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Research article

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

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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

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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

the reliability parameters.

The pedigree matrix of Weidema and Wesnaes (1996) was used in this research for three reasons: (i) it is within the Society of Environmental Toxicology and Chemistry (SETAC) framework for determining data uncertainty, based on 'data inaccuracy' and 'lack of specific data' (i.e. data gaps and unrepresentative data) (May and Brennan, 2003); (ii) the methods of Rousseaux et al. (2001) and Wrisberg et al. (1997) were derived from Weidema and Wesnaes (1996); but (iii) the indicators used by Weidema and Wesnaes (1996) are at the data level only, unlike those of Rousseaux et al. (2001) and Wrisberg et al. (1997), which consider indicators across many levels. Thus the original method was considered most suitable for this work.

The objective of this study was to evaluate and assess seven allocation methods applied to grass based dairy production in terms of data quality. The methods of allocation assessed were: economic, energy, emergy, protein, mass of liveweight (LW), mass of carcass weight (CW) and physical causality. The use of emergy to allocate from a dairy system between milk and meat was novel. The data quality (pedigree) was assessed using (1) reliability of the source and completeness; (2) temporal correlation; (3) geographical correlation; and (4) technological correlation, which is in keeping with the data quality requirement stipulations set out by the ISO (2006).

2. Material and methods

2.1. Dairy farming system and data acquisition

The data (Table 2) were derived from the 2012 Irish National Farm Survey (Hennessy et al., 2012) as described by O'Brien et al. (2015). The survey was carried out on 256 dairy farms in 2012 and was weighted according to farm area to represent the national population of specialized dairy farms (15,600). All the dairy farms in the survey used grass-based spring calving with seasonal milk supply matched to grass growth (Shalloo et al., 2014) to maximise grazed grass intake (Dillon et al., 1995; Kennedy et al., 2005).

2.2. Life cycle assessment

The LCA methodology was applied according to the ISO (2006) guidelines. The goal was to evaluate allocation between milk and meat using seven allocation methods for an economically average (€/ha) Irish dairy farm. The system boundary was 'cradle to farm gate', including foreground processes of milk production and background processes for production and transportation of mineral fertilizer, cultivation, processing and transportation of concentrate feed. Infrastructure (animal housing, slurry storage facilities, and roads), machinery (tractor, milk cooling system)(following Frischknecht et al., 2007), medicines, pesticides, and disposal of silage plastic (following O'Brien et al., 2014) were not included due to their known small influences (Frischknecht et al., 2007). The functional unit was 1 kg of fat and protein corrected milk (FPCM) normalised to 4% fat and 3.3% protein (Yan et al., 2011), where FPCM (kg/yr) = Production (kg/yr) × (0.1226 × Fat % + 0.0776 × True Protein % + 0.2534).

The emissions of methane (CH_4), nitrous oxide (N_2O), carbon dioxide (CO_2) and halocarbons (F-gases) were calculated using the model of O'Brien et al. (2014) that was certified by the Carbon Trust (Carbon Trust, 2010). On-farm emissions from N fertilizer were estimated using Intergovernmental Panel on Climate Change (IPCC) guidelines (IPCC, 2006a, p11.5 – p11.13). Enteric CH_4 emissions were calculated according to the Irish GHG national inventory methods (Duffy et al., 2012). CO_2 from fossil fuels (IPCC, 2006b, p.2.15 and p2.22) lime (IPCC, 2006a, p11.29 – p11.33) and fertilizer (IPCC, 2006a, p11.34 – p11.38) used on-farm were estimated using the IPCC (2006a, b) guidelines.

Animals, crops and manure, as short-term biogenic sources and sinks of CO_2 were considered GHG neutral because the IPCC (2006a, b) state that all C absorbed by animals, crops and manure is quickly released back to the atmosphere through respiration, burning and decomposition (IPCC, 2006b, p10.7). Permanent pasture was assumed by O'Brien et al. (2014) not to sequester C because the IPCC (2006a, b) guidelines recommend that soils under permanent pasture do not lose or store C after 20 years (IPCC, 2006b, p2.13 and p.2.30). The review of Soussana et al. (2010) questioned the guidelines for permanent pasture and the rate of C sequestration by permanent Irish grassland was estimated as 1.36 t CO_2/ha/yr (Soussana et al., 2010), which was used in this research. Off-farm emissions from imported inputs such as diesel, were calculated with emission factors from the Carbon Trust (2013) except where Irish data were available e.g., electricity generation (Howley et al., 2011). For imported feeds that generate emissions from land use change such as Malaysian palm kernel, emissions were estimated from average land use change emissions for country of origin (Carbon Trust, 2010). All other data were taken from Ecoinvent (2010).

GHG emissions were converted to CO_2-equivalents (CO_2-eq) using the IPCC (2007) revised guidelines for global warming potential to establish the farm CO_2-eq emissions. The potentials used were 1 for CO_2, 25 for CH_4 and 298 for N_2O, assuming a 100 year time horizon (IPCC, 2007, p.212). The CF of both milk and meat were estimated by allocating the GHG emissions between milk and meat.

2.3. Allocation methods

Emergy allocation was based on 'embodied energy' (seJ) in milk and meat from culled cows and surplus calves, where Emergy (seJ) = Energy (J) * Transformity (seJ/J) (Brown and Herendeen, 1996) (SI Eq. #1 and 2). Allocation was then expressed as seJ/kg FPCM and seJ/kg total meat (carcass weight). Allocation by physical causality was based on the IDF (2015) guidelines and reflected the underlying use of feed energy by the dairy animals to produce milk and meat. The allocation factors for milk and meat were calculated using equations from Thoma et al. (2013a) (SI Eq. # 3 and 4). Economic allocation was based on sales receipts for milk and animals from culled cows and surplus calves at the farm gate (SI Eq. # 5–9).

Table 2
Key technical measures collected by Hennessy et al. (2012) for the bottom, mean and top third of a sample of 221 Irish dairy farms ranked in terms of gross margin/ha. The sample was weighted to represent a national population of 11,563 farms.

Item	Bottom third	Mean	Top third
Dairy farm area, ha	36	35	34
Milking cows, number	58	67	75
Culled cows, %	19	17	15
Stocking rate, cows/ha	1.59	1.89	2.24
Soil class 1[a]	48%	59%	71%
FPCM yield, kg/cow	4541	5181	5822
Fat, %	3.9	3.94	3.97
Protein, %	3.37	3.4	3.43
FPCM[b] yield, kg/ha	7288	9776	13031
Milk solids yield[c],kg/cow	339	387	436
Concentrates, kg DM/cow	929	898	929
Grazing days	221	239	249
N fertilizer, kg/ha	149	196	253
Purchased fuel, l/ha	114	110	113
Electricity, kWh/cow	184	182	188
Gross margin, €/ha	1030	1758	2666

[a] Soil Class 1 = Free draining soil.
[b] Fat and protein corrected milk.
[c] Total combined fat and protein in kilograms, kg.

Table 3
Individual pedigree component scores for contributors to allocation calculations regarding meat.

Scored components	Indicator					Total	Method of allocation where used						
	Reliability	Completeness	Temporal	Geographical	Technological		Mass of Liveweight	Mass of carcass weight	Protein content	Energy content	Emergy	Economic	Physical causality
Number of culled cows	1	1	1	1	1	5	x[a]	x	x	x	x	x	x
Culled cow KgLW/hd	1	1	1	2	1	6	x	x	x	x	x	x	x
Culled cow KO%	1	4	4	3	3	15		x	x	x	x	x	
Culled cow KgCW/hd	1	1	1	2	1	6			x	x	x	x	
Culled.cow carcass protein %	1	5	2	5	1	14			x	x	x	x	
Culled.cow carcass fat%	1	5	2	4	5	17				x	x	x	
Number of surplus calves	1	1	1	1	1	5	x	x	x	x	x	x	x
Surplus calf kgLW/hd	2	2	3	1	1	9	x	x	x	x	x	x	x
Surplus calf Ko%	1	4	4	3	4	16		x	x	x	x	x	
Surplus calf kgCW/hd	1	1	1	2	1	6			x	x	x	x	
Surp.calf carcass protein%	1	4	5	4	5	19			x	x	x	x	
Surp.calf carcass fat%	1	5	2	4	5	17				x	x	x	
Prot.Energy(J)	1	5	4	5	5	20				x	x	x	
Fat energy(J)	1	5	4	4	5	19				x	x	x	
Beef emergy (seJ/J)	1	5	4	4	5	19					x	x	
Culled cow €/kgCW	1	5	1	2	1	10						x	
Surplus male dairy calf (€/hd)	3	5	1	2	1	12						x	
Surplus female beef calf (€/hd)	3	5	1	2	1	12						x	

[a] Indicates inclusion of scored component in the allocation method algorithm.

Mass allocation was based on the weight of milk and weight of culled dairy cows and surplus calves. The mass of animals was calculated in terms of liveweight and carcass weight (SI Eq. # 10–17). Allocation by protein was expressed in kg of protein and based on the edible protein in milk and meat from culled cows and surplus calves (SI Eq. # 18–21). Energy allocation was expressed in joules (J) of energy and based on edible energy in milk and meat from culled cows and surplus calves (SI Eq. # 22–26).

2.4. Scenario analysis

Parameters, activity data and assumptions affect LCA results. For each allocation method it is unknown whether the specifics of the system and the quantity of meat and milk produced affects the allocation calculations. To test this, the model was run with two additional scenarios: (i) the mean of the top third (€/ha) of NFS 2012 farms and (ii) the mean of the bottom third (€/ha) of NFS 2012 and all allocation methods were applied. For each scenario the calculated carbon footprint of milk was normalised by dividing the scenario/allocation method value by the mean NFS 2012 farm value for that allocation method (thus the normalised carbon footprint for the mean was 1 for all allocation methods). It was then possible to compare allocation methods by whether they amplified or attenuated differences between scenarios.

2.5. Pedigree matrix

The quality of the data was assessed by the pedigree matrix of Weidema and Wesnaes (1996; Table 1) for each allocation method. The overall pedigree score was calculated for each allocation method (SI Table # 1 and 2), based on the sum of the component scores weighted by proportional contribution to the calculation where this could be assessed (e.g. proportional mass of milk and meat) (Tables 3 and 4). The methods were then ranked based on pedigree score. For each allocation method the highest possible score was 25 and the lowest was 5 (Table 1) and a lower score represented a better data pedigree.

3. Results

3.1. Influence of allocation method on carbon footprint

The carbon footprint of milk from grass based milk production depended on allocation method (Table 5). For the economically average Irish dairy farm, the allocation factors ranged from 75% for physical causality to 89% for mass of carcass weight, which in turn resulted in a 17% difference in the carbon footprint ranging from 1.04 to 1.22 kg CO_2-eq/kg FPCM. The carbon footprint of milk was lowest for the physical causality method followed by the economic and energy methods. The allocation method that yielded the greatest carbon footprint of milk was mass of carcass weight, followed by the mass of liveweight, protein and emergy methods.

The different allocation methods caused greater differences in the carbon footprint of the meat co-product than the CF of milk. The carbon footprint of meat was estimated to range from 0.61 to 7.49 kg CO_2-eq/kg meat, which is a >12-fold difference (Table 5). The allocation method that resulted in the lowest carbon footprint of meat was mass of carcass weight followed by mass of liveweight, emergy and protein content. Allocation according to physical causality generated the greatest carbon footprint of meat, followed by economic and then energy content.

3.2. Pedigree of the allocation methods

The pedigree matrix results showed that a varying degree of qualitative uncertainty around component data existed (SI Table # 1 and 2). With regards to FPCM, data uncertainty was greatest for the energy content and emergy allocation methods (Table 5; score = 14.3 and 15.0 respectively), whilst with regards to meat, both of these methods were shown to have similar qualitative uncertainty, having pedigree score of 12.4 and 12.9, respectively (Table 5). With regards to both FPCM and meat, all other allocation methods had a matrix score of less than 10. Also, with regards to FPCM and meat, mass liveweight was shown to have the least qualitative uncertainty around its component data, having a matrix

Table 4
Individual pedigree component scores for contributors to allocation calculations regarding milk.

Scored components	Indicator					Total	Method of allocation where used						
	Reliability	Completeness	Temporal	Geographical	Technological		Mass of Liveweight	Mass of carcass weight	Protein content	Energy content	Emergy	Economic	Physical causality
Parameter (Thoma et al., 2013a)	1	1	3	4	3	12							x
Non corrected milk,kg	1	2	1	1	1	6	X [a]	x	x	x	x	x	x
Total protein produced,kg	1	2	1	1	2	7			x	x	x		
Total fat produced,kg	1	2	1	1	4	9				x	x		
Total Lactose produced (kg)	1	3	3	3	2	12				x	x		
Prot.Energy(J)	1	5	4	5	5	20				x	x		
Fat energy(J)	1	5	4	4	5	19				x	x		
Carbohydrate energy (J)	1	5	4	4	5	19				x	x		
Milk emergy (seJ/J)	1	5	4	4	5	19					x		
Fat, kg sold	1	2	1	1	4	9						x	
Protein, kg sold	1	2	1	1	2	7						x	
Revenue milk fat (€)	1	1	1	2	2	7						x	
Revenue milk protein (€)	1	1	1	2	2	7						x	
C parameter	1	1	1	2	2	7						x	

[a] Indicates inclusion of scored component in the allocation method algorithm.

score of 6 and 6.3 respectively (Table 5).

With regards to milk, and in relation to mass of liveweight, mass of carcass weight, protein and economic allocation methods, the component making greatest contribution to the pedigree score was that of 'non-corrected milk kg' (SI Table # 1), under the completeness indicator (Table 4). In relation to energy content and emergy allocation methods (SI Table # 1) the components making greatest contribution to the pedigree score were those of 'fat energy (J)' and 'protein energy (J)', and in that order (Table 4). For energy content, the geographical and temporal indicators score (Table 4) contributed most towards its pedigree score, whilst for emergy both the completeness and technological indicator scores contributed most (Table 4). In relation to physical causality, the components making greatest contribution to the pedigree score (Table 5) were those of 'culled cow kg LW/hd', followed by 'surplus calf kg LW/hd' (SI Table # 2), under the geographical and technological indicators (Table 4).

With regards to meat and in relation to mass of liveweight (SI Table # 2), mass of carcass weight, and protein allocation methods, the components making greatest contribution to the pedigree score (Table 5) were those of 'culled cow kg LW/hd' and 'surplus calf kg LW/hd', in that order, under the geographical indicator for the culled cow, and under the temporal indicator for the surplus calf (Table 3). In relation to energy content and emergy allocation methods the components making greatest contribution to the pedigree score (Table 5) were those of 'fat energy (J)' and 'protein energy (J)', and in that order (Table 3). For energy content, the completeness and technological indicators scores (Table 3) contributed most towards its pedigree score, whilst for emergy both the completeness, geographical and technological indicator scores contributed most (Table 3). In relation to economic allocation, the 'culled cow kg LW/hd' and 'surplus female beef calf (€/hd)' components (SI Table # 2) contributed most to the pedigree score (Table 5) under the geographical indicator for culled cow and under

Table 5
The effect of method of allocating greenhouse gas (GHG) emissions between milk and meat on the carbon footprint [a] of both products for the bottom third, mean and top third of Irish dairy farms in terms of gross margin/ha.

	Method of allocation							
	Farm category	Mass of Liveweight	Mass of carcass weight	Protein content	Energy content	Emergy	Economic	Physical causality
GHG allocated to milk	Bottom	85%	87%	80%	80%	83%	75%	70%
	Average	88%	89%	83%	81%	84%	77%	75%
	Top	90%	91%	86%	86%	88%	81%	79%
kg CO2-eq/kg FPCM [b]	Bottom	1.34	1.36	1.26	1.26	1.30	1.17	1.10
	Average	1.21	1.22	1.15	1.11	1.15	1.06	1.04
	Top	1.14	1.15	1.09	1.09	1.11	1.02	1.00
kg CO2-eq/kg meat	Bottom	1.34	0.68	3.61	3.74	2.57	6.23	8.34
	Average	1.21	0.61	3.28	4.60	3.18	6.52	7.49
	Top	1.14	0.57	3.10	3.23	2.20	6.33	7.01
Bottom deviation from Ave.		0.11	0.11	0.10	0.13	0.12	0.10	0.06
Top deviation from Ave.		0.06	0.06	0.05	0.02	0.04	0.04	0.03
Bottom deviation: Top deviation		2	2	2	5	3	2	2
Pedigree score FPCM		6.0	6.0	6.5	14.3	15.0	7.2	7.2
Pedigree score meat		6.3	9.3	10.1	12.4	12.9	8.4	7.2

[a] Carbon footprint of products was calculated according to cradle to farm gate life cycle assessment using the model of O'Brien et al. (2014).
[b] kg CO_2-eq/kg FPCM = kg CO_2 equivalent/kg of fat and protein corrected milk.

the completeness and reliability indicators for the surplus female beef calf (Table 3).

3.3. Scenario analysis

The ranking order of the carbon footprint of milk and meat for the different allocation methods was the same for all three scenarios (Table 5). Energy content, followed by emergy appeared to have an amplifying effect by widening the range across scenarios (Table 5). The other allocation methods had a similar effect on the range over scenarios. The effect of allocation method across scenarios was mirrored by the final pedigree score, except for the physical causality methodology (Table 5), but there is no obvious causal relationship.

4. Discussion

As carbon footprint is now such an important tool for analysing and communicating the environmental impact of GHG emissions from dairy systems it is important to understand the ramifications of method choice. The results of this study showed the influence of allocation method on the carbon footprint for raw milk (and associated meat co-product), but these were achieved with data of widely varying pedigree. The pedigree method was not very sensitive to operator assigned score for each of the indicators as changing any indicator score by 1 made no difference to the total pedigree score for the allocation method. The results reported are not universal, but specific to the case of Ireland and the data available for this specific study. If the same methods were applied in a different situation different pedigree scores would be found, and thus a different ranking of allocation methods based on the pedigree. The discussion will focus on an analysis of why each allocation method was scored as it was and the implications of source data quality.

4.1. Mass methods (liveweight and carcass weight)

The good pedigree score for liveweight and carcass weight (Table 5) arose because obtaining current, site-specific data on milk output (SI Table # 1) and the liveweight of culled cows was relatively easy at the national scale (SI Table # 2). Farm level sales receipts and farm management databases are available in Ireland, and in many countries, and the life of all animals is recorded in national breeding and animal identification databases. For this specific study (at national scale) national average data could be used that were consistent with the activity data for the life cycle inventory. The Irish Cattle Breeding Federation (ICBF) data on animal slaughter included carcass weight and kill out percentage (KO%) were used to estimate an average animal liveweight. If conducted at a farm scale, the data would still be of good pedigree because the ICBF has data on each individual animal that has been slaughtered throughout Ireland (ICBF, 2015). Liveweight data for live calves (<3 weeks of age) are not commonly recorded so representative data from other studies or surveys had to be used. As the calf data represent a small proportion ($\approx$34% on a liveweight basis) of the total mass output of the system, its data quality had little effect on the overall pedigree score (Table 5). The data for milk (SI Table # 1), liveweight and carcass weight (SI Table # 2), were Irish, i.e. country specific and for the same year as the activity data i.e. temporally specific (Table 4). An advantage of the mass allocation methods is that they can be applied in situations where markets are absent or very localized, and therefore not comparable across regions and they are relatively stable over time.

There were some shortcomings in the data that will apply to many dairy LCA studies: not differentiating between 1 kg of hide and 1 kg of liveweight; ignoring stomach contents, offal and products for rendering; properly capturing replacement rates; and the fact that culled cows (end of life) and calves (co-product input to a beef production supply chain) are treated as being at the same life cycle stage. Using liveweight and carcass weight for allocation did not have an attenuating effect on range of carbon footprints across the scenarios compared to the other methods (Table 5). While there is no objective method of selecting an allocation method, one that attenuates differences between types of farm within a production system category is perhaps less desirable for communicating continuous improvement messages to farmers and consumers. Based on scenario analysis and pedigree, mass allocation by liveweight or carcass weight would be a robust option for studies using the types of data available for Ireland at a national scale.

4.2. Protein content

For milk the pedigree of the protein content allocation was similar to that of mass allocation. However, for meat, the pedigree of available data to calculate protein content allocation was not as good as either of the mass allocation methods (Table 5). Milk protein content is recorded for each farm and is used for quality premium payments to farmers so obtaining data on the protein content of milk from the computer sales receipts of the milk processor, and overview data from NFS means good pedigree data are possible. A similar situation applies in most countries with a developed milk market. Obtaining data on the protein content of culled cows and surplus calves (SI Table # 2) tends to be more difficult because it is not common practice to record protein content per kg of meat by the primary processor. The low pedigree score for protein allocation was because data were predominantly recent and Irish (geographical and temporal specificity; Table 3) except for calf carcass data taken from Kirton et al. (1972) (SI Table # 2), which had a very small weighted contribution to the overall score.

Gerber et al. (2010) used a protein-based allocation because it was believed to best relate to the respective functionality of milk and beef. As the primary function of dairy production is to provide humans with high value edible protein (Schau and Fet, 2008; van Beek et al., 2010) and the possibility of using protein for direct comparison with other food products (Flysjö et al., 2011; Gerber et al., 2011; Roy et al., 2009), there is a case to support using this allocation method. In addition, protein content can be used when markets are absent or very localized and it is relatively stable over time. However, as the meat co-product at the dairy farm gate has not (calf) or cannot (culled cow in some enterprises) achieve the function of supplying food chain beef meat without further live stages it can be argued that the different life cycle stage of milk, calves and culled cows makes such a functional comparison unnecessary. It can also be argued that milk and beef are important for supplying calcium, potassium and fat (Thoma et al., 2013b) and not all proteins are equal (milk has greater mg amino acid per g protein than beef), so amino acid profile should be considered.

Protein allocation had a small effect (equal to the mean range of 0.15) on the normalised CF across scenarios so appeared to slightly attenuate scenario difference compared to the mass allocation methods (Table 5). Use of protein allocation is reasonable regarding pedigree provided suitable quality data exist that do not attenuate system differences.

4.3. Economic

The pedigree of economic data for milk was similar to that for protein and mass allocation but was poorer for meat (Table 5). Data on culled cows and surplus calves can be obtained at farm level from sales receipts and at national scale from databases and media summaries (SI Table # 2). Regarding meat, for CF, the economic allocation effect was the same as that of mass liveweight and mass carcass weight (Table 5), whilst having different pedigree scores (Table 5), contributed to by the same indicators (Table 3). However, for non-corrected milk, the indicator with most influence on the final pedigree score was completeness, with a score of 2 (Table 4). The indicators scores (Table 4) reflected the fact that the economic value of the milk was based on its average national market value, coupled with the fact that this market price was applied to the different dairy production enterprises sampled within the NFS.

Economic allocation is consistent with ISO (2006) guidelines as the relationship is causal. The guidelines suggest that where physical relationship alone cannot be established as the basis for allocation, then inputs should be allocated to reflect other relationships. Economic allocation is the recommended method for PAS 2050 (BSI, 2011), but is subject to uncertainty because of price fluctuation, which is not related to actual emissions and impacts (Pelletier and Tyedmers, 2011). It can only be used when there is a market for all co-products (usually the case for agricultural production), but this can mean that the price ratio does not really reflect either proportional contribution to the biophysical system function or consumer demand.

In the case of both milk and meat products produced in Ireland, it is not possible to link economic payments to farmers to local consumer demand because prices reflect global trade in the products. Furthermore, economic allocation does not necessarily consider the other functions of a product such as nutritional or cultural value, but in the case of Irish milk at least, there is a quality (protein content) supplement earned for better quality milk that might be used to capture other functions.

Economic allocation had a small effect (equal to the mean range of 0.15) (Table 5) on the normalised CF across scenarios so appeared to slightly attenuate scenario difference compared to the mass allocation methods. Use of economic allocation is reasonable regarding pedigree provided suitable quality data exist that do not attenuate system differences, but use of national average values at farm scale would seem to be a poor choice because the resultant allocation would not necessarily reflect farmer efforts to improve quality and reduce environmental impact.

4.4. Physical causality

The pedigree of data used for physical causality allocation was poorer than mass, protein and economic methods. The main reason for this was a lack of Irish data for the calculations, and the reliance on an algorithm (SI Eq. # 3) developed using US data (Thoma et al., 2013a) (SI Table # 1 and # 2). This meant that geographical (source data from 5 regions of the USA), technological (a mix of production systems) and temporal (calculations for feed energy required for milk and meat, were based on NRC (2001) as cited in Thoma et al., (2013a), i.e. 11 years old) indicators were poor (Tables 3 and 4). While data are available in Ireland (and elsewhere) that can be used to calculate cow efficiency for converting feed to milk and meat (O'Mara, 1996), the relationships are not widely available to undertake this type of calculation, and specifically to parameterise at anything other than national scale.

Physical causality allocation can avoid the shortcomings of economic allocation because it does not suffer market fluctuation, but this also means its parameterisation cannot reflect changes in animal breeding, nutritional management and management efficiency. It is theoretically preferred in the ISO hierarchy and has been adopted by the International Dairy Federation to ensure consistency between studies (Thoma et al., 2013a). However, this is open to question because cows less than two years old cannot produce milk but allocating their growth emissions to meat production does not seem appropriate.

Physical causality allocation caused the most attenuation in normalised carbon footprint between the maximum and minimum scenarios (Table 5) so it will tend to minimise differences within the production system making the results less useful for farmer communication and continuous improvement schemes. It also places greater impact on the meat co-product, which for most intensive dairy systems is unreasonable because milk is the overwhelming reason for their existence and management functions. Given the poor pedigree of the data generally available to implement physical causality allocation it is difficult to see why it should be preferred over the simpler mass allocation methods.

4.5. Energy and emergy

The energy and emergy allocation methods had the poorest data pedigree. The energy content data scored poorly for representativeness (unknown), geographical specificity (US data) and temporal specificity (data was from 2002) (Tables 3 and 4) which also applied to the emergy calculation, with the additional uncertainty of relying on statistical data from Florida (Fluck et al., 1992) and unknown technology for estimating seJ per J or kg (Brandt Williams, 2002) (SI Table # 1 and 2).

The emergy approach was difficult to reliably implement because of its complexity. The calculation of solar energy (seJ) (SI Eq. # 1 and 2) for various imported feeds, fertilizers, pasture, conserved forage, infrastructure and energy stored in the animal and its products required transformity data. These are dependent on location, aspect, height above sea level and climate of a given farm, grass species and cow breed, so obtaining high quality data specific to a given LCA study will always be difficult and probably not worth the time investment required to achieve a good pedigree.

It has been argued by Ayer et al., (2007) that in the context of food production systems, gross chemical energy content represents a common physical property of food co − products both within and between production systems. A similar argument could be made for emergy, and both are value neutral factor, and did not attenuate differences in CF between scenarios, so energy or emergy should be sound approaches to allocation. However, the difficulty in obtaining good pedigree data means the theoretical value is negated by the practical reality of implementing the methods.

5. Conclusion

Based on pedigree score and factoring in attenuation of differences between systems, the simple mass allocation methods by liveweight or carcass weight were the best options for handling co-products. However, protein content with its low pedigree score could also be viewed as best for solely milk. Energy and Emergy were the least desirable and the others fitted in between. In most cases it was only the scores for one or two indicators that dominated the final pedigree score for each method. This was also observed by Weidema and Wesnaes (1996) so we can conclude that if a particular method is to be used for theoretical reasons, then focused effort will be required to ensure the best possible data pedigree in order to justify a method other than the most simple ones. A further reason to be careful with the more complex methods is that they are built on a foundation of the simple methods with a cascade of additional data. This study showed the importance of using country, technology and temporally specific data so the goal and scope specification for the study should be consistent with the time that can be committed to the allocation calculations. There is no reason to use a complex method if time cannot be committed to obtaining good pedigree data. It was also noted that when assessing meat co-products the method chosen can be used to bias the study. From the data presented here it seems that physical causality will be biased in favour of milk, and in the case of physical causality, obtaining good pedigree data to justify such an approach is difficult.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2017.06.071

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