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LCA FOR AGRICULTURE

Regional variability of emissions and environmental impacts in agricultural LCA: a product-level analysis

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Abstract

Purpose Emissions and resource use are influenced by soil and climate as well as by farm management. In addition, characterisation factors (CFs) used in life cycle assessment (LCA) to translate emissions and resource use into environmental impacts also depend on the location. The purpose of this study was to evaluate how regional differences in emissions, resource use, and CFs influence the variability of the environmental impacts of agricultural products from the perspective of an LCA practitioner.

Methods We examined four databases—AGRIBALYSE®, SALCA, WFLDB, and Agri-footprint®—differentiating both emissions/resource uses and their environmental impacts at the country level. Only the Agri-footprint® database had data from at least ten different countries considered sufficient for a statistical analysis. The country-specific environmental impacts of the products in Agri-footprint® were calculated according to the Swiss Agricultural Life Cycle Assessment (SALCA) method using Brightway and analysed for seven spatially explicit impact categories: water use, land occupation, terrestrial acidification, eutrophication, water scarcity, soil quality, and biodiversity.

Results and discussion Spatial differences in emissions, resources, and CFs contributed to the spatial variability of environmental impacts at the product level. For nutrient-related impacts, such as eutrophication and acidification, the spatial variability of the contributing emissions had a stronger influence than the variability of the CFs. This is evident for marine and freshwater eutrophication, where characterisation is assumed to be uniform across all countries. For biodiversity the variability in CFs was more dominant. Most of the impact categories showed more significant positive than significant negative correlations between agricultural land occupation and the impact score. A higher yield per area thus generally leads to lower impacts per product unit. In summary, a spatial differentiation is needed if the parameters driving the impacts show high spatial variability or have a strong influence on the emission, and this emission has an important contribution to the impact.

Conclusions Our analysis highlighted that emission fluxes and CFs significantly influence the spatial variability of midpoint-level environmental impacts. Inventory flows exhibited greater variability than CFs, except for the land-use-related impact categories. Most impacts correlated positively with agricultural land occupation, showing a strong effect on yield levels. Our results underlined the importance of accounting for the spatial variability of emissions and CFs to adequately reflect the environmental impacts of agricultural products. The results are primarily representative of European conditions and temperate regions, as Agri-footprint® mainly includes products cultivated in Europe.

Keywords Life cycle assessment · Agriculture · Regionalisation · Environmental impacts · Emissions · Impact pathway · Characterisation factors

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1 Introduction

The life cycle assessment (LCA) methodology was originally developed for the environmental impact evaluation of industrial processes throughout entire lifecycles and focused on global environmental impacts, such as cumulative energy demand or global warming (McManus and Taylor 2015). With the increasing number of LCA studies focusing on the primary sector, the role of regional differences has received increasing attention. Agriculture is one of the sectors where spatial differences are highly relevant.

In agriculture, the types and amounts of direct emissions vary with environmental conditions, such as climate, soil, and topography conditions, which themselves differ to a huge extent spatially and temporally (Reinhard et al. 2017). The variability of resources, emissions, and product output is further caused by different management (e.g. fertilisation, plant protection, irrigation, machinery use, and animal feed rations; Roesch et al. 2024). For example, ammonia (NH_3) emissions are higher in alkaline soils, sandy soils increase the risk of nitrate (NO_3) leaching, and a high slope increases the risk of soil erosion by water. Furthermore, the management of agriculture depends on site conditions. In arid zones, irrigation might be required, and soils poor in P need higher fertiliser rates. The yield also strongly depends on the soil and the climate. The factors driving the variability of environmental impacts are numerous and complex (Fig. 1), indicating the need for a better understanding to provide robust decision support.

In the last two decades, the literature has increasingly shown that the location of an emission may strongly affect impacts such as acidification and eutrophication (Hauschild and Potting 2005; Verones et al. 2020). In life cycle impact assessment (LCIA), characterisation factors (CFs) translate emissions into environmental impacts and are generally composed of multiple sub-factors following a cause-effect chain from emissions to midpoint impacts and finally endpoint impacts. The variety of environmental conditions, including the prevalence of nutrient limitations, requires regionalised CFs. For example, the LC-impact method (Verones et al. 2020) or the ImpactWorld+ method (Bulle et al. 2019) laid a special emphasis on the regionalisation of the CFs. The latter depends on soil and climate conditions

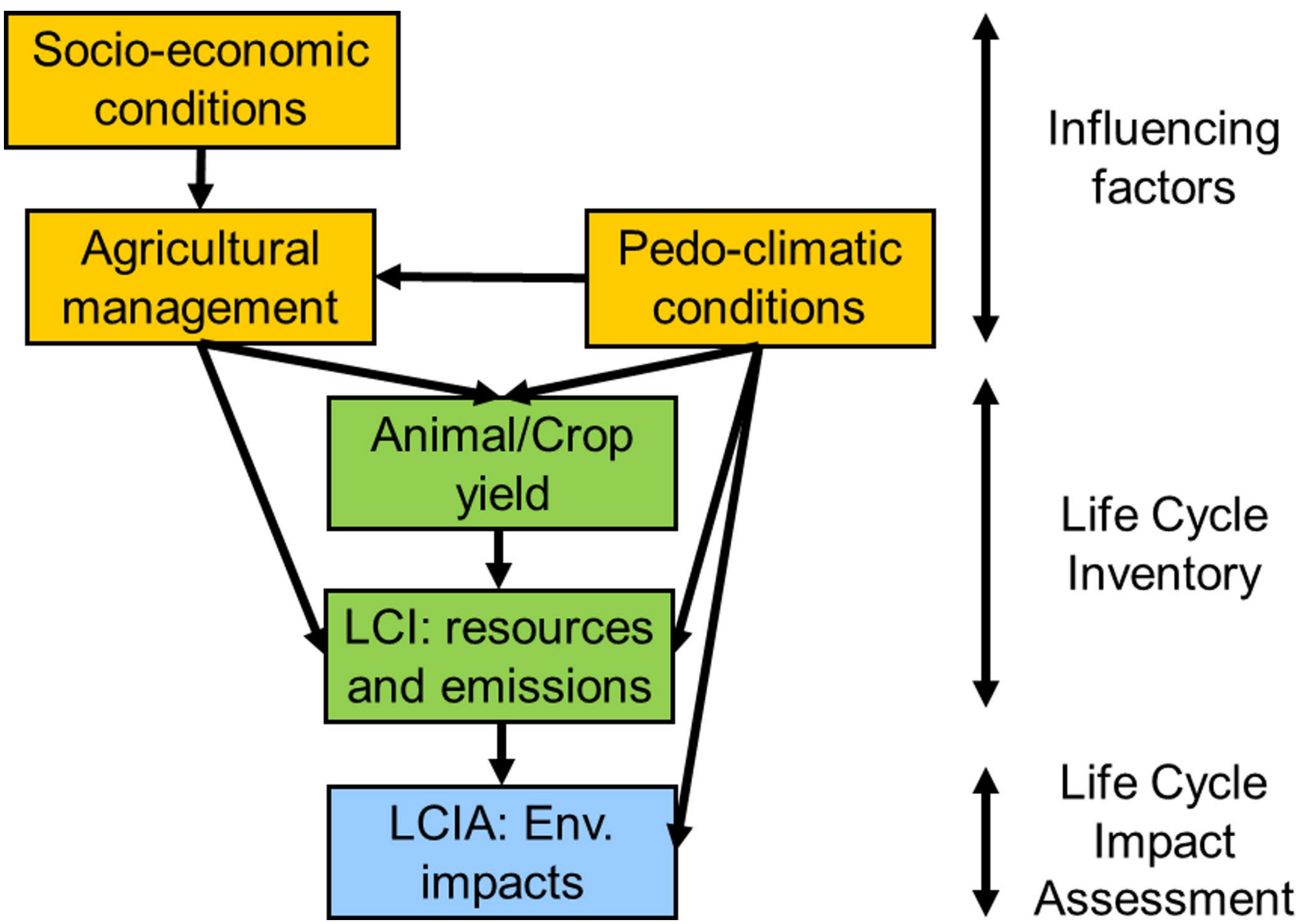

Fig. 1 Factors influencing the variability of environmental impacts. (adapted from Roesch et al. 2024).

and human population density for impacts on human health (Roesch et al. 2024).

Regional differences in inventory exchanges and the environmental impacts of agri-food systems are increasingly taken into account in recent LCA studies. Röös et al. (2010) showed that soil humus content and N_2O emission factor strongly influenced the climate impact of table potatoes, with yield shown to be the most important factor. Nemecek et al. (2012) analysed the global variability of climate impact for 27 crops, based on extrapolated impacts at country level. Climate impact was more variable per area unit than per kg, which means that part of the variability in the impacts per area could be explained by different yields. Yang et al. (2018) evaluated the impact variability of four major crops in the USA and found that the toxicity-related impact categories showed the highest variability. Liao et al. (2020) highlighted the crucial role of land-use change in the variability of the climate impact of plant-based spreads. A large regional variability in environmental impacts was also found for Italian olives (Gulotta et al. 2025) and Canadian pulses (Bamber et al. 2024). Poore and Nemecek (2018) showed that the best 10% of products have at least four times lower climate impacts than the worst 10% on a global scale. The variability is caused by different site conditions (climate, soil, and topography) on the one hand and by differences in management on the other. Consideration of regional variability is also crucial to achieving consistent assessments across spatial scales (Morais et al. 2017).

As the output of the product (typically a mass unit, such as kg) is generally used as the functional unit, the yield has a strong influence on the inventory exchanges and, eventually, on the impact scores. It is one of the key factors in the environmental impacts of agricultural products (Roches et al. 2010; Röös et al. 2010; van der Werf et al. 2020). For crops, this can be explained by the fact that some emissions and impacts are closely related to the occupied area, which is the inverse of the yield. Examples include soil erosion and nutrient leaching. A higher area will most likely increase such emissions and related impacts. For livestock production, a higher production intensity often comes with decreasing impacts. One of the reasons is that the energy and nutrient requirements for maintaining the animals are significant and independent of the production intensity. In such cases, the related environmental impacts will decrease per output unit as the yield increases. By contrast, higher yields require more inputs, such as fertilisers, pesticides, machinery use, or irrigation water, which in turn can increase the impact per product unit. Therefore, analysing the relationship between agricultural land occupation (ALO) and various impacts can provide useful insights into the driving factors of environmental impacts and a potential basis for adjusting impacts to different yield levels. To the best of our knowledge, a systematic analysis of yield or land occupation effects on the environmental impacts of agricultural products has yet to be conducted.

The variability of environmental impacts in the LCA of agricultural products stems from the combination of the variability of site factors and management that drive the emissions, affect resource use, and influence the yield on the one hand and the variability of CFs on the other hand (Fig. 1). Understanding these relationships is crucial for a more accurate and specific assessment. Thus far, LCA studies taking into account regional differences in agri-food systems are limited to a certain region, few impact categories, or selected products. A systematic analysis at the inventory and impact level that spans several impact categories and many products on a global scale is lacking.

Understanding the sources of variability is important for various stakeholders. Farmers can adapt their management to specific site conditions to mitigate impacts. They can also try to select adapted crops or optimise the animal production system. Policymakers can target subsidies to products and production systems to compensate for lower competitiveness due to environmentally friendly production or difficult production conditions (e.g. in mountain areas). Food manufacturers are committed to choosing ingredients with low environmental impacts. Understanding impact variability is needed for eco-labelling of food, so that retailers and consumers can select food products with low environmental impacts.

The overall objective of this study is to analyse the regional variability of the environmental impacts of various food products. In the databases analysed in this study, LCA data are generally provided at the national level. Consequently, the present analysis is limited to country-level data.

In particular, we investigated the following research questions:

1. What is the variability of relevant resources and emissions?
2. What is the variability of CFs?
3. How does the variability of elementary flows in the inventory and that of the CFs relate to the variability of the impact scores?
4. What is the effect of yield on impact scores?

Section 2 presents the data and methodology. The results for various products are shown in Sect. 3, followed by a discussion in Sect. 4. Conclusions and recommendations are provided in Sect. 5. The analysis in this paper was carried out using life cycle inventory (LCI) databases and LCIA methods available in current software tools.

2 Methods and data

2.1 Databases

We evaluated the following four databases for their suitability in our analysis: AGRIBALYSE®, SALCA, WFLDB, and Agri-footprint®. These four databases are often used in the context of agricultural LCAs. The analysis of the available data showed that only the Agri-footprint® database was suitable for our purpose, as it was the only database that provided product-specific LCIs at the country level for a sufficient number of countries. As detailed in Sect. 2.5, our statistical approach required country-level LCI data for more than ten countries per product. To avoid introducing additional variability resulting from methodological differences between databases, only one database was selected for analysis.

The Agri-footprint® database contains LCIs for the production of agricultural raw materials and their processing into animal feed. The Agri-footprint® database is therefore an essential data source for the Global Feed Lifecycle Institute (GFLI) database (Tyszler 2022). While the database has a strong geographic focus on Europe, other world regions are partially covered. In total, it includes country-level product LCIs for 63 countries. However, product coverage varies substantially between countries. The coverage is heavily skewed towards Europe: 20 European countries provide more than ten product LCIs, whereas only six non-European countries—Australia, Brazil, China, India, Russia, and the United States—meet this threshold. Emissions of N_2O, NH_3, NO_3, CO_2, NO_x, P, and heavy metals are calculated mainly using Tier-1 emission models from IPCC (IPCC 2019) and EMEP/EEA (European Environment Agency 2016). Exceptions are NH_3 emissions from mineral fertilisation (EMEP/EEA Tier-2), P emissions that are modelled with an emission factor based on the default modelling of ReCiPe described by Huijbregts et al. (2016), and heavy metal emissions, whose modelling followed that of Nemecek and Schnetzer (2011). Note that the prevailing Tier-1 modelling approaches imply that emissions are predominantly driven by differences in agricultural management practices (i.e. an input-oriented perspective), while pedoclimatic conditions are largely ignored.

2.2 Life cycle inventory indicators

LCI indicators are emissions or resources at the inventory level. We investigated regional variability for two LCI indicators: (i) water use and (ii) land occupation. These two LCI indicators directly influence land-related impacts: water use influences water scarcity, and land occupation influences soil quality and biodiversity.

2.2.1 Water use

Water use, expressed in cubic meters (m^3), represents the total amount of blue water consumed throughout the life cycle of the studied system. Blue water refers to water extracted from surface and underground sources, such as lakes, rivers, and groundwater. This LCI indicator essentially reflects the sum of all water uses recorded in the inventory (Frischknecht et al. 2007). The conversion from mass to volume is based on a standard water density of 1000 kg/m^3.

2.2.2 Land occupation

Land occupation, expressed in m^2a, is equal to the area of occupation (m^2) multiplied by the duration of occupation (a) required for a certain production process. This LCI indicator is based on the ReCiPe Midpoint Hierarchist v2008 method (Goedkoop et al. 2013). In this analysis, we focus exclusively on agricultural land.

2.2.3 Analysed emissions

Gaseous emissions of NH_3 and NH_4^+ from crop production and animal husbandry are mainly caused by fertilisation and manure management, that is, the decomposition of nitrogenous compounds from farm manure or the dissociation of the NH_4^+ contained in mineral fertilisers (Cameron et al. 2013; Riedo et al. 2002). NH_3 emissions depend on the local climate and soil conditions, such as air temperature and humidity or soil saturation deficit and pH. NH_3 has potentially adverse effects on human health, animal health, and the acidification and eutrophication of water bodies. The extent of the acidifying effect strongly depends on the background concentration and can therefore vary greatly from region to region (Hauschild et al. 2011). Leaching of NO_3 is a major source of nutrient loss from fertiliser applications (Wowra et al. 2021). It is largely influenced by soil type, water regime, and fertiliser management, such as the fertiliser type and the time of application. Nitrous oxide (N_2O) in agricultural soils is primarily produced by the microbial processes of nitrification and denitrification, both of which are enhanced by nitrogen fertilisation practices that increase inorganic nitrogen levels (Signor and Cerri 2013). Furthermore, NO_x comes from agricultural soils and combustion processes, for example, machinery use.

P can be discharged from agricultural land via leaching to groundwater, surface runoff, soil erosion, and drainage losses to surface waters (Cordell and White 2014; Prasuhn 2006), which causes eutrophication in aquatic ecosystems (Tilman et al. 2001). Various spatially highly variable factors, such as soil composition and slope gradient and the amount of soil erosion, influence the amount of P loss. The main source of SO_2 is the combustion of sulphur-containing fossil fuels in industries, power plants, and transportation (Zhong et al. 2020). The deposition harms plants by disrupting photosynthesis and leads to the acidification of soils and water bodies, thus seriously affecting vulnerable ecosystems.

2.3 Analysed midpoint impact categories

We chose LCIA categories with country-specific CFs. This excluded impact categories with constant CFs at the global level, such as climate change, ozone depletion, or abiotic resource depletion. For such categories, only the variability at the inventory level could be analysed. This further excluded toxicity-related impacts, for which CFs are provided at the continental or subcontinental level at maximum. We used the environmental impacts at the midpoint level following the SALCA-LCIA v2.01 methodology which combines LCIA methods best suited for the representation of agricultural processes. A detailed description can be found in Douziech et al. (2024) and a summary is given below. The evaluation of all LCIA categories was performed at the national level. The CFs of the analysed impact categories as well are provided in Online Resource 2.

2.3.1 Terrestrial acidification

This impact category quantifies the effect of acidifying substances emitted to the air on vulnerable terrestrial ecosystems. For agricultural systems, the impacts are dominated by emissions of NH_3, SO_2, and NO_x. Changes in acidity levels are potentially harmful to ecosystems. The terrestrial acidification model proposed in ReCiPe 2016 v1.1 (Hierarchist) was implemented in SALCA-LCIA v2.01 to evaluate the impact in kg of SO_2-equivalents of the emission of acidifying substances on ecosystems.

2.3.2 Eutrophication

Eutrophication refers to an increase in the levels of nutrients, such as P and N, in the environment. Freshwater eutrophication is, for example, responsible for algae bloom and, in turn, the disappearance of other freshwater species. Marine, freshwater, and terrestrial eutrophication are included in SALCA-LCIA v2.01. Marine eutrophication is mainly driven by N emissions, and freshwater eutrophication by P emissions, so they are sometimes referred to as N and P eutrophication. They are expressed in kg N-equivalent and kg P-equivalent. SALCA-LCIA v2.01 uses the models proposed in ReCiPe 2016 v1.1 (Hierarchist) for marine and freshwater eutrophication, and so follows the fate model recommendations of GLAM (Life Cycle Initiative 2022).

2.3.3 Water scarcity

We applied the AWARE method (Boulay et al. 2018) as a water scarcity (WS) midpoint indicator, quantifying the relative available water remaining per area in a watershed after the demand of humans and aquatic ecosystems has been met. Water use in AWARE refers to water extracted from lakes/rivers and groundwater (blue water), mainly for irrigation, to produce 1 kg of product. Production countries with missing information on blue water use, that is, countries with no irrigation applied, were not considered in the statistical evaluation. We ignored the water fluxes related to turbine use and cooling, as they are irrelevant in the context of agriculture.

2.3.4 Soil quality

The LANCA model quantifies soil quality impacts caused by different land use types (Bos et al. 2016). It accounts for five different soil functions covering several ecosystem services: erosion resistance, mechanical filtration, physicochemical filtration, groundwater regeneration, and biotic production. De Laurentiis et al. (2019) derived a single-score soil quality index (SQI) by aggregating and rescaling the "Occupation" CFs from the LANCA model to enable the quantification of impacts on soil quality. The model considers soil quality in more general terms and can therefore be applied to any geographical context as well as to soil-quality impacts of non-agricultural activities (e.g. through resource extraction or construction work), but it is not sensitive to agricultural practices. The unit of the SQI is in points per m^2 and year. The highest values are assigned to artificial areas, while the lowest (i.e. the best) values are assigned to wetlands. Negative impact scores indicate a potential improvement against the reference situation.

2.3.5 Land use – biodiversity – species loss potential

Chaudhary and Brooks' (2018) method uses species–area relationships to estimate the potentially disappeared fraction (PDF) of species due to a specific land use or land use change. It distinguishes between five land use types (forest, plantation, cropland, grassland, and urban) and three intensity levels for each land use type. The effect on five indicator species groups (plants, reptiles, amphibians, birds, and mammals) is taken into account. The method provides regional, national, and global CFs. Regional factors describe the potential of land use or land use change to eliminate species in the ecoregion where the land use occurs, while global factors describe the potential to eliminate species globally and thus emphasise the damage caused by products from regions with a high number of threatened or endemic species (Chaudhary and Brooks 2018). This method was recommended by the second GLAM phase (Life Cycle Initiative 2022).

2.4 Statistical evaluation

The analysis was carried out at three levels:

1. The CFs for all countries (only LCIA, see Sect. 2.4.1),
2. Variability of foreground emissions, related CFs and environmental impacts for the countries in the sample $N \geq 10$ (LCI and LCIA, see Sect. 2.4.2),
3. Relationships between environmental impacts over the full life cycle and ALO for the countries in the sample $N \geq 10$ (LCIA, see Sect. 2.4.3).

The detailed formulas for the statistical evaluation are provided in Online Resource 1.

2.4.1 Key statistical measures for characterisation factors

The distribution of all country-specific CFs as implemented in SimaPro was assessed by providing quartile values and the coefficient of variation (CV), that is, the ratio of the standard deviation to the mean.

2.4.2 Product level: variability for inventories, characterisation factors and environmental impacts

For each product and impact category, we calculated the CV of the contributing emissions and its associated CFs. This allows variabilities to be made comparable across different emissions and impact categories. Low values of CV indicate a narrow distribution, while higher values indicate a wide distribution. Assuming a positive arithmetic mean, CV < 1 and CV > 1 imply that the standard deviation (SD) is smaller or larger than the arithmetic mean. For simplicity, we labelled the CV of the characterisation factor as *CV_CF*, and the CV of the environmental impacts at the midpoint level as *CV_LCIA*. The CV of an impact category labelled with two capital letters *XY* will be called *CV_XY*, for example, CV_TE for terrestrial eutrophication (TE). To ensure that only meaningful results are presented and discussed, we ignored emissions and resources that contribute less than 3% to the total impact.

We restricted the analysis to products for which LCIs were available for more than ten countries to ensure reasonably robust statistical results. Note that there is no universal threshold guaranteeing solid measures across all statistics. A quantitative justification for how the sample size affects the accuracy of basic statistical measures has been provided by Schillaci (2022). Several empirical studies have suggested that key statistical measures become sufficiently accurate for sample sizes above 10–30 (Kelley 2007; Memon et al. 2020; Lakens 2022). Thus, the threshold $n = 10$ is a pragmatic rule of thumb between accuracy and feasibility. We emphasise that the accuracy (e.g. the 95% confidence interval) depends not only on the sample size but is also influenced by, for example, the distribution and the data quality of the given country-specific product LCIs. Furthermore, we stress that the number of production countries varies by product, since agricultural crops require specific climatic conditions for growth.

To ensure a fair comparison of the variability of emissions and impacts, it is important to note that, for any given product, we took only the emissions in the foreground unit process into account. The system boundary was therefore the country of production.

2.4.3 Correlations between land occupation and environmental impacts

The environmental impacts of agricultural products are influenced by multiple factors, including yield, irrigation practices, fertiliser application, pesticide use, and pedoclimatic conditions. Among these, yield is a key driver of the variability of environmental impacts, particularly because impacts are commonly expressed per kilogram of product. The influence of yield on the environmental impacts of agricultural products has been debated for a long time (Nemecek et al. 2012; van der Werf et al. 2020). To test the hypothesis that higher yields result in lower environmental impacts per product unit, we calculated the correlation between various impacts and ALO (m^2a/kg), which corresponds to the inverse of the yield (kg/(m^2a)). ALO was chosen instead of yield, since the relationship of environmental impacts to yield will follow a non-linear hyperbolic function in case of a constant impact per area, while the relationship of environmental impacts to ALO will be roughly linear for that case. Therefore, a positive correlation between environmental impacts and ALO signifies decreasing environmental impacts per kg, a negative correlation in turn increasing impacts per kg. We calculated correlations between different environmental impacts (according to Douziech et al. 2024) and ALO. To avoid artefacts, we excluded the impact categories directly related to land occupation. In contrast to our analysis of the variability of emissions and impacts (where we only considered the foreground emissions, see Sect. 2.4.2), we are here considering the ALO and environmental impacts over the entire life cycle. A Spearman rank correlation analysis was performed between ALO and environmental impacts. Although the rank correlation is less powerful than the parametric Pearson correlation analysis, we chose the former, as many of the distributions are not normal and skewed. Furthermore, non-parametric analysis is less prone to influential outliers. Significant correlations were considered at the 5% level.

3 Results

3.1 Inter-country variability of CFs

We begin by presenting key statistics for the currently implemented national CFs in SimaPro at the midpoint level. National CFs are provided for 242 countries. Table 1 provides an overview of the spatial variability of national CFs according to Douziech et al. (2024), as implemented in SimaPro. The spatial variability of the CFs strongly depended on the impact category: the CVs were highest for biodiversity, followed by water scarcity, terrestrial acidification, and terrestrial eutrophication. For marine and freshwater eutrophication, the national CFs were identical for all countries worldwide. For NOx emissions contributing to terrestrial eutrophication, identical values were set for a substantial share of all countries.

Spatially explicit CFs at the country level often do not reflect the native spatial scale used for these CFs. The CFs for AWARE, for example, are originally at the watershed scale but are aggregated at the country level to match the common spatial resolution of LCIs. In addition, some CFs implemented in SimaPro are assumed to be identical worldwide, or use constant values for large parts of the world,

Table 1 Key statistics of national CFs at the midpoint level for the current SimaPro version

(a)

Midpoint	Emission	Unit of CF	Compartment	Subcomp.	Min	Q1	Median	Q3	Max	CV
TE	Ammonia	mol N-eq/kg	Air	unspec.	1.085	13.47	13.47	13.47	21.2	0.24
TE	Nitrogen dioxide	mol N-eq/kg	Air	unspec.	0.3	4.26	4.26	4.26	4.26	0.27
TE	Nitrogen monoxide	mol N-eq/kg	Air	unspec.	constant (CF=6.53)					
TA	Ammonia	kg SO_2-eq/kg	Air	unspec.	0.01	0.14	0.31	0.73	1.96	1.1
TA	Nitrogen dioxide	kg SO_2-eq/kg	Air	unspec.	0.01	0.14	0.31	0.51	1.34	0.75
TA	Nitrogen monoxide	kg SO_2-eq/kg	Air	unspec.	0	0.22	0.48	0.77	2.05	0.75
TA	Sulphur dioxide	kg SO_2-eq/kg	Air	unspec.	0	0.45	1	1.39	3.61	0.72
TA	Sulphur trioxide	kg SO_2-eq/kg	Air	unspec.	0	0.36	0.8	1.11	2.89	0.72
ME	Nitrogen	kg N-eq/kg	Water	unspec.	constant (CF=0.297)					
ME	Nitrogen	kg N-eq/kg	Water	Ocean	constant (CF=1.0)					
ME	Nitrogen	kg N-eq/kg	Soil	unspec.	constant (CF=0.126)					
ME	Nitrate	kg N-eq/kg	Water	unspec.	constant (CF=0.0671)					
ME	Nitrogen	kg N-eq/kg	Water	Ocean	constant (CF=0.226)					
FE	Phosphate	kg P-eq/kg	Water	unspec.	constant (CF=0.33)					
FE	Phosphorus	kg P-eq/kg	Water	unspec.	constant (CF=1.0)					

(b)

Midpoint	Resource	Unit of CF	Compartment	Subcomp.	Min	Q1	Median	Q3	Max	CV
WS	Water, lake/river	m^3/m^3	water withdrawal for any purpose		0	2.2	12.51	48	96	1.06
SQ	Occupation, annual crop	Pt/m^2a	Land	unspec.	-45.1	50.2	63.8	107.7	250	0.73
SQ	Occupation, grassland/pasture	Pt/m^2a	Land	unspec.	-46.3	35.6	55.2	82.2	179.1	0.73
SQ	Occupation, permanent crop	Pt/m^2a	Land	unspec.	-45.1	50.2	63.8	107.7	250	0.73
BD	Occupation, annual crop	PDF year/m^2a	Land	unspec.	0	5.52E-16	2.11E-15	6.94E-15	1.51E-13	2.18
BD	Occupation, grassland/pasture	PDF year/m^2a	Land	unspec.	0	2.89E-16	1.29E-15	3.77E-15	1.61E-13	2.54
BD	Occupation, permanent crop	PDF year/m^2a	Land	unspec.	0	3.41E-16	1.51E-15	4.76E-15	1.48E-13	2.38

CV: coefficient of variation; Q1=1st quartile, Q3= 3rd quartile

(a) TE: terrestrial eutrophication; TA: terrestrial acidification; ME: marine eutrophication; FE: freshwater eutrophication. Unspec.: the subcompartment is not relevant/refers to all possible subcompartments

(b) WS: water scarcity (AWARE); SQ: soil quality (LANCA); BD: biodiversity (Chaudhary). AWARE CFs refer to water withdrawal from lakes and rivers for any purpose (e.g. irrigation) thus representing a further simplification. If possible, working with the native spatial scale of the CFs will increase the accuracy of the estimates.

3.2 Spatial variability of emissions and midpoints

Note that the results for the country–product combinations are limited to the available data and therefore cover fewer countries than those presented in Table 1. We provide separate analyses of the spatial variability of the emissions, resources, and CFs, allowing a separate analysis of their contribution to the respective midpoint. Terrestrial acidification and terrestrial/marine/freshwater eutrophication are assessed in detail, as these nutrient-related midpoints show pronounced regional variability at both the inventory and impact levels.

3.2.1 Terrestrial acidification

Table 2 shows that the variabilities in the terrestrial acidification (TA) impact differed substantially among the 18 investigated products. As for TE, the two emissions NH_3 and NO contributed to TA. The number of countries with valid LCI data varied between 13 (beans) and 41 (wheat grain). The differences between the products can be attributed to differences in countries (name and number) and product-dependent cultivation methods. The variability of the NH_3 emissions (CV = 0.81) was slightly higher than that

Table 2 Spatial variability of emissions contributing to terrestrial acidification (TA). The CV for emissions (CV_E), for the respective CFs (CV_CF), and for the resulting impact TA (CV_TA) caused by this emission are provided for all products where the Agri-footprint® database contained data for more than 10 countries. For TA, the compartment is always 'air'. Note that the number of countries differs between the analysed agricultural products. Emissions that contribute less than 3% to TA were ignored

Product	Emission	Compartment	# countries	CV_E	CV_CF	CV_TA
Barley grain, at farm	Ammonia	air	38	1.340	0.386	1.063
Barley grain, at farm	Nitrogen monoxide	air	38	0.811	0.386	0.660
Beans, dry, at farm	Ammonia	air	13	0.962	0.413	1.112
Beans, dry, at farm	Nitrogen monoxide	air	13	0.920	0.413	1.118
Groundnuts, with shell, at farm	Ammonia	air	16	0.517	0.529	0.932
Groundnuts, with shell, at farm	Nitrogen monoxide	air	16	0.614	0.529	1.056
Linseed, at farm	Ammonia	air	25	1.753	0.286	1.915
Linseed, at farm	Nitrogen monoxide	air	25	1.663	0.287	1.827
Maize, at farm	Ammonia	air	36	1.014	0.457	1.173
Maize, at farm	Nitrogen monoxide	air	36	1.052	0.457	1.175
Oat grain, at farm	Ammonia	air	36	0.844	0.333	0.729
Oat grain, at farm	Nitrogen monoxide	air	36	0.535	0.333	0.493
Peas, dry, at farm	Ammonia	air	31	0.759	0.295	0.848
Peas, dry, at farm	Nitrogen monoxide	air	31	0.700	0.295	0.766
Potatoes, at farm	Ammonia	air	34	0.543	0.265	0.553
Potatoes, at farm	Nitrogen monoxide	air	34	0.359	0.265	0.408
Rapeseed, at farm	Ammonia	air	34	0.612	0.343	0.736
Rapeseed, at farm	Nitrogen monoxide	air	34	0.459	0.343	0.587
Rice, at farm	Ammonia	air	23	0.743	0.471	1.135
Rice, at farm	Nitrogen monoxide	air	23	0.600	0.471	0.971
Rye grain, at farm	Ammonia	air	30	0.895	0.246	0.846
Rye grain, at farm	Nitrogen monoxide	air	30	0.676	0.247	0.530
Sorghum grain, at farm	Ammonia	air	13	0.542	0.470	0.613
Sorghum grain, at farm	Nitrogen monoxide	air	13	0.485	0.470	0.623
Soybeans, at farm	Ammonia	air	29	0.650	0.448	0.777
Soybeans, at farm	Nitrogen monoxide	air	29	0.585	0.448	0.747
Sugar beet, at farm	Ammonia	air	22	0.526	0.237	0.577
Sugar beet, at farm	Nitrogen monoxide	air	22	0.271	0.237	0.366
Sugar cane, at farm	Nitrogen monoxide	air	14	0.488	0.690	1.073
Sugar cane, at farm	Ammonia	air	14	0.484	0.690	1.073
Sunflower seed, at farm	Ammonia	air	26	0.674	0.418	0.650
Sunflower seed, at farm	Nitrogen monoxide	air	26	0.484	0.418	0.607
Triticale grain, at farm	Ammonia	air	21	0.784	0.228	0.744
Triticale grain, at farm	Nitrogen monoxide	air	21	0.514	0.228	0.427
Wheat grain, at farm	Ammonia	air	41	0.867	0.390	0.823
Wheat grain, at farm	Nitrogen monoxide	air	41	0.507	0.390	0.557

of NO emissions (CV = 0.65). The high variability of the linseed results can be explained by the high variability of the yields. The two contributing emissions NH_3 and NO had the same CV_CF for the analysed product-country combinations, indicating that their CFs were correlated. Averaged over all analysed products and emissions, the CVs were 0.73 and 0.38 for the emissions and CFs, respectively. Thus, the emissions were spatially almost twice as variable as their CFs. The mean CV_TA was 0.84 (Table A2 in Online Resource 1).

In summary, this evaluation revealed that the variability of the emissions (expressed as CV_E) was higher than the variability of the associated CFs (expressed as CV_CF). As emissions are closely related to different production methods and management practices, such as manure application, the use of machinery, and local climatic conditions, it is crucial to assess these factors to improve the accuracy of (regional) emission fluxes. Figure 2 shows the distribution of the CVs of emissions, CFs, and impact scores across all products.

3.2.2 Eutrophication (terrestrial/ marine/ freshwater)

We describe the results from the analysis of the emissions and characterisation of terrestrial eutrophication (TE), followed by those of marine eutrophication (ME) and freshwater eutrophication (FE). Table A1 (Online Resource 1) shows that the regional variability of the emission fluxes contributing to TE strongly varied among the different analysed products: both emissions related to linseed varied most among the 25 production countries (with CV_E above 1.6), while the variability was clearly lower for the other analysed products and lowest for NO emissions in sugar beet cultivation (CV_E = 0.27; see Table A1, Online Resource 1). Again, the result for linseed could be explained by the high variability in the yields.

As the main emissions contributing to TE and TA were the same (NH_3 and NO), it was evident that the CV_E averaged over all 18 analysed agricultural products was also identical for those two substances (CV_E = 0.729). For TE, the mean CV_CF was 0.24, which was lower than that for CV_E. While the national CFs for NO were identical (CV_CF = 0), they substantially differed for NH_3. The spatial variability of NH_3 emissions was significantly higher than its characterisation, with CV for emissions and CFs equalled 0.48 and 0.81, respectively.

Comparing TE with TA revealed that CV_TE was lower than CV_TA, as the regional CFs of TE for NO emissions were site-generic; that is, they were identical for all producing countries (CV_CF = 0). It is noteworthy that the variability of the CFs related to NH_3 averaged over all 18 analysed products was distinctly higher for TE than TA (CV_CF = 0.48 for TE and CV_CF = 0.38 for TA), thus leading to a higher mean variability of TE than TA (CV_TE = 0.99 and CV_TA = 0.91 for NH_3).

Figure 3 summarises the key statistical results for the spatial variability of eutrophication and its contributing

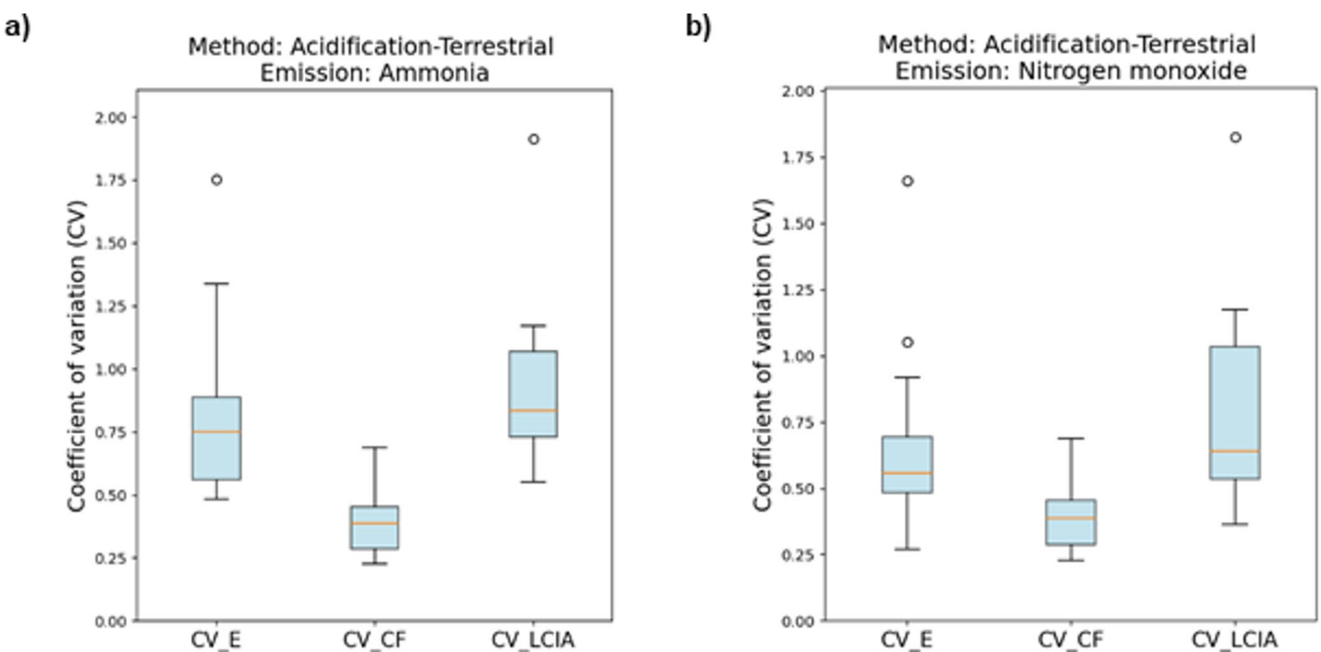

Fig. 2 Spatial variability of emissions contributing to TA over 18 agricultural crops (as listed in Table 2). Data source: Agri-footprint® database. Boxplots for CV_E, CV_CF, and CV_LCIA. Panel (**a**) TA induced by ammonia emissions; (**b**) TA induced by nitrogen monoxide emissions. Both ammonia and nitrogen monoxide are emitted into the compartment 'air'

emissions. The median of the CV for all emissions contributing to TE/FE/ME was between 0.55 and 0.75—that is, the standard deviation (SD) was between 55% and 75% of the mean. Figures 2 and 3 reveal that for both TA and TE/FE/ME, the emissions showed a larger interquartile range (the range between the first and third quartiles) than the CFs.

Figure 3c and d show that the CFs for both FE and ME were identical for all production countries (CV_E = CV_LCIA and thus CV_CF = 0). The spatial variability of the P and NO_3 emissions was thus identical to the variability of FE/ME, since the national emissions are always multiplied by the same (constant) CF.

3.2.3 Biodiversity

The LCI for biodiversity refers to the land occupation of the investigated products. Therefore, *CV_LU* describes the spatial variability of the arable land area required to produce 1 kg of product. Across all 18 products, the average CV_LU was 0.47, indicating that the standard deviation was approximately 47% of the mean land use per kg of product (Table 3).

As an initial approximation and assuming that land use in upstream supply chains is negligible, the mean land use per kg of product (m^2a/kg) can be interpreted as the inverse of the crop yield (kg produced/(m^2a)). Table 3, column CV_LU, reveals that the spatial variability of land use (at the country level) significantly differed among the products. The CV for sugar cane, based on data from 14 producing countries, was 0.21, indicating relatively low spatial variability in land use per kg of product. By contrast, linseeds showed a much higher CV of 0.90 across 25 producing countries, meaning that the SD of land use was nearly equal to the mean. This implies that the spatial variability in yields for sugar cane was much lower than that for linseed.

The averages over all 18 analysed products for CV_LU and CV_CF were 0.47 and 0.88, respectively. This suggests that the characterisation contributed more to the total spatial variability of the BD midpoint than to differences in land use (and, thus, yield amounts). The differences in the spatial variability of CF, expressed as *CV_CF* (Table 3),

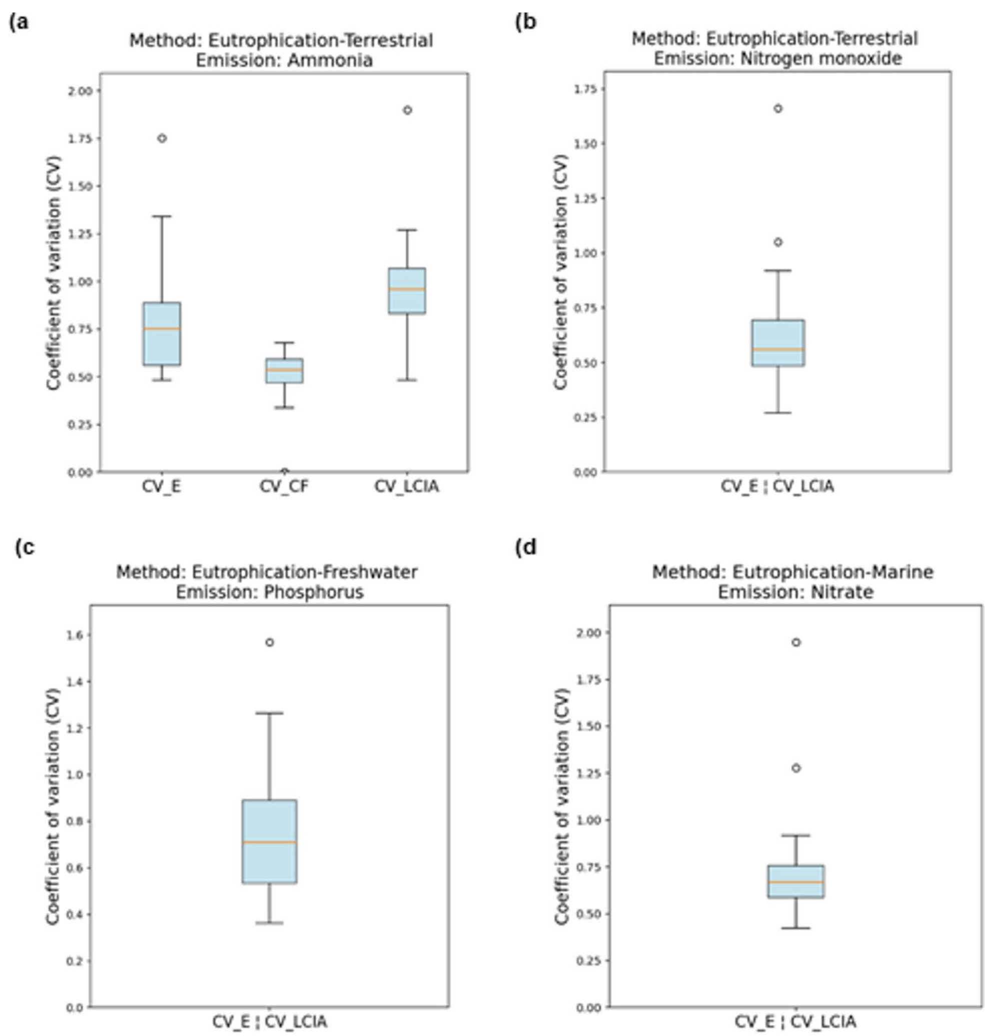

Fig. 3 Spatial variability of emissions contributing to TE, FE, and ME. Data for 18 agricultural crops (as listed in Table 2). Data source: Agri-footprint® database. Boxplots for CV_E, CV_CF, and CV_LCIA. (**a**)/(**b**): TE for ammonia and nitrogen monoxide emissions, respectively; (**c**) FE induced by phosphorus emissions; (**d**) ME induced by nitrate emissions. Nitrate and phosphorus fluxes are emitted into water, ammonia, and nitrogen monoxide into air

Table 3 Spatial variability of the biodiversity (BD) score to produce 1 kg of the product. CV_LU refers to the spatial variability of land use (LU) required to produce 1 kg of the product. CVs given for all products for which the Agri-footprint® database contains data for more than 10 countries. Note that the number of countries differs between the analysed agricultural products

Product	Resource	Compartment	# Countries	CV_LU	CV_CF	CV_BD
Barley grain, at farm	annual crop	land	38	0.585	1.167	2.658
Beans, dry, at farm	annual crop	land	13	0.417	0.673	0.777
Groundnuts, with shell, at farm	annual crop	land	16	0.647	0.885	0.997
Linseed, at farm	annual crop	land	25	0.897	0.761	1.408
Maize, at farm	annual crop	land	36	0.413	0.947	1.221
Oat grain, at farm	annual crop	land	36	0.451	1.184	1.813
Peas, dry, at farm	annual crop	land	31	0.354	0.742	0.832
Potatoes, at farm	annual crop	land	34	0.376	1.189	1.343
Rapeseed, at farm	annual crop	land	34	0.387	0.769	1.060
Rice, at farm	annual crop	land	23	0.393	0.835	1.111
Rye grain, at farm	annual crop	land	30	0.576	0.815	1.293
Sorghum grain, at farm	annual crop	land	13	0.653	0.908	1.126
Soybeans, at farm	annual crop	land	29	0.332	0.923	1.175
Sugar beet, at farm	annual crop	land	22	0.278	0.708	0.739
Sugar cane, at farm	annual crop	land	14	0.206	0.830	0.822
Sunflower seed, at farm	annual crop	land	26	0.474	0.856	1.332
Triticale grain, at farm	annual crop	land	21	0.420	0.614	0.980
Wheat grain, at farm	annual crop	land	41	0.630	1.103	2.121

were relatively minor across the individual products. This relates to the fact that the land use type "annual crop" was assigned to all products. The observed variability in the CF, therefore, primarily reflects the species loss observed for this land use type. The spatial variability of biodiversity impacts (*CV_BD*, Table 3) for several cereals, such as wheat, oat, and barley, were often in the upper range, while sugar beet/sugar cane and peas/beans showed the lowest *CV_BD* values among the 18 analysed agricultural products. On the one hand, this resulted from differences in yields that transformed into different ALOs. On the other hand, the countries where the crops were grown had more or less different CFs. For example, CV_LU was quite similar for wheat and groundnuts, indicating a similar variability of yields. However, the CFs varied much more for wheat than for groundnuts, eventually driving impacts that were much more variable for wheat. The opposite was also observed: CV_CF was very similar for barley and potato, while CV_LU was higher for barley, resulting in a much higher variability in biodiversity impacts.

3.2.4 Soil quality

The spatial variability at the country level for soil quality using the LANCA model is shown in Table A3 (Online Resource 1). CV_LU was identical to biodiversity, as shown in Table 3. The mean of CV_LU and CV_CF for all 18 agricultural products was very similar and amounted to 0.47 and 0.46, respectively. This implies that the spatial variation for the arable land used to produce 1 kg of the product was similar to the spatial variability of the CFs in the respective producing countries. This fell between the other midpoints analysed, with the mean CV_CF being lower than CV_E for eutrophication and acidification, or higher for biodiversity. This was at least partly due to the representation of soil quality in the LANCA model, which assumes a similar or equal effect of annual crop production on ecosystem quality—expressed as country-specific CFs—for 'reasonably large' groups of countries.

3.2.5 Water scarcity

Table A4 (Online Resource 1) shows the spatial variability of blue water used for the 12 products with non-zero water demand (for irrigation). The evaluation revealed a large spatial variability in water use (blue water demand) for all products, with an average CV_WU of 1.77, suggesting that irrigation strongly differed among the different production countries. The average was 1.15 for CV_CF and 2.25 for CV_WS. This was the highest variability among the investigated impact categories.

Table A4 clearly reveals that both the spatial variability of WU and its characterisation were generally high for the analysed agricultural products, with CV_WU and CV_CF often above 1. Despite large regional differences in the average water remaining to cover human and environmental water consumption, the mean spatial variability of CV_WU was higher than that of CV_CF. This indicates that spatial differences in water use through irrigation varied more than water scarcity in the respective countries. However, there is also a synergistic effect: in arid countries, the need for irrigation is high, with water scarcity also tending to be high, eventually resulting in a very high spatial variability.

3.3 Relationship between land occupation and environmental impacts

As shown in the previous analyses, yield and ALO were relevant factors for environmental impacts. We systematically analysed this relationship for all impact categories. We found a clear prevalence of positive over negative correlations between ALO and most midpoint impact indicators if only significant relationships were considered (Fig. 4). Overall, 43% of the correlations between land occupation and the analysed environmental impacts showed significant positive, 2% showed significant negative, and 55% showed non-significant relationships. Given the strong variability observed in the data, these findings are remarkable. They confirm the hypothesis that a higher yield, implying a lower land occupation, tends to lead to lower environmental impacts per kg in most impact categories.

Relevant differences were found according to the considered impact category (Fig. 4). Land-use related categories, such as biodiversity, land transformation, and soil quality, showed a close dependency on the occupied area with many positive correlations and high correlation coefficients R. Therefore, the differences in land occupation were higher than the differences in the quality of the land use (i.e. impact per area unit). The same finding was observed for climate change, ozone formation, particulate matter, and water scarcity/water use. The picture was less clear for ecotoxicity, eutrophication, acidification, and ozone depletion, for which negative correlations were more frequent and the R values lower. For marine eutrophication, which was driven by N emissions to water, negative correlations prevailed. Therefore, it seems that for impact categories driven by N losses (with dominating emissions in brackets: terrestrial acidification [NH_3], marine [NO_3] and terrestrial eutrophication [NH_3], and ozone depletion [N_2O]), a higher N fertilisation intensity tended to increase the impacts per kg. This was also partly the case for ecotoxicity, mainly driven by the use of pesticides and heavy metal pollutants.

Next, we analyse the same dataset by product. Most of the investigated products followed the same trend: positive correlations clearly prevailed, and the correlation coefficients were quite high (Fig. 5). The three livestock products showed particularly high R and many significant positive correlations. A notable exception was sugar beet, with negative R and prevailing negative correlations. This could be because the yield of sugar beet is less driven by fertiliser than, for example, cereals, and high N rates favour shoot growth and can be detrimental to quality. The positive trend was also less pronounced for beans, groundnut, and rapeseed. The former two are legumes, not needing any N fertiliser, which could explain the different relationships.

4 Discussion

4.1 Spatial variability of inventory exchanges, characterisation factors and impact scores

Our results show that the spatial variability of emissions for a specific agricultural product grown in different countries exceeds the variability of national CFs for several impact categories. This suggests that the variability of the impact score is driven more by the LCI than by the LCIA. This is, for example, the case for terrestrial acidification (Fig. 2), terrestrial eutrophication (Fig. 3a), and water scarcity (Table A4). We acknowledge that these results are based on the LCIA methods, as they are implemented in the LCA database and software. The contrary was observed for biodiversity (Table 3); with the exception of linseed (due to its high yield variability), the CFs showed a higher variability than the related inventory flows. This is because species extinction risk—and consequently the corresponding CFs—can greatly vary across countries, whereas land occupation, the inventory flow driving biodiversity impacts in the considered LCIA method, varies less (Scherer et al. 2023; Ball et al. 2025). Regarding soil quality, assessed by the LANCA method, the results are intermediate: the inventory flows showed more variability for half of the products, while for the others, the CFs were more variable. It seems, therefore, that the sources of the variability of land use-related impacts, such as biodiversity and soil quality, are different from those of the variability of impacts related to nutrient losses or water scarcity.

In most cases, the variability in the final impact assessment results was higher than the variability in the emissions (CV_E) (or CV_LU soil quality and CV_WS for water scarcity) and in the characterisation factor (CV_CF). This seems logical since the impact is the product of the emission or resource use and its associated characterisation. We expect the product of two independent random variables to have a higher variability than both of these variables, and therefore, we expect the highest value for CV_LCIA. However, the analysis revealed a few exceptions, mostly linked to terrestrial acidification. The variability in emissions (CV_E) for ammonia was higher than CV_LCIA for the following six out of the 18 analysed products: barley grain, oat grain, rye grain, sunflower seed, triticale grain, and wheat grain (see Table 2). This indicates that in these cases, the two variables were not independent, and in fact, we found negative correlations between the country-specific emissions and the associated characterisation (although mostly non-significant) in

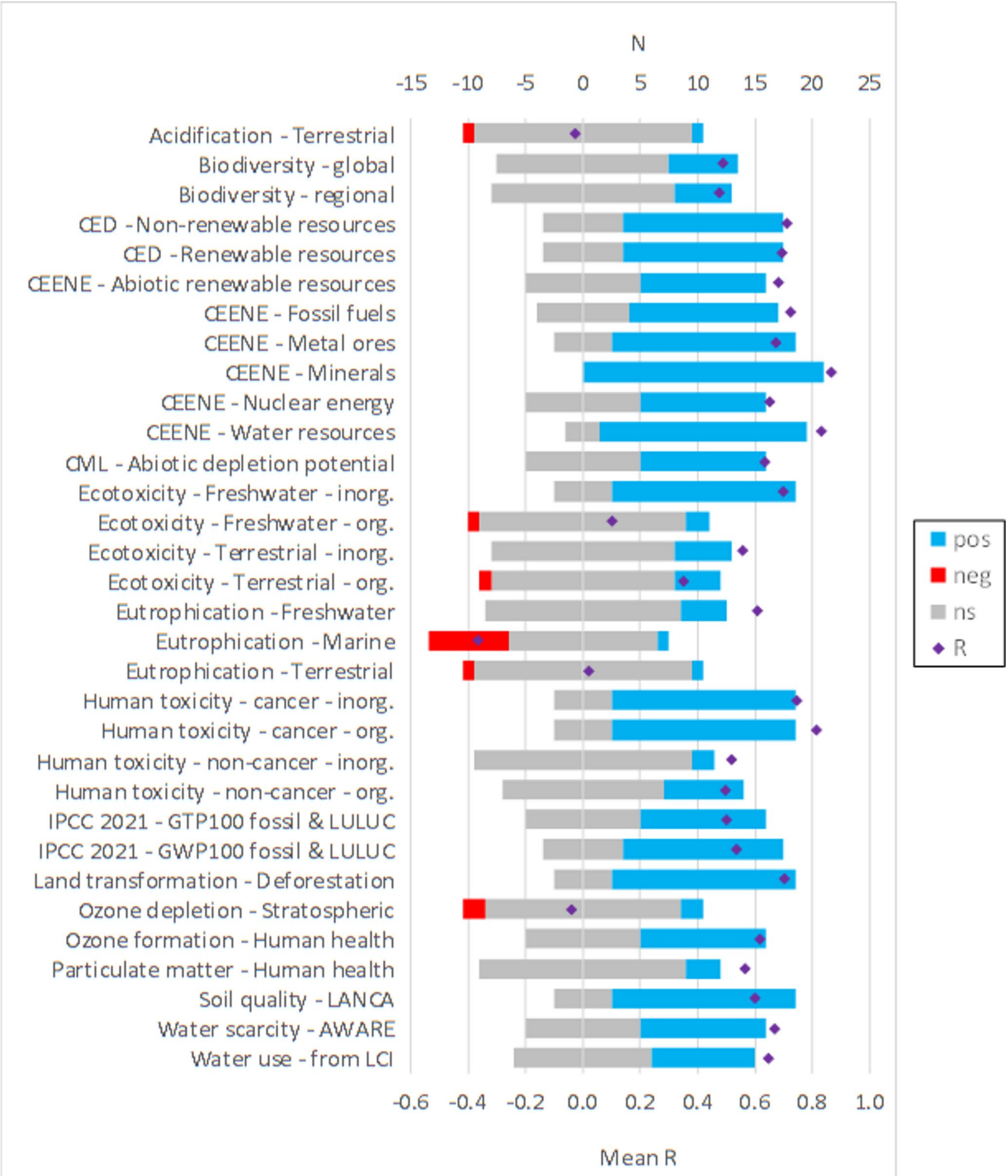

Fig. 4 Spearman rank correlation coefficient between agricultural land occupation and midpoint environmental impacts. The number (N) of significant positive (pos), significant negative (neg), and non-significant (ns) correlations are shown for each product as well as the mean correlation coefficient (R) for all significant correlations

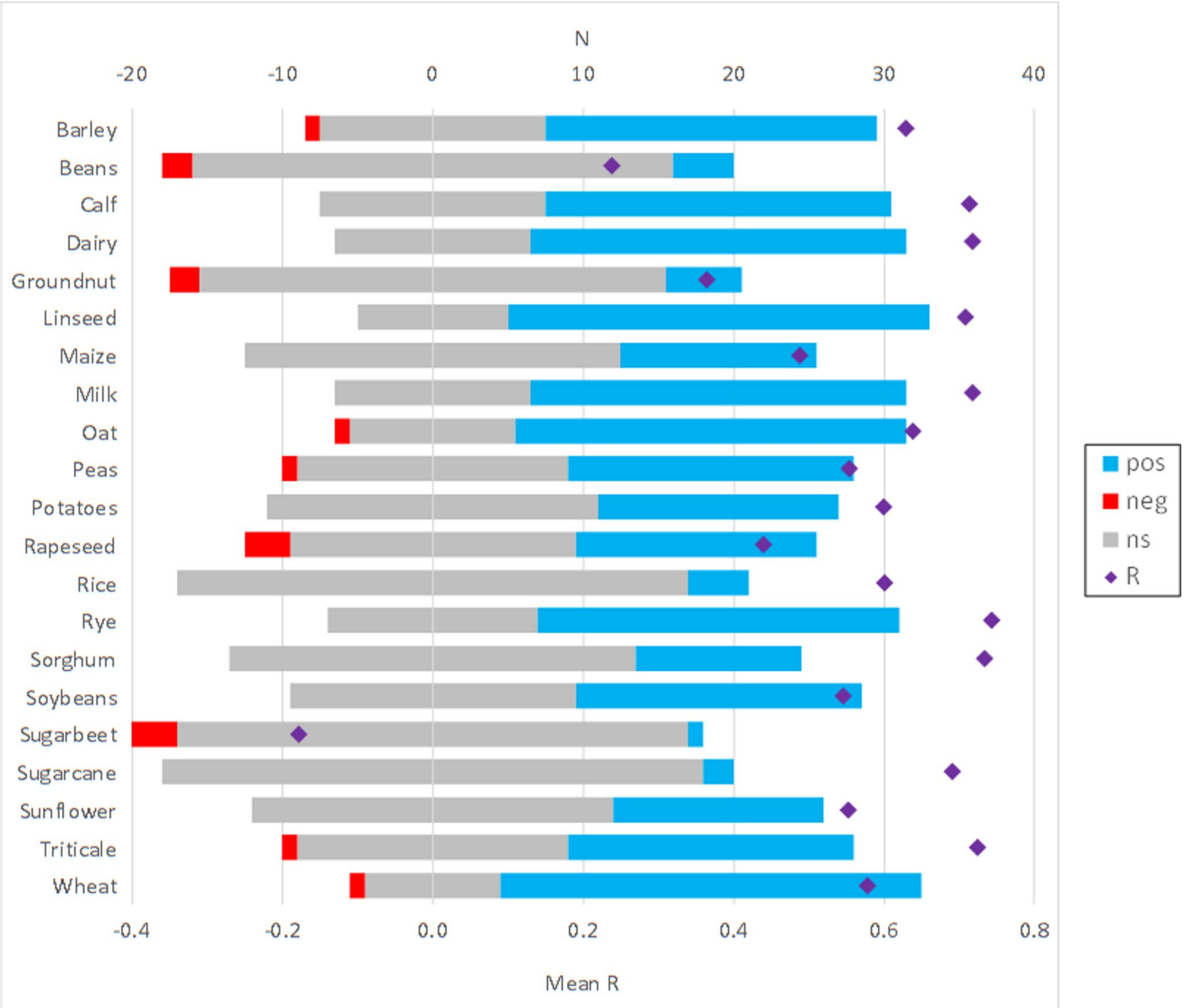

Fig. 5 Spearman rank correlation coefficient between agricultural land occupation and midpoint environmental impacts. The number (N) of significant positive (pos), significant negative (neg), and non-significant (ns) correlations are shown for each product as well as the mean correlation coefficient R for all significant correlations

most of these cases, which means that countries with higher emissions tended to have lower CFs. However, a negative correlation did not necessarily lead to this phenomenon. The sample size does not allow a deeper analysis, but it might be worth further analysing the relationships between the level of emissions and CFs in future studies.

Given the substantial regional- and country-level differences in impact pathways, the variability of environmental impacts as currently implemented in LCA models is likely underestimated. This has practical implications for users applying standard LCA software, whose implementations are driven primarily by practical considerations rather than methodological completeness. Achieving a fully regionalised impact assessment requires that the geographical resolution of both LCIs and LCIA methods be aligned. Data availability at the LCI level is a major limiting factor in this regard.

Water scarcity provides an illustrative example. Environmentally, actual water scarcity is defined at the scale of water catchment areas, which is also the resolution used in the AWARE method. However, most LCA software either represent water flows generically, without geographical differentiation, or at the country level—reflecting the resolution of available input data, for instance, from trade statistics. Consequently, the AWARE method is often applied at this coarser resolution, despite its native higher resolution. Furthermore, irrigation data are frequently unavailable for all water catchments. As a result, both inventory modelling and impact assessment are conducted at a lower geographical resolution than is methodologically feasible. In practical applications, it is essential to clearly define the research question to select the appropriate approach and the most suitable spatial resolution of the data. This is further detailed in Sect. 4.2.

In addition, we identified methodological gaps in some LCIA methods (Roesch et al. 2024). One example is marine eutrophication, for which initial national approaches to characterisation models currently exist (Henryson et al. 2017), but no globally applicable models are available. Wowra et al. (2021) found that N-based emissions are covered to varying degrees in different models used to assess terrestrial eutrophication, which emphasises the need for harmonisation between the models. Some other models lack sufficient differentiation in terms of environmental compartments; for example, Fantke et al. (2015) stated that a groundwater compartment is missing in USEtox to properly assess toxicological impacts.

4.2 Common drivers for emissions and impacts

An understanding of the drivers for emissions and impacts is key to adequately assessing them. Roesch et al. (2024) identified key parameters that influence both the generation of agricultural emissions and the resulting environmental impacts. These parameters are particularly important for the regionalisation of LCA models, as they represent an interface between emission generation and impact pathways, thus enabling consistent modelling along the entire cause-effect chain. The most important common influencing factors include the physical and chemical properties of the soil, in particular soil texture, soil organic carbon (SOC) content, and pH value. Soil texture, defined by the proportions of sand, silt, and clay, influences the sensitivity to erosion, water retention capacity, and permeability of the soil. These properties are crucial for the mobilisation and transport of nutrients (e.g. P, NO_3) and pollutants (e.g. pesticides, heavy metals), which is reflected both in the level of emissions and in the sensitivity of the exposed ecosystems. The organic carbon content of soil is a key factor in determining the carbon footprint of agricultural land, as it determines the soil's ability to store carbon. At the same time, SOC influences microbial activity and thus N_2O emissions and nutrient availability, which, in turn, have an impact on climate change and eutrophication. The pH value of the soil has a direct effect on the conversion processes of N compounds and influences the bioavailability of heavy metals. It is also a decisive factor in the sensitivity of ecosystems to acidification. In addition to soil-related parameters, climatic factors such as air temperature and precipitation play a central role. These parameters control the microbial processes in the soil that are responsible for greenhouse gas emissions, influence nutrient leaching and water availability, and therefore influence climate change, eutrophication, and water scarcity.

4.3 Relationships between land occupation and environmental impacts

The observed positive correlations between land occupation and the many midpoint impact categories observed here show that a higher yield tends to result in lower environmental impacts per output unit, as previously highlighted (e.g. van der Werf et al. 2020). In our results, 43% of the correlations were significantly positive, and only 2% were significantly negative. This finding has two implications:

1) A strategy for reducing environmental impacts by lowering production intensity and reducing yields bears the risk of increasing impacts per kg, although the impacts per area unit will most likely decrease. This is the case if the decrease in environmental impacts per area is slower than the decrease in the yield per area. In other words, eco-efficiency can deteriorate by lowering production intensity. Therefore, a promising mitigation strategy would be to improve the efficiency of input use, so that the same yield can be produced with less inputs, or at least the eco-efficiency of the production should not be hampered.

2) In many cases, LCA practitioners are missing some datasets for agricultural products and approximate them by extrapolating from similar situations (soil, climate, and management practices). Hence, differences in yield should be taken into account by applying a yield correction, as shown, for example, by Roches et al. (2010). However, this can only be a rough approximation, since not all inputs and impacts have the same relationship with the yield, and no simple and generically applicable formula exists. A differentiated approach distinguishing inputs and production factors, such as fertilisers, pesticides, irrigation, and machinery use, is more promising (Rimbaud et al. 2025).

4.4 Need for spatial differentiation in different LCA study contexts

The need to use spatially explicit methods to estimate resource use, emissions, and impacts depends on the goal of the LCA study. A regional differentiation is needed if some environmental impacts are significantly changed, and the conclusions of the study might depend on the production region. Regional differentiation is most relevant if the following three conditions are met (see Fig. 6): (1) Driving parameter D shows high spatial variability, (2) a strong relationship exists between the driving parameter D and the emission E or resource R, and (3) emission E or resource R has an important contribution to impact I.

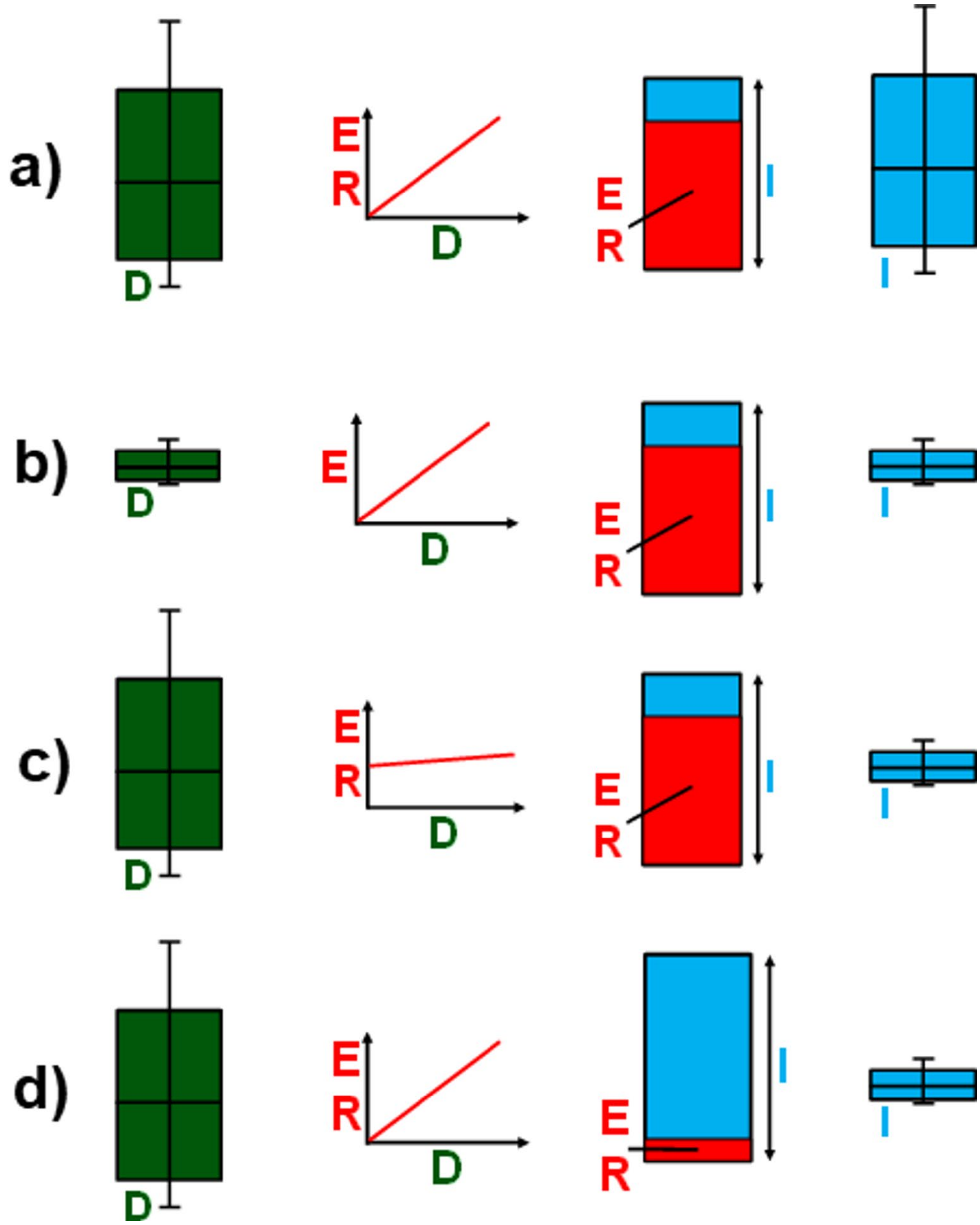

Fig. 6 Schematic representation of the influence of driving force D on resource R or emission E and eventually impact I. In case (**a**), D has a large variability, a strong influence on E or R, which in turn has a high contribution to I. In the other cases, the effect of D on I is minor due to a low variability of D (case **b**), a low influence of D on E (case **c**), or a small contribution of E to I (case **d**)

If one of these conditions is not met, a high spatial differentiation of *D* or *E* is not needed to achieve the study goal, as the results for impact *I* will hardly change. As the resources to carry out LCA studies are always limited, it is crucial to identify the factors and processes with the highest influence on the environmental impact results and the final conclusions. For example, if the goal is to compare different production techniques or production systems in the same region and in similar site conditions, spatial differentiation is not a priority. However, if the goal is to compare food products originating from different regions or countries, spatial differentiation is likely to be highly relevant for the results, as also shown by the statistical analysis in this paper.

4.5 Limitations of this study

We identified a number of limitations that are mostly related to the limited amount of currently available LCI and LCA data:

- Because the number of products and product × country combinations is limited, variability could only be analysed for a limited number of products and countries.
- The use of the Agri-footprint® database limits crop representativity, as the LCIs available for a sufficient number of countries data meeting our conditions are primarily oriented towards grains and tuber crops, while data for fruits and vegetables are largely missing. This may

affect results due to differences in management practices (e.g. fertilisation, crop protection measures, soil tillage practices or crop rotation). The results should therefore be interpreted as representative of the crop mix and management practices captured in Agri-footprint®, rather than as fully generalisable across all agricultural systems. Furthermore, because the analysis focuses on European countries and temperate zones, the variability of emissions and impacts at global scale is likely to have been underestimated. The inclusion of tropical regions is expected to increase the variability of biodiversity impacts (Chaudhary et al. 2015), while the inclusion of the arid zone will increase the variability of water scarcity (Boulay et al. 2018).

- The study is limited to the level of national CFs. The size of countries greatly differs; higher (than national) spatial resolution would help to extract more effects of increasing the spatial resolution. This, however, requires an alignment between inventory flows and CF currently not available at lower scales than countries.
- Due to a lack of LCI data, the effects of different production systems, such as conventional and organic, could not be analysed.
- Representing the yield by the inverse of ALO has certain limits. On the one hand, agricultural land is also used for seed production, but this area is relatively small (not more than a few percent), and seed production also generates environmental impacts. On the other hand, land occupation is only an approximate representation of the yield of animal products. The output of meat or milk per animal could be a better indicator; however, it is also indirectly reflected in ALO.

4.6 Further research directions

To improve confidence in (regionalised) LCI data and LCA modelling approaches to compute CFs, the following research needs should be addressed to fill current knowledge gaps:

- Use of improved models:

The Tier-1 emission models implemented in several LCI databases should be enhanced through the integration of process-based Tier-2 models, enabling a more accurate representation of regional variability in soil and climatic conditions. This should be supplemented by a systematic comparison of Tier 1- and Tier 2-based emission estimates using identical input datasets to ensure methodological consistency and to quantify the influence of model complexity on the results.

- Improve data quality and spatial resolution of enquired input data. This involves several key components:

(i) The use of high-resolution climate data on temperature, precipitation, and evapotranspiration as inputs for emission models.
(ii) The compilation of high spatial resolution datasets on site characteristics, such as soil properties, including soil texture, SOC, and soil pH.
(iii) Enhancing data on management and spatial distribution of the production,
(iv) Use of global GIS-based data with sufficient spatial and temporal resolution to derive regionalised CFs with global coverage. For example, Li et al. (2021) introduced a framework to integrate GIS within LCA, which could serve as a starting point.
(v) Harmonisation of nomenclatures and definitions related to the spatial dimension in LCA, as shown by Patouillard et al. (2018), who reviewed how to integrate geographic aspects at every LCA stage. The authors proposed a decision-support diagram to guide LCA practitioners.
(vi) Harmonisation of various available LCA databases to allow for the comparison of country-specific products from different databases.

- Analyse the relationships between yield resp. ALO on the one hand, and various environmental impacts, on the other hand, to derive formulas for extrapolating impacts in the case of differences in yields.
- Consolidation of impact modelling, for example, by building broadly accepted consensus methods, such as the GLAM initiative (Frischknecht et al. 2019). Furthermore, it is crucial to generalise impact models that are tuned to a certain limited region to make them applicable worldwide. The level of uncertainty in regionalised models should be addressed in detail, as shown by Mutel et al. (2019).
- Build an information technology structure that allows for performing spatially differentiated characterisation in a systematic and easy way.

5 Conclusions

This study systematically analysed the regional variability of emissions, resource use and environmental impacts of agricultural products at the product level using country-specific LCI data from the Agri-footprint® database and national CFs. In this context, regionalisation was defined as the differentiation of both inventory flows and impact characterisation at the national scale, meaning that emissions, resource uses, and CFs were country-specific.

We conclude from our analysis that emissions, resource use and their characterisation play a crucial role in the spatial variability of environmental impacts at the midpoint level. The spatial variability of the CFs strongly depends on the impact category: it was highest for biodiversity, followed by water scarcity, terrestrial acidification and terrestrial eutrophication, if all country values were analysed. The inventory flows (emissions or resources) showed a higher variability than the CFs for most impact categories, except for the land use-related categories biodiversity and soil quality. Note that the actual regional variability of emissions could be underestimated due to the simplified Tier-1 modelling approach implemented in Agri-footprint®, in which pedoclimatic conditions are largely ignored. A similar limitation applies to the CFs, where regional differences are likewise insufficiently represented. Consequently, the findings of this study should primarily be interpreted in the context of current LCA practice and are therefore particularly relevant for LCA practitioners relying on existing databases, tools and software implementations.

The overall variability of impacts for the investigated product-country combinations was highest for water scarcity, followed by biodiversity, terrestrial acidification, and eutrophication, and lowest for soil quality. Significant positive correlations between ALO and most environmental impacts clearly dominated significant negative correlations. As ALO is closely related to the inverse of yield, this statistical analysis confirms that most environmental impacts per product unit tend to decrease with higher yields.

Besides model development, the key physical processes of emissions and associated pathways towards their potential impacts can be better captured by improving and facilitating the handling of software tools for rapid adaption to appropriate regional resolution. Spatial differentiation at the country level might not be sufficient to capture the full variability of emissions, resources, and impacts. The relevance of better spatial differentiation strongly depends on the goal and scope of the study and the systems being compared.

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Data availability The relevant data are included in the manuscript and in the supplementary information.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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