LCI METHODOLOGY AND DATABASES

Critical analysis of life cycle inventory datasets for organic crop production systems

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Abstract

Purpose Organic agriculture (OA) has gained widespread popularity due to its view as a more sustainable method of farming. Yet OA and conventional agriculture (CA) can be found to have similar or varying environmental performance using tools such as life cycle assessment (LCA). However, the current state of LCA does not accurately reflect the effects of OA; thus the aim of the present study was to identify gaps in the inventory stage and suggest improvements.

Methods This article presents for the first time a critical analysis of the life cycle inventory (LCI) of state-of-the-art organic crop LCIs from current and recommended LCA databases ecoinvent and AGRIBALYSE®. The effects of these limitations on LCA results were analyzed and detailed ways to improve upon them were proposed.

Results and discussion Through this analysis, unrepresentative plant protection product (PPP) manufacturing and organic fertilizer treatment inventories were found to be the main limitations in background processes, due to either the lack of available usage statistics, exclusion from the study, or use of unrepresentative proxies. Many organic crop LCIs used synthetic pesticide or mineral fertilizer proxies, which may indirectly contain OA prohibited chemicals. The effect of using these proxies can contribute between 4–78% to resource and energy-related impact categories. In a foreground analysis, the fertilizer and PPP emission models utilized by ecoinvent and AGRIBALYSE® were not well adapted to organic-authorized inputs and used simplified modeling assumptions. These critical aspects can be transferred to respective LCAs that use this data, potentially yielding unrepresentative results for relevant categories. To improve accuracy and to contribute novel data to the scientific community, new manufacturing LCIs were created for a few of the missing PPPs, as well as recommendations for fertilizer treatment LCIs and more precise emission models for PPPs and fertilizers.

Conclusions The findings in the present article add much needed transparency regarding the limitations of available OA LCIs, offers guidance on how to make OA LCIs more representative, allow for more accurate comparisons between conventional and OA, and help practitioners to better adapt LCA methodology to OA systems.

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1 Introduction

Agriculture not only contributes to more than a quarter of all global greenhouse gas emissions (Springmann et al. 2016) but is also the number one anthropogenic source of nitrogen emissions (Ward et al. 2018) and a danger to an estimated 53% of threatened terrestrial species (Tanentzap et al. 2015). Currently, organic agriculture (OA) is becoming popular due to its view as a more sustainable way of farming and is endorsed by the European Commission's Green Deal, aiming to have at least 25% of the EU's agricultural land under organic farming by 2030 (European Commission 2017). It places emphasis on the use of more natural products and

environmentally friendly techniques, preserving ecosystems, conserving resources, and excluding all techniques that can potentially damage the quality of the final product.

OA systems have been found to be either superior or similar to conventional and integrated farming systems in Europe in terms of resource conservation, biodiversity, reduced eco-toxicity, and increased soil organic matter (Blanco-Canqui et al. 2017; Kok et al. 2020; Nemecek et al. 2011). OA can reduce average product-based greenhouse gas (GHG) emissions by 36–65% in herbaceous crops (Aguilera et al. 2015a) and by 39% in orchards compared to conventional agriculture (CA) (Aguilera et al. 2015b). A more recent study (Smith et al. 2019) has shown that OA can lower direct GHG emissions compared to CA by 20% in crops, 4% in livestock, and 6% overall at national scale in England and Wales. Smith et al. (2019) also found that the lower GHG emissions under organic cropping are largely due to replacement of mineral N fertilizer with biological N fixation in leys, resulting in less CO_2 and N_2O from fertilizer manufacture and less N_2O per unit of production.

Studies such as those cited above often use Life Cycle Assessment (LCA) methodology as it is one of the most comprehensive and transparent tools that aims to assess damages in the three areas of protection: (1) human health, (2) ecosystems and (3) natural resources. It is internationally standardized under ISO 14040 (ISO 2006a, 2020a) and 14044 (ISO 2006b, 2017, 2020b) and is currently recommended by UNEP (Verones et al. 2017) and the European Commission (Environmental Footprint initiative, https://eplca.jrc.ec.europa.eu//EnvironmentalFootprint.html). Since LCA is able to quantitatively address multiple impact categories, it is a suitable methodology in comparative assessments (e.g., organic vs. conventional) as some systems may perform better in some categories than others, thus offering a more comprehensive view of any burden-shifting between categories. Meta-studies that use LCA to model the environmental performance of OA compared to CA, found that the environmental performance of OA is not always the clear winner—its performance can be higher or lower than conventional products depending on the impact category studied and the functional unit (FU) used, such as yield or cultivated area (Clark and Tilman 2017; Meier et al. 2015; Tuomisto et al. 2012). Tuomisto et al. (2012) found that LCAs modeling global warming potential, eutrophication of waterbodies, and soil and air acidification tend to have higher impacts in OA compared to CA per product unit but lower impacts per land area due to larger areas used in OA. On the other hand, OA products perform better in human toxicity and eco-toxicity as well as non-renewable resource depletion potential than CA products due to the fact that synthetic pesticides and mineral fertilizers are not used in OA (Meier et al. 2015; Tuomisto et al. 2012). Clark and Tilman (2017) found that OA may tend to cause more eutrophication, emit

similar GHG quantities as CA, require more land, but use less energy. In general, impacts per product unit may be higher in OA compared to CA due to the higher yields in CA (De Ponti et al. 2012; Seufert et al. 2012) and significantly lower temporal yield stability in OA (Knapp and van der Heijden 2018), but results were highly dependent crop groups and regions. However, a study by Hayashi (2013) found that, in the context of organic conversion, the use of product-oriented FUs such as product weight or land-oriented FUs such as land area, need to be used complementarily, as the use of one or the other will not allow the practitioner to conclude if the conversion minimized impacts per area unit and per product unit. In other words, using land-oriented FU will allow practitioners to determine if there were trade-offs between impact per area unit and yield per area unit or if it was a win–win, lose-lose situation. Using product-oriented FU will allow practitioners to determine if the conversion was efficient (low impact per product unit) or inefficient (high impact per product unit); hence, using a combination of both can determine if the system had trade-offs and was efficient or inefficient. Hayashi (2013) also recommended that besides the use of FUs, decision criteria should also be used. Specifically, decisions should be made in regard to two important criteria, minimize impacts per area unit and maximize yield per area unit.

Although these meta-studies as well as a plethora of other organic crop and animal LCA case studies exist worldwide, only a few studies discuss the limitations in applying LCA methodology to OA (Meier et al. 2017; Tuomisto et al. 2012; van der Werf et al. 2020). These studies focused mainly on the importance of including biodiversity and ecosystem service indicators when assessing organic systems and the lack of functional units (other than solely yield-focused) that represent the multi-functionality of organic systems such as preserving ecosystem quality. However, these critical aspects are not only applicable to LCA for OA but more so for agricultural LCAs in general since the same land and its surroundings would be affected by any type of land use activities. To the best of our knowledge, no article has analyzed the limitations more specific to OA, such as the life cycle inventories of organic crop products.

Therefore, this study presents a novel in-depth critical analysis of the life cycle inventory (LCI) choices of available OA crop datasets and how these limitations can affect life cycle impact assessment (LCIA) results and, furthermore, specific ways to improve these limitations. LCA databases such as ecoinvent (referred to as EI hereafter) (Wernet et al. 2016) are widely used and accessible as background and foreground[1] data in LCA studies, along with other important

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[1] Background processes are activities upstream of farm activities, such as production of inputs used on the farm (e.g., fertilizer manufacturing), as opposed to foreground processes which are any activi-

Table 1 State-of-the-art LCA databases that include organic agricultural products

Database	Crop type				Intercrop	Livestock		Country	Year
	Cereals	Vegetable/legumes	Fruit	Oil Seed		Animals	Feed		
ecoinvent v3.5	11	3	0	1	0	0	7 [a]	Switzerland	1996–2011 [b]
AGRIBALYSE® v3.0	47	8 / 28	7	5	14	40	12	France	2011–2015
ESU	12	30	16	0	0	16	15	Switzerland	1997–2012 [c]

[a]Excluding nested datasets and conventional soy production

[b]Most up to 2002

[c]Most up to 2009

agricultural databases such as AGRIBALYSE® (referred to as AG hereafter) (AGRIBALYSE 2020) and ESU World Food LCA database (ESU 2012). Hence, critical limitations on the inventory level can be potentially transferred to any respective LCA study that uses these data, showing the importance of analyzing state-of-the-art LCA databases and their effects on LCIA results. Practitioners should be fully aware of the limitations presented here, as well as suggestions on how to advance in these aspects.

Our study aims to improve the preparation of LCI's for organic crop production systems, where the specific goals were:

1. Explore and document currently available state-of-the-art crop LCI data for OA
2. Analyze gaps in existing datasets and their possible consequent effects on LCA results
3. Suggest recommendations for improving OA LCI datasets

2 Methods

In order to assess the accuracy of current organic crop LCIs, existing databases were searched for organic crop datasets, and then background data and emission modeling were analyzed, with special emphasis on fertilizers and plant protection products (PPPs).

2.1 Existing organic agricultural datasets

The Global LCA Data access network (GLAD, https://www.globallcadataaccess.org/) was used to find existing European LCA organic crop datasets. The databases ecoinvent v3.8 (Wernet et al. 2016), AGRIBALYSE® v3.0

Footnote 1 (continued)

ties done on the farm (e.g., application of fertilizer and subsequent emissions), following system boundaries in Corrado et al. (2018).

(AGRIBALYSE 2020), ESU (ESU 2012), and Agri-footprint v5.0 (van Paassen et al. 2019) were found to be the most comprehensive and up-to-date agricultural LCA databases for crops in Europe. However, only ecoinvent v3.8, AGRIBALYSE® v3.0 and ESU were the only databases that contained datasets for organic crop and/or animal products in Europe, where a summary of the datasets can be found in Table 1. Crops ranged from cereals to vegetables and perennial fruits. Therefore, a critical analysis of organic crop datasets from ecoinvent v3.8 and AGRIBALYSE® v3.0 was the focus of the present study, excluding animal and animal feed products. The EI system model "allocation, cut-off by classification" was used for the critical analysis. The ESU database was not included due to its similarities with ecoinvent (both based on data in Switzerland), the extra cost required for download, and the fact that it is only compatible with background databases ecoinvent v2.2 or v3.2, whereas in this study v3.8 was used. The organic crop datasets in EI and AG are publicly available for use; hence, critical issues could be passed on to any respective studies that use these datasets, showing the importance of the present study.

Since a particular trait of organic production systems is the use of "natural" PPPs and fertilizers (as opposed to synthetic or mineral ones used in conventional production systems), the background and foreground processes relevant to PPP products and fertilizers were the main focus of the present study. Thus, a selection of organic crops from EI and AG that had PPPs and fertilizers in their LCIs was made. Moreover, only those datasets that were representative of the country or region were selected. Some organic crop datasets in AG represent a typical case and are not representative of a national or regional average (such as barley, winter wheat, fava, wine grape and soybean). We wanted to analyze those datasets that were representative at a larger scale, since the aim of the present study is to analyze LCI of organic agriculture in general; thus those "typical cases" were excluded from the present study. There were two datasets for organic sunflower available, one for the Gers region and one for Pays de la Loire. The Gers dataset was chosen because

it contained more fertilizer inputs for us to analyze. In addition, survey data from organic farms in the European Horizon 2020 project Organic-PLUS (Grant agreement 774,340) (called ORG + hereafter) helped us to identify other requirements for background PPP and fertilizer LCI data. The final selection of organic crops and their relevant data from EI, AG and ORG + analyzed in this study are listed in Table S1. It must be noted that for the orchards and vineyards in AG, the main production stage "full production" was assessed, excluding the stages seedling, plantation and destruction, and first production years. This stage had the highest impacts out of all the stages and spanned most of the lifetime of the orchard, thus allowing us to focus on the main inputs required for fruit production.

In summary, the organic crop LCIs were analyzed in regard to two main aspects, the PPPs and fertilizers used in the LCIs; thus the results and discussion were divided into these two main areas. They were analyzed according to their compliance with European OA regulations (European Commission 2008), representativeness of background fertilizer, and PPP manufacturing datasets and representativeness of foreground emissions modeling for fertilizer and PPP application.

The data quality of relevant PPP and fertilizer background datasets were discussed using a weighted average data quality rating (W-DQR). The indicators used to calculate the DQR were reliability, completeness, temporal and geographical correlation, and further technological correlation using the pedigree matrix approach from Weidema (1998) and modified in Weidema et al. (2013) (refer to pg. 76 for explanation) and the Product Environment Footprint, PEF (European Commission 2017). A score of 1 means excellent data quality, 2 good quality, 3 fair quality and 4–5 poor quality. The initial scores for each LCI dataset were provided by the LCA database providers. Using these scores, a W-DQR was calculated in the present study by first averaging the initial DQR of each input/output within a dataset (e.g., electricity in the kaolin PPP LCI, average $DQR_{electricity} = 3$), then weighted each of these DQRs by its contribution to the total impact for each category (e.g., electricity contributed 47% to total climate change in the kaolin dataset), then averaged all DQRs of inputs/outputs across all categories to get a final W-DQR (e.g., $W\text{-}DQR_{kaolin} = 3.0$, fair). According to the PEF data quality requirements (European Commission 2017), 90% of environmentally relevant data within an LCI shall be at least of fair quality, hence the importance of using a W-DQR average. Details on the information used to calculate the average W-DQR can be found in Supplementary material (Tables S3, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18 and S19).

2.2 Effect of critical aspects on LCA results

To demonstrate how and to what degree the identified limitations in organic crop LCI datasets, namely, the choices in PPP and fertilizer datasets and their on-field emissions, affect LCA results, life cycle impact assessments were conducted using the Environmental Footprint v3.0 (EF) characterization method (Fazio et al. 2018) as implemented in the software SimaPro v. 9.1.1.7. The midpoint impact categories climate change potential (CCP, kg CO2 eq), ozone depletion potential (ODP, kg CFC-11 eq), terrestrial acidification (ADP, mol H + eq), freshwater eutrophication (FEP, kg P eq), marine eutrophication (MEP, kg N eq), resource energy carrier use (REP, MJ), and resource mineral and metal use (RMP, kg Sb eq) were selected because of their relevance to agricultural production and energy-related processes. Respiratory inorganics and water scarcity midpoint impact categories were not analyzed due to insufficient data flows in the AG database. Toxicity categories were also not included due to the lack of impact characterization factors for many PPPs used in the datasets (discussed in the Results and Discussion).

Since the focus of the study was to demonstrate to what degree the limitations in PPP and fertilizer datasets and their on-field emissions have on the LCA results of each crop, a contribution analysis of each input was carried out. Inputs included machinery, on-field emissions, land and water use, fertilizer production, PPP production, transport, seed production, mechanical weeding, infrastructure, and transport of workers, where applicable. The absolute value results were not reported as comparing impacts between products was not the aim of our study.

2.3 Recommendations for improvement

Recommendations on how to improve aspects of the LCI stage in application to OA were suggested, in order to reflect OA practices more accurately and to allow a fairer comparison between OA and CA. In respect to improving PPPs, a search was conducted in Google Scholar to find studies that could model LCIs for microbial-derived products used as PPPs in OA, such as *Bacillus subtilis*, *B. thuringiensis*, and Spinosad, using the keywords "life cycle assessment" AND "inventory" AND "microbial products." The study by Harding (2008) and Harding and Harrison (2016a, b) was found to be the most relevant and practical study that provided a tool to calculate LCIs for microbial products called, the CeBER Bioprocess Modeller (Centre for Bioprocess Engineering Research at the University of Cape Town, Department of Chemical Engineering). This model estimates the life cycle inventory needs of industrial microbial processes such as material and energy balances and equipment volumes and utility needs. This would include

both the microbial growth and product formation as well as any downstream processing such as separation and filtration techniques.

Additional LCIs were suggested for other types of PPPs that already had available LCI datasets (Bordeaux mixture, copper oxide, copper sulfate, essential plant oils, kaolin, pyrethrin) by searching in the databases EI or AG, or if only their precursors were available in EI or AG, the proper ratios were suggested (which was the case for mineral oil, and potassium soap). Other PPPs such as chitosan and neem oil did not have any available LCI datasets, thus new ones were suggested by searching Google Scholar for studies that supplied data regarding their industrial manufacturing, resulting in Pighinelli (2019) and Hoqani et al. (2020) for chitosan and (Kumar et al. 2021) for neem oil.

In terms of suggestions for improving organic fertilizer emissions modelling used in EI and AG, the meta-study by Andrade et al. (2021) was used to determine which model may be more sufficient, as well as expert opinion (Angel Avadí, French National Institute for Agricultural Research, personal communication). Specific PPP emission modelling problems with copper can be found in the Results Sect. 3.1.2, as its explanation was more suitable for the Results.

3 Results

3.1 Critical analysis of PPPs used in organic datasets

3.1.1 Background PPP manufacturing

Upon inspection of the LCIs for organic crops in EI and AG (Table S1), the relevant PPP manufacturing datasets that are available in LCA databases include copper oxide, copper sulfate, sulfur, and kaolin (Table 2), which are some of the most prevalent ones used in OA. The only biological control agents (BCA) that had some input regarding its manufacturing were *Trichogramma* in the EI maize crop dataset, and *Bacillus thuringiensis* in AG, where the electricity required for manufacturing was accounted for. Ecoinvent stated that no further details on *Trichogramma* could be incorporated due to data confidentiality.

Furthermore, it was found that several of the PPPs were only inventoried as output emissions to soil, without having inventoried them as inputs. This was largely due to a dire lack of manufacturing LCIs, especially for botanical PPPs and BCAs (Table 2). Although this allows for transparency regarding the PPPs that were actually used, no mass balance was achieved. For example, the botanical- and microbial-derived PPPs rotenone, pyrethrin, and spinosad were used in organic crops apple, peach, and grape in AG (inventoried only as output emissions), but no manufacturing

datasets were available for them. Thus, impacts regarding their manufacturing would be excluded from any assessment that uses these crop datasets from these databases. It is recommended to include them as inputs in the LCI even as "empty" processes for greater transparency to users, with a disclaimer noting that the inventory is unknown. Through the ORG + project, it was found that many BCAs were used as natural insecticides in the cultivation of aubergine and tomatoes (Table S1) and botanical PPPs, such as pyrethrin or plant essential oils which are also widely used in organic agricultural pest management (Andrivon et al. 2019, a report from the ORG + project).

In regards to whether the crop datasets follow the EU regulations for organic production (European Commission 2008), EI datasets followed strictly with OA principles, in that only organic-authorized PPPs were used. On the other hand, AG applied a general rule to use the "pesticide, unspecified" background dataset from EI as a proxy for unavailable PPP manufacturing datasets, and in the case of organic crops, this was the proxy for the insecticide Spinetoram, an analogue of Spinosad (Grasselly et al. 2017). This "pesticide, unspecified" manufacturing dataset represents a European average of all 78 synthetic PPPs, some of which are not authorized in European OA regulations, such as glyphosate (European Commission 2008), hence indirectly including impacts from synthetic PPP manufacturing. Petrol was also used as a proxy for mineral oil production and low voltage electricity was a proxy for *Bacillus thuringensis* production, which may or may not be better than not including it at all, but more adequate manufacturing datasets are needed.

Additionally, rotenone is no longer permitted in OA in Europe, with its final authorization withdrawn in 2011 (European Commission 2008). In AG, the reference period for some crops and animal products was from 2005 to 2009; thus Rotenone was still permitted in France during that time period. Therefore, if one wishes to use these datasets, it is important to check if the reference period and the PPPs inventoried are similar to the system under investigation and follows local OA regulations.

In respect to the data quality for those PPPs with available manufacturing datasets (Table 2, refer to Tables S3, S4, S5, S6, S7, S8 and S9 for detailed calculation of DQRs), kaolin and sulfur were found to have good data quality ratings between 2 and 3. Copper oxide had poor W-DQR (4.8, i.e., poor) mainly due to the market for copper metal production; this process contributes to > 90% of the total impact of copper oxide, hence demonstrating its relevance and importance. Specifically, the completeness, temporal and geographical correlation, and technological correlation had poor quality ratings that should be improved. Copper sulfate had fair W-DQR due to the poor quality of the copper oxide manufacturing dataset nested within that dataset, accounting for 64–99% of the total impact across all categories. Paraffin oil had a poor

Table 2 List of plant protection products used in organic crop cultivation in Europe and corresponding availability of manufacturing datasets and data quality information

Type of PPP	PP /CAS No	Use(s)	Manufacturing dataset available? – Database?	Average W-DQR, weighted by impact contribution to total
Metal/Mineral-based	Copper gluconate/527 09 3	Fungicide	No	
	Copper oxide/1317–38-0	Fungicide	Yes—ecoinvent	W-DQR$_{CuO}$ = 4.67 (i.e., poor) across all processes W-DQR$_{Cu}$ = 4.8 (i.e., poor)
	Copper oxychloride/1332–40-7	Fungicide	No	
	Copper sulphate/7758–98-7	Fungicide	Yes- ecoinvent	W-DQR = 3.26 (i.e., fair)
	Kaolin (aluminium silicate)/1332–58-7	Repellant	Yes- ecoinvent	W-DQR = 3.0 (i.e., good)
	Lime sulphur/1344–81-6	Acaricide, Fungicide, Insecticide	No	
	Paraffin oil/8042-47-5	Acaricide, Insecticide	Yes- ecoinvent	W-DQR = 3.57 (i.e., poor)
	Potassium hydrogen carbonate/298–14-6	Fungicide	No	
	Potassium soap	Insecticide	No	
	Sulfur/7704-34-9	Acaricide, Fungicide, Repellant	Yes- ecoinvent	W-DQR = 2.4 (i.e., good)
Botanical	Cinnamon oil (a.i. cinnamaldehyde)/104–55-2	Repellant	Yes – AGRIBALYSE® 3.0	Proxy used: Conventional vanilla production, Madagascar, ecoinvent v3. W-DQR$_{Van}$ = 1.84 (i.e., very good), reported DQR$_{Van}$ = 2.7 (good)
	Citrus oil (a.i. limonene active ingredient)/5989–27-5	Fungicide, Insecticide	No	
	Eucalyptus oil (a.i. 1, 8 – cineole)/470–82-6	Pesticide	No	
	Neem oil (a.i. azadiractin)/11141–17-6	Insecticide	No	
	Oregano essential oil (a.i. carvacrol)/499–75-2	Anti-microbial, Insecticide	No	
	Pyrethrin/8003–34-7	Insecticide	Yes—ecoinvent	W-DQR = 3.4 (i.e., fair)
	Thyme essential oil (a.i. thymol)/89–83-8	Fungicide	Yes—AGRIBALYSE®	Proxy used: Conventional mint production in India. Reported DQR = 2.7 (i.e., good)
	Rotenone/83–79-4	Insecticide	No	
Microbial-derived	*Bacillus subtilis*/68038–70-0	Bactericide, Fungicide	No	
	Bacillus thuringiensis/68038–71-1	Insecticide	No	
	Nesidiocoris tenuis (predatory insect)	Insecticide	No	
	Reynoutria sachalinensis extract (giant knotweed)	Fungicide	No	
	Spinosad/168316–95-8	Insecticide	No	
	Trichoderma harzianum/67892–31-3	Insecticide	No	
	Trichogramma pretiosum/41198–08-7	Insecticide	No	

W-DQR (3.6) due to the poor quality of the chemical factory data (4.8) and fair quality of the heat data from sources other than natural gas (3.2). Specifically, the chemical factory data had poor reliability, completeness, temporal and geographical correlation, and further technological correlation, whereas the heat data had poor ratings only for the first three indicators. Therefore, the aforementioned datasets do not comply with the PEF data quality requirements (European Commission 2017) where 90% of environmentally relevant data within an LCI shall be at least of fair quality.

Thyme and cinnamon production had good W-DQR's (both 2.7); however, they both used proxies for their production, which in reality would result in a very low DQR. The thyme in particular uses a conventional mint proxy cultivated in India, which would not be a suitable proxy for European or organic contexts, as some of the inputs used are not permitted in Europe nor in organic systems, in addition to the fact that thyme and mint can be grown in Europe. Cinnamon and vanilla, on the other hand, cannot be grown in European climates; thus, vanilla could be considered a good proxy. Therefore, more research is needed to improve the DQR of these existing datasets.

In regard to more specific organic pest management techniques, OA focuses mainly on preventative measures that rely on maintaining a healthy soil biology and overall biodiversity. This may include providing a habitat for beneficial organisms and diverse rotations, using resistant varieties, intercrops, and proper soil and nutrient monitoring and management, among others. When such preventative measures are insufficient to prevent or control pests, diseases, and weeds, the addition of permitted PPPs would normally be the last resort. Such preventative techniques are difficult to account for in LCA and were not included in the EI and AG organic crop datasets, except crop rotations and intercrops to some extent in AG, where they allocate PPP and fertilizer manufacturing, emissions from PPP and fertilizer applications and diesel consumption among the crops in that sequence. Mechanical weeding was also accounted for in some of the AG crop datasets (Table S1). The other preventative measures that require diverse ecological structures to increase biodiversity and habitats for beneficial organisms, which may also be referred to as ecosystem services, are difficult to account for in LCA as they are difficult to quantify and/or reach a consensus as to how to measure it. However, some studies aim to, for example, estimate the vascular plant biodiversity in organic and conventional cropland in Europe (Knudsen et al. 2017; Koellner and Scholz 2008; Mueller et al. 2014; Schryver and Goedkoop 2010), which may be a good start.

3.1.2 PPP emission modeling

The main critical aspect found to be relevant to environmental assessments of OA was that the total PPP dose in compound form (e.g., $CuSO_4$) was often used as the emission output rather than the active ingredient (e.g. Cu ion).

Copper-based PPPs are one of the most widely used and most generously applied PPP in OA and CA, especially in fruit trees and grape vines (Agrios 2005). Since OA cannot use other synthetic pesticides, organic farmers depend greatly on copper PPPs, and thus copper emissions are relevant and important. However, it seems there is confusion surrounding how to calculate emissions from copper-based PPPs; in AG, they used the mass of the compound (e.g. copper sulfate, copper oxide, etc.) as the on-field emission output, instead of using the mass of the active ingredient, Cu ion. This can consequently over-estimate toxicity results due to the higher, total mass used, especially when applied in solution or in acidic environments where the Cu is more likely to be a free ion. For example, the total input dose used in the organic apple dataset in AG was 109.871 kg Cu/ha, which was equal to the total sum of output emissions (41.072 kg copper sulfate/ha and 68.799 kg copper oxychloride/ha), showing that the total dose was used instead of the amount of Cu active ingredient. EI did not have any organic crop datasets, such as fruits, that used copper-based PPPs, hence was not mentioned here.

3.1.3 Effect of PPP critical aspects on LCIA

Figure 1 shows the contribution of processes to the total impact for those organic crop datasets in EI and AG where relevant criticisms regarding PPP inputs were reflected in the life cycle impact assessment. This demonstrates how and to what degree the limitations discussed in the previous section affect LCA results, in order to show the importance these limitations have on current and future LCA studies.

Perennial fruit and nut production in AG used more PPPs than the other crops, which was clearly reflected in the results where PPP production notably contributed between 4 and 30% to ozone depletion (ODP), 6 and 11% to acidification (ADP), 7 and 64% to freshwater eutrophication (FEP), 7 and 55% to resource energy carrier use (REP), and 22 and 78% to resource mineral (RMP) (Fig. 1). These PPPs constituted copper and sulfur fungicides, kaolin, pesticide unspecified proxy for spinetoram, petrol proxy for mineral oil, and electricity proxy for *Bacillus thuringiensis*. Of these values, copper-related PPP production was the main contributor to FEP due to upstream phosphate emissions and RMP due to depletion of resources, whereas sulfur production was the main contributor to REP, demonstrating the energy-intensiveness of its production (Figure S1). Therefore, it is important that adequate copper datasets are chosen when carrying out an LCA of crops that use copper, and it is pertinent that the data quality of these copper datasets is improved or is discussed in the LCA. However, this is based on the assumption that the copper used in the
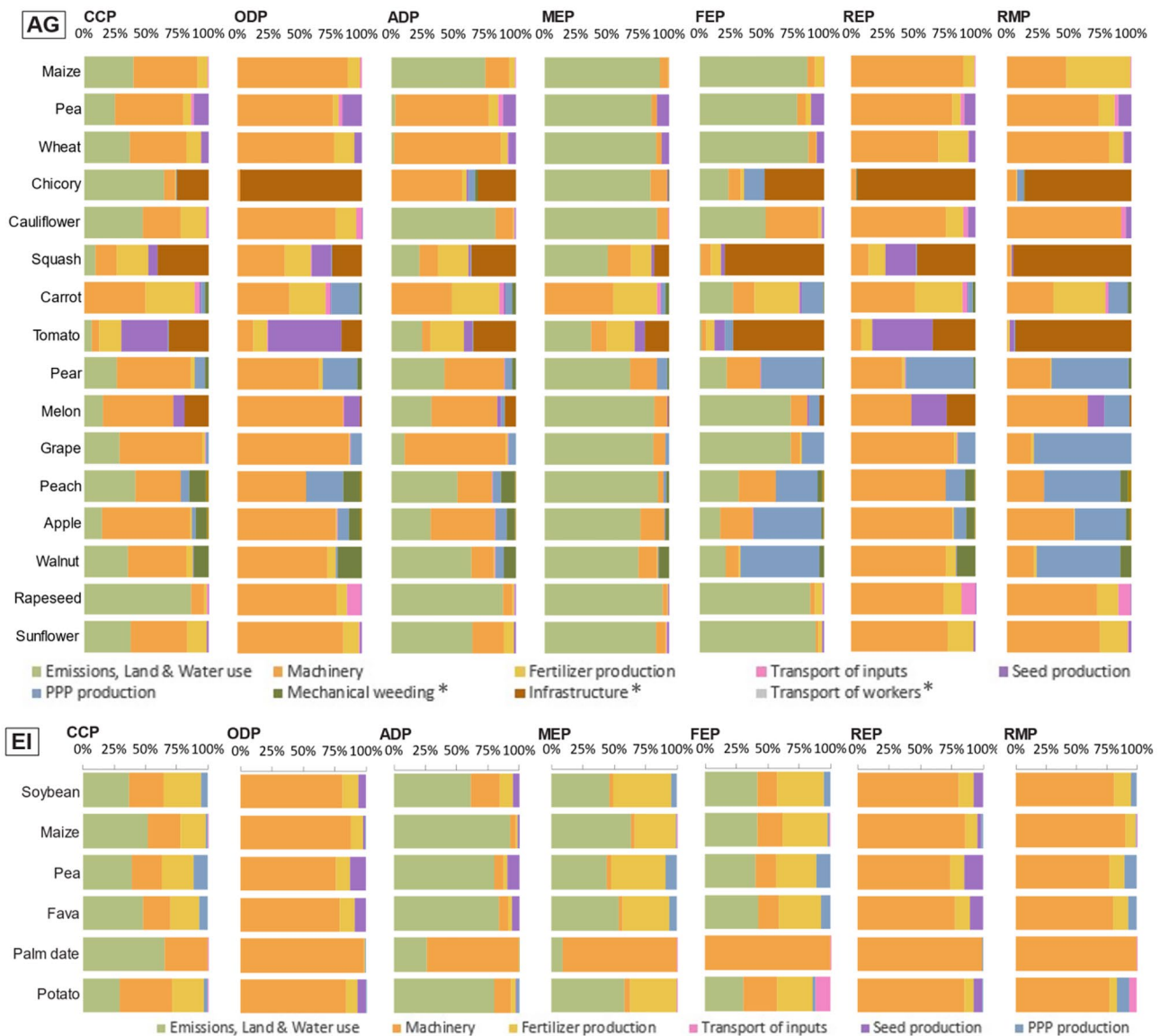
Fig. 1 Contribution of relevant cultivation processes in organic crops from databases AGRIBALYSE® (AG) and ecoinvent (EI) to potential impact categories climate change (CCP), ozone depletion (ODP), acidification (ADP), marine (MEP) and freshwater (FEP) eutrophication, resource energy carrier use (REP), and resource mineral use (RMP). Machinery includes field work such as tillage, planting, har- vesting, irrigation, PPP and fertilizer application, and the production of diesel, electricity and machinery required to carry out these opera- tions. *Mechanical weeding was only present in walnut, pear, chicory, peach, apple, wine grape and carrot. *Infrastructure was only present in chicory, squash, tomato and melon. *Transport of workers was only present in wine grape, apple and peach

EI database is of virgin origin, whereas in reality 40–50% of all pre-manufactured copper is sourced from recycled copper scrap (Davenport et al. 2002). However, in regard to the characterization of the impacts due to these cop- per compound emissions, the characterization method EF 3.0 (used in this study) and even another commonly used method ReCiPe 2016 (Huijbregts et al. 2017) do not have toxicity CFs for these compounds or they are not properly accounted for in SimaPro. Thus, the toxicity impacts of cop- per oxide, copper sulfate, and copper oxychloride emissions would not be accounted for, which is why toxicity impact categories were not included in this study. Therefore, if EF 3.0 or ReCiPe is the characterization method of choice, it is recommended to use copper (CAS Number 007440–50-8) as the output emission, since these impact methods assign the CFs for the oxidized form of copper (Cu(II)) to the metal- lic form. Therefore, this change is important for crops that use large amounts of copper fungicides, potentially affecting categories that are affected by copper emissions to soil, i.e., freshwater ecotoxicity and human toxicity non-cancer. In

summary, it is recommended to (i) use the amount of active ingredient (e.g. Cu ion) as the output emission in crop LCIs, instead of the compound (e.g., copper sulfate), if applicable, and (ii) use copper (CAS Number 007440–50-8) as the output emission instead of the compound (e.g., copper sulfate).

Of the AG crops that inventoried pesticide unspecified as a proxy for Spinetoram (Table S1), peach had the highest amount of pesticide unspecified applied with 51.48 kg/ha followed by carrot with 13 kg/ha (other crops were in the range of 0.00702 kg–7.6 kg/ha). Looking at these two crops, it is evident that these high amounts of pesticide unspecified can sway the results away from copper and sulfur impacts, causing high contributions in FEP (15%) and REP (13%) (Fig. S1). Since the amount of "pesticide unspecified" used in peach production is relatively smaller compared to copper ($1.3 \times$ lower) or sulfur inputs ($36 \times$ lower), these results indicate that even a small amount of this PPP can greatly influence LCA results.

The impact of mechanical weeding was estimated apart from machinery processes, in order to separately account for other methods of weed removal that may be used in OA instead of herbicides. Mechanical weeding was used in the AG perennial crops datasets (apple, peach, pear, walnut, and carrots). Since mechanical weeding consisted of the use of a tractor and its implements, it was found to potentially contribute 3–15% to CCP, 2–20% to ODP, 3–14% to ADP, 3–15% to MEP, 2–15% to REP, and 2–9% to RMP (Fig. 1). Therefore, it is important to separately account for this when carrying out an OA LCA.

3.2 Critical analysis of fertilizers used in organic crop datasets

3.2.1 Background fertilizer manufacturing datasets

Organic fertilizers are essential in OA, due to the prohibition of mineral fertilizers. Thus, after analyzing the OA datasets, it was found that the main LCI modeling issue regarding the manufacturing of organic fertilizers and amendments was the exclusion of treatment and storage processes of the fertilizers (e.g., composting, anaerobic digestion) and the use of mineral fertilizer proxies (Table 3). This was likely due to the lack of usage statistics for organic fertilizers for the treatment to be included. For example, in AG and in EI, most crops had "organic farm or manure empty processes" to represent animal manure- or slurry-based fertilizers; thus, they were assumed to carry zero environmental burden from the animal production system. However, further valorization treatments of processes were not included in most of the crop datasets, with the exception of sunflower, rapeseed, tomato, squash, and chicory. Given the dependence of OA on organic fertilizers and the growing number of organic

farms and market for organic products in Europe (European Commission 2017), organic residue treatment may shift from mere treatment to economic valorization and entry into the market, showing the importance to include this in future LCAs.

With respect to the use of mineral fertilizers proxies in AG, average French P_2O_5 or K_2O mineral fertilizers were inventoried in organic grape, carrot, sunflower, and pea, in addition to average European N mineral fertilizers in grape (Table S1), which are not authorized in OA. Only crude or rock phosphate and organic fertilizers are permitted (all authorized fertilizers for organic production are listed in Table S3, from the European Commission 2008).

In regard to the data quality for those fertilizers with available manufacturing datasets (Table 3, refer to Tables S10, S11, S12, S13, S14, S15, S16, S17, S18 and S19 for detailed calculation of DQRs), green manure, compost, all three average mineral fertilizers of N, P_2O_5, and K_2O and potassium chloride had good W-DQRs between 2 and 3. Poultry manure had fair W-DQR between 3 and 4, due to poor completeness and temporal correlation ratings across all inputs and outputs. EI stated that this dataset is a rough estimation extrapolated from literature sources and that it is recommended to update this dataset as soon as possible. Horn meal also had a fair rating due to poor temporal correlation across all inputs and outputs, especially electricity and heat processes, possibly due to the extrapolation of data from 1993 to 2019.

3.2.2 Fertilizer emission modeling

Fertilizer application emissions can affect acidification, eutrophication, climate change, and toxicity potential and are calculated first and foremost as a function of nutrient and heavy metal content (e.g., 0.55 TAN in dairy cattle manure applied, European Commission 2017), as well as other factors such as climate and application technology. Thus, we highlight three main limitations that can greatly influence impacts in regard to fertilizer application emission modeling in not only OA but also any agricultural production system that uses organic fertilizers:

1. No differentiation is made between the nutrient content for manure derived from OA and CA systems.
2. Fertilizer emissions model such as those used by AG and EI (and hence European Commission 2017) are too simple for accounting nutrient balance and heavy metal emissions from organic (and conventional) fertilizer application.
3. Use of averages for nutrient content composition for organic fertilizers can yield unrepresentative emissions due to high variability.

Table 3 List of fertilizers and amendments used in organic crops from EI and AG databases and the ORG + project and corresponding availability of manufacturing datasets and data quality information

Fertilizer	Manufacturing/treatment dataset available? – Database?	Average W-DQR weighted by impact contribution to total
Liquid and solid farmyard manure (empty process, only accounted for in terms of direct field emissions)	N/A	N/A
Digestate	Yes—AG v3.0	2.60[a]
Composted farmyard manure with and without substrates	Yes—AG v3.0	2.60[a]
Green manure	Yes – EI	2.04
Horn meal	Yes – EI	3.20
Compost (type not specified)	Yes – EI and AG	2.17
Average P_2O_5 mineral fertilizer	Yes – EI	2.32 (based on Phosphate fertilizer, as P_2O_5, monoammonium phosphate production as it was the input with the highest proportion) 2.36 (based on Phosphate fertilizer, as P_2O_5 triple superphosphate production)
Average K_2O mineral fertilizer	Yes – EI	2.81 (based on Potassium chloride production, as K_2O as it was the input with the highest proportion)
Average N mineral fertilizer	Yes – EI	2.23 (based on ammonium nitrate production, as N as it was the input with the highest proportion)
Poultry manure	Yes – EI	3.07
Potassium chloride	Yes – EI	2.81
Magnesium oxide	Yes – EI	4.04
Potassium sulfate	Yes – EI	2.33
Commercial liquid fertilizer (Calcium (7) and magnesium)	No	N/A
Commercial pelletized cow manure	No	N/A
Commercial liquid vegetable-based fertilizer	No	N/A

[a]This is not a weighted DQR, this could not be weighted due to unavailable DQR for each individual input for that dataset, thus, the average of the quality assessments given in (Avadí et al. 2020, Table 4, from which these LCIs were derived) are shown here

The average nutrient composition of organic fertilizers used in EI and AG were based on manure from all types of agricultural systems, such as from CA and OA. However, due to the higher number of conventionally managed farms in Europe compared to OA, the nutrient content is often based only on manure from CA. This is an issue for two main reasons: the (1) use of manure from factory farming as fertilizer is prohibited under EU OA regulations, and (2) N-content in manure from CA can be higher than OA due to higher protein content in the feed. The latter is rarely ever considered in LCA inventories and may be an important explanation for unaccounted N surplus in LCAs of organic products, especially for animal products (Meier et al. 2015). Thus, Meier et al. (2015) state that ammonia emission models should be adapted to different farming systems, such as taking the diet-related N-flows into account, to allow more accurate estimates for acidification, terrestrial eutrophication, and climate change potential, especially within comparative LCAs of animal products.

In respect to the second limitation, the fertilizer application emission modeling in AG and EI did not take into consideration the application method by which fertilizers, whether organic or not, are applied when estimating ammonia emissions. This is extremely applicable to OA since some organic fertilizers emit more ammonia than mineral fertilizers (e.g., default air emission factor for organic fertilizers is 0.24 kg NH_3/kg N applied and 0.12 kg NH_3/kg N applied for synthetic fertilizers, European Commission 2017). Moreover, misrepresenting NH_3 emissions can also affect NO_x emissions generated through nitrification and N_2O emissions through denitrification. AG state that lack of fertilizer application data in France made it impossible to create correction factors for ammonia. In the estimations for EI data, it was assumed that no additional measures were taken to reduce ammonia emissions. AG also explain that their nitrate emissions were estimated using the COMIFER-Tailleur model (Tailleur et al. 2012), which does not take into account the dose of nitrogen supplied, and the time at which it made the contribution. Additionally, AG and EI used the SALCA-P model which does not take into account the fact that P balances are not always balanced, with exports being stronger than inputs. For example, AG state that this

is a limitation in their study since successions with alfalfa export a lot of P; thus without adapted agricultural practices, P stocks in soil are likely to decrease (Nitschelm et al. 2020).

Heavy metal (HM) contaminants can be found in both organic and mineral fertilizers; however, higher levels have been found in organic fertilizers and/or are more readily available, although uptake may be lower due to organic matter content in the fertilizers (Ugulu et al. 2021; Zaccone et al. 2010). Therefore, HM emission modelling is a very critical aspect to consider. For both AG and EI, the SALCA-heavy metal soil emission methodology (Prasuhn 2006) was applied; a balance between heavy metals (HM) inputs into soil (seeds, fertilizers, pesticides and deposition), and outputs from the soil (exported biomass, leaching and erosion) were made, resulting in either positive or negative emissions. One major difference between AG and EI fertilizer emissions modeling is that AG includes the effects of crop rotation on emissions, but these have resulted in negative net HM emissions. AG state that a negative emission means a net export of HM to water bodies or to the harvested product such as food, feed, or straw through uptake or residue. However, the uptake values were based on average HM contents of specific crops and specific fertilizer types for France or Switzerland. AG further stated that trace HM leached to aquifers is strongly linked to the geology of the soil, so the values they used from Switzerland (the average amount of HM leached per ha per year) should be used with care when applying it to other countries. Furthermore, AG adds a disclaimer that considering the uncertainties of these parameters, a negative balance should not be interpreted as complete export of HMs from the field but mainly as a result of uncertainty in input and output data. Therefore, LCA practitioners must bear this in mind when interpreting emission results that use balancing methods like SALCA-HM emission modeling in the LCI, and it is recommended to report results with and without negative HM emissions (i.e., zero emissions if the value is negative).

In regard to the third limitation, information regarding nutrient content in organic fertilizers is often unavailable or reported only as the total amount of fertilizer applied. Thus, proxies or national weighted averages based on market data are often used but may not be representative of the region or fertilizer type under investigation and could lead to under- or over-estimation of emissions. However, therein lies the limitation, it is difficult to create proxies for organic fertilizers due to the large number of fertilizer types available and high variability in nutrient content among them. For example, from the data gathered for the ORG + reference scenarios, pelletized fertilizers, or commercial liquid vegetable fertilizers were used on-field, but no representative nutrient contents nor emission fractions could be found for

these fertilizers. Thus, if emissions are to be estimated, proxies would need to be used which can increase uncertainty of results. For instance, pelletized fertilizer usually has lower emission rates than solid manure or digestate (Pampuro et al. 2018).

The variability of nitrogen content among organic fertilizers is quite high depending on the database or source chosen (Fig. 2). Koch and Salou (2016) for AG had the lowest variability, and Flisch et al. (2009) for EI had the highest variability, illustrated by the size of the boxplots in Fig. 2. If an average is taken (e.g., 11 kg N/ton in Flisch et al. 2009), there is a 50% chance that the actual nutrient content of a specific fertilizer may be more than double the average (e.g., > 22 kg N/ton). Another important point that can be derived from Fig. 2 is that the "outliers" all represent nutrient values for poultry manure, hence showing that this type of fertilizer is statistically different from the rest.

3.2.3 Allocation of manure

One other important point regarding inventory modeling of organic fertilizers is how to allocate organic residues (e.g., manure) that are exported off-farm. Since this study also aims to guide LCA practitioners in applying LCA to OA products, we will discuss how current literature and databases deal with allocation, so that future LCA studies can allocate with more consistency. The allocation of manure is one aspect that can be part of either the animal or crop production system, and because it is at the interface of both, it is important to have a clear and consistent approach as to where the manure should be allocated. This is especially relevant to OA due to the strict use of organic fertilizers mainly derived from manure, but also relevant to conventional agriculture that may use a mixture of organic and mineral fertilizers. This is a crucial aspect that must be properly and consistently assessed seeing as manure management processes can represent high contributions to impact categories such as climate change, acidification, particulate matter and eutrophication, due to methane and nitrogen-related emissions.

The Livestock Environmental Assessment and Performance (LEAP) Partnership by the Food and Agriculture Organization of the United Nations (FAO 2016, 2018) offers clear and robust guidance for the allocation of manure. This Partnership is a multi-stakeholder global initiative that seeks to improve the environmental sustainability of the livestock sector through harmonized methods, metrics, and data, particularly guiding the use of LCA in livestock systems. The LEAP Partnership recommends to first classify the organic residue as either a co-product (of the producing system), a residual or a waste. This allows the system to be separated into two areas, where all post-farm

emissions from manure use are assigned to that use (e.g., fertilization), while all on-farm management is assigned to the main product(s) from the farm (e.g., milk, manure, live animals, draught power). Table 4 summarizes how to classify an organic residue as a co-product, residual or waste, where and how to allocate any further treatments, and any associated criticisms. The LEAP guidelines state that the application of consequential modelling by system expansion and substitution is not supported by the guidelines so that greater harmonization among the different guidelines may be achieved. The allocation methods described therein are to be used for attributional LCAs, but system expansion may be used in the context of including expanded functionality, though it is a conventional approach. Seeing as the LCI datasets used in the current study were created using an attributional approach, i.e., an average technology mix as opposed to the consequential marginal technology approach, the attributional approach is discussed here for greater consistency.

Manure can be classified as a co-product if it can be sold as a source of revenue for the farmer, similar to the other outputs of the farm (e.g., milk, live animals, wool). Since there is more than one product that exits the animal farm, a biophysical or economic allocation method can be used. However, it is important that the same allocation method is used throughout the supply chain for consistency. Please refer to (Food and Agriculture Organization 2016) for specific steps on how to carry out the allocation. Manure is classified as a waste when it is has no value nor is reused, such as in the following two situations, (i) deposition in a landfill, incineration, or treatment facility or (ii) when applied to the field in excess of crop requirements, and emissions from deposition and field application are allocated to the animal product(s). If an LCA on animal production is being carried out, it is pertinent that the most accurate dataset for disposal method is chosen or modified to suit the actual situation. For accurately estimating how much of the manure is in excess, the LEAP guidelines provide the steps required (Food and Agriculture Organization 2016). Finally, a manure is considered to be residual if the manure is of no value to the farmer but exported off-farm for value-added processes or application to crop fields within crop nutrient requirements. This follows the "cut-off" system separation, where the manure does not contribute any burdens to the animal product(s) nor to the off-farm processes; they come "burden-free" from the animal system to subsequent uses. Therefore, any burdens associated with off-farm processes such as value-added processes (e.g., anaerobic digestion, composting to make a fertilizer) are allocated to the system consuming it (e.g., crop system consuming it as fertilizer). It is essential that the value-added processes are not double-counted in both the animal system and crop system when carrying out a livestock LCA.

Table 4 Summary of LEAP guidelines on allocation procedures of manure exported off-farm (Food and Agriculture Organization 2016). Additionally, these guidelines have a decision tree to aid the decision-making process

	Definition	Method for allocation	Critical aspects to consider
Co-product	It is a coproduct when manure is a valuable output of the farm, and if the system of manure production cannot be separated from the animal production system. The full animal supply chain to the farm gate are shared between all the co-products (e.g., milk, live animal, manure)	1. Biophysical: based on the energy required for digestion to utilize nutrients and create manure 2. Economic: based on a value:quantity ratio. Used if energy content of feed is unknown and if function of product is not for energy (e.g. fertilizer instead)	Recommended to use the same allocation method throughout the supply chain, if inconsistencies occur, practitioners must transparently report possible impacts of this on the results
Waste	Classified as a waste in two situations: 1. When disposed in a landfill, incineration without energy recovery, or sent to a treatment facility 2. When applied in excess of crop nutrient requirements	1. All emissions associated with disposal technique are assigned to animal product(s) 2. Fraction that is in excess of crop requirements are classified as waste, thus field application emissions or disposal are assigned to the animal product(s) Fraction of manure applied that meet crop needs are defined as residual	Choosing the most suitable dataset for disposal techniques Accurately estimating how much of the manure is in excess, guidance is given in LEAP (Food and Agriculture Organization 2016)
Residual	When manure is of no value to the animal farmer and is exported in the condition in which they were created. This classification is equivalent to the "cut-off" system separation, where the manure comes "burden-free" from the animal system as the boundary was cut-off after its transport off-farm	Value-added processes and associated emissions as well as field application emissions are assigned to the system consuming it, e.g., crop system consuming it as a composted fertilizer	Must ensure no double counting of manure management in both the animal and feed systems if carrying out a livestock LCA
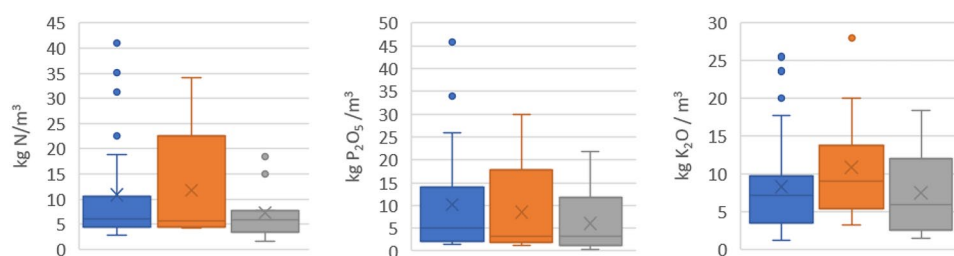
Fig. 2 Comparison of nutrient content (kg N, P2O5 and K2O per m3 or ton) in different types of organic fertilizer derived from animal and sewage waste from Catalonia, Spain (Sío et al. 2013) in blue, ecoinvent (Flisch et al. 2009) in orange, AGRIBALYSE® (Koch and Salou 2016) in grey. Each boxplot shows the median of all values (line through the box), mean (cross), flanked by the first (bottom) and the third (top) quartiles (limits of the box) and first (bottom) and ninth (top) deciles (whiskers), outliers are plotted as individual points. This graph is based on data from Table S2

In both EI and AG crop datasets, farmyard manure was classified as residual, thus came "burden-free" from the animal production system. However, only the field application emissions were accounted for in the crop datasets and no value-added processes were included. It was not clear in the EI and AG documentation if this was because the manure was applied raw without further value-added treatment, but since no extra value-added processes were included in the LCI, it can be assumed that raw application was used. In the European Regulations on organic food and labeling (European Commission 2008), the composting or treatment of raw manure before application on field is preferable to reduce contaminants, pathogens, and aid decomposition. Thus, crop datasets that include value-added processes for manure would be useful or should be added to the LCI at the practitioner's discretion.

In the potato and legume EI datasets, green manure was treated as a residual, therefore, the production of the green manure in the rotation was allocated to the main crop under study (potato and legume). EI also treated horn meal, dried poultry manure and compost as residuals, where methodological documents for EI (Nemecek and Kägi 2007) state that the treatment and recycling of organic by-products and transport to and including regional storage are normally included in the datasets of these types of organic fertilizers, but under greater inspection of the LCIs, only transport to the farm was inventoried in the cut-off processes of these datasets.

Another novel approach to manage the allocation of burdens associated with recycling of organic residues is the Circular Footprint Formula (CFF). It is an end-of-life modeling formula that accounts for benefits and burdens for recycling, energy recovery and the use of secondary materials, from the European Commission's Product Environmental Footprint Category Rules (European Commission 2017). This could be used if the practitioner would like to comply with the PEFCR, especially for European products, but currently, there is no adapted CFF for the use of by-products for organic fertilizer use.

3.2.4 Effect of fertilizer critical aspects on LCIA

The fertilizer production contributions in Fig. 1 include both mineral and organic fertilizer manufacturing datasets, where applicable (see Table S1 for further information). Focusing on the mineral fertilizer manufacturing impacts, the sunflower, maize, winter rapeseed and pea datasets in AG all used average mineral fertilizers K_2O and P_2O_5, which contributed between 2 and 8% to CCP, 4 and 10% to ODP, 1 and 8% to ADP, 2 and 7% to FEP, 2 and 15% to REP, 10 and 51% to RMP, and most notably 70 and 107% to freshwater ecotoxicity (FEx), except for maize (Table S21). The freshwater ecotoxicity impacts were due to the upstream emissions of sulfur to river water from the production of potassium chloride, a precursor of K_2O. Carrot in AG inventoried ~ 10 × more average K_2O and P_2O_5 mineral fertilizer than the other relevant crops, thus having higher contributions to CCP (11%), ADP (10%), FEP (26%), and RMP (11%) (Table S22), demonstrating the influence mineral fertilizer production proxies can have across these categories.

In regard to the fertilizers permitted in OA and used in AG, horn meal, lime, quicklime, compost, potassium chloride, wheat straw, magnesium oxide, industrial biowaste compost, and inorganic chemical production (proxy for other organic fertilizers) had upstream burdens allocated to it in terms of treatment, transport, and infrastructure, where applicable. Horn meal was used in soft wheat, sunflower grains, apple, walnut, and pear crops, but looking only at soft wheat where horn meal was the only input besides machinery, transport, and seeds, it can be clearly seen that the most relevant categories for horn meal were CCP, ODP, FEx, REP, and RMP, with contributions of 11.64%, 15.94%, 33.53%, 23.61%, and 11.26%, respectively (Table S21). The other four crops had many other fertilizers and/or PPP inputs; thus the impacts for horn meal were lower as the overall impacts were more spread among them; however, the same pattern of relevant categories for these crops can also be seen (Tables S21, S22 and S23). Since these categories were the most affected, it shows the energy intensiveness of horn meal processing.

Quicklime was used in the cauliflower, chicory root production and tomato datasets, but similar to horn meal in soft wheat production, quicklime was the only input in the cauliflower dataset besides machinery, transport, and seeds, hence showing high contributions to CCP (21%), ODP (17%), FEx (15%), REP (14%) (Table S22), compared to chicory and tomato (contributions between 0.007% and 3% across all categories, Table S23).

Average compost, from green waste, biowaste, sludge, manure, and slurry, was used in sunflower, squash, and tomato AG datasets, where the most relevant categories were CCP, ODP, ADP, MEP, and REP with contributions between 10 and 25%, 6 and 19%, 6 and 25%, 0.83 and 21% (mean 12.54%), and 9 and 12%, respectively (Tables S21, S22 and S23). This shows the importance treatment processes may contribute to the life cycle assessment of crops.

Potassium chloride was used as K_2O fertilizer in carrot, tomato, and apple AG datasets and had low contributions across all categories between 0.03 and 6%, except FEx with 34% in carrot, 17% in tomato, and 2% in apple (Tables S22 and S23).

Biowaste industrial compost and inorganic chemical organic fertilizer proxy had low contributions across all categories in the relevant crop datasets in AG, with values between 0.05 and 6%, showing its possible low importance overall (Tables S22 and S23).

Magnesium oxide and lime had very low contributions across all categories in the relevant crop datasets in AG, with values between 0.001 and 0.58% (Table S23).

Wheat straw was used as mulch for carrot production in large quantities (20,000 kg/ha) and had high contributions between 24 and 32% to CCP, ODP, ADP, MEP, REP, and RMP (Table S22), as this flow includes baling and transport from the cultivating area, showing its possible high importance overall.

The only organic fertilizers with upstream production burdens in the EI database were green manure in soybean, fava bean, pea, potato, and maize in EI, where it included all activities related to its cultivation. Green manure had similar contributions in all related crops, with high average contributions to CCP (23%), FEP (30%), MEP (39%), and RMP (10%) (Fig. 1). Also, poultry manure in palm cultivation included upstream production burdens, but only the transport to the farm, and as expected, the transport had between 0 and 1% contributions across all categories.

4 Discussion

The discussion was divided into two topics, spread over four sections, the first topic and section explains general criticisms about the EI and AG database (Sect. 4.1), and the second topic includes recommendations for improving organic crop LCIs, with respect to fertilizer inventories (Sect. 4.2) and PPP inventories (Sect. 4.3). Finally, a summary of the

main recommendations is given in Sect. 4.4. The purpose of these recommendations is to provide proxies, guidance, as well as oriented prioritization of further research.

4.1 General analysis of the EI and AG databases

The organic datasets, made by AG, were based on "a typical case" from one or a few case farms, as well as expert opinion and thus do not represent average national data for France, but may represent regional data, as stated in the methodological document by Nitschelm et al. (2020). Due to this, organic datasets cannot be used in the same way as the data in CA in the AG database and, thus, cannot be used to make comparisons between OA and CA, without explicitly highlighting the limits of such a comparison. However, they can be used to: "…characterize part of the diversity of organic farming systems and some of their environmental impacts; identify areas for improvement and carry out eco-design work; perform sensitivity analyses; or even make system choices in a given context" (Nitschelm et al. 2020, Pg. 8). The EI organic crop datasets were based on statistics, pilot networks, documents from extension services, and information provided by retailers and expert knowledge and represent regional data, though only for cases in lowland Switzerland, and, thus, could be used in comparative contexts. In general, we found that the inventory for AG included more information that was readily available in the LCI itself. Particularly useful was the inclusion of emissions even for those inputs that did not have manufacturing LCIs (e.g., PPPs like biological control agents), as well as comments on what that input was used for (e.g., plant protection), allowing for more transparency. AG also provides specific methodological documents on OA (Grasselly et al. 2017), whereas EI provides only general methodology guidelines, none specific to OA.

4.2 Plant protection product inventory improvements

In regard to the lack of manufacturing LCIs for many organic-authorized PPPs (Sect. 3.1.1), improvements were suggested in the form of new LCIs for Spinosad and *Bacillus subtilis* (Tables S25 and S26), using the CeBER Bioprocess Modeler (Harding and Harrison 2016a b) for building LCIs for microbial-derived products. The energy and carbon source requirements for their production (major hotspots in production, Harding 2008) and available proxies are summarized in Table 5. The authors state that the data was drawn from various industrial norms and academic sources, as well as stoichiometrically calculated values and hence can be the source of inventory variations from other literature studies. The model is quite robust and complete in

Table 5 Prevalent plant protection products (PPPs) used in organic agriculture (OA) in Europe in alphabetical order and their subsequent manufacturing datasets or suggested inputs (electricity and/or other significantly impacting inputs) that can be used as a proxy

Prevalent PPPs used in OA	Suggested LCI for manufacturing of PPP	Reference
Bacillus subtilis	Electricity: 1.41 MJ/kg *B. subtilis* Glucose: 0.064 g/kg *B. subtilis* (These are the most impacting inputs, refer to Table S26 for full LCI)	Model: (Harding and Harrison 2016a, b) Data used for model: (Korsten and Cook 1996; Posada-Uribe et al. 2015; Rowe and Margaritis 2004)
Bacillus thuringiensis	Proxy: *B. subtilis* data from above	
Bordeaux mixture	ecoinvent Bordeaux mixture	(Wernet et al. 2016)
Chitosan	Electricity: 5957.6 kWh/kg chitosan (This is the most impacting input, refer to Table S27 for full LCI)	(Pighinelli 2019; Said Al Hoqani et al. 2020)
Copper oxide	ecoinvent Copper oxide	(Wernet et al. 2016)
Copper oxychloride	Proxy: ecoinvent Copper oxide	(Wernet et al. 2016)
Copper sulphate	ecoinvent Copper sulphate	(Wernet et al. 2016)
Essential plant oils (e.g., cinnamon)	AGRIBALYSE® 3.0	(AGRIBALYSE 2020)
Kaolin	ecoinvent Kaolin	(Wernet et al. 2016)
Mineral oil	ecoinvent Paraffin oil Other: kerosene oil has similar production processes and has been used in LCAs (Niccolo et al. 2018) For output emission proxy: Petrol, low sulfur production, used by AG for output"	(Wernet et al. 2016)
Neem seed oil	Diesel: 17.3 L/ha/y Electricity: 5.56 MJ/kg neem seed	(Kumar et al. 2021)
Nesidiocoris tenuis (predatory insect)	Needs further research	
Potassium soap	ecoinvent potassium hydroxide (KOH) + sunflower/vegetable oil (ratio of 100 g KOH:50 mL oil)	(Wernet et al. 2016)
Pyrethrin	Proxy: ecoinvent pyrethroid-compound production	(Wernet et al. 2016)
Reynoutria sachalinensis (giant knotweed) extract	Needs further research	
Spinosad	Electricity: 10.49 MJ/kg Spinosad Glucose: 0.055 g/kg Spinosad (These are the most impacting inputs, refer to Table S25 for full LCI)	Model: (Harding and Harrison 2016a, b) Data used for model: (Lu et al. 2017; Xue et al. 2013)

generating LCIs for microbial processes, as seen upon testing and comparing to literature studies (Harding 2008), but the authors state that if LCA comparison results are within 5% of each other, they may not be significantly different owing to uncertainty in the inputs and LCA inventory datasets. To generate the LCI for *Bacillus subtilis,* the CeBER model already contained an LCI for *B. subtilis*; thus, default values were cross-referenced and updated, if necessary, with literature data (Korsten and Cook 1996; Posada-Uribe et al. 2015; Rowe and Margaritis 2004). The same was done for Spinosad using the literature data in Table 5. These two new LCIs were judged to have an average DQR of 1.8 (derived from pedigree matrix values of 1,1,2,4,1, reliability, completeness, temporal correlation, geographical correlation, further technological correlation, respectively).

A new LCI was also created for Chitosan, a natural sugar-based pesticide and plant growth enhancer derived from the shells of crustaceans, using industrial production data from Pighinelli (2019) and Hoqani et al. (2020), where summarized data can be found in Table 5 and detailed data in Table S27. Table 5 also provides information on PPPs that already have LCI datasets, and where further research is still needed.

This data could be a first step towards making a more suitable proxy for organic-authorized PPPs in Europe, rather than the use of "pesticide unspecified" default datasets, as done in AGRIBALYSE®. This proxy could be created by calculating a weighted average of all organic-authorized PPPs used in Europe. However, further research is needed on market data and new manufacturing datasets for other missing and prevalent PPPs (Table 2).

With respect to accounting for the correct amount of copper active ingredient emission to the ecosphere (Sects. 3.1.2 and 3.1.3 for effects on LCA results), stoichiometry can be used to calculate the copper active ingredient mass from the dose of the copper compound. Table 6 shows the

Table 6 Percent of copper, Cu, (w/w) in each type of compound using stoichiometric ratios

Copper compound	Percent (%) Cu
Copper (II) sulphate	39.813
Copper (II) oxide	79.887
Copper oxychloride	59.509
Copper (II) gluconate	14.003

percent of copper in each relevant compound used as fungicides in agriculture. To calculate the amount of copper a.i. emitted, multiply the percent Cu by the dose of copper compound applied. For the apple example (Sect. 3.1.2), 41.072 kg copper sulfate/ha and 68.799 kg copper oxychloride/ha were applied on-field. To calculate the amount of copper a.i., multiply the dose by their corresponding % Cu in Table 6 (39.813% and 59.509%, respectively), to get 16.351 kg Cu and 40.941 kg Cu, respectively. Hence, by accurately accounting for copper emissions, freshwater toxicity results may be reduced since the amount of copper emitted to the soil has decreased.

4.3 Fertilizer inventory improvements

In order to improve organic fertilizer LCI proxies (Sect. 3.2.1), organic fertilizer LCIs should be used instead of mineral fertilizer proxies, such as those from Avadí et al. (2020) which were based on secondary data in France, follow a gate-to-gate scope, and resulted in an important step forward. A summary of default values for the average electricity, heat, and water needed for the treatment of organic residues under different treatment processes is shown in Table 7 derived from Avadí et al. (2020) and EI database. One may choose to adapt these processes to the country/region of the case study if data is available or use them as a proxy (and transparently reporting this and the possible uncertainties). However, adaptation is prioritized over the use of proxies, since variability in nutrient content and emissions from the manufacturing process and field application is very high, as we have seen in Sect. 3.2.2 and further supported by these studies (Hayashi et al. 2016; Montemayor

et al. 2019; Avadí 2020). Thus, an example of a methodology to create more representative organic fertilizer LCIs include the methodology proposed by Avadí (2020) and Avadí et al. (2020). Additionally, Koch and Salou (2016) outline a methodology for creating average mineral fertilizer datasets and could be used for organic fertilizer if usage and nutrient statistics are available for each organic fertilizer in that region.

Additionally, Table S3 provides suggestions regarding which LCI datasets from AG and EI could be used for each type of organic fertilizer or amendment permitted in OA in Europe. This work could be improved by the inclusion of other common commercial organic fertilizers and amendments such as pelletized cow manure and liquid vegetable-based fertilizers (based on our ORG + surveys, see Table 1), for instance, adapting the process for pelletizing poultry manure in EI to other types of pelletized animal manure, or use it as a proxy.

Additionally, a list of organic fertilizers and their nutrient content (Table S2) adds variability to which the user can find suitable proxies or compare nutrient composition data for common organic fertilizers. If applying LCA on a case-by-case basis, instead of at national or high level, it is important that the practitioner knows at the very least, the type/source of fertilizer used (e.g., cattle manure, poultry manure, digestate) and use only the values for these types of fertilizers due to the high variability in nutrient content among organic fertilizers. This will ensure that accurate nutrient values and, consequently, accurate emissions are estimated. Nutrient compositions given in Avadí et al. (2020) can also be used as a proxy if the production and use of organic fertilizers in France is similar to the practitioner's case study.

In terms of advancing fertilizer application emission modeling (Sect. 3.2.2), many dynamic emissions models exist that may be suitable for organic fertilizers, such as Daisy (Hansen et al. 2000) and Animo (Rijtema and Kroes 1991) which can be more dynamic than the SALCA model used by EI. These models have been reviewed in (Andrade et al. 2021) for their robustness and applicability in LCA, among other characteristics, and the practitioner can decide which is more suitable for their case. Indigo v3.0 (Bockstaller et al. 2020, submitted) is another model that looks at all types of emissions from

Table 7 Average of main resources needed for different organic treatments. Data are reported per 1 kg fresh mass input (own elaboration based on Avadi 2020 and ecoinvent database)

Treatment process	Output (kg)	Electricity (kWh)	Heat (MJ)	Water (kg)
Composting	4.40E-01	4.57E-03	3.99E-03	5.70E-03
Pelletizing	4.42E-04	4.87E-02	2.29E-01	
Digestate	9.30E-01	6.00E-03	1.28E-01	
Coffee processing (hulls, spent grounds)		6.60E-01	8.46E+00	8.57E+00
Olive processing		3.80E-01	0.00	3.28E+00
Pomace processing		3.00E-02	3.83E+00	0.00
Rendering of animal by-products		1.60E-01	4.37E+00	0.00

Table 8 Summary of critical analysis within LCA when assessing organic agriculture (OA) and the relevant recommendations and further research needed to advance in these aspects

Aspect	Critical aspects	Rationale for criticality	Recommendation(s)
Fertilizer manufacturing data	Production of organic fertilizers (treatment and recycling) often not included in LCA of organic crops	Additional processing flows need to be taken into account for representativeness and for fair comparison with mineral fertilizer production	Classify manure according to LEAP guidelines. Include upstream treatment and storage of organic residues in the life cycle of the product, using LCIs or methodology from Avadi et al. (2020), summarized in Table 5, and datasets suggested in Table S3
	Average mineral fertilizer production datasets were used in AGRIBALYSE® due to unavailable proxy for organic fertilizer production	Mineral fertilizers are prohibited in OA, and inclusion can cause high impacts in energy-related impact categories	Include only organic fertilizers to comply with OA regulations. Follow methodology from Avadi et al. (2020) or (Koch and Salou 2016). If organic fertilizer is the same as those in AG (Avadi et al. 2020), they can be used as proxies
Fertilizer emission modelling	No additional technical measures to reduce NH_3 emissions considered when modelling NH_3 emissions	Can under- or over-estimate NH_3 emissions and potential acidification and climate change if other more mitigating techniques are used. This can also affect NO_x (nitrification) and N_2O (denitrification) emissions	Account for fertilizer application techniques in NH_3 emissions modelling, using correction fractions such as in (Table S24, derived from Bittman et al. 2014; Soogard et al. 2002; Brentrup et al. 2000, Montemayor et al. 2019). Regulations on how fertilizers are applied to the field should be made
	Nutrient content for manure-based organic fertilizers is not adapted to organic agriculture	Manure used as fertilizer from factory farming is prohibited in organic agriculture	Take into account the diet-related N-flows in the organic animal farm to increase representativeness
		N-content in conventional manure is higher than organically sourced manure due to high protein feed	Further research is needed on N-content of organic farm-derived manure (or general difference between organic and conventionally-derived manure)
	Negative heavy metal (HM) emissions	Swiss Agricultural LCA (SALCA) methodology was used in AGRIBALYSE® (AG) and EI, but in AG, this caused negative toxicity impacts, practitioners may interpret this as advantageous	Negative HM emissions and toxicity scores should not be interpreted as complete export of HMs from the field, but rather as a result of uncertainty LCI data. Impact results should be reported separately from the total toxicity results. Further research needed in reducing uncertainty
	Unbalanced P in inventory and poor accounting of nitrate emissions	SALCA-P model used for P emissions, but often results in unbalanced P in inventory	Practitioners can use other more dynamic models that take these aspects into account: Indigo v3.0 (Bockstaller et al. submitted), Daisy (Hansen et al. 2000) and Animo (Rijtema and Kroes 1991), with meta-study by (Andrade et al. 2021)
		The COMIFER-Tailleur model used for NO_3^- emissions in AG, does not take into account dose and time of application	
Plant protection products (PPP)	"Pesticide unspecified" dataset was used as a proxy for unavailable PPP production datasets	This contains synthetic pesticides that are not authorized by OA regulations in Europe	More research needed to create a regional "average OA-authorised PPP" dataset to replace "average pesticide, unspecified"
	Lack of PPP manufacturing datasets	Possible exclusion of relevant burdens from manufacturing	New LCIs for a few PPPs have been created in the present study, or use suitable proxies for missing/prevalent OA-authorized PPPs given in Table 6
	Rotenone inventoried as emission output in AGRIBALYSE®	Though rotenone was permitted in France during the reference period of the datasets that use it, it is now prohibited since 2011 in Europe	Remove this emission output from the LCI if your reference period is after 2011 or if your crop does not use rotenone
	The total compound dose (e.g., copper sulphate) is often used as the emission, rather than the active ingredient Cu	Could over-estimate toxicity results, as the mass of e.g., copper sulphate is 2.5 × higher than the mass of copper within the compound	Use stoichiometry to calculate the amount of copper within the compound as the output emission (Table 7), especially if applied in solution or in acidic environments

fertilizers (N, P, K and HMs). It takes into account crop, climate, and soil characteristics, mineral and organic fertilizer characteristics, and a wide range of organic fertilizers and their nutrient content at the global scale, making it more versatile than SALCA and the model used by AG, as they are only applicable in Switzerland and France. The integration of the Indigo v3.0 model into the modeling used in AG is planned for the future. In regard to ammonia emission modeling from fertilizer application, correction factors are available (Table S24) and can be applied according to the weather conditions, fertilizer application machinery used (e.g., hoses, injection), and the time between fertilizer deposition and incorporation (Bittman et al. 2014; Brentrup et al. 2000; Søgaard et al. 2002). An example of its site-specific adaptation and use can be found in Montemayor et al. (2019). By changing the application technique of liquid slurry, the ratio of $N-NH_3$ emitted per total ammoniacal nitrogen (TAN) can range from 0% $N-NH_3$/kg TAN by injection to 48% $N-NH_3$/kg TAN emissions by broad sprayer, not incorporated, both in favorable weather conditions (Table S24).

4.4 Summary of recommendations for improvements

Table 8 summarizes critical arguments and our recommendations for improving organic LCI datasets.

5 Conclusion

LCA presents some gaps in the adequate assessment of organic land management practices and their effects on agroecosystems, as there is a lack of background inventory datasets for the manufacturing of organic fertilizers and plant protection products and insufficient emission modeling. Therefore, it is important that the users of organic agricultural product datasets such as those from ecoinvent and AGRIBALYSE® understand what limitations exist, as these can greatly affect the final LCA results. Practitioners should be fully aware of the limitations presented here, which are not clearly reported in the methodological documents of the databases. Users should account and adapt to regional differences including differences in organic agricultural policies such as prohibited practices and organic fertilizer composition. In the present study, the shortcomings of state-of-the-art organic agriculture LCI methodology were highlighted and suggestions on how to advance were given, such as:

- Creation of new LCIs for plant protection products used in organic agriculture
- Suggestions and examples on how to create more representative organic fertilizer LCIs

- Improve organic fertilizer and plant protection product emission modelling using recommended studies

The findings in the present article add much needed transparency regarding the limitations of available OA LCIs, offer guidance on how to make OA LCIs more representative, allow for more accurate comparisons between conventional and OA, and help practitioners to better adapt LCA methodology to OA systems. Further research is still needed in the creation of other plant protection product manufacturing datasets and regional organic fertilizers. LCA is an appropriate methodology to perform environmental assessment due to its comprehensive and system-based scope but it should be improved to better reflect organic agricultural practices.

Declarations

Competing interest The authors declare no competing interests.

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