Influence of methodological choices in farm sustainability assessments: A word of caution from a case study analysis of European dairy farms

Abstract

In a context where sustainability assessments are increasingly popular, this perspective article discusses the influence of methodological choices on measurements of farm sustainability. We build the argumentation on the premises that sustainability is a multi-dimensional concept that can be measured through an indicator approach and use examples from a case study analysis of seven European dairy farms. Specifically, the article demonstrates how and why indicator selection, estimation methods, and reporting frameworks can influence measured performance and thereby affect wider sustainability conclusions about production systems and practice change. Overall, we highlight that while in practical terms, methodological choices are necessary to conduct a farm sustainability assessment, important limitations can arise from the process. Of particular concern are farm conclusions and recommendations that lead to perverse outcomes and generate further sustainability issues outside of study scope. Practical guidance is provided to aid methodological choices with a more comprehensive and critical view of farm sustainability assessments. Importantly, we call for a more upfront recognition of methodological shortcomings in farm analyses.

Keywords: Farm sustainability assessment; methodological choices; indicator selection; estimation methods; reporting frameworks; case studies.

1 Introduction

In recent times, advancements in research methodologies and more prolific data access have opened doors to a better understanding of farm sustainability (Díaz de Otálora et al., 2021; Dillon et al., 2016; Kamilaris et al., 2017). As a result, farm sustainability assessments have become increasingly popular and serve multiple purposes, such as informing public debate and policies, accessing price premiums on the market, and identifying areas of improvement at the farm level (Chopin et al., 2021; Magrini and Giambona, 2022). All these applications can have a large impact on farmers' livelihoods and operating conditions, thus justifying the vested interest in assessment methodologies. In the research and policy making spheres, issues have previously arisen from restrictive analytical lenses (Bareli et al., 2020; Guerra et al., 2016). For example, an analysis focused on a narrow set of sustainability indicators can lead to perverse outcomes that generate further sustainability issues. On a path of continuous progress, efforts have been made to address important knowledge gaps, notably through a rebalancing of the economic, environmental, and social sustainability dimensions in the literature (Latruffe et al., 2016; Lebacq et al., 2013; Lynch et al., 2019) and the improvement of science to estimate sustainability aspects that are difficult to observe and/or measure (Desjardins et al., 2018; Gavrilova et al., 2019; Oertel et al., 2016). However, with ever-increasing sustainability pressures and continued need for widespread practice change in agricultural production, the rapidly growing body of literature in the sustainability area must continue to improve and produce credible, science-based claims.

While methodological choices are undoubtedly important when conducting sustainability assessments on large datasets (Saltelli et al., 2020), their influence is even more potent when evaluating farms on an individual basis. This is because acceptable trade-offs between bias and accuracy can be found in statistical analyses at the mean (Athey and Imbens, 2017), while these can be misleading when drawing sustainability conclusions for individual farms. The average farm is a statistical construct, which does not necessarily have an equivalent in farming reality (Gonzalez-Mejia et al., 2018; Weersink, 2018). Consequently, it can be difficult for farmers who operate in less-than-average conditions to relate during extension activities and feel represented in agri-environmental policy, thus slowing down efforts to support the transition towards greater sustainability. In a sense, the academic literature and public policies have already progressed towards more localised approaches that aim for tailored, farm specific solutions and recognise, to a greater extent, farm heterogeneity (de Krom, 2017; Díaz de Otálora et al., 2022; Hasler et al., 2022). This is notably reflected in recent changes to the European Union (EU) Common Agricultural Policy where Member States can now tailor their strategic plans to reflect more local priorities (Council of the European Union, 2023). Nonetheless, this view is still in its infancy and requires more practical guidance to improve case-by-case analyses of farm sustainability. Overall, individual farm figures can come under greater scrutiny, thereby highlighting the even more pressing need for critical appraisals of methodological choices in case study analyses.

This perspective article is based on the following premises: Sustainability is a multidimensional concept, best decomposed into three dimensions: economic, environmental, and social (Dillon et al., 2016; Latruffe et al., 2016; Lebacq et al., 2013). Sustainability dimensions are themselves comprised of multiple aspects, which can be measured through quantitative and qualitative indicators. In this context, we specifically explore how indicator selection, estimation methods, and reporting frameworks can influence measured farm sustainability performance. To build our argumentation, we use examples from a case study analysis of seven European dairy farms from Ireland (IE), France (FR), Germany (DE), and Norway (NO). In the text, farms are numbered consecutively with their country code. The case studies and their characteristics are presented in detail in Appendix A. While we provide some practical advice for practitioners, we also raise important limitations related to the measuring of farm sustainability through an indicator approach. We call for a more upfront recognition of methodological shortcomings in farm sustainability assessments.

2 How does indicator selection influence measured farm sustainability performance?

In this section, we describe measured sustainability performance of case study farms across a set of sustainability indicators and explore how indicator selection can influence sustainability conclusions. Our objective is to build an argument around the need for critical appraisals of selected indicators and more comprehensive farm sustainability assessments. Sustainability indicators utilised in this section are defined in Appendix B, notably in Table B.1. It is worthwhile to mention that the list of selected sustainability indicators provides examples and is thus not exhaustive.

Table 1 gathers performance figures by economic, environmental, and social sustainability dimension across case study farms. To facilitate interpretation, the table is colour coded. Specifically, for indicators that are continuous in nature, the results of the two best performing case study farms are in green colour. The performance of the two worst performing farms is in red colour, while the middle performing farms appear in yellow colour. For indicators whose sustainability performance can only be interpreted as positive or negative, corresponding cells are coloured in either green or red, respectively. This is the case of three social indicators that are dichotomous in nature (i.e., farmer workload, farm economic viability, and organic production or participation in an agri-environmental scheme), and milk fat-to-protein ratio that points out good animal health status when in the [1.0; 1.5] range (Cabezas-Garcia et al., 2021; Toni et al., 2011).

Table 1 reveals that none of the case study farms performs equally across and within sustainability dimensions. In other words, for all sampled farms, measured sustainability performance varies across selected indicators. Differences can even be extreme. For instance, within the economic sustainability dimension, FR2 indicates results amongst the lowest performances for farm gross output per unpaid labour unit, farm gross margin per unpaid labour unit, milk yield per cow, and percentage of subsidies to total earnings. Conversely, this farm achieves some of the highest performances for farm net income per unpaid labour unit and direct production costs per farm gross output. Within the environmental sustainability dimension, NO1 moves from worst to best performing farm category depending on the indicator under investigation. While its nitrogen (N) efficiency is the second highest of the sample, all six other environmental indicators are coloured in red in Table 1 (i.e., greenhouse gas (GHG) emissions per utilised agricultural area (UAA), dairy GHG emissions per fat-protein-corrected-milk (FPCM) sold, eutrophication per UAA, air acidification per UAA, total energy demand per UAA, and land occupation for dairy production). As for the social sustainability dimension, it is DE1 that oscillates between positive and negative measures of sustainability performance. Specifically, on this case study farm, measured social sustainability is positive for farmer workload, farm economic viability, and milk fat-to-protein ratio. However, DE1 does not perform well for labour input per UAA, days at grass, and organic production or participation in an agri-environmental scheme.

The immediate implication of such observations is that measured sustainability performance is highly influenced by indicator selection. We will always only observe a skewed picture of farm sustainability when narrowing down indicator selection. This issue should not be taken lightly as we may be largely blind to some negative sustainability consequences of promoted farming strategies, or be misled into favouring certain agricultural systems over others (Salou et al., 2017). From a practical perspective, this may seem like a rather trivial point as it is impossible to focus on and detail the whole sustainability concept across every sub-dimension. With this in mind, finding a happy medium is a necessary evil to advance technological progress. In that regard, the academic literature has published a wide body of work on the definition of unbiased, external guidelines and criteria to inform indicator selection (Bélanger et al., 2012; Kanter et al., 2018; Latruffe et al., 2016; Lebacq et al., 2013), with some general conclusions. Potential indicators should be considered in the light of pre-established criteria to avoid assessment subjectivity (Bélanger et al., 2012; Latruffe et al., 2016; Lebacq et al., 2013). They should allow for the consideration, interpretation, and communication of findings about the three sustainability dimensions separately, while comprehensively and reliably representing the complexity of agricultural systems (Lebacq et al., 2013). Bélanger et al. (2012) also suggest that sustainability indicators should be easy to implement, immediately understandable, reproducible, sensitive to variations, adapted to objectives, and relevant for users. Nonetheless, a central dilemma arises as guiding indicator selection with these criteria will undoubtedly still influence the outcome of the analysis (Latruffe et al., 2016). By nature, it will be impossible to fully resolve subjectivity and simplification challenges in farm sustainability assessments (Waas et al., 2014). However, our view is that a more upfront description of and reflection upon limitations associated with indicator selection is necessary to improve the quality, effectiveness, and reach of study findings; that is, assessments of shortcomings and transparency are key guiding principles in sustainability analyses.

Through farm benchmarking, the exercise performed in Table 1 can be used to identify farm sustainability strengths and weaknesses, and thereby highlight areas for improvement. However, before inferring wider conclusions for production systems or individual farms, it is important to acknowledge the role of external factors on farm sustainability, as well as variations in socio-economic and environmental contexts (German et al., 2017; Pradhan et al., 2015). To some extent, these are outside of farmer control and inherent to localised biophysical and climatic conditions, which underlines the need to contextualise sustainability assessments before conducting farm comparisons. For instance, while there might be scope to increase the length of grazing season on farms such as FR1, DE1, DE2, and NO1, it would be unrealistic to expect a similar performance to that of IE1 and IE2. In fact, for this sustainability indicator, IE1 and IE2 benefit from a comparative advantage due to the Irish temperate climate and resulting bountiful grass growing seasons (Kelly et al., 2020; O'Brien et al., 2018). Additionally, external factors influence farmer management decisions to thrive in localised conditions (Feola et al., 2015; Gardezi and Bronson, 2020; Morton et al., 2017). For example, Irish farmers predominantly operate seasonal, grass-based production systems (such is the case of IE1 and IE2) (Butler, 2014). Their breeding strategies and management are aligned accordingly to have robust cows that can walk long distances between the milking parlour and grass paddocks (Hennessy et al., 2020; Roche et al., 2018). In broad terms, because pasture-based cows (are bred to) dedicate a relatively larger amount of energy to animal maintenance, a lesser portion is available for productive functions (Horan et al., 2005; Neave et al., 2021). This partially explains the per-cow milk yield gap observed between Irish case studies and sampled farms which operate more confined systems, e.g., FR1 and DE1 (Neave et al., 2021). Interestingly, Table A.1 in Appendix A shows that IE2 achieves the lowest milk yield of 5362 litres (l) per cow and the longest grazing season of 259 days. Conversely, DE1 operates a fully confined system (i.e., zero day at grass) and performs the best in terms of milk production (i.e., 10870 l per cow). In this example, achieving the same level of cow productivity on Irish case study farms as that of, say, DE1 would necessitate an adjustment in breeding strategies and management likely to be unsuited to the current Irish grass-based production system (Horan et al., 2005). As such, increasing cow productivity on IE1 and IE2 could reallocate the relatively poor milk yield performance onto other sustainability indicators, e.g., a reduction of days at grass.

Localised biophysical and climatic conditions offer opportunities and constraints on the path towards more sustainable production systems (Cavender-Bares et al., 2015; Lerner et al., 2017). Thus, this requires greater recognition in scientific work, farmer extension advice, and public policy. A one-size-fits-all approaches should be avoided by better accounting for the interrelations between biophysical and climatic farm conditions, farmer management decisions, and farm sustainability (Giller et al., 2015; Kanter et al., 2018; Repar et al., 2017). Overall, the results presented in Table 1 emphasise the need to be as comprehensive as possible in farm sustainability assessments so that synergies and trade-offs across sustainability aspects are made apparent for specific farm conditions (Defries et al., 2016; Schader et al., 2016). Hence, the indicator selection process should also be guided by this objective[1] (Kanter et al., 2018). This could help to identify adapted sustainability enhancing solutions, as well as to avoid promoting strategies that will lead to unintended trade-offs or undesired sustainability outcomes in areas potentially excluded from restrictive analytical lenses.

[1] An important point related to indicator selection, which is not discussed in this perspective article, is the need to choose indicators that have a high correlation with the sustainability aspects under investigation (Dillon et al., 2016; van Calker et al., 2001). This is particularly important for sustainability aspects that are difficult (or expensive) to observe and/or measure.

Sustainability indicator	Measurement unit	IE1	IE2	FR1	FR2	DE1	DE2	NO1
ECONOMIC								
Farm gross output per unpaid labour unit	€ / AWU	184236	267858	202014	114936	239225	256474	120601
Farm gross margin per unpaid labour unit	€ / AWU	140949	187240	112717	95788	144189	185565	57030
Farm net income per unpaid labour unit	€ / AWU	93386	61341	29547	62254	28526	52403	35822
Milk yield per cow	l / cow	6012	5362	9567	5433	10870	7127	7833
Direct production costs per farm gross output	€ / €	0.23	0.30	0.44	0.17	0.40	0.28	0.53
Percentage of subsidies to total earnings (i.e., farm gross output and subsidies)	%	7.6	4.9	10.2	24.4	3.8	9.3	35.6
ENVIRONMENTAL								
GHG emissions per UAA$_a$	t CO_2e / ha	11.4	13.5	9.5	5.2	20.8	5.6	17.5
Dairy GHG emissions per FPCM sold$_a$	kg CO_2e / kg	1.28	1.12	1.34	2.02	0.95	1.63	2.61

Sustainability indicator	Measurement unit	IE1	IE2	FR1	FR2	DE1	DE2	NO1
Eutrophication per UAA[a]	kg $PO_4^{3-}e$ / ha	28.6	38.3	41.4	28.7	86.5	23.6	82.3
Air acidification per UAA[a]	kg SO_2e / ha	64.7	93.0	87.0	29.9	154.2	31.4	202.5
Total energy demand per UAA[a]	MJ / ha	32698	23025	28098	7437	84117	9753	78735
Land occupation for dairy production[a]	m^2 / (year*kg FPCM)	0.51	0.49	0.79	4.62	1.30	0.88	2.54
N efficiency	%	22.4	21.5	25.0	18.0	34.1	22.8	26.3
SOCIAL								
Total labour input per UAA	AWU / ha	0.024	0.032	0.021	0.014	0.052	0.023	0.058
Farmer workload[b]	No unit	Y	N	Y	N	N	Y	N
Farm economic viability[b]	No unit	Y	Y	Y	Y	Y	Y	[c]
Days at grass	Days	239	259	61	206	0	43	91

Sustainability indicator	Measurement unit	IE1	IE2	FR1	FR2	DE1	DE2	NO1
Milk fat-to-protein ratio[b]	No unit	1.17	1.30	1.21	1.32	1.18	1.23	1.26
Organic production or participation in an AE scheme[b]	No unit	N	N	N	Y (AE)	N	Y (Organic)	Y (AE)

Table 1: Measured sustainability performance of case study farms, by sustainability dimension

Note: € = euro; AWU = annual work unit; l = litres; GHG = greenhouse gas; UAA = utilised agricultural area; t = tonnes; CO_2e = carbon dioxide equivalent; ha = hectare; FPCM = fat-protein-corrected-milk; kg = kilogram; $PO_4^{3-}e$ = phosphate equivalent; SO_2e = sulphur dioxide equivalent; MJ = megajoules; m2 = square meters; N = nitrogen; Y = yes; N = no; AE = agri-environmental. Colour legend: green = two best performing farms; yellow = three middle performing farms; and red = two worst performing farms. [a] Environmental indicators estimated with the LCA approach. [b] Indicators with only two sustainability levels, which appear in green if positively associated with sustainability, and red otherwise. [c] Norway does not have a minimum wage. Thus, the economic viability indicator, which necessitates information about the national minimum wage, is not estimated for NO1. The corresponding cell is reported in neutral colour. The minimum wage data for other European farms is based on Eurostat (2022a). Please refer to Table B.1 in Appendix B for a detailed description of indicators and measurement units.

3 How do estimation methods influence measured farm sustainability performance?

This section examines differences in performance results when using varying estimation methods. We focus specifically on GHG emissions to investigate this question. Previous literature has compared GHG estimation methods in review articles (Hutchings et al., 2018; Rotz, 2018; Schils et al., 2007). In this article, we demonstrate, through a case study analysis, how and why estimation results can vary considerably based on selected method. We then provide practical guidance to aid methodological choices.

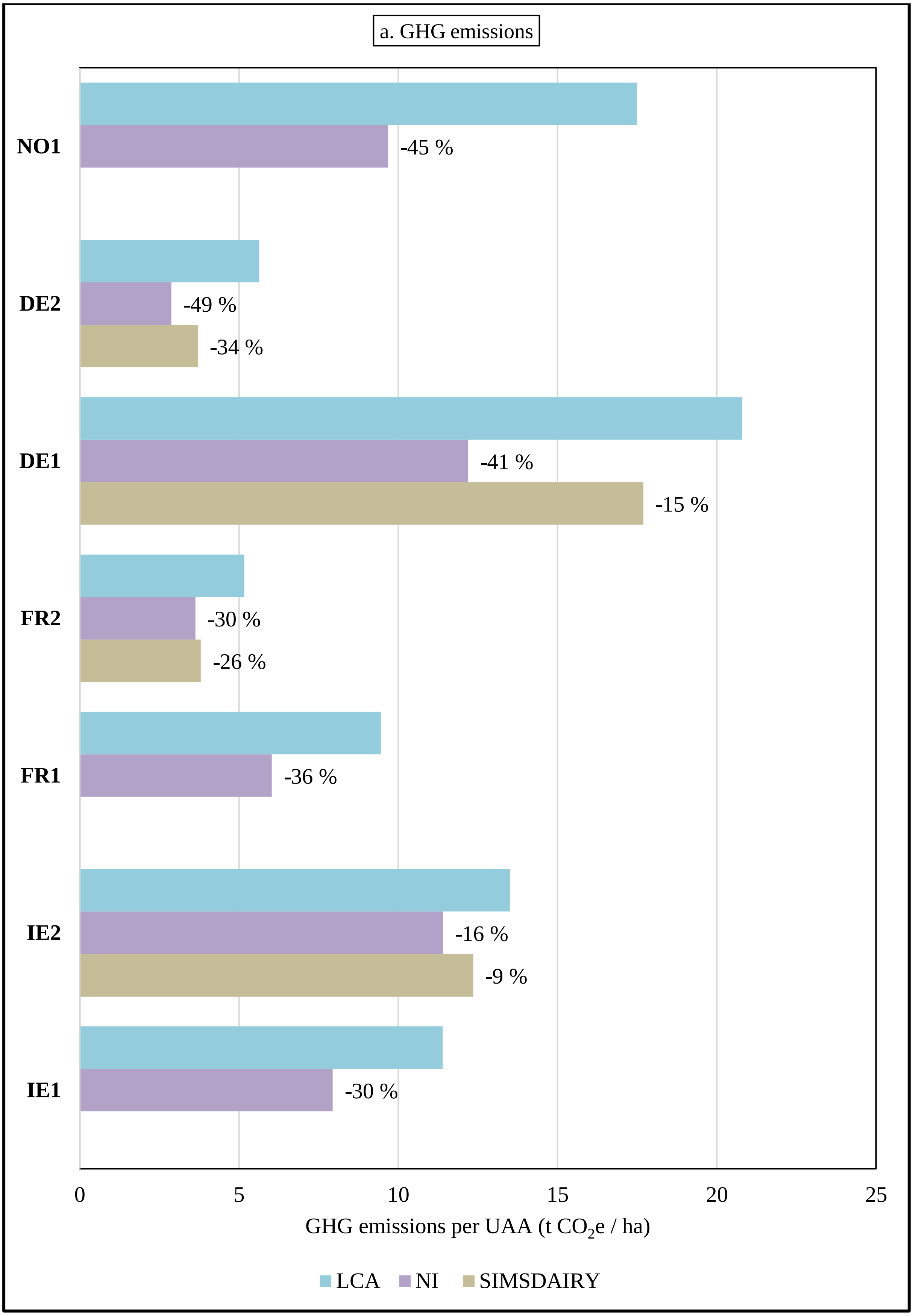
Figure 1 compares GHG emission results by case study derived from the application of three different methodological approaches: the life cycle assessment (LCA) framework, the national inventory (NI) framework, and the Sustainable and Integrated Management System for Dairy Production ($SIMS_{DAIRY}$) process-based model. Detail about how these approaches were implemented in the context of this perspective is provided in Appendix B for the LCA, and Appendix C for the NI and $SIMS_{DAIRY}$. Emissions are reported per UAA to facilitate comparisons across farms. Results from the NI and $SIMS_{DAIRY}$ methods are compared to LCA figures by calculating percentage differences. It should be noted that the $SIMS_{DAIRY}$ model does not account for farm beef enterprises. Thus, the GHG emissions of case study farms that perform beef fattening (i.e., IE1, FR1, and NO1 as mentioned in Table A.1 in Appendix A) are only estimated with the LCA and NI approaches. Figure 1.a represents all GHG emissions estimated by each method. Emissions are then broken down into different categories to shed light on the reasons for observed differences through some examples. Specifically, Figure 1.b separates on- and off-farm emissions. Figure 1.c provides detail about methane (CH_4) emissions from enteric fermentation.

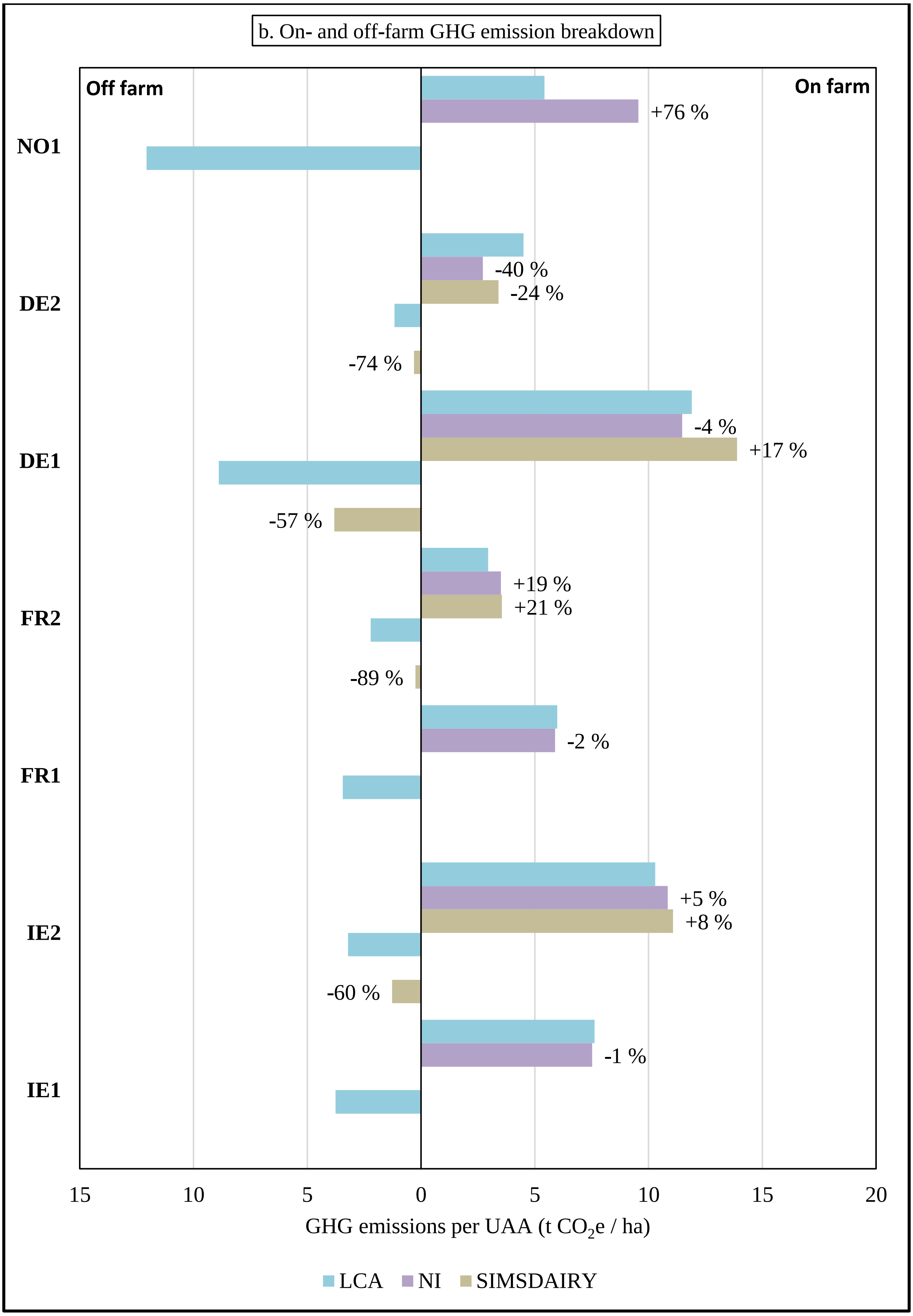
Overall, the methods yield GHG results with significant differences, as shown in Figure 1. On average, GHG emissions vary in absolute value by approximately 35% between LCA and NI results, and 21% between $SIMS_{DAIRY}$ and LCA estimations. Off-farm emissions represent approximately 38% of GHG emissions estimated with the LCA approach, while these are not accounted for in the NI method. When focusing on the four case study farms that do not have a beef enterprise, the LCA method estimates off-farm emissions to represent approximately 33% of GHG emissions, and $SIMS_{DAIRY}$ estimates that figure to be 12%. An evident reason for these differences relates to system boundaries. As already mentioned, the NI method does not estimate GHG emissions that occur outside of the farm but are associated with farm production (e.g., production and transport of inputs). Indeed, this method is derived from the Intergovernmental Panel on Climate Change (IPCC) guidelines developed to build national GHG emission inventories, where emissions are estimated for each separate production entity with the purpose of aggregating all emissions and avoiding double counting. This stands in contrast with the LCA approach, which is interested in the whole environmental footprint associated with farm production. For instance, the LCA includes an estimation of off-farm emissions generated during the production and transport of materials for farm machinery, infrastructures, energy, and equipment, in addition to feed and soil improvers. It is worthwhile to mention that such emissions are calculated in other categories than agriculture when following the IPCC approach (Intergovernmental Panel on Climate Change, 2006). As for $SIMS_{DAIRY}$, the model only provides an estimation of GHGs emitted in production and transport processes of concentrate feed and fertiliser.

When considering differences in system boundaries, it can be deduced that the LCA is the most comprehensive method in this study. It is thus not surprising to find in Figure 1.a that for all case study farms, LCA-estimated GHG emissions are higher than NI- or $SIMS_{DAIRY}$-estimated figures. However, the level of difference varies between -16% (IE2) and -49% (DE2) for the NI method, and between -9% (IE2) and -34% (DE2) for $SIMS_{DAIRY}$. Because farms operate heterogeneous production systems and thus do not rely to the same extent on external inputs, we strip out differences related to off-farm emissions in Figure 1.b. In this way, we further compare methods within similar system boundaries. Significant variations in on-farm emissions are still observed across methods. Surprisingly, we now observe that for certain case study farms, NI- or $SIMS_{DAIRY}$-estimated on-farm emissions are overestimated relative to LCA results. For example, NI-estimated emissions are +76% higher for NO1, +19% higher for FR2, and +5% higher for IE2. $SIMS_{DAIRY}$-estimated emissions are +21% higher for FR2, +17% higher for DE1, and +8% higher for IE2. In all other cases, on-farm emissions are underestimated relative to the LCA, with differences up to -40% (DE2) for the NI method and -24% (DE2) for $SIMS_{DAIRY}$. While small variations in within-farm system boundaries contribute to the gap in on-farm emissions[2], discrepancies in method accuracy are responsible for most of observed differences.

To further investigate how estimation methods and notably differences in their accuracy can affect the results, we detail CH_4 emissions from enteric fermentation in Figure 1.c. On average, CH_4 emissions from enteric fermentation vary in absolute value by approximately 11% between the NI and LCA methods, and 27% between $SIMS_{DAIRY}$ and the LCA. In the NI results, we observe that emissions are sometimes overestimated (i.e., +20% for NO1) and sometimes underestimated (i.e., from -2% for IE2 up to -35% for DE2) when compared to LCA figures. In this enteric fermentation example, $SIMS_{DAIRY}$ always yields lower CH_4 emissions than the LCA method for all case study farms, ranging from -17% (DE1) to -48% (DE2).

[2] For instance, the LCA method is the only one to account for CH_4 emissions from field deposition, which affects the emissions of all case study farms except DE1 (Table A.1 in Appendix A). $SIMS_{DAIRY}$ does not consider carbon dioxide (CO_2) emissions from urea application, liming, or the consumption of heating fuels, which notably affects the performance of IE2.


a. GHG emissions
NO1
DE2
DE1
FR2
FR1
IE2
IE1
-45 %
-49 %
-34 %
-41 %
-15 %
-30 %
-26 %
-36 %
-16 %
-9 %
-30 %
0
5
10
15
20
25
GHG emissions per UAA (t CO_2e / ha)
LCA
NI
SIMSDAIRY


b. On- and off-farm GHG emission breakdown
Off farm
On farm
NO1
DE2
DE1
FR2
FR1
IE2
IE1
+76 %
-40 %
-24 %
-74 %
-4 %
+17 %
-57 %
+19 %
+21 %
-89 %
-2 %
+5 %
+8 %
-60 %
-1 %
15
10
5
0
5
10
15
20
GHG emissions per UAA (t CO_2e / ha)
LCA
NI
SIMSDAIRY

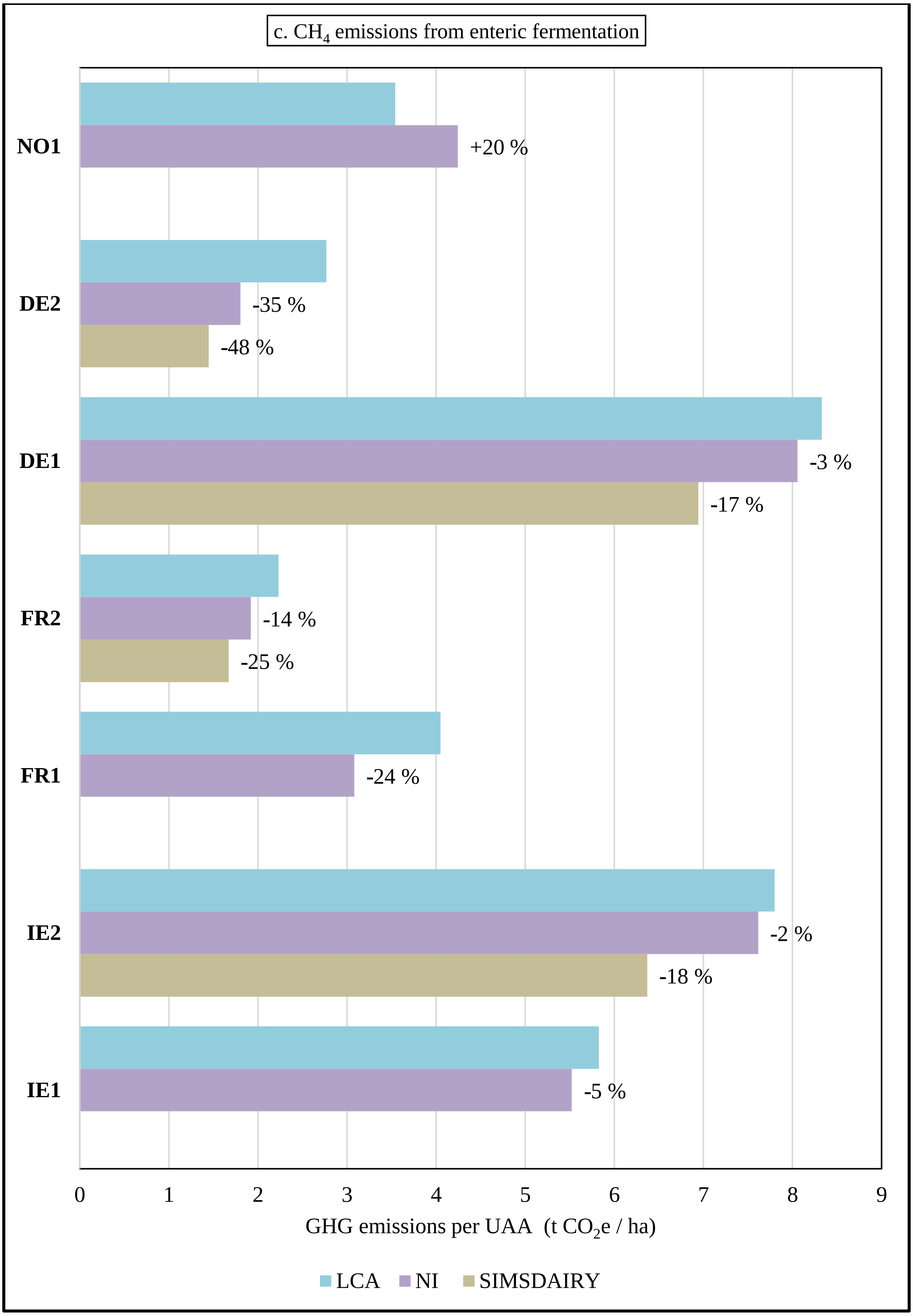


Figure 1: Comparisons of GHG emission results with varying estimation methods

Note: GHG = greenhouse gas; UAA = utilised agricultural area; t = tonnes; CO2e = carbon dioxide equivalent; ha = hectare; LCA = life cycle assessment; NI = national inventory; $SIMS_{DAIRY}$ = Sustainable and Integrated Management System for Dairy Production; CH_4 = methane. Data labels indicate percentage differences between NI or $SIMS_{DAIRY}$ results and LCA figures.

While all three methods use farm-recorded animal numbers as one of the input parameters to estimate enteric CH_4 emissions, differences are observed in the level of disaggregation of input data assumed by the methodology and thus the methods' ability to account for farm specific feeding strategies and animal diets. These have been proven to have a large impact on GHG emissions, notably during the enteric fermentation process (Arndt et al., 2022; Knapp et al., 2014), thereby explaining differences observed across our three methods. The LCA method relies on a Tier 3 approach (Noziere et al., 2018). For this emission source, Tier 3 takes into account detailed information about animal diets by animal type and age category for each case study farm. Multiple diets are considered throughout the production year based on seasonality, animal energy requirements, and data availability. In other words, the Tier 3 approach allows for the calculation of farm specific emission factors (EF) for enteric fermentation, which account for differences in feeding strategies and rates with a high level of disaggregated farm data. Conversely, the NI method relies on a Tier 2 approach, where EF are based on country specific, average information about animal diets by animal type and age category (Citepa, 2021; Duffy et al., 2021; Federal Environment Agency, 2021; Norwegian Environment Agency, 2021). These input parameters are thus not sensitive to farm specific feeding strategies. In a sense, the ability of the NI method to accurately reflect CH_4 emissions from enteric fermentation depend on how average the farm under focus is. As for $SIMS_{DAIRY}$, the calculations for enteric CH_4 emissions follow a Tier 2 approach with selected farm specific data at a more aggregated level than the LCA[3]. Notably, relevant information about purchased concentrate feed is averaged over the production year to calculate farm specific input parameters such as digestibility, gross energy, metabolisable energy, crude protein, and neutral detergent fibre content of purchased feed (Gavrilova et al., 2019).

The three methods under consideration can serve different purposes, and present advantages and disadvantages depending on the scale, scope, and unit of investigation. Table 2 summarises information about them to give guidance in choosing a suitable GHG estimation method. In our view, the LCA approach is the gold standard as it takes into account as much farm detail as possible to estimate environmental performance. However, it is also important to highlight that its ability to perform well depends on the level of specificity of EF and sub-models used throughout the estimation. This method can be used not only to draw an accurate picture of GHG emissions associated with farm production, but also to estimate other environmental indicators of interest (e.g., acidification, eutrophication, ecotoxicity, land use, cumulative energy demand, and resource depletion). In this way, the LCA can be used to identify pollution swapping phenomena while comparing different improvement strategies (De

[3] The $SIMS_{DAIRY}$ model was built to work with more aggregated data, mainly to overcome difficulties in accessing detailed farm data, a common issue in analytical studies.

Vries et al., 2015; Yan et al., 2011). Thus, this methodological framework is a useful tool to evaluate the effect of environmental mitigation strategies; that is, the LCA is able to account for the whole cascade of implications associated with a change in production parameters. This means that the effect of practice change can be evaluated within a wide analytical framework, thereby limiting undesired reallocation of environmental burdens outside of study scope. Additionally, because of its ability to accurately reflect farm specificities, the LCA approach can be applied to compare GHG emission performance and profile across farms that operate under different conditions.

A main disadvantage of the LCA approach is how data intensive its applications are. This can limit options to use this estimation approach and may orientate practitioners towards other, less data-intensive methodologies. Depending on study objectives, the NI method or a model such as $SIMS_{DAIRY}$ may be preferred. The NI method is useful to build on-farm GHG inventories based on a relatively small dataset or from secondary data sources such as the EU Farm Accountancy Data Network (FADN) (Buckley and Donnellan, 2022; Dabkienė et al., 2020; Syp and Osuch, 2018). For instance, NI-estimated results can be of interest to farmers and agricultural advisors to better understand farm emission sources and contributions from different gases within the farm gate. However, this method can prove misleading for farm profiles that are not average relative to national production systems. This is because the method uses national average values for certain input parameters (such as animal performance and diet). Moreover, because the method does not account for off-farm emissions associated with farm inputs, certain farms may incorrectly appear advantaged when comparing production systems and benchmarking farms against each other. More precisely, farms that rely heavily on external inputs, with a larger relative share of off-farm emissions, might comparatively perform better than more extensively driven farms whose majority of emissions occur within the farm gate. The NI method is not suitable to analyse the effect of GHG mitigation strategies that may have an influence on off-farm emissions or other environmental aspects because of its restrictive focus. Hence, it should be used with caution to provide advice on practice change to farmers. Overall, it is important to re-emphasise that the NI method, as implemented in this perspective, is adapted from the IPCC methodology that was created for the purpose of setting up national GHG inventories (Gavrilova et al., 2019; Intergovernmental Panel on Climate Change, 2006). In other terms, the IPCC methodology was not developed to account for individual farm emissions. Its adaptation into our NI method is a simple, non-data intensive tool which presents some limitations.

Method	**NI**	**LCA**	**SIMS$_{DAIRY}$**
Objective / Application	**Building inventories of on-farm GHG emissions based on an adaptation of a methodology designed to calculate agricultural GHG emissions at the national level**[a]; **Analysing contributions from different emission sources.**	**Building cradle-to-farm-gate inventories of on- and off-farm GHG emissions, which are adapted to each farm under study**; **Analysing contributions from different emission sources**; **Comparing footprint estimates across different farms;** **Evaluating environmental mitigation measures**.	**Simulating the interactions between management, climate, and abiotic components of the farm and their effect on N losses and GHG emissions;** **Evaluating the single and combined effect of GHG and N emissions mitigation options**.
Level of detail from methodological approach	**Farm activity data;** **Combination of Tier 1 and Tier 2 approaches** (Tier 3 should be considered if available, but was not used in this study[b])**;** **Intermediary calculations based on national averages for input parameters (retrieved from national inventory reports).**	**Very detailed farm activity data;** **Combination of Tier 1, Tier 2, and Tier 3 approaches**; **Intermediary calculations based on farm specific input parameters, with disaggregated farm data.**	**Detailed farm activity data;** **Combination of Tier 1, Tier 2, and Tier 3 approaches;** **Intermediary calculations based on farm specific input parameters, with aggregated farm data and some model assumptions.**

Method	NI	LCA	$SIMS_{DAIRY}$
Farming enterprises accounted for	**Dairy, beef, and crop production.**	**Dairy, beef, and crop production.**	**Dairy and crop production.**
System boundaries	**On-farm emissions from enteric fermentation** (CH_4), **manure management** (CH_4 and direct and indirect N_2O from housing and storage), **mineral and organic fertilisation** (direct and indirect N_2O from application of chemical and organic fertiliser, CO_2 from urea application and liming), **excretion at pasture** (direct and indirect N_2O from field deposition), **crop residues** (direct and indirect N_2O from cropland), and **energy consumption** (CO_2 from on-farm electricity and fuel consumption).	**On-farm emissions from the NI method**; **Additional on-farm emissions from excretion at pasture** (CH_4 from field deposition) **and crop residues** (indirect N_2O from grassland); **Off-farm emissions from production and transport of farm inputs** (such as commercial feed, mineral and organic fertilisers, litter, water, electricity, fuel, chemical products, phytosanitary products); **Off-farm emissions from production of farm infrastructures** (such as silo, manure and slurry pits, animal housing barns);	**On-farm emissions from enteric fermentation** (CH_4), **manure management** (CH_4 and direct and indirect N_2O from housing and storage), **chemical and organic fertilisation** (direct and indirect N_2O from application of chemical and organic fertiliser, including the simulation of soil organic N dynamics), **excretion at pasture** (direct and indirect N_2O from field deposition), and **energy consumption** (CO_2 from on-farm electricity and diesel consumption); **Off-farm emissions from production and transport of concentrate feed and chemical fertiliser** (CO_2)**.**

Method	NI	LCA	$SIMS_{DAIRY}$
		Off-farm emissions from production of farm equipment and machinery (such as tractors, tankers, cultivators, rollers).	
Summary of data requirements	Animal numbers and percentage of time spent in building by animal type and age category; Type of stored manure and manure storage by animal type and age category; *If straw for bedding:* quantity of straw used by animal type and age category; Quantities of nitrogen applied in fields under the form of chemical fertiliser by fertiliser type; Quantity of lime applied; Quantity of manure applied on grassland and cropland by manure and animal type, and spreading season; *For slurry only:* application method;	Data requirements from the NI emissions; Quantities fed to animals by animal type, age category, and feed type; Whether or not the different feed types were produced on farm or purchased; Concentrate feed composition; *If multiple diets fed during the year*: dates of beginning and ending of each diet by animal type and age category; Milk yield, milk wasted, milk used to feed calves, and milk composition; Dates and frequency at which manure storage is emptied by manure type;	Average monthly climatic conditions (i.e., temperature, rainfall, rainy days, and wind speed). Dairy animal numbers and housing dates by age category; Type of stored manure and manure storage by dairy animal age category; *If straw for bedding*: quantity of straw used; Quantities of nitrogen applied in fields under the form of chemical fertiliser by fertiliser type; Percentage of manure applied on grassland and cropland by manure type; Manure application method;

Method	NI	LCA	SIMS$_{DAIRY}$
	Excluding grassland: Yield per crop product; where applicable, whether or not straw was produced and exported off field; Quantity of electricity used$_c$; Quantity of diesel used$_c$; Quantity of heating fuels used$_c$.	Information about previous crops and cover crops on cropland and grassland, including crop rotation; Information about sowing of cropland and grassland; Fertilisation dates and method on cropland and grassland by fertiliser type; Harvest dates and method by crop product; Grassland yield; Average regional temperatures; Dimensions and types of farm infrastructures; Origin of water (i.e., harvested on farm or from off-farm distribution system) and energy sources (i.e., renewable or non-renewable); Average rainfall$_d$; Average soil type of the farm$_d$;	Dates at which the slurry tank is emptied; Milk yield and composition; Quantities fed to animals by dairy animal age category and feed type; Concentrate feed composition; Quantity of electricity used; Quantity of diesel used.

Method	NI	LCA	SIMS$_{DAIRY}$
		Quantities of phytosanitary product applied on grassland and cropland by phytosanitary product$_{d}$; Machinery types used in each cropland and grassland operation.	
Summary of outputs (potentially beyond the content included in this perspective)	**GHG emissions** (CH_4, N_2O, and CO_2) **aggregated by emission source** (enteric fermentation, manure management, agricultural soils, and energy consumption)**;** **NH_3 emissions aggregated by emission source** (manure management - housing and storage, agricultural soils)**.**	**GHG emissions** (CH_4, N_2O, and CO_2) **aggregated by emission source** (enteric fermentation, manure management, agricultural soils, energy consumption, and imports of farm inputs and materials)**;** **NH_3 emissions aggregated by emission source** (manure management - housing and storage, agricultural soils); **Inventory of other pollutants** (such as heavy metals, NO_3^-, P, PO_4^{3-}, and other chemical products); **Aggregation of all emissions and pollutants into several potential impact categories (i.e., midpoint indicators)**, where the type and number of categories	**GHG emissions** (CH_4, N_2O, and CO_2) **aggregated by emission source** (enteric fermentation, manure management, agricultural soils, energy consumption, and imports of concentrate feed and fertilisers)**;** **N losses** (NO_3^-, NH_3, N_2O, and NO_x) **aggregated by emission source** (manure management - housing and storage, silage production, yards, and agricultural soils)**;** In the original version developed for British dairy farms, P losses and different sustainability attributes (including animal welfare, biodiversity, milk quality, and

Method	NI	LCA	$SIMS_{DAIRY}$
		depends on characterisation methods (the most common indicators include climate change, ozone depletion, human toxicity, acidification, eutrophication, ecotoxicity, land use and resource depletion); **For outreach and policy makers, potential aggregation at a higher level (i.e., endpoint indicators)** to focus on wider areas of environmental protection such as impacts on human health, the natural environment, and natural resources.	soil quality) were also scored (Del Prado et al., 2011).
Further reading	Buckley and Donnellan (2022), Dabkienė et al. (2020), and Syp and Osuch (2018).	European Commission (2018a, 2013), Food and Agriculture Organization of the United Nations (2016a, 2016b, 2016c, 2010), Manfredi et al (2012), and Notarnicola et al. (2015)	Del Prado et al. (2013, 2011, 2010) and Del Prado and Scholefield (2008)

Table 2: Overview of GHG estimation methods under study

Note: NI = national inventory; LCA = life cycle assessment; $SIMS_{DAIRY}$ = Sustainable and Integrated Management System for Dairy Production; GHG = greenhouse gas; N = nitrogen; CH_4 = methane; N_20 = nitrous oxide; CO_2 = carbon dioxide; NH_3 = ammonia; NO_3^- = nitrates; P = phosphorus; PO_4^{3-} = phosphate; NO_x = nitrogen (mono/di) oxide. [a] GHG emissions derived from on-farm energy consumption are also included based on the IPCC energy category (Intergovernmental Panel on Climate Change, 2006). [b] It is worthwhile to note that the level of Tier used in national inventories is determined by the level of detail of farm activity data in corresponding countries, and can thus vary across different national inventory reports. [c] Data requirements necessary to estimate on-farm energy consumption in the NI method based on the IPCC energy category. [d] Data requirements that are not needed to estimate GHG emissions but can be included to obtain additional environmental indicators through the LCA model.

As for the $SIMS_{DAIRY}$ model, its farm data requirements are substantially lower than those of a LCA approach, while still allowing for the simulation of emissions with farm specific detail. This process-based model analyses the interactions and synergies among different farm components. Because it was designed to represent these interactions, a strong feature of $SIMS_{DAIRY}$ is the ability to build a variety of dairy production scenarios and evaluate their GHG emissions and N losses. As a consequence, the tool can be effectively applied to the assessment of mitigation measures on an individual or combined basis (Del Prado et al., 2010; Díaz de Otálora et al., 2024). In addition, due its modular construction, $SIMS_{DAIRY}$ can be extended to add new farm aspects to the modelling framework, or account for more disaggregated levels of input data based on its availability. For instance, while the model does not yet take into account beef enterprises, these could be incorporated in the future to improve the analysis of farms with dual-purpose animals. As a main drawback, the model, like other process-based models, relies on a series of assumptions, which create uncertainty when dealing with certain farm typologies and may lead to a simplification of results (Del Prado et al., 2011). Concretely, this means that this type of modelling approach is not suitable for building GHG inventories but can be effectively used to provide farm specific advice on practice change.

While we focused on GHG estimation methods throughout this argumentation, the points that we put forward can be applied to other sustainability indicators. In a nutshell and in line with previous literature, selected methods must be adapted to objectives (Díaz de Otálora et al., 2021). Their application must be feasible in terms of data availability. Lastly, it is important to recognise their limitations and reflect upon how these influence sustainability conclusions to avoid extrapolating study findings.

4 How do reporting frameworks influence measured farm sustainability performance?

This section investigates the influence of different reporting frameworks on measured farm sustainability performance. The choice of reporting frameworks in sustainability assessments creates significant debate when comparing agricultural production systems. For this reason, such a question has been extensively explored in the literature, notably for LCA reporting purposes in the context of functional units (Baldini et al., 2017; Detzel et al., 2022; Notarnicola et al., 2017; Salou et al., 2017) or allocation methods[4] (Ijassi et al., 2021; Kyttä et al., 2022; Wilfart et al., 2021).

In this article, we show through a graphical examination how the indicator performance of case study farms can vary depending on how it is reported. Detail about the reporting frameworks considered in this study is provided is Table B.1 in Appendix B. We broadly categorise them into two groups, i.e., output- and input-based, and suggest that measured sustainability performance can be sensitive to

[4] Please note that a wider discussion around allocation methods in the LCA approach is outside the scope of this perspective article.

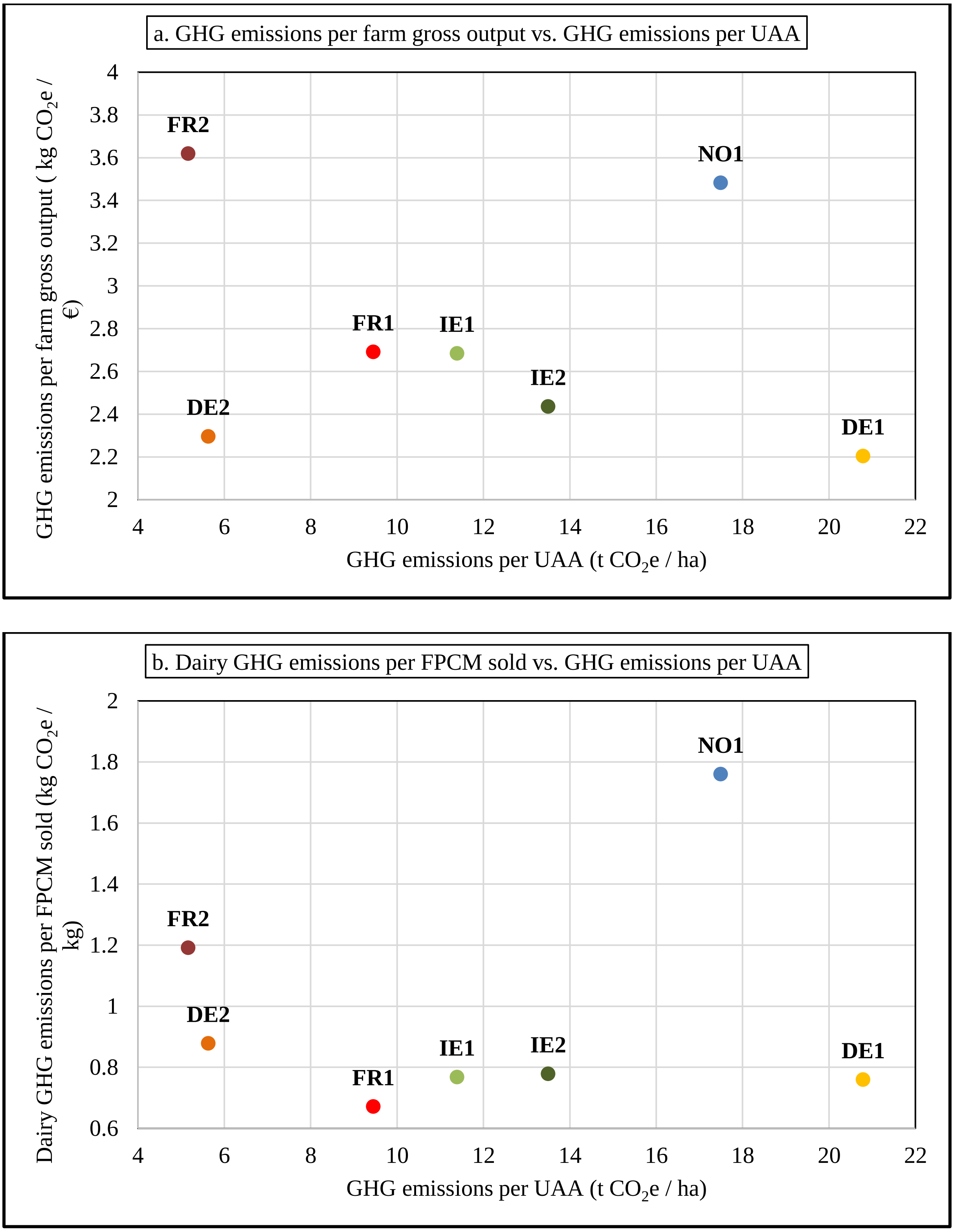
selected framework. To build our argumentation, we present scatterplots to perform descriptive pairwise comparisons between proposed frameworks, where all case study farms are represented according to their X and Y coordinates. In the main body of the text, we focus only on the LCA-estimated GHG example. For the GHG emission indicator, the output-based reporting frameworks under study include GHG emissions per farm gross output, per N content of farm production, and per calorie included in farm production, as well as dairy GHG emissions per FPCM sold. The input-based reporting framework is GHG emissions per UAA. We present three comparisons between reporting frameworks in Figure 2, while the rest are reported in Figure D.1 in Appendix D. As the issue of selecting reporting frameworks is also relevant in the economic and social sustainability dimensions, additional examples are provided in Appendix D based on the farm net income and labour input indicators (please refer to Figure D.2 and Figure D.3, respectively).

In Figure 2.a, we compare GHG emissions per farm gross output against UAA. The per-farm-gross-output metric gives an indication of GHGs emitted per euro (€) produced. Hence, it is an efficiency measure, which takes into account all farming enterprises. The per-UAA measure distributes GHGs emitted over the farmland area and controls for differences in farm size. When taking two extreme farm examples in Figure 2.a, we find that DE1 achieves the worst performance on a per-UAA basis and the best performance for GHGs emitted per farm gross output. FR2 is the largest emitter per farm gross output, while reaching the best GHG level per UAA. These performances are partially driven by the level of farming intensity. While DE1 is a very heavily stocked farm (i.e., 2.57 livestock units (LU) per ha (Table A.1)) with a high per-cow milk yield (i.e., 10870 l per cow (Table 1)), FR2 has a much lower farm stocking rate (i.e., 0.77 LU per ha (Table A.1)) and less productive cows (i.e., 5433 l per cow (Table 1)). However, farm gross output may vary depending on national prices, thereby potentially affecting the GHG efficiency metric on a per-farm-gross-output basis when comparing farms in different countries.

To strip out the effect of national prices, we compare another efficiency metric against GHG emissions per UAA in Figure 2.b; namely, GHGs per FPCM sold, which is a popular choice in the LCA literature (Basset-Mens et al., 2009; Bava et al., 2014; De Vries and de Boer, 2010; Koch and Salou, 2016). As this functional unit is solely focused on the product from the dairy enterprise, we allocate GHG emissions to the dairy herd to avoid overestimating emissions for sampled farms that are less dairy-specialised. This is notably the case of NO1 and FR1, which have a significant share of income derived from additional farming enterprises (Table A.1). When comparing dairy GHG emissions per FPCM sold to GHG emissions per UAA, DE1 remains amongst the top performers in terms of GHG efficiency. Interestingly, after stripping out differences in prices and additional farming enterprises, both French farms achieve much better performances in terms of dairy GHG emissions per FPCM sold. For instance, FR1 moves from being ranked fifth best performing farm on a per-farm-gross-output basis to best performing farm on a per-FPCM basis. FR1 is also an intensive farm, with by far the highest rates of mineral fertiliser application in the sample (Table A.1) and a milk yield of 9567 l per cow (Table 1).

For both Figures 2.a and 2.b, an important observation is that the position of case study farms in scatterplots does not align in a straight line. In other words, the relationship between the GHG efficiency measures (i.e., per farm gross output or FPCM sold) and GHGs emitted per UAA is not linear. Concretely, this implies that choosing between these reporting frameworks will affect measured sustainability performance. The variation might be driven by differences in farm characteristics (such as farming intensity), but a larger sample would be needed to verify this through a statistical analysis. It is worthwhile to mention that previous studies have identified that intensive farms tend to have larger GHG emissions per ha than extensive farms, while their GHG efficiency is generally better (Basset-Mens et al., 2009; Crosson et al., 2011; Kiessé et al., 2022, 2020; Salou et al., 2017).

In Figure 2.c, we compare two additional reporting frameworks, i.e., GHG emissions per calorie or kg of N included in farm production. These have been proposed in the literature as means to compare different agri-food systems, and notably plant- and meat-based foods (Batlle-Bayer et al., 2019; McAuliffe et al., 2020; McLaren et al., 2021). Because crop and livestock-based products vary in N and calorie content, we expect to observe differences in farm performance depending on the level of dairy specialisation (see Table A.1 in Appendix A) (Food and Agriculture Organization of the United Nations, 2018; INRAE et al., 2021; Laisse et al., 2018; Teagasc, 2016; U.S. Department of Agriculture, 2022). Surprisingly, the position of case study farms in Figure 2.c reveals a linear relationship between GHG emissions per calorie and kg of N. In other words, this descriptive study suggests that the choice between both reporting frameworks would lead the same measured sustainability performance. A potential reason for this is that the degree of dairy specialisation in our sample is too high to observe hypothesised differences. Future research comparing several farming systems could use these functional units to provide more advanced conclusions for practitioners. This would be particularly valuable to analyse the performance of mixed crop-livestock farms.


a. GHG emissions per farm gross output vs. GHG emissions per UAA
GHG emissions per farm gross output (kg CO2e / €)
GHG emissions per UAA (t CO2e / ha)
FR2
NO1
FR1
IE1
IE2
DE2
DE1
2
2.2
2.4
2.6
2.8
3
3.2
3.4
3.6
3.8
4
4
6
8
10
12
14
16
18
20
22
b. Dairy GHG emissions per FPCM sold vs. GHG emissions per UAA
Dairy GHG emissions per FPCM sold (kg CO2e / kg)
GHG emissions per UAA (t CO2e / ha)
NO1
FR2
DE2
IE1
IE2
FR1
DE1
0.6
0.8
1
1.2
1.4
1.6
1.8
2

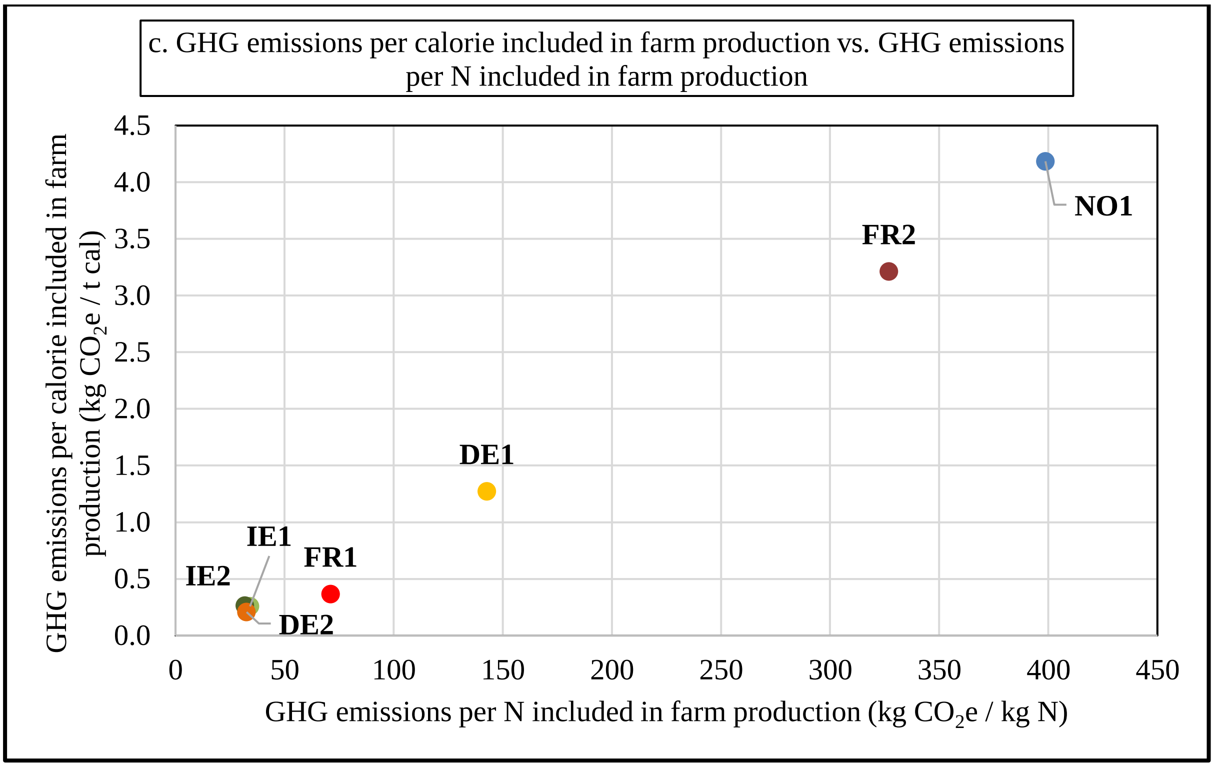


Figure 2: Pairwise comparisons of GHG emission results with varying reporting frameworks

Note: GHG = greenhouse gas; UAA = utilised agricultural area; kg = kilograms; CO_2e = carbon dioxide equivalent; € = euro; t = tonnes; ha = hectare; FPCM = fat-protein-corrected-milk; N = nitrogen; cal = calorie.

Overall, we suggest to always present results with a combination of reporting frameworks to give a more comprehensive view of farm sustainability. This is because the choice of reporting frameworks can affect indicator performance, as demonstrated by our case study data. Focusing solely on one reporting framework could predetermine the winner before conducting the analysis when performance is driven by farm characteristics. It is worthwhile to mention that this argument is the main reason why international guidelines (such as the EU Product Environmental Footprint Category Rules or the Livestock Environmental Assessment and Performance Partnership of the Food and Agriculture Organization of the United Nations) were developed to harmonise frameworks by activity sector (European Commission, 2018a, 2013; Food and Agriculture Organization of the United Nations, 2016a, 2016b, 2016c; Manfredi et al., 2012). Farm GHG emissions can be reported per € of farm gross output as an efficiency indicator. However, while it is a useful measure to compare farms that are subject to the same input and output prices, cross-country comparisons may favour other measurement units. Using other output-based reporting frameworks, such as kg of farm product, can be a good alternative, but it is important to ensure that the same system boundaries are applied to both numerator and denominator (e.g., farm level vs. farm level, or dairy level vs. dairy level) to avoid over- or under-estimating GHG performance. In that regard, transitioning towards output-based frameworks that can account for both crop and livestock products (such as N or calorie content) is important to analyse farms with multiple farming enterprises. Additionally, combining a product-based efficiency metric with

GHG emissions per UAA is important when analysing the effect of mitigation strategies to avoid unintended pollution swapping across farming enterprises or trade-offs between emission efficiency and pressure. In this context, it is worthwhile to mention that previous literature has proven that farm intensification strategies can show benefits in terms of GHG emission efficiency, while simultaneously leading to an increase in absolute emissions (Crosson et al., 2011; Salou et al., 2017).

Finally, it should be highlighted that reporting frameworks can serve different purposes. On the one hand, the food industry may be interested in demonstrating that it sells low carbon products (i.e., high GHG efficiency) for marketing reasons. On the other hand, GHG inventories are performed at the national level and carbon reduction targets have been established on a country basis. While the GHG efficiency argument is suitable on a global scale to produce food in the most environmental efficient manner, it can be difficult to reconcile it with national carbon commitments that aim at reducing absolute GHG emissions. In that regard, analyses complemented by per-ha metrics might prove more informative to identify a path towards greater farm sustainability.

5 Concluding remarks

This perspective article discussed the influence of methodological choices in farm sustainability assessments. The argumentation was built on the premises that sustainability is best decomposed into economic, environmental, and social dimensions, and can be measured through an indicator approach (Dillon et al., 2016; Latruffe et al., 2016; Lebacq et al., 2013). Based on a case study analysis of seven European dairy farms, we demonstrated how and why indicator selection, estimation methods, and reporting frameworks can affect performance. Practical guidance was provided to help practitioners and advance the level of knowledge on sustainability assessments.

Overall, it is important to recognise that choice undoubtedly implies restricting the analytical lens and, in practical terms, is a necessary step to conduct a farm sustainability assessment via quantifiable sustainability indicators. However, significant limitations arise from such process and, more generally, indicator-based sustainability measurements. Of particular concern are farm conclusions and recommendations on practice change that may lead to perverse outcomes through a reallocation of negative impacts (e.g., pollution swapping phenomena) outside of study scope, ultimately resulting in further sustainability issues. Some methodological choices may even favour certain farm typologies and operating conditions before conducting the analysis. Thus, we highlight the need to routinely assess and report the shortcomings of analytical frameworks.

While this perspective article was framed in the context of case-by-case analyses of farm sustainability, our conclusions and practical guidance equally apply to large datasets. For instance, methodological choices that were addressed in this study will gain even more attention when the European Union officially transitions from Farm Accountancy Data Network to Farm Sustainability Data Network to better monitor agri-environmental policy (European Commission, 2020a). Hence, improving our understanding of methodological biases through statistical analyses, while considering data constraints, is an important avenue for future research.

Finally, it is important to acknowledge the fundamental bias and reductionism involved in the technocratic decision to assess sustainability via separate, quantifiable indicators divided across dimensions (Reid and Rout, 2020). Although this approach is widespread, the predominant focus on metrics and the division into separate categories limit our ability to analyse interconnectedness within sustainability issues (Hebinck et al., 2021). Metrics-based frameworks can cause us to lose scope to recognise and work with multiple objectives or joint impacts. They also reduce the complexity of the sustainability concept (Reid and Rout, 2020), which can lead us to overlook variations in context for the sake of identifying workable, quantifiable indicators (as demonstrated, to some extent, by the GHG example in this article). Additionally, the reliance on quantified measures can lead us to put aside concepts that are difficult, or even impossible, to measure, which can be particularly problematic in sensitive socioecological contexts (Hebinck et al., 2021; Reid and Rout, 2020). In this regard, a growing body of literature recognises the importance of qualitative methodologies to navigate agricultural sustainability, notably participatory, deliberative, and multi-actor approaches where implicit assumptions can be challenged and the risks of perverse outcomes mitigated (Carmenta et al., 2023; Hebinck et al., 2021; Lowery et al., 2020; MacLeod et al., 2022). More research is needed to progress and unify both approaches of sustainability assessments.

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Appendix A: Data collection and farm characteristics

The data used in this article was collected on seven case study farms in the winter of 2021. The team of data recorders used the Baillet et al. (2022c, 2022a) survey tools to record farm information through a combination of face-to-face visits and phone interviews. Recorded data refers to the accounting year of 2020.

Case study farms were recruited to represent key dairy production systems from Ireland (IE), France (FR), Germany (DE), and Norway (NO). These farms are specialised in dairy production, with over two third of their gross output derived from the dairy enterprise (Eurostat, 2022b). The sample includes two Irish farms, two French farms, two German farms, and one Norwegian farm. Their characteristics are presented in Table A.1.

Characteristic	Measurement unit	IE1	IE2	FR1	FR2	DE1	DE2	NO1
UAA	ha	89	87	103.5	161	71	230	30
Dairy herd size	cows	125	185	75	73	138	110	24
Total livestock units	LU	179.5	234.5	130.5	124.2	182.6	125.8	38.7
Farm stocking rate	LU / ha	2.02	2.70	1.26	0.77	2.57	0.55	1.29
Percentage of cropland to UAA	%	0	0	61.2	5.4	45.1	28.3	0
Percentage of grassland to UAA	%	100	100	38.8	94.6	54.9	71.7	100
Mineral N application rate	kg N / ha	58.1	42.8	133.1	7.2	38.1	0	109.3
Organic N application rate	kg N / ha	59.4	156.3	36.1	37.1	29.0	28.8	325.0
Percentage of dairy product and animal sales to total farm sales	%	85.9	98.9	81.1	91.6	98.4	99.2	74.8
Additional farming enterprise(s)	No unit	Beef	N/A	Beef + Crops	Beef + Crops	N/A	Crops	Beef

Table A.1: Characteristics of case study farms

Note: UAA = utilised agricultural area; ha = hectare; LU = livestock units; N = nitrogen; N/A = non applicable.

Appendix B: Selected sustainability indicators

The sustainability indicators presented in this article are defined in Table B.1. They were selected to assess the sustainability of European dairy farms across the three dimensions based on expert knowledge and a literature review (Latruffe et al., 2016; Lebacq et al., 2013; Lynch et al., 2019). Please refer to Baillet et al. (2022b) for a more detailed description of selected economic and environmental indicators.

Economic indicators are adapted from the European Union (EU) Farm Accountancy Data Network (FADN) methodology (European Commission, 2020b, 2018b, 2018c) and the Teagasc National Farm Survey (NFS) sustainability assessment method (Buckley and Donnellan, 2022). Overall, they measure the level of farm output and profitability, as well as cost efficiency and reliance on subsidies.

Environmental indicators were chosen to represent environmental impacts of farm production, resource use, and environmental management. Six out of seven environmental indicators are estimated through a cradle-to-farm-gate life cycle assessment (LCA) approach (marked by the subscript $_b$ in Table B.1) (Baldini et al., 2017; Meul et al., 2014; Mu et al., 2017). The nitrogen (N) efficiency indicator is estimated based on information from Dulphy and Grenet (2001), INRA (2007), and Noziere et al. (2018).

The LCA results compiled in this study are estimated using the Simapro 9.3.0.3 software and the MEANS IN-OUT online platform (Auberger et al., 2018). Indicators are calculated through the ILCD 2011 Midpoints indicators for greenhouse gas (GHG) emissions (European Commission et al., 2012), the CML-IA baseline v3.05 for eutrophication and acidification (Guinée et al., 2002), and CED 1.11 for energy consumption (Frischknecht et al., 2015). The background data used in the model comes from the ECOALIM database for feed ingredients (Wilfart et al., 2016), the Agribalyse® database for agricultural operations, machinery, and inputs (Colomb et al., 2015), and ecoinvent v3.8 for information about national energy mixes and infrastructure (Ecoinvent, n.d.). Emissions are calculated based on the Koch and Salou (2016) guidelines, with emission factors (EF) adapted for each country and farm when necessary. Nitrate leaching is calculated according to the INDIGO® method and the RUSLE model (Avadi et al., 2020; Renard et al., 1991).

As for social sustainability, we follow the Lebacq et al. (2013) definition and propose indicators to represent internal social sustainability, related to the well-being of the farmer and his/her family, and external social sustainability, focused on society's expectations of agriculture. Social indicators are then derived from a combination of literature sources (Brennan et al., 2022b, 2022a; Buckley and Donnellan, 2022; Lynch et al., 2019; Mills, 2012).

Sustainability indicator	Description	Measurement unit(s) and reporting framework(s)	Expected direction of association with sustainability
		ECONOMIC	
Farm gross output	Total farm production value	€ reported per unpaid labour unit (AWU $_a$)	+
Farm gross margin	Profit equal to total farm gross output, minus production costs directly associated with farm production	€ reported per unpaid labour unit (AWU)	+
Farm net income	Net income before depreciation, measured as farm gross margin, plus subsidies, minus all operating costs and farm taxes This indicator gives an estimation of the farm's capacity to remunerate production factors, such as unpaid labour, land, and capital.	€ reported per unpaid labour unit (AWU) or UAA (ha)	+
Milk yield	Partial productivity measure equal to the total amount of milk produced per dairy cow	l reported per dairy cow (cow)	+
Direct production costs	Production costs directly associated with farm production	€ reported per farm gross output (€)	-

Sustainability indicator	Description	Measurement unit(s) and reporting framework(s)	Expected direction of association with sustainability
Percentage of subsidies to total earnings (i.e., farm gross output and subsidies)	Reliance on subsidies rather than the market	%	-
ENVIRONMENTAL			
GHG emissions [b]	GHG emissions associated with farm production Depending on the estimation method, this indicator can include off-farm emissions associated with the production and transport of farm inputs.	t or kg of CO_2e reported per UAA (ha), farm gross output (€), N [c] or calorie [d] included in farm production (kg N and t cal, respectively) This indicator is estimated with three different methods: The LCA method, the NI method, and the $SIMS_{DAIRY}$ model.	-
Dairy GHG emissions [b]	GHG emissions allocated to the dairy herd	t or kg CO_2e reported per kg of FPCM [e] sold This indicator is estimated with the LCA approach.	-
Eutrophication [b]	Potential effect of excess N and phosphorus inputs (i.e., over-fertilisation) on water quality	kg of $PO_4^{3-}e$ reported per UAA (ha) This indicator is estimated with the LCA approach.	-

Sustainability indicator	Description	Measurement unit(s) and reporting framework(s)	Expected direction of association with sustainability
Air acidification b	Potential effect of acidifying pollutants, such as sulphur dioxide, nitrogen (mono/di) oxide, and ammonia, on the environment	kg of SO_2e reported per UAA (ha) This indicator is estimated with the LCA approach.	-
Total energy demand b	Energy demand associated with farm production This includes direct demand (recorded at the farm level) and indirect demand (estimated with the LCA approach).	MJ reported per UAA (ha) This indicator is partially estimated with the LCA approach.	-
Land occupation for dairy production b	Amount of land dedicated to a year's worth of dairy production	m^2 reported per year*kg FPCM sold This indicator is estimated with the LCA approach.	-
N efficiency	Percentage of total N inputs recovered in the milk production process	%	+
INTERNAL SOCIAL			
Total labour input	Farm labour input, including both unpaid family labour and wage earners	AWU per UAA (ha) or farm gross output (€)	-
Farmer workload	Dichotomous variable, indicating whether or not the main farm holder declared working more than 55 hours per week.	Y if more than 55 hours per week, N otherwise	-

Sustainability indicator	Description	Measurement unit(s) and reporting framework(s)	Expected direction of association with sustainability
	Working more than 55 hours per week is considered as a health hazard by the World Health Organization (2021).		
Farm economic viability	Dichotomous variable, indicating whether or not the farm net income per unpaid labour unit is higher than the country’s minimum wage, as reported in Eurostat (2022a)	Y if higher, N otherwise	+
EXTERNAL SOCIAL			
Days at grass	Length of grazing season for dairy cows	Days	+
Milk fat-to-protein ratio	Ratio of milk fat content to protein content, as an indication of dairy cow energy balance and thus animal health	No unit	+ if in [1.0; 1.5] range (Cabezas-Garcia et al., 2021; Toni et al., 2011)
Organic production or participation in an AE scheme	Dichotomous variable, indicating whether or not the farm produces under the organic label or participates in an agri-environmental scheme	Y if organic or participation, N otherwise	+

Table B.1: Description of selected sustainability indicators

Note: € = euro; AWU = annual work unit; UAA = utilised agricultural area; ha = hectare; l = litres; GHG = greenhouse gas; t = tonnes; kg = kilogram; CO_2e = carbon dioxide equivalent; N = nitrogen; cal = calorie; LCA = life cycle assessment; NI = national inventory; $SIMS_{DAIRY}$ = Sustainable and Integrated Management System for Dairy Production; FPCM = fat-protein-corrected-milk; $PO_4^{3-}e$ = phosphate equivalent; SO_2e = sulphur dioxide equivalent; MJ = megajoules; m^2 = square meters; Y = yes; N = no AE = agri-environmental. [a] Based on the EU methodology, the amount of hours worked by each labourer is capped at 1800 hours per year (Eurostat, 2019). 1 AWU is equal to 1800 hours. [b] Estimated with the LCA approach. [c] The N content of farm products is estimated based on information from Food and Agricultural Organization of the United Nations (2018), INRAE et al. (2021), Teagasc (2016), and U.S. Department of Agriculture (2022). [d] The energy content of farm products is estimated based on INRAE et al. (2021), Laisse et al. (2018), Teagasc (2016), and U.S. Department of Agriculture (2022). [e] Based on International Dairy Federation (2015), FPCM are calculated with the following equation: $FPCM = Milk * (0.01226 * Fat\% + 0.0776 * Protein\% + 0.2534)$.

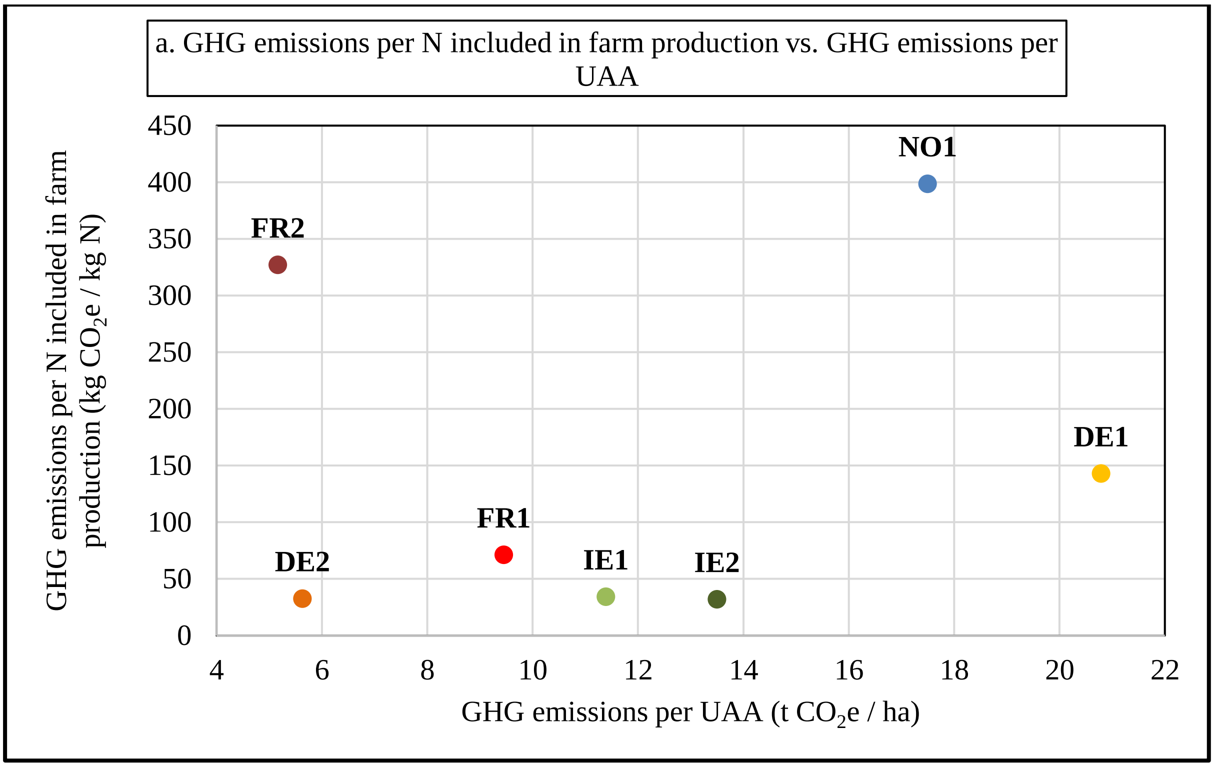
Appendix C: Information about additional GHG estimation methods

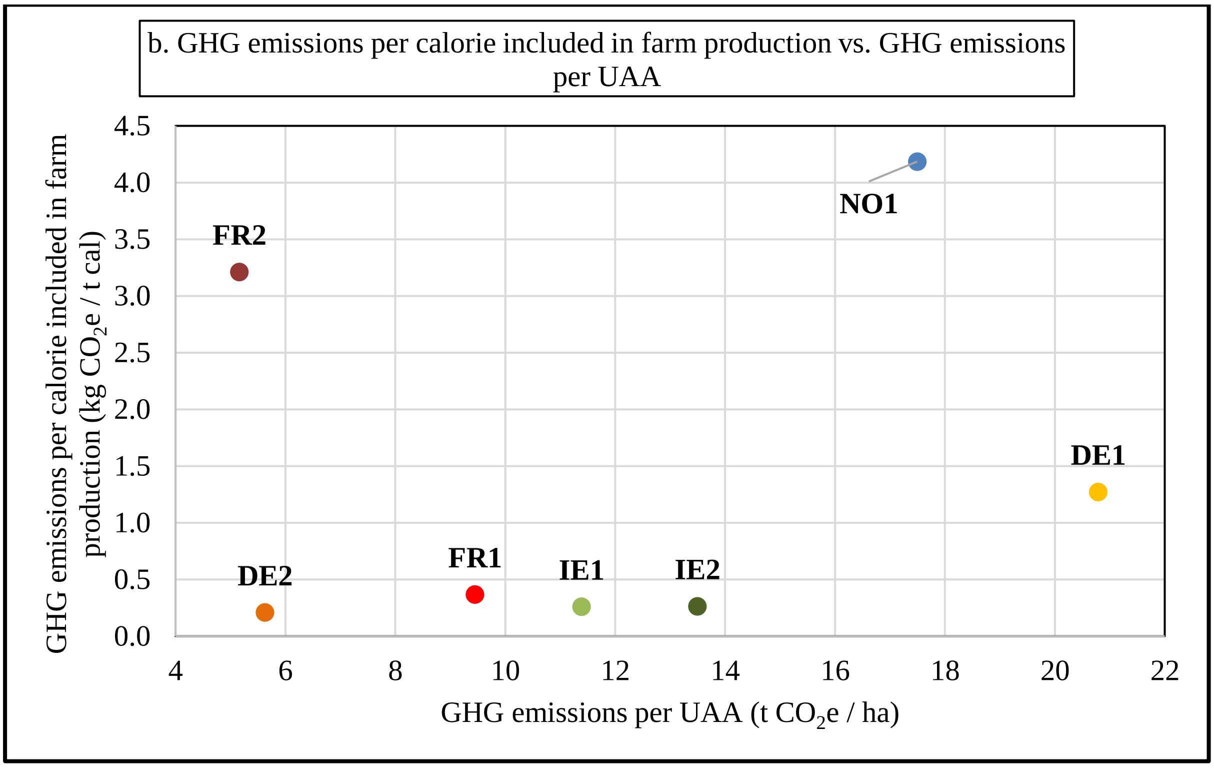
The GHG emission indicator is not only estimated with the LCA approach, but also with two additional methods: the national inventory (NI) method and the Sustainable and Integrated Management System for Dairy Production ($SIMS_{Dairy}$) model.

Regarding the NI method, we adapt the Intergovernmental Panel on Climate Change (IPCC) guidelines used to build national inventories for the agricultural sector to conduct farm GHG assessments. This method focuses only on on-farm emissions, which stands in contrast with the cradle-to-farm-gate LCA approach that incorporates all on- and off-farm emissions associated with farm activities (Buckley and Donnellan, 2022). Following Buckley and Donnellan (2022), we also include emissions associated with on-farm energy consumption, estimated based on the IPCC guidelines for the energy sector (Intergovernmental Panel on Climate Change, 2006). In the NI method, emissions are estimated based on farm activity data and EF with the highest Tier level available per case study country (Citepa, 2021; Duffy et al., 2021; Federal Environment Agency, 2021; Norwegian Environment Agency, 2021).

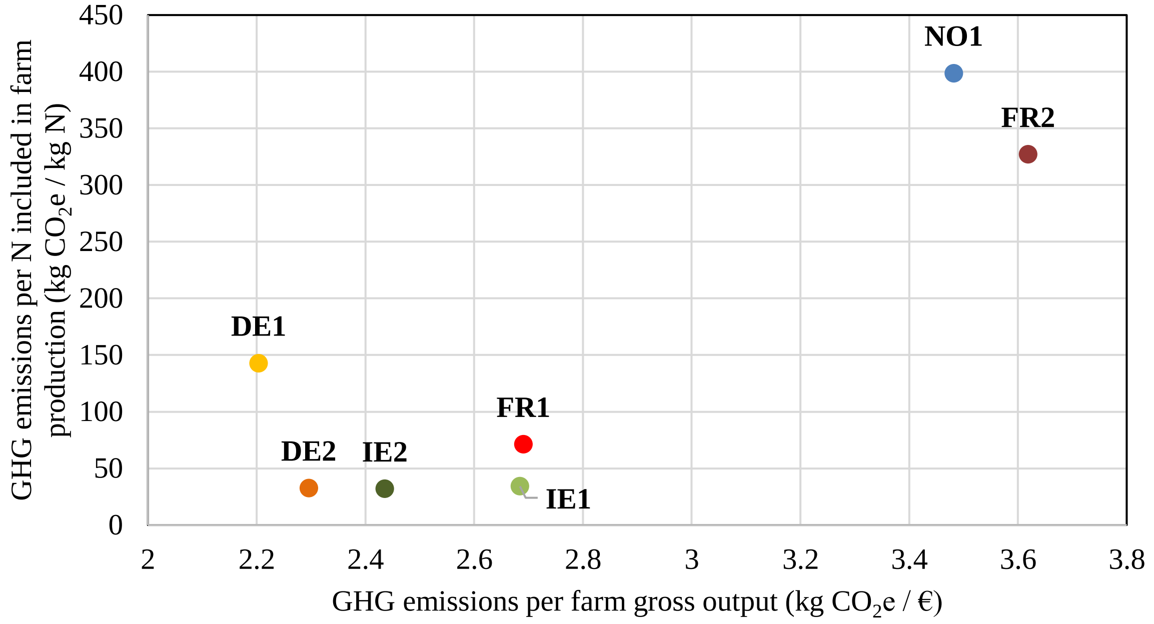
As for the $SIMS_{DAIRY}$ model, it describes the interacting nutrient flows and transformations within the soil, plant, and animal components of the farm system (Del Prado et al., 2011). The model simulates N and carbon losses in response to nutrient inputs, farm management practices, and climatic and biophysical conditions. Based on the most recent IPCC guidelines (Gavrilova et al., 2019), $SIMS_{DAIRY}$ uses a process-based approach and applies a series of empirical and dynamic equations to simulate GHG emissions at a monthly time-step or for the full year. This method focuses on on-farm emissions, as well as off-farm emissions associated with feed and fertiliser imports.

Appendix D: Pairwise comparisons of measured sustainability performance results with varying reporting frameworks

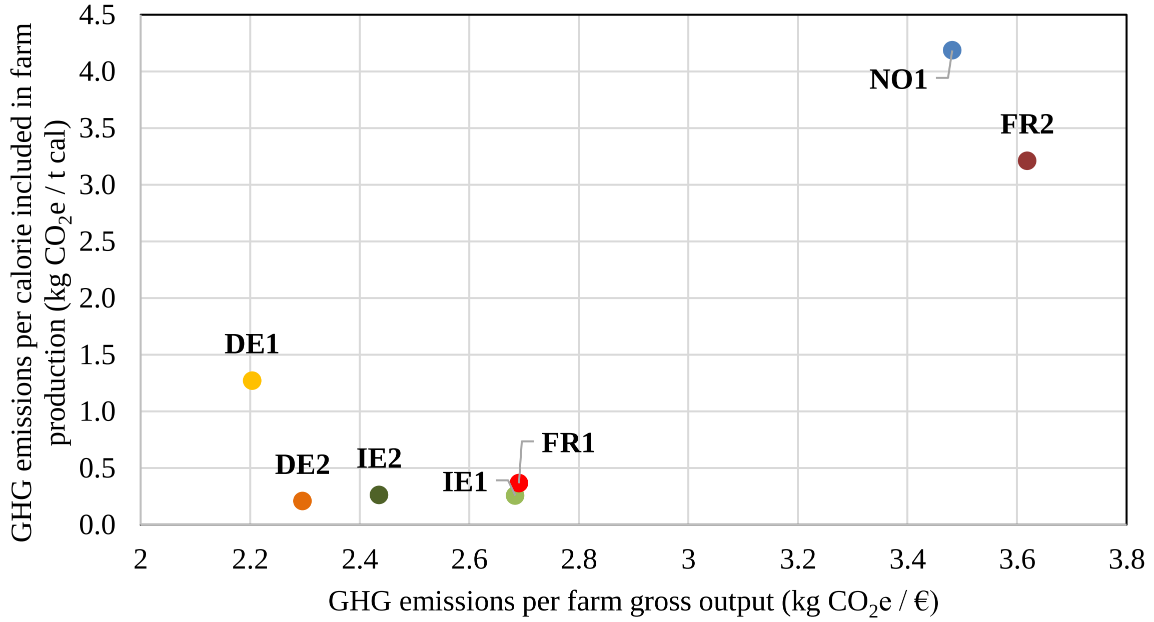


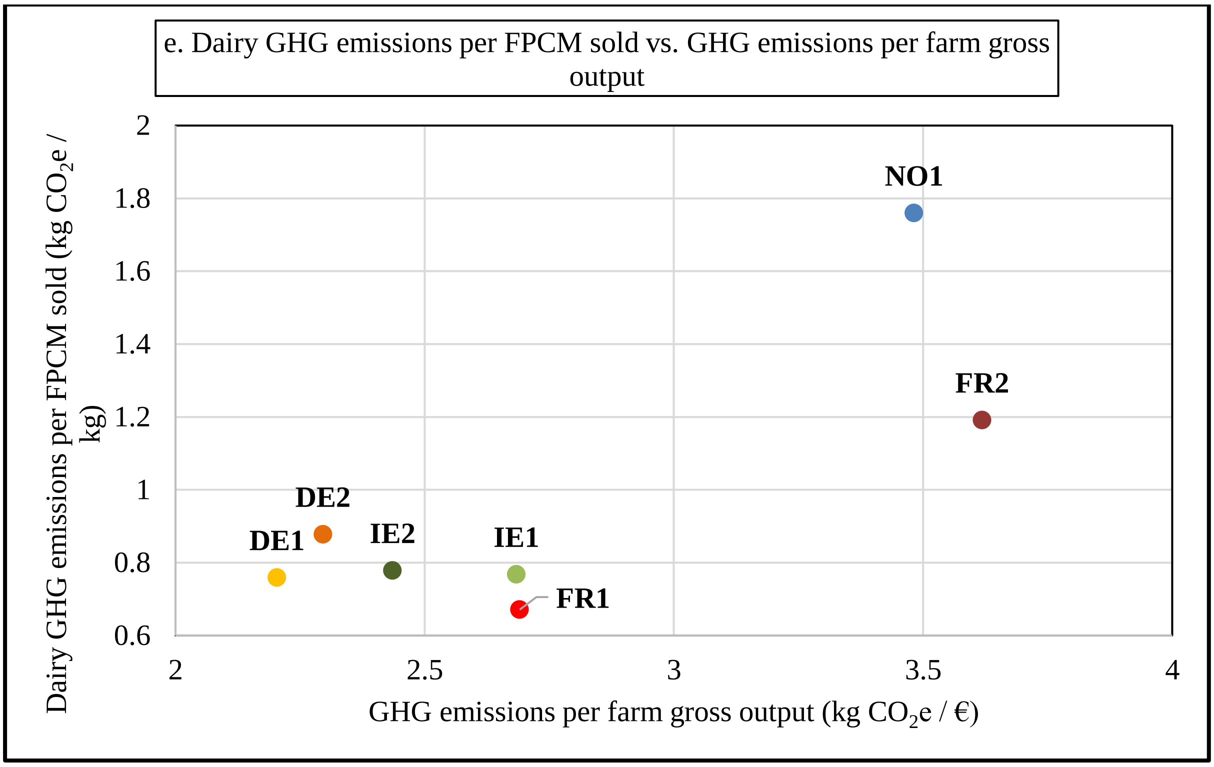


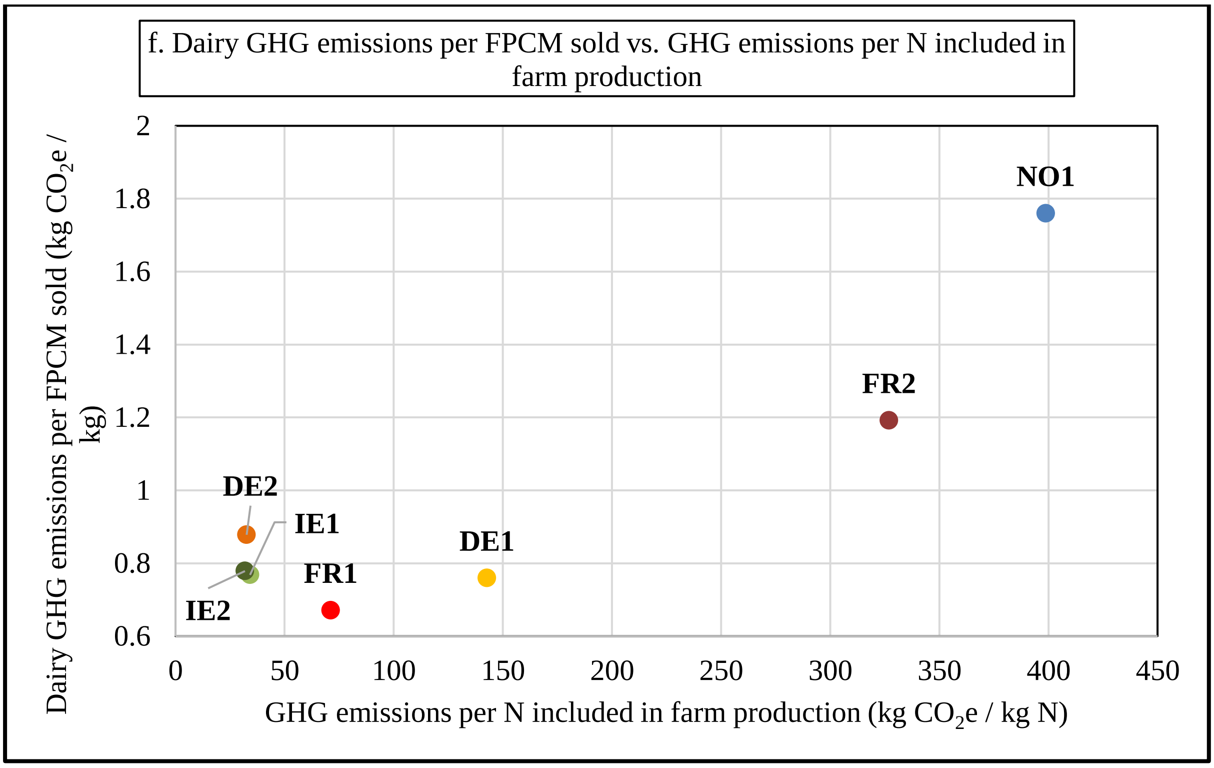
c. GHG emissions per N included in farm production vs. GHG emissions per farm gross output



d. GHG emissions per calorie included in farm production vs. GHG emissions per farm gross output




e. Dairy GHG emissions per FPCM sold vs. GHG emissions per farm gross output
Dairy GHG emissions per FPCM sold (kg CO_2e / kg)
GHG emissions per farm gross output (kg CO_2e / €)
2
1.8
1.6
1.4
1.2
1
0.8
0.6
2
2.5
3
3.5
4
NO1
FR2
DE2
DE1
IE2
IE1
FR1


f. Dairy GHG emissions per FPCM sold vs. GHG emissions per N included in farm production
Dairy GHG emissions per FPCM sold (kg CO_2e / kg)
GHG emissions per N included in farm production (kg CO_2e / kg N)
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0
50
100
150
200
250
300
350
400
450
NO1
FR2
DE2
IE1
DE1
FR1
IE2

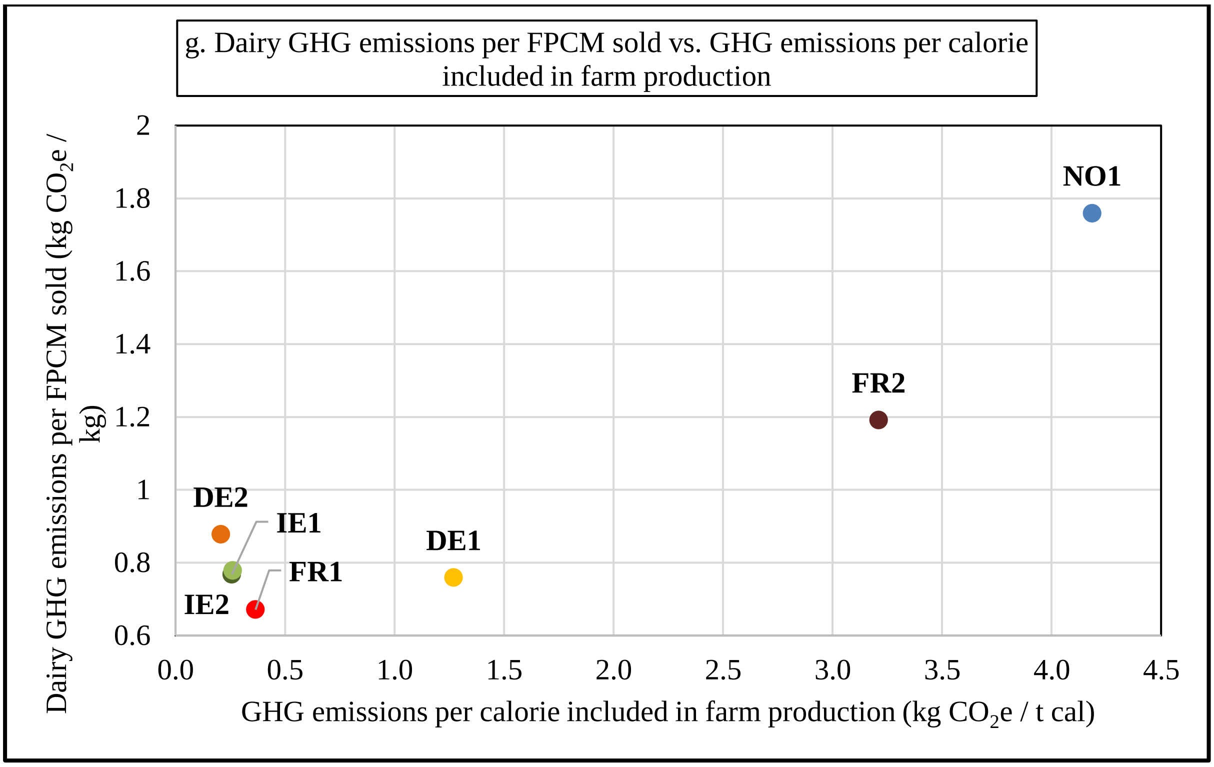


Figure D.1: Additional pairwise comparisons of GHG emission results with varying reporting frameworks

Note: GHG = greenhouse gas; N = nitrogen; UAA = utilised agricultural area; kg = kilograms; CO_2e = carbon dioxide equivalent; t = tonnes; ha = hectare; cal = calorie; € = euro; FPCM = fat-protein-corrected-milk.

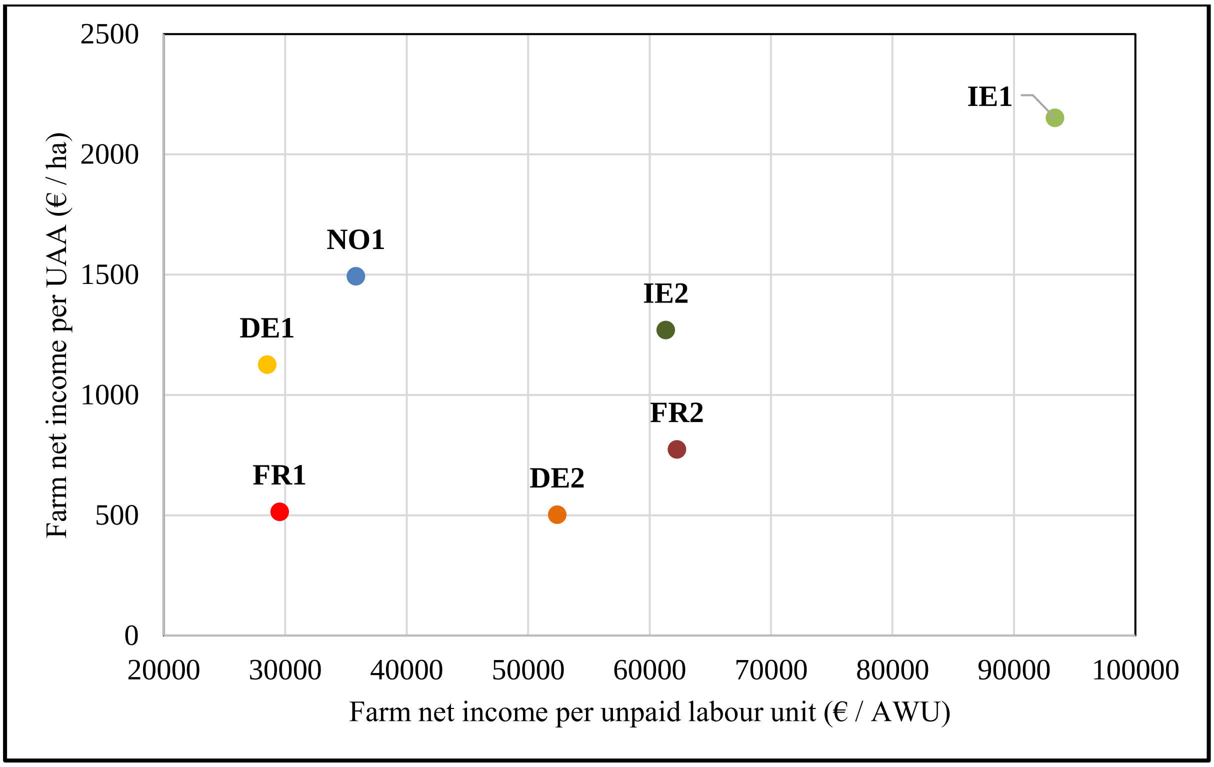


Figure D.2: Pairwise comparison of farm net income results per UAA and per unpaid labour unit

Note: UAA = utilised agricultural area; € = euro; ha = hectare; AWU = annual work unit.

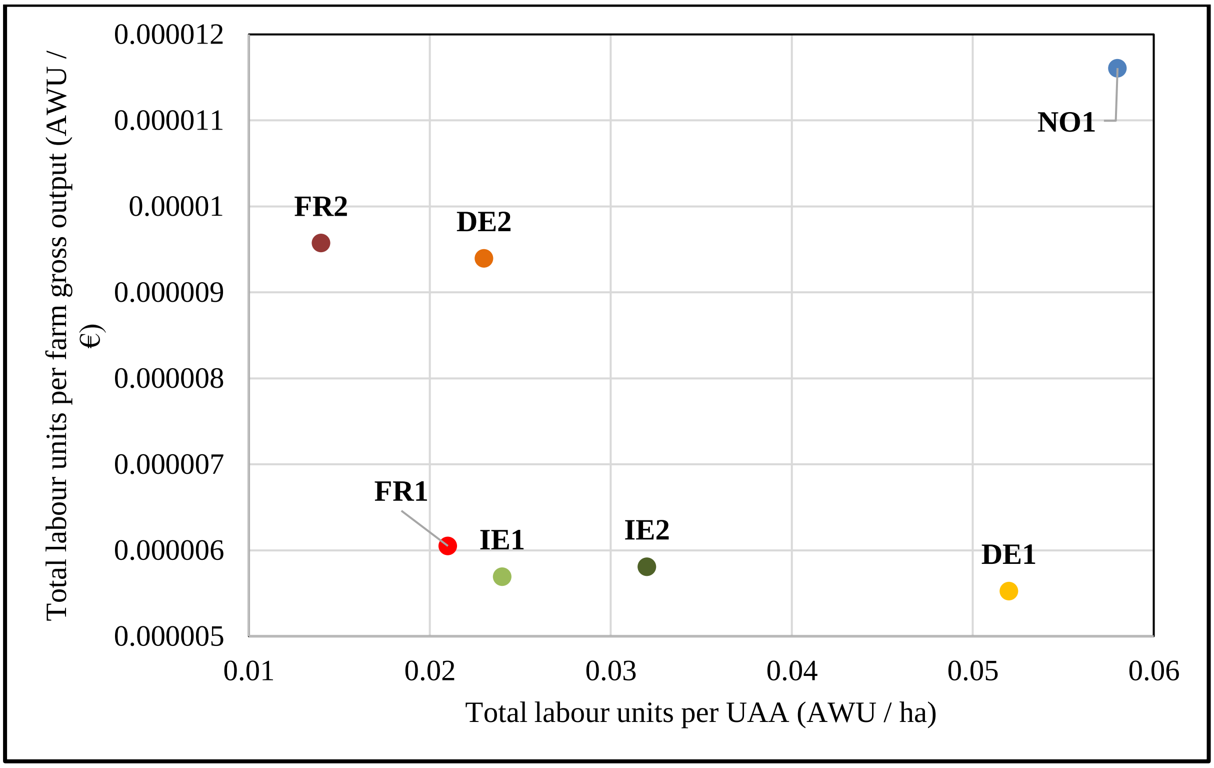


Figure D.3: Pairwise comparison of labour input results per farm gross output and per UAA

Note: AWU = annual work unit; € = euro; UAA = utilised agricultural area; ha = hectare.