Cederberg and Flysjö, 2004; Hospido and Sonesson, 2005; van der Werf et al., 2009). Some studies have applied system expansion (Cederberg and Stadig, 2003; Hospido and Sonesson, 2005; Thomassen et al., 2008), but most dairy LCA studies use economic allocation for upstream and downstream processes, in the absence of detailed process data (De Vries and De Boer, 2010). More recently, Kiefer et al. (2015) used a variation on economic allocation that incorporated ecosystem services based on the proportion of farm income derived from payments for sustainable practices, while Dalgaard et al. (2014) used cut-off criteria to define 'switches' for including specific components in each part of the model calculations. Nguyen et al. (2013) examined co-product handling using protein content on a live weight basis of culled cows and surplus calves.

Another method available is emergy allocation, but to our knowledge, this method has not been used for dairy systems. The emergy concept, expressed as solar emjoules (seJ) was created by Odum (1983) to account for the energy requirements for producing a product capturing those sources not accounted for by conventional energy measurement (e.g., kcal or kWh). The emergy approach calculates the energy required to transform sunlight energy into a higher quality or more usable energy such as grass. Emergy can be used for allocation because it can be defined as the available energy (exergy) that is used in transformations to directly and indirectly to make a product (Odum, 1996), thus it is possible to calculate the emergy for each co-product (Brown and Herendeen, 1996).

It is well documented that data quality influences the uncertainty and robustness of LCA results (Henriksson et al., 2011; May and Brennan, 2003; Weidema, 1998). ISO standards recommend that data quality be reported, but this is not that common. Consequently, it is necessary to make judgement with respect to the accuracy of LCA outcomes. While a data quality scoring/judgement matrix has been developed (Rousseaux et al. (2001); Wrisberg et al. (1997); Weidema and Wesnaes, 1996), the concept has never been applied in the context of allocation and the choice of method.

Rousseaux et al. (2001) proposed the data generation method be examined regarding the degree to which it had the capacity to provide accurate data (justness), the extent of the inclusion of the whole population (completeness), the extent to which the whole population is represented (representativeness) and the potential to repeat an outcome (repeatability). These indicators were used to assess flows, processes, and the system. Rousseaux et al. (2001) suggested the 'justness' of the life cycle inventory should be evaluated at the flow level, while the assessment of geographical representativeness is sufficient at the process level due to the uniformity of geographical conditions describing each process. They scored each from 1 (best) to 5 (worst) and the approach was derived from Weidema and Wesnaes (1996; Table 1). and Wrisberg et al. (1997). The use of 'repeatability' by Rousseaux et al. (2001) was novel and innovative.

The semi quantitative approach of Wrisberg et al. (1997) was designed to provide an indication of the quality of data used in an LCA and identification of hotspots of poor data quality. The method is also implemented at flow, process, and system levels with scores from 1 to 5. The assessment is subjective but transparent using reliability, completeness and representativeness. The mean score is taken as indicative of data quality. A distinction is made between environmental flows and economic flows as a result of aggregating

Table 1
The data quality pedigree matrix of Weidema and Wesnaes (1996) used for this study.

Indicator	Indicator Score				
	1	2	3	4	5
Independent of the study in which the data are applied:					
Reliability of the source	Verified data based on measurements	Verified data partly based on assumptions or non-verified data based on measurements	Non-verified data partly based on assumptions	Qualified estimate (e.g. by and industrial expert)	Non – qualified estimate or unknown origin
Completeness	Representative data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Representative data from a smaller number of sites but for adequate periods	Representative data from an adequate number of sites but for shorter periods	Representative data from a smaller number of sites and shorter periods, or incomplete data from an adequate number of sites and periods	Representativeness unknown or incomplete data from a smaller number of sites and/or from shorter periods
Dependent on the goal and scope of the study:					
Temporal correlation	Less than 3 years of difference to year of study	Less than 6 years of difference to year of study	Less than 10years of difference to year of study	Less than 15 years of difference to year of study	Age unknown or more than 15 years of difference to year of study
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from an unknown area or with very different production conditions
Technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes and materials but from same technology	Unknown technology or data on related processes or materials but from different technology