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Assessing regionalization of LCI datasets of fossil-based and biodegradable bio-based polymers used for food packaging in the European context

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ABSTRACT

This study examines the influence of choosing generic and country-specific Life Cycle Inventory (LCI) datasets on Life Cycle Assessment (LCA) outcomes for key fossil-based (FB) and bio-based (BB) polymers produced in Europe. Although regionalized data are increasingly demanded, site-specific datasets are often absent, leading to reliance on generic datasets. Despite Europe offering the most country-specific coverage, comparative studies remain limited. This analysis uses regionalized datasets for FB polymers (HDPE, LDPE, LLDPE, and PP) and BB polymers (PLA/starch, and TPS) from Managed LCA Content (MLC) Databases, applying the EF 3.1 method, and using "1 kg of granulate polymer for packaging" as functional unit. Results were evaluated based on i) the occurrence of burden shifting from FB to BB polymers and ii) the influence of European country-specific datasets compared to RER datasets. Acidification and Eutrophication impacts were found to increase in BB polymers. In Climate Change, no decrease was observed because EF 3.1 lacks standardized biogenic carbon accounting, preventing this from being captured. Significant variations were found in Ionizing Radiation, Land Use, Ozone Depletion, and Water Use, both in the FB and BB datasets. The importance of regionalization in BB datasets was highlighted due to differing agricultural practices. In conclusion, enhanced inventory and impact regionalization are recommended to capture regional dynamics accurately.

1. Introduction

Life Cycle Assessment (LCA) plays a relevant role in decision-making and policy-making due to its holistic approach to environmental impacts. It identifies hotspots, possible trade-offs, and burden shifting among life cycle stages or impact categories (Sala et al., 2021). Academic, business, and policy arenas have increased the application of LCA over the past decades (Dai et al., 2020; Mutel et al., 2019; Yang, 2016). Historically, LCA has been based on global rather than regional data and models. However, although LCA is traditionally site generic (i.e., it disregards the spatial information), it should be increasingly regionalized to provide more accurate environmental impact assessment results to avoid misleading conclusions. The importance of considering spatial differentiation was demonstrated (Patouillard et al., 2018; Ross and Evans, 2002), especially for materials and products involving agricultural phases along their life cycle (Chaplin-Kramer et al., 2015; Yang and Suh, 2015). Including it in LCA can reduce the inaccuracies and uncertainties associated with site generic LCA (Patouillard et al., 2019) and increase its credibility (Potting and Hauschild, 2006). In Patouillard et al. (2018) (Patouillard et al., 2019), the term *regionalization* is used to describe the representativeness of the processes and phenomena of a given region. Such geographic dimension can be included in each phase of the LCA methodology, with different specificities and names, i.e., in the goal and scope when defining the object of the study and its spatial requirements, in Life Cycle Inventory (LCI) through *inventory regionalization* and *inventory spatialization*, in Life Cycle Impact Assessment (LCIA) through *impact regionalization*, and in the interpretation when identifying the potential transfer of impacts from one geographic location to another (Patouillard et al., 2018; Nitschelm et al., 2016; Liu et al., 2014; Mutel and Hellweg, 2009). However, in this study, the main focus will be on investigating the regionalization occurring in LCI, while regionalization in LCIA will be briefly touched upon.

At the LCI level, as previously mentioned, regionalization can be distinguished into *inventory regionalization* and *inventory spatialization*. The former refers to adapting inputs or outputs of datasets to better account for regional technological specificities or recontextualizing datasets to better account for the specific background of an activity (Patouillard et al., 2019; Lesage and Samson, 2016). The latter refers to adding spatial information to attribute a geographic location to the activities and elementary flows inherited from the process they stem from (Patouillard et al., 2018). Both regionalization efforts are performed by

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Abbreviations:

AWaRe Available Water REmaining
BB polymer/dataset: Bio-based polymer/dataset
BE Belgium
CFs characterization factors
DE Germany
EF 3.1 Environmental Footprint 3.1
ES Spain
EU European Union
FB polymer/dataset: Fossil-based polymer/dataset
FR France
ICs: Impact Categories
IT Italy
LCA Life Cycle Assessment
LCA FE LCA For Expert
LCI Life Cycle Inventory
LCIA Life Cycle Impact Assessment
MLC Databases Managed LCA Content Databases
Mt Million tonnes
NL: the Netherlands
OEF Organizational Environmental Footprint
PEF Product Environmental Footprint
RER Europe

Abbreviations used for polymers
HDPE polyethylene high density
LDPE polyethylene low density
LLDPE polyethylene linear low density
MDPE polyethylene medium density
PA polyamides
PBAT Polybutylene adipate terephthalate
PBS Polybutylene succinate
PE polyethylene
PET Polyethylene Terephthalate
PHAs Polyhydroxyalkanoates
PLA Polylactic Acid
PP Polypropylene
PTT Polytrimethylene Terephthalate
TPS Thermoplastics Starch

Abbreviation for ICs
AC Acidification
CC Climate Change
ECOTOX, fw Ecotoxicity, freshwater
EUTR, fw Freshwater Eutrophication
EUTR, marine: Marine Eutrophication
EUTR, terrestrial Terrestrial Eutrophication
HT, cancer Human Toxicity, cancer
HU, non-cancer Human Toxicity, non-cancer
IR Ionizing Radiation
LU Land Use
OD Ozone Depletion
PM Particulate Matter
POF Photochemical Ozone Formation
RU, fossils Use, fossils
RU, mineral and metals Resource Use, mineral and metals
WU Use

LCI database developers (i.e., third-party database developers) aiming to provide secondary data (i.e., LCI datasets) with a geographical representation that should be as realistic as possible. As an example, in the Managed LCA Content Databases (MLC Databases, formerly known as GaBi Databases) (Lopes Silva et al., 2019; Pauer et al., 2020), inventory regionalization is implemented by means of the so-called "4-level regionalization approach" (Sphera, 2022a), depicted in Fig. 1.

Moreover, in the same database, an example of inventory spatialization is provided by the elementary flow for which a specific geographic location is indicated (e.g., "Arable, irrigated, intensive, regionalized, IT").

At the LCIA level, impact regionalization refers to providing regionalized characterization factors (CFs) to assess spatialized elementary flow representative of specific geographic areas (i.e., those resulting from inventory spatialization). LCIA method developers have long recognized that, for many impact categories, the impact of a given elementary flow depends on where that flow occurs, and have therefore provided regionalized CFs (Mutel et al., 2019; Potting and Hauschild, 2006). As an example, in the Environmental Footprint (EF) 3.1 method, regionalized CFs are available for *Acidification, Ecotoxicity, Freshwater, Terrestrial Eutrophication, Marine Eutrophication, Land Use, Photochemical Ozone Depletion, Particulate Matter,* and *Water Use.*

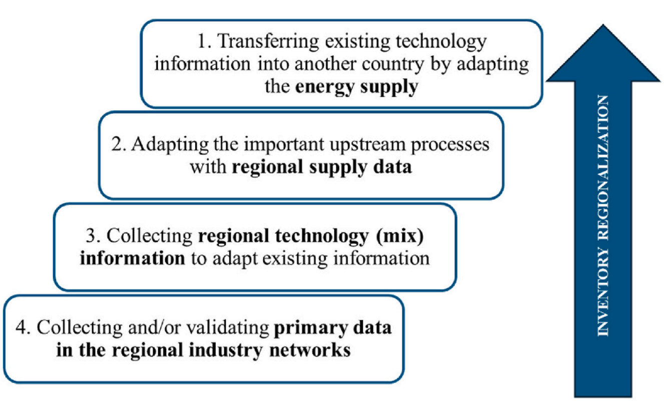

Fig. 1. Schematic representation of the "4-level regionalization approach" for inventory regionalization in MLC Databases.

As anticipated, the agricultural sector is particularly susceptible to regionalized data and methods due to its significant variations across space and time (Patouillard et al., 2018; Ross and Evans, 2002). This means that whenever a bio-based material or product is assessed through LCA, attention should be paid to the availability of regionalization efforts at both LCI and LCIA levels. Although the demand for more regionalized data is rising within LCA studies (Dai et al., 2020), very often, site specific (e.g., country-specific) datasets are missing and less representative surrogate (i.e., generic) datasets must be used to fill data gaps (Henriksen, 2019), thus introducing inaccuracies. Some approaches have been proposed in the literature to address gaps in regionalized inventory data (Olivetti et al., 2013): introduced an under-specification approach, while (Dai et al., 2020) proposed a multi-level modeling method, and (Meron et al., 2020) suggested the use of selected proxies. Despite these advancements, a debate continues on how to identify analogous datasets and select appropriate proxies, and the overall issue remains unresolved in the absence of a systematic regionalization of data, as all the proposed approaches require a robust basis for the application of their statistical methods. Consequently, LCA practitioners face challenges in interpreting the implications of using generic datasets (i.e., RER datasets) when site specific datasets are unavailable. It must be noted that the only site specific datasets currently available in third party databases are those at country level, although datasets at topologic (e.g. watershed) level or at a level based on a homogeneous set of natural conditions (e.g. climate zone) (Patouillard et al., 2018) could be more appropriate for ICs such as Water Use and

Land Use. In this context, this study aims to assess the potential impacts of selecting generic proxy datasets versus country-specific LCI datasets (e.g., Germany, DE, dataset) within a comparative analysis of fossil-based (FB) and bio-based (BB) plastics in Europe. FB and BB plastics were selected as case study because, as reported by (Walker and Rothman, 2020), the findings of comparative LCA analysis among FB and BB solutions can show variations of the order of 200 %–400 % among studies on the same polymer with the same scope in literature. Europe was selected as geographic boundary because, as highlighted by Edelen et al. (2018) (Edelen et al., 2018), data sources for LCI datasets are predominantly European. Indeed, European plastics production is still significant. According to Plastics Europe, out of 414 Mt of fossil-based plastics produced globally in 2023, 12.3 % was produced in Europe. The percentage increases to 25.2 % in the case of the bio-based plastics for which the global production was equal to 3.0 Mt in 2023 (Carlesso et al., 2024). Moreover, in Europe, approximately 40 % of food is packaged in plastic packaging (Plastics Europe, 2023). Plastics are the dominant material for packaging in the food and beverage field (European Bioplastics, 2023) thanks to their lightness, durability, versatility, and cost-effectiveness. Among available and commonly used third-party LCI resources, MLC Databases are currently the most extensively regionalized within the plastics and bioplastics sectors, surpassing Ecoinvent, which is the most used database in similar LCA studies (Carlesso et al., 2024). Indeed, Ecoinvent database provides datasets for FB and BB polymers at continental (e.g., Europe - RER), and global (RoW, GLO) levels only, although the underlying data are the same used by MLC Databases. The analysis was performed on a set of FB and biodegradable BB datasets selected from MLC Databases by using the method EF 3.1 and the software LCA For Expert (LCA FE, previously known as GaBi Software).

2. Methodology

The following section is structured into four main parts: i) the rationale behind the selection of FB and BB polymers; ii) the selection of the datasets; iii) the applied LCIA method and the selected impact categories; and iv) the criteria outlined for discussion of the results.

2.1. Selection of polymers

The selection of FB and BB polymers for analysis was based on the list of the most manufactured polymers in Europe. In 2022, according to Plastics Europe (2023) (Plastics Europe, 2023), European plastics production was equal to 58.7 million tonnes (Mt), comprising 47.2 Mt of FB polymers and 11.5 Mt of polymers deriving from chemically recycled, bio-based and mechanically recycled polymers (including both post-consumer and pre-consumer plastics waste). Concerning FB polymers, 37.5 % of those manufactured in Europe were polypropylene (PP), and 41.3 % were polyethylene-based polymers. Among the latter, 19.2 % were polyethylene low density/linear low density (LDPE/LLDPE), and 22.1 % were polyethylene high density/medium density (HDPE/MDPE), while the other FB polymers individually contributed less than 10 %. Still, in 2022, according to European Bioplastics (2023) (European Bioplastics, 2023), the global production of BB polymers amounted to 2.22 Mt, of which 52.1 % of biodegradable bio-polymers. The non-biodegradable polymers were biobased polymers, such as polyethylene – PE (14.80 %), polyethylene terephthalate – PET (4.20 %), polypropylene – PP (3.90 %), and drop-in solutions, such as polyamides – PA (11.10 %) and polytrimethylene terephthalate – PTT (13.30 %). Among the biodegradable BB polymers globally produced, 40.2 % were polylactic acid (PLA), 37.8 % were starch blends (e.g., thermoplastics starch – TPS – and PLA), while the remaining 22 % included

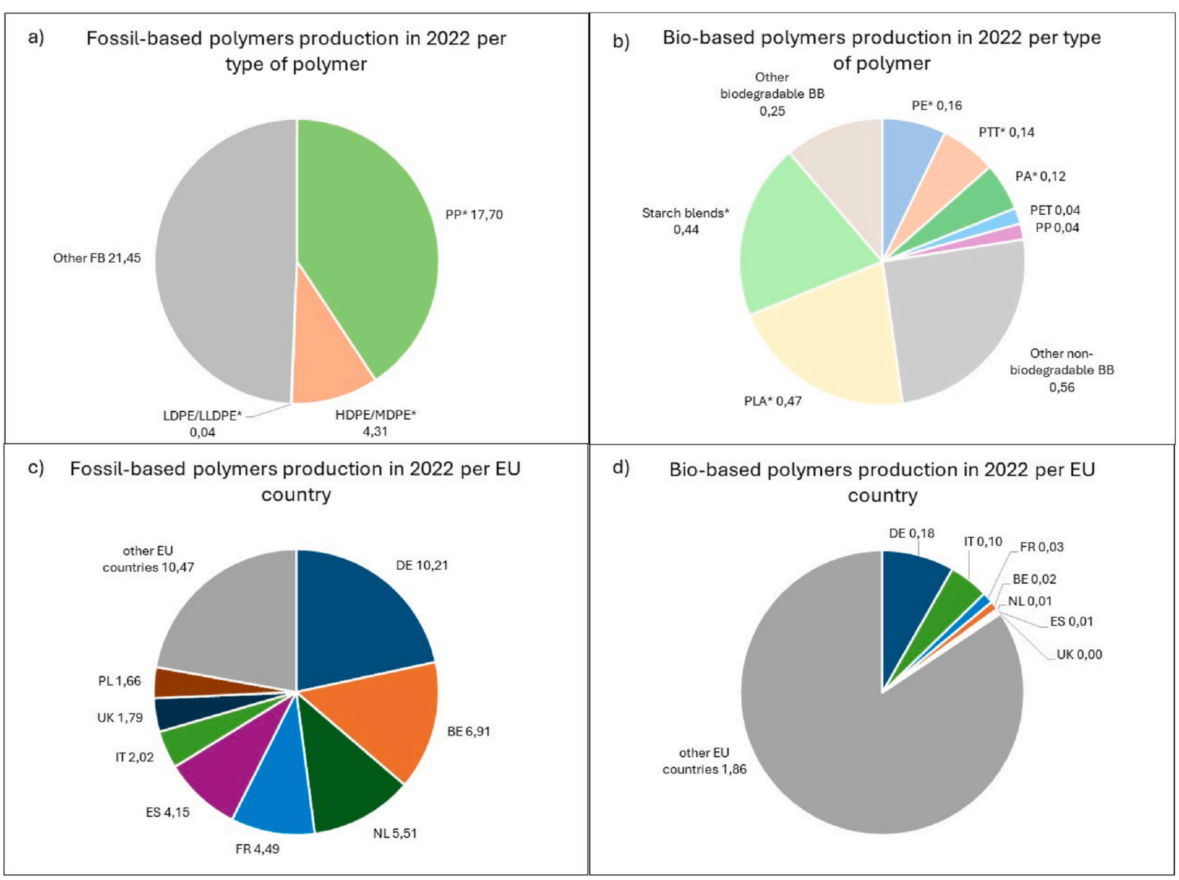

Fig. 2. Amounts (in Mt) of FB and BB polymers produced in 2022 in Europe, per country in a) and b), and per type of polymer in c) and d). * indicates the polymers most manufactured in Europe preliminarily selected for this study.

polybutylene adipate terephthalate (PBAT), Polybutylene succinate (PBS), Polyhydroxyalkanoates (PHAs), and cellulose films (namely regenerated cellulose films). The amounts (in Mt) of FB and BB polymers produced in 2022 in Europe are reported in Fig. 2(a and b), which includes also the amounts (in Mt) of total FB and BB polymers produced by main producing European countries (c and d).

Accordingly, the polymers most manufactured in Europe preliminarily selected for this study (highlighted with an asterisk in Fig. 2a and b) were: for FB polymers, PP, HDPE, MDPE, LDPE, and LLDPE, and for BB polymers, the non-biodegradable PE, PTT and PA and the biodegradable TPS and PLA.

2.2. Selection of Life Cycle Inventory datasets within the chosen database

The database selected for analysis of the datasets was MLC Databases within the LCA For Expert (LCA FE) software. The features of this database are to provide aggregated and regionalized datasets. As was pointed out in the introduction to this paper, all the datasets in the MLC Databases are developed following the “4-level regionalization approach”. Specifically, in accordance with the handbook “GaBi databases & modelling principles” (Sphera, 2022a), where a dataset is indicated as country-specific, at least level 2 is applied. However, as all the datasets are aggregated, information can only be reconstructed up to level 2. Consequently, it is worth anticipating that a notable limitation of the study is that the dataset aggregation prevents the direct linking of elementary flows to their specific sources, hindering detailed analysis, as will be discussed in Section 3.3.

The available LCI datasets for each FB and BB polymer selected in 2.1 were searched at both European country-specific (e.g., France, FR) and European (i.e., RER) levels. No datasets were found for polyethylene medium density (MDPE), for the non-biodegradable BB polyethylene (PE), polytrimethylene terephthalate (PTT) and polyamides (PA), while for PLA only blend datasets between PLA and starch were available.

Table 1 reports the complete list of selected datasets, ranked in descending order based on the number of country-specific datasets available. For instance, HDPE is represented by six country-specific datasets, whereas LLDPE, PLA/starch, and TPS have only one country-specific dataset each. Accordingly, Table 1 also reports the final list of FB and BB polymers used in this study, while relevant metadata are reported as Supplementary Material in the file “SM1_Metadata_MLC_db”.

The reference unit to which the environmental performance of the product is related is “1 kg of granulate polymer for packaging”. It is indicated as functional unit (FU) in Table 1 as it defines a quantified performance of a product system. The production of the packaging, its use and end of life are all out of the scope of this assessment, as its focus is on understanding the effects of regionalized data on the upstream and core phases of FB and BB polymers produced for food packaging.

2.3. Selection of Life Cycle Impact Assessment method

The selected LCIA method was Environmental Footprint (EF) 3.1. This method is recommended by the framework Product and Organizational Environmental Footprint (i.e., PEF and OEF), developed for evaluating the environmental impacts produced by products or services in the European Union. EF 3.1 includes the following 16 Impact Categories (ICs): *Acidification; Climate Change; Ecotoxicity, Freshwater; Eutrophication (Freshwater, Marine, Terrestrial); Ozone Depletion; Photochemical Ozone Depletion; Ionizing Radiation; Human Toxicity (Cancer and Non-Cancer Effect); Land Use; Particulate Matter; Resource Use, Mineral and Metals; Resource Use, Fossils;* and *Water Use.* Moreover, it implements impact regionalization in the following 8 ICs (Andreasi Bassi et al., 2023): *Acidification; Ecotoxicity, Freshwater; Terrestrial Eutrophication; Marine Eutrophication; Land Use; Photochemical Ozone Depletion; Particulate Matter;* and *Water Use,* by providing regionalized CFs.

Table 1
For each polymer and dataset, the information provided is the dataset name, functional unit (FU), dataset type, and Universally Unique Identifier (UUID). The UUID is an identification number which allows to identify unique flows.

Polymer type	Dataset name	FU	Dataset type	UUID
HDPE	RER: Polyethylene high-density granulate (HDPE/PE-HD) Sphera	1 kg	aggregated	{5b30a5ab-bc4e-4316-bb18-f6605b382648}
	BE: Polyethylene high-density granulate (HDPE/PE-HD) Sphera	1 kg	aggregated	{d77338ac-85ac-4f83-850e-207345998a42}
	DE: Polyethylene high-density granulate (HDPE/PE-HD) Sphera	1 kg	aggregated	{b5ea9896-dea8-402e-98c3-3b285a9a32d8}
	ES: Polyethylene high-density granulate (HDPE/PE-HD) Sphera	1 kg	aggregated	{16381451-72d0-4b5d-9a82-5591ec628c1a}
	FR: Polyethylene high-density granulate (HDPE/PE-HD) Sphera	1 kg	aggregated	{f8182a6f-1d40-4303-a3bb-c854a1869b16}
	IT: Polyethylene high-density granulate (HDPE/PE-HD) Sphera	1 kg	aggregated	{082d0a8f-2ebc-45d1-b0fb-47a70f4769de}
	NL: Polyethylene high-density granulate (HDPE/PE-HD) Sphera	1 kg	aggregated	{6e607b38-6f68-4e1d-9fee-c8eab2db79b6}
PP	RER: Polypropylene granulate (PP) Sphera	1 kg	aggregated	{64c5a926-a337-4b62-bff2-d5ef29ecfae2}
	BE: Polypropylene granulate (PP) Sphera	1 kg	aggregated	{f61f7d61-cbb2-4ef7-925a-22da58e428ad}
	DE: Polypropylene granulate (PP) Sphera	1 kg	aggregated	{c8e9efd5-fd8f-4da2-89ed-5a78e7ba6e42}
	FR: Polypropylene granulate (PP) Sphera	1 kg	aggregated	{46b8224f-efea-43ae-9e2c-ce4cfa12f36b}
	NL: Polypropylene granulate (PP) Sphera	1 kg	aggregated	{68dbabaf-bfa5-4822-85a9-d718d1f5fa58}
LDPE	RER: Polyethylene low-density granulate (LDPE/PE-LD) Sphera	1 kg	aggregated	{df6a564c-f46e-4325-9689-022bbfe009db}
	BE: Polyethylene low-density granulate (LDPE/PE-LD) Sphera	1 kg	aggregated	{958d2c28-151d-43c0-bbaa-8ececa5826e8}
	DE: Polyethylene low-density granulate (LDPE/PE-LD) Sphera	1 kg	aggregated	{6de31fe6-71e3-41f9-a166-4afc89961653}
	ES: Polyethylene low-density granulate (LDPE/PE-LD) Sphera	1 kg	aggregated	{ecf39a03-2264-4de0-b2dc-2b2df5ea4832}
LLDPE	RER: Polyethylene linear low-density granulate (LLDPE/PE-LLD) Sphera	1 kg	aggregated	{27b2f25c-ccec-43cf-97b9-bc97f0f95f49}
	DE: Polyethylene linear low-density granulate (LLDPE/PE-LLD) Sphera	1 kg	aggregated	{a8906b25-31d2-403b-a537-43722f84665a}
PLA/ starch	RER: Starch/polylactic acid (PLA) blend Sphera	1 kg	aggregated	{e872387e-c0d7-48c3-94cc-cbd3429af732}
	DE: Starch/polylactic acid (PLA) blend Sphera	1 kg	aggregated	{1b638d26-a0f4-420b-a5bc-d33d538f0c5c}
TPS	RER: Thermoplastic starch polymer (TPS), unblended Sphera	1 kg	aggregated	{d80e3cc3-b6c6-406e-9241-f68c281b1cd3}
	DE: Thermoplastic starch polymer (TPS), unblended Sphera	1 kg	aggregated	{bc676ef8-ed24-4f76-a304-870ef5355ff5}

2.4. Assessment criteria

To analyze the results from each dataset and for each IC, two criteria were used: i) the occurrence of burden shifting from FB to BB polymers, and ii) the influence of European country-specific datasets compared to RER datasets. These will be explained further in the following paragraphs.

2.4.1. First criterion: occurrence of burden shifting

The first criterion aims to verify the occurrence of burden shifting, as transitioning from FB to BB feedstock for polymer production can move environmental impacts from one IC to another. It was observed that while the contribution to *Climate Change* usually decreases when moving from FB to BB polymers, the contribution to *Acidification* and *Eutrophication* ICs increases (Walker and Rothman, 2020; European Bioplastics, 2023; Koch and Mihalyi, 2018). Therefore, the ICs results were discussed to verify whether such burden shifting is also occurring in the investigated datasets.

2.4.2. Second criterion: influence of European country-specific datasets compared to RER datasets

The second criterion aims to identify which ICs are mostly affected by the use of generic (i.e., RER) datasets, compared to European country-specific datasets, and to investigate the reasons behind that.

To this end, for each polymer and each country reported in Table 1, percentage variation from RER results was calculated for each IC. Then, the average percentage variation (in absolute value) was calculated and used as a threshold to identify those ICs mostly affected by the use of generic versus country-specific datasets. More specifically, an IC was selected as relevant for further investigation and discussion when the calculated percentage variation exceeded the threshold for at least half of the 14 FB and of the 2 BB country-specific datasets (i.e., for a number of country-specific datasets $\geq$7 in case of FB polymers and for at least one of the two country-specific datasets available for BB polymers).

For each IC selected according to this method, regionalization efforts were analyzed at the LCI level and discussed. More specifically, inventory spatialization was investigated by searching for any elementary flow specifically linked to a geographic location available in the country-specific datasets (i.e., any spatialized elementary flow, which is marked by the term *regionalized* in the elementary flow nomenclature). Then, the spatialized elementary flows contributing more than 1 % of the calculated impact were analyzed to understand how inventory regionalization was implemented and to investigate their contribution to the differences observed in the calculated impact for country-specific and RER datasets.

3. Results and discussion

This section presents ICs results, which are discussed according to the two criteria explained in 2.4.1 and 2.4.2.

3.1. First criterion: occurrence of burden shifting

According to the criterion described in Section 2.4.1, the occurrence of burden shifting was analyzed in the selected datasets. The focus was first on the three ICs for which burden shifting was reported in the literature when transitioning from FB to BB feedstock: *Climate Change*, *Acidification,* and *Eutrophication*, the latter including *Freshwater, Marine and Terrestrial Eutrophication.* For the five ICs, Figs. 3 and 4 show the results at the dataset level reported as percentages, with 100 % assigned to the dataset obtaining the highest value (percentages are reported in tables in the Supplementary Material file “SM2_C1_Results”).

Focusing on *Acidification* and *Eutrophication* ICs (Fig. 3), the burden shifting from FB to BB datasets is clearly visible. Indeed, results for FB and BB datasets (data not reported) are higher by an order of magnitude difference in *Acidification, Marine* and *Terrestrial Eutrophication* and two orders of magnitude difference in *Freshwater Eutrophication*. However, it must be noted that for BB polymers only one country-specific dataset is currently available. Expanding the availability of country-specific datasets for BB polymers could lead to differences in the burden shifting results (i.e., less or more pronounced shift in *Acidification* and *Eutrophication* ICs), as they depend on localized agricultural practices, which are highly influenced by factors like precipitation, soil characteristics, and agroecological conditions.

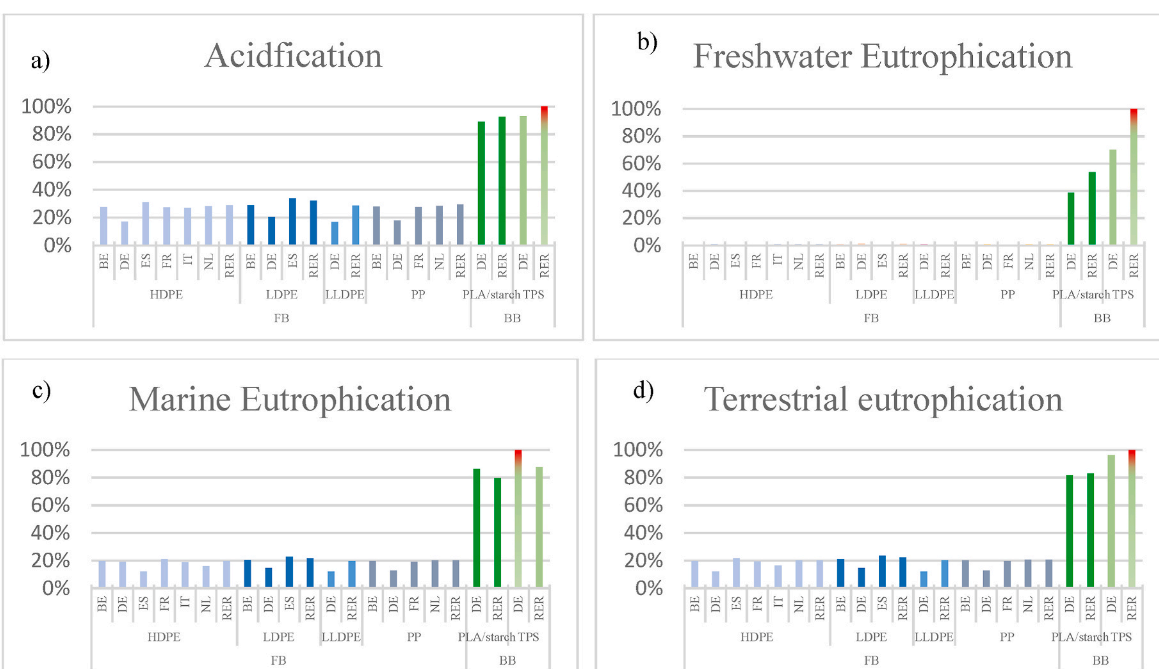

Fig. 3. Results (%) of Acidification (a), Freshwater (b), Marine (c), and Terrestrial Eutrophication (d) ICs for the selected FB and BB datasets, where 100 % (highlighted in red) is assigned to the highest obtained value.

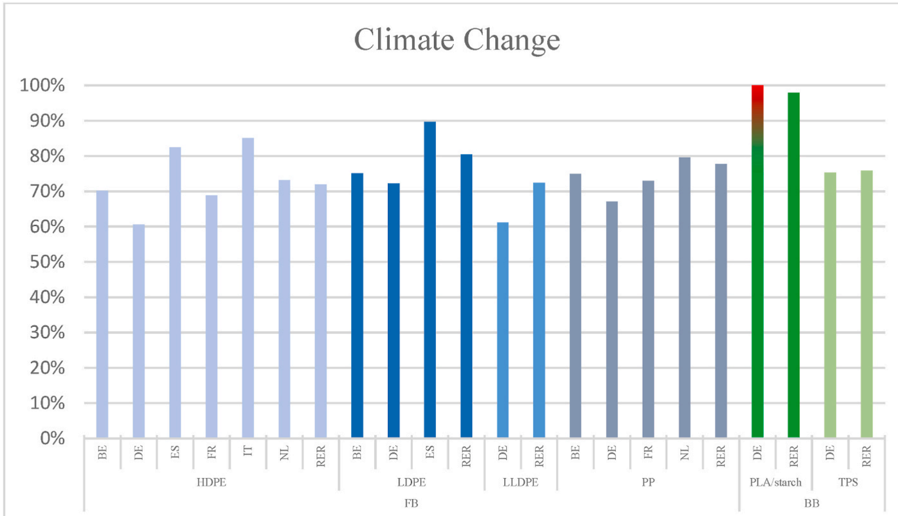

Fig. 4. Results (%) of the Climate Change IC for the selected FB and BB datasets, where 100 % (highlighted in red) is assigned to the highest obtained value.

Fig. 5. Results (%) of Human Toxicity (Cancer (a) and Non-Cancer Effect (b)), Land Use (c), Particulate Matter (d), and Resource Use, Mineral and Metals (e) ICs for the selected FB and BB datasets, where 100 % (highlighted in red) is assigned to the highest obtained value.

On the other hand, focusing on *Climate Change* (Fig. 4), the burden shifting from FB to BB datasets reported in the scientific literature (Walker and Rothman, 2020; European Bioplastics, 2023; Koch and Mihalyi, 2018) could not be observed. All datasets produced similar results within a range of values between 60 % and 100 %. Furthermore, the BB dataset's results from the PLA/starch blend reported the highest calculated values for both DE and RER datasets. It must be noted that the analysis focused on the upstream phase of a plastic food packaging (as the FU is 1 kg of granulate polymer for packaging) and the results could be different when including core (e.g., production) and downstream (e.g., waste management) processes.

However, here the difference with the literature results is to be ascribed to the chosen LCIA method and, specifically, to how the EF 3.1 method (Paragraph 2.3) considers biogenic carbon dioxide in calculating *Climate Change* impact. Indeed, in EF 3.1 the default characterization factors for biogenic carbon dioxide uptake and release are set to zero (0), in accordance with "The plastics LCA method" issued by JRC in 2021, stating that "for intermediate products such as polymers or unspecified plastic parts (cradle-to-gate studies), the biogenic carbon content at the factory gate (physical content) shall always be reported as 'additional technical information', along with the non-biogenic (e.g. fossil) carbon content". This way, the unintended imbalance between carbon uptakes and releases modelled in the inventory does not ultimately compromise the LCA results for the Climate Change IC. Such methodological choice is supported by the fact that the consensus in the scientific community on the approach to handle and account for biogenic carbon emissions and removals from products (i.e., temporary carbon storage and carbon neutrality) has yet to be achieved (European Bioplastics, 2023; Nessi et al., 2021).

The results of burden shifting analysis for the other calculated ICs are reported in SM2_C1_Results. For five of them (*i.e., Human Toxicity (Cancer and Non-Cancer Effect); Land Use; Particulate Matter; Resource Use, Mineral and Metals)* burden shifting is clearly visible (Fig. 5), while it less noticeable for *Water Use* (Fig. 6a), mainly because the impacts calculated at EU level (RER dataset) for BB polymers are much lower than the country-specific (DE dataset) impacts, and in line with those calculated for FB polymers.

For *Ecotoxicity, Freshwater* (6b), an inverse burden shifting can be observed (i.e., lower impact values when transitioning from FB to BB feedstock) but only for one (i.e., TPS) out of two BB polymers. The considerations drawn up for *Acidification* and *Eutrophication* can be extended to these seven ICs. Indeed, as for BB polymers only one country-specific dataset is currently available, expanding the availability of country-specific datasets for BB polymers could bring to different burden shifting results. However, the available data currently indicate that the transitioning from FB to BB feedstocks can bring additional significant environmental impacts, mainly due to the upstream phase activities. This information cannot be overlooked and should be complemented by similar analysis for the core and downstream phases to better inform decision making processes.

3.2. Second criterion: influence of European country-specific datasets compared to RER datasets

According to the second criterion (Paragraph 2.4.2), the threshold obtained from the calculation of average percentage variation (in absolute value) is 20.23 %. In Table 2, the results of the 16 ICs calculated using EF 3.1 for the six selected polymers (HDPE, LDPE, LLDPE, PP, PLA/starch, and TPS) are reported. The table shows the percentage variation for each IC and polymer between each country-specific dataset and the reference RER dataset, while the underlined values are those exceeding the average absolute variation (i.e., 20.23 %) used as a threshold. Based on this threshold, *Ionizing Radiation, Land Use, Ozone Depletion,* and *Water Use* showed results above average for most (i.e., more than half) country-specific datasets, for both FB and BB polymers. In addition to them, *Resource Use, minerals and metals, Human Toxicity, cancer and non-cancer,* and *Freshwater Eutrophication* showed results' variations mainly for BB datasets. The following discussion will focus on these eight ICs. First, each IC will be individually discussed in this Section, while a cross-sectional discussion will follow in Section 3.3.

Ionizing Radiation (IR). It is classified as local-scale impact (Paulillo et al., 2023), but, in the investigated datasets and in the adopted LCIA method, no efforts on inventory spatialization and impact regionalization were present, respectively. Therefore, the following discussion focuses on inventory regionalization. Regardless of the dataset, 99 % of the calculated impact depends on two elementary flows associated with the "Radioactive emissions to air" within the "Emission to air" compartment. These are Carbon (C14) and Radon (Rn222), with C14, which is typically released in the form of CO_2 (Paulillo et al., 2023), accounting for about 93 % of IR impact in all the analyzed datasets. In Table 2, the results' variations between country-specific and RER datasets range from −68,02 % (for HDPE) to +216.11 % (for PP). Only FR datasets, available for HDPE and PP, showed positive variations compared to RER datasets (+183.52 % and +216.11 %, respectively). The lowest negative variations, around −12 and −15 %, were reported by available BE datasets for HDPE, LDPE and PP. More significant negative variations, around −50 %, were obtained by available ES datasets for HDPE and LDPE, followed by available NL datasets for HDPE and PP (−56.48 % and −61.98 %, respectively), DE datasets for HDPE, LDPE, LLDPE, PP and TPS (around −62/65 %, with the only exception of PLA/starch with −42.83 %), and IT dataset for HDPE (−68.02 %). All these results are driven by the country-specific energy mix, particularly the fraction of nuclear energy employed. As supported by the International Energy Agency (IEA), 14 EU member countries had nuclear power in 2019 (I. E. A. International Energy Agency, 2020a). Nuclear energy dominates the French energy supply (72 % of its national electricity mix in 2019), followed by Belgium (49 %), while the share of Spain, Germany and The Netherlands is below 20 % (I. E. A. International Energy Agency, 2020a). As for Italy, its energy mix is dominated by natural gas and oil (about 80 %), while nuclear energy (mainly imported from France) plays a marginal role in the remaining 20 % (I. E. A.

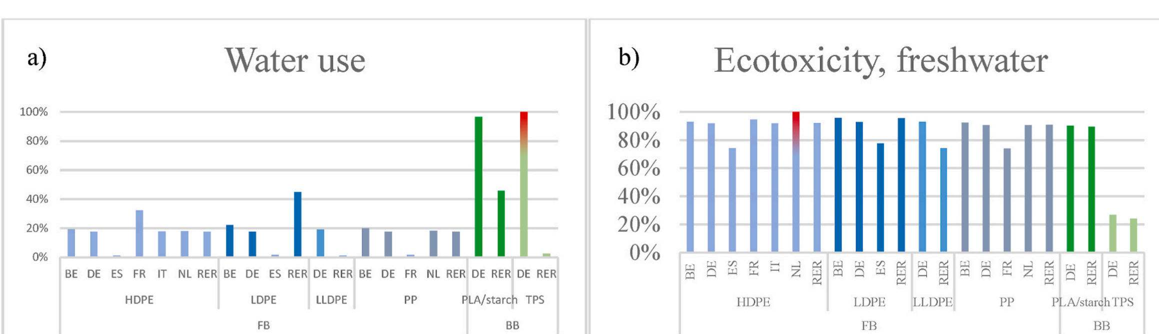

Fig. 6. Results (%) of Water Use (a) and Ecotoxicity, freshwater (b) ICs for the selected FB and BB datasets, where 100 % (highlighted in red) is assigned to the highest obtained value.

Table 2
Results of the 16 ICs calculated by EF 3.1. For each IC and polymer, the reported percentages indicate the LCIA characterized results' variation between each country-specific dataset and the reference RER dataset. The colour scale highlights higher values in red and lower values in green, while the underlined values represent those exceeding the absolute average variation (i.e. 20.23 %). The impact categories are abbreviated as follows: Acidification (AC); Climate Change (CC); Ecotoxicity, freshwater (ECOTOX, fw); Freshwater Eutrophication (EUTR, fw); Marine Eutrophication (EUTR, marine); Terrestrial Eutrophication (EUTR, terrestrial); Human Toxicity, cancer (HT, cancer); Human Toxicity, non-cancer (HU, non-cancer); Ionizing Radiation (IR); Land Use (LU); Ozone Depletion (OD); Particulate Matter (PM), Photochemical Ozone Formation (POF); ResourceUuse, fossils (RU, fossils); Resource Use, mineral and metals (RU, mineral and metals); Water Use (WU).

	Fossil-based plastics														Bio-based plastics	
	HDPE						LDPE			LLDPE	PP				PLA/starch	TPS
	BE	DE	ES	FR	IT	NL	BE	DE	ES	DE	BE	DE	FR	NL	DE	DE
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
AC	-4.05%	-40.91%	7.75%	-4.67%	-6.88%	-2.70%	-10.31%	-36.95%	4.94%	-40.85%	-5.57%	-39.26%	-6.37%	-3.66%	-3.88%	-6.94%
CC	-2.38%	-15.82%	14.70%	-4.20%	18.32%	1.74%	-6.64%	-10.28%	11.42%	-15.63%	-3.53%	-13.70%	-6.04%	2.40%	2.11%	-0.72%
Ecotox	-1.13%	-20.01%	1.66%	-1.11%	7.72%	-0.98%	-3.19%	-18.68%	-0.13%	-20.02%	-1.66%	-19.61%	-1.63%	-1.42%	-0.96%	-10.45%
Fresh, EU	-3.72%	11.46%	-21.46%	-12.66%	12.89%	0.91%	-6.31%	37.35%	-32.32%	10.68%	-4.12%	21.84%	-17.05%	2.70%	-27.77%	-29.94%
Marine, EU	-2.39%	-38.05%	6.82%	-3.72%	-18.81%	-0.43%	-5.80%	-31.60%	5.23%	-38.10%	-2.97%	-35.73%	-4.76%	-0.25%	8.41%	13.95%
Terrestrial, EU	-2.45%	-39.86%	6.97%	-3.79%	-18.90%	-0.53%	-5.94%	-33.47%	5.59%	-39.79%	-3.01%	-37.29%	-4.80%	-0.36%	-1.66%	-3.73%
HT, cancer	-1.79%	-11.91%	-2.73%	-1.92%	3.81%	-0.21%	-4.53%	-9.87%	-0.54%	-11.89%	-2.33%	-11.27%	-2.66%	0.87%	8.85%	26.64%
HT, non-cancer	-1.24%	2.18%	-18.17%	-1.52%	4.13%	-0.40%	-3.64%	2.03%	-19.32%	2.23%	-2.20%	2.16%	-2.32%	-0.67%	31.76%	32.66%
IR	-13.76%	-63.69%	-47.31%	183.52%	-68.02%	-56.48%	-15.01%	-64.61%	-49.63%	-63.29%	-12.53%	-63.44%	216.11%	-61.98%	-42.83%	-62.53%
LU	-5.38%	42.88%	-44.52%	-45.63%	15.15%	-22.99%	0.00%	52.69%	-45.12%	44.25%	-2.76%	47.25%	-50.48%	-23.46%	-19.10%	-27.43%
OD	9.07%	89.87%	-36.06%	-34.35%	31.40%	10.48%	14.71%	94.05%	-37.11%	92.02%	14.53%	96.13%	-36.47%	16.45%	88.64%	79.91%
PM	-3.69%	-26.60%	3.44%	-4.30%	-2.80%	-1.83%	-12.26%	-33.33%	2.25%	-38.20%	-7.04%	-36.83%	-7.95%	-3.26%	-8.57%	-14.22%
POF	-1.47%	-40.74%	-3.91%	-2.16%	-17.77%	-0.39%	-4.37%	-43.71%	-4.45%	-40.74%	-2.02%	-42.54%	-3.04%	-0.38%	-4.30%	-16.82%
RU, fossils	-0.07%	-6.88%	-0.12%	0.40%	0.85%	-0.49%	0.32%	-7.16%	-0.43%	-6.79%	0.30%	-6.99%	1.05%	-0.37%	-4.25%	-8.49%
RU, mineral and metals	1.44%	10.67%	-5.42%	-12.52%	2.12%	-0.75%	4.35%	24.45%	-2.03%	10.45%	3.12%	16.41%	-16.42%	0.35%	-38.25%	-49.46%
WU	-8.74%	-93.81%	67.74%	-6.89%	-6.02%	-8.50%	-20.25%	-92.71%	102.27%	-93.60%	-11.30%	-91.90%	-8.77%	-10.92%	-52.60%	-97.33%

International Energy Agency, 2023).

Ozone Depletion (OD). It is classified as a global-scale impact (Jensen et al., 1997). Hence, as expected, no efforts on inventory spatialization and impact regionalization were present in the investigated datasets and in the adopted LCIA method, respectively. Focusing on inventory regionalization, similarly to the previously analyzed IC, regardless of the dataset, 99 % of its impact depends on two elementary flows, both associated with the "Halogenated organic emissions to air" within the "Emission to air" compartment. These are two hydrochlorofluorocarbons (HCFC): R 141b (dichloro-1-fluoroethane) and R 142b (chlorodifluoroethane). The R 141b elementary flow, which accounts for more than 98 % of OD impact in all the analyzed datasets, refers to the release of refrigerant gas used in plastic production life cycle phases (UNEP, 2015).

In Table 2, results' variations between country-specific and RER datasets range from −37,11 % (for LLDPE) to +96,13 % (for PP), where the highest positive variations, around 80–96 %, were reported by DE datasets, available for all the investigated FB and BB polymers. The second highest positive variation was obtained by the available IT dataset for HDPE (31.40 %), followed by BE and NL, with variations around 9–16 % for HDPE, LDPE, and PP, and HDPE and PP, respectively. Around −34 and −37 % variations were obtained for available FR datasets for HDPE and PP and ES datasets for HDPE and LDPE.

Water use (WU). It is classified as a local-scale impact for which both impact regionalization and inventory spatialization were implemented. For impact regionalization, regionalized CFs are made available by the EF 3.1 method (as anticipated in Paragraph 2.3). For inventory spatialization, some elementary flow related to WU are linked to specific geographic locations in the MLC Databases. They are marked by the term *regionalized* in the elementary flow nomenclature, followed by the country's local code (e.g., "Lake water to turbine, regionalized, IT"). Regardless of the dataset, the input and output elementary flows contributing more than 1 % to the calculated impact are reported in Table 3. Among them, only the input EF "River water" is not available as spatialized, although it provides a relevant contribution (i.e., up to 35 % for BB polymers).

In Table 3, the percentage variations between country-specific and RER datasets range from −97.33 % (for TPS) to +102.27 % (for LDPE). Only ES datasets available for LDPE and HDPE showed positive variations compared to RER datasets (102.27 % and 67.74 %, respectively). Conversely, DE datasets reported the lowest negative variations for both FB and BB polymers, with an average value of −95 %. BE, FR, IT and NL obtained less significant negative variations with values ranging between −6 % and −20 %.

The spatialized elementary flow contributes to outlining the source of impact of aggregated datasets. As an example, a comparative analysis of ES and RER datasets for HDPE and LDPE, for which a high positive variation was pointed out, is discussed here. Percentage contributions reported in Table 4 highlight that in more than half of ES datasets, WU impact is determined by spatialized elementary flows associated with Spain, as 64.72 % of ES dataset impact for HDPE and 75.80 % for LDPE is due to "Ground water, regionalized, ES", "Lake water to turbine,

Table 3
Relevant input and output elementary flows for Water Use impact category.

Input elementary flow	Output elementary flow
Ground water	Cooling water to river
Ground water, regionalized	Cooling water to river, regionalized
Lake water	Turbined water to river
Lake water to turbine, regionalized	Turbined water to river, regionalized
River water	
River water to turbine	
River water to turbine, regionalized	

Table 4
Percentage contribution of the most relevant spatialized elementary flows within ES and RER datasets available for HDPE and LDPE.

Elementary flows	HDPE		LDPE	
	ES dataset	RER dataset	ES dataset	RER dataset
Upstream				
Groundwater, regionalized, ES	3.80 %	<1 %	2.07 %	<1 %
Lake water to turbine, regionalized, ES	25.72 %	1.96 %	31.15 %	2.14 %
River water to turbine, regionalized, ES	5.20 %	<1 %	6.27 %	<1 %
River water to turbine, regionalized, IT	2.00 %	18.40 %	1.00 %	20.05 %
River water to turbine, regionalized, FR	2.73 %	7.13 %	2.76 %	7.76 %
River water to turbine	<1 %	5.05 %	<1 %	5.36 %
Downstream				
Cooling water to river, regionalized, ES	4.99 %	<1 %	6.02 %	<1 %
Turbined water to river, regionalized, ES	25.01 %	1.91 %	30.29 %	2.08 %
Turbined water to river, regionalized, IT	2.11 %	19.40 %	1.04 %	21.14 %
Turbined water to river, regionalized, FR	2.81 %	7.34 %	2.85 %	7.99 %
Turbined water to river	1.15 %	5.26 %	<1 %	5.45 %
Total	75.52 %	66.45 %	83.45 %	71.97 %

regionalized, ES", "River water to turbine, regionalized, ES", "Cooling water to river, regionalized, ES" and "Turbined water to river, regionalized, ES", indicating that significant contributions to water use impact primarily arise from hydroelectricity generation.

Such spatialized elementary flows linked to Spain are also included in RER datasets but with a minor role (i.e., maximum percentage contribution of around 2 %). The most relevant elementary flows in RER datasets are two non-spatialized elementary flows ("River water to turbine" and "Turbined water to river", with around 5 % contribution each) and the same elementary flows, spatialized for both Italy (around 20 % contribution each) and France (around 7 % contribution each). Accordingly, the main contribution is provided by spatialized elementary flows for IT, accounting for 37.80 % (HDPE) and 41.19 % (LDPE), followed by spatialized elementary flows for FR, accounting for 14.47 % (HDPE) and 15.75 % (LDPE). In ES datasets, the percentage contribution of such elementary flow reaches values around 2–3 %. Such modelling choices and the calculation method used determine the WU results of RER and ES datasets. As for the method, in EF 3.1 WU calculation is based on AWaRe (i.e., Available Water REmaining). This midpoint indicator quantifies the relative available water remaining per area once the demand of humans and aquatic ecosystems has been met. Although the available water remaining for Italy and Spain can be considered similar, as in both countries water scarcity conditions prevail according to the most recent WEI+ (Water exploitation index plus) data published by EEA (European Environmental Agency, 2025), in AWaRe the regionalized CFs of the two countries are very different, as shown in Table 5.

More specifically, in AWaRe regionalized CFs for Spain are approximately twice those for Italy and 10-fold greater than those for France. Such difference can be ascribed to the fact that the last WEI + data published by EEA refers to 2022 (European Environmental Agency, 2025), while last update of AWaRe CFs dates back to 2018 (Boulay et al., 2018), when water scarcity conditions in Italy were less severe than in Spain (European Environmental Agency, 2024). The CFs values reported in Table 5 along with the percentage contributions reported in Table 4,

Table 5
Regionalized CFs for France, Italy, and Spain distinguished in three different use classes: agricultural water use, non-agricultural water use, and unspecified water use (Boulay et al., 2018)*. The agricultural water use is an annual aggregated characterization factor for agricultural/irrigation water consumption on the basin level. The non-agricultural water use is an annual aggregated characterization factor for all water consumption sectors except irrigation/agriculture on the basin level. The unspecified water use is an annual aggregated characterization factor for unspecified water consumption sectors on basin level* (Sphera, 2022b).

	Agricultural water use CF	Non-agricultural water use CF	Unspecified water use CF
France (FR)	9.487	3.051	8.151
Italy (IT)	46.401	16.678	43.214
Spain (ES)	80.760	31.411	79.334

can explain the different WU impact obtained by ES and RER datasets for HDPE and LDPE. The analysis performed for the other country-specific datasets (results not shown) led to similar results.

Land Use (LU). As for Water Use, it is a local-scale effect IC for which both impact regionalization and inventory spatialization were implemented. For impact regionalization, regionalized CFs are made available by the EF 3.1 method (as anticipated in Paragraph 2.3). For inventory spatialization, some spatialized elementary flows are available (e.g., "Forest, used, regionalized, IT"). The elementary flows contributing more than 1 % to the calculated impact, regardless of the dataset, are the following: "Arable"; "Arable, irrigated, intensive, regionalized"; "Arable, non-irrigated, intensive, regionalized"; "Forest, used, regionalized"; "Permanent crops, regionalized". Out of them, "Arable, irrigated, intensive, regionalized, DE" is always providing a major contribution to LU impact in both country-specific and RER datasets, followed by "Arable, non-irrigated, intensive, regionalized, DE" which provides a relevant contribution to country-specific and RER datasets related to FB polymers only (Table 6).

In Table 2, results' variations between country-specific and RER datasets range from −50.48 % (for PP) to +52.69 % (for LDPE), where the highest positive variations were reported by all available DE datasets for FB polymers. Focusing on FB polymers, the second highest positive variation was obtained by IT dataset for HDPE (+15.15 %). BE datasets showed results very similar to RER datasets for LDPE (0 %), PP (-2.76 %), and HDPE (−5.38 %), while NL datasets showed negative variations, around −23 %, for HDPE and PP. Finally, the lowest negative variations, around −45/50 %, were reported by ES and FR datasets for HDPE, LDPE and PP. For BB datasets, results' variations between the available DE and RER datasets were negative (−19.10 % for PLA and −27.43 % in TPS), indicating an opposite result compared to FB polymers.

For FB polymers, the results are mainly driven by the country specific energy mix, as they reflect the land used for energy production, while for BB polymers, LU impact is determined by both energy production and agricultural activities needed for feedstock cultivation.

The major contribution provided by the "Arable, irrigated, intensive, regionalized, DE" and "Arable, non-irrigated, intensive, regionalized, DE" elementary flows (Table 6), can be explained by the fact that Germany is a large producer and net exporter of renewable energy in Europe (I. E. A. International Energy Agency, 2020b).

Freshwater Eutrophication (EUTR fw), Human Toxicity, cancer (HT, cancer) and non-cancer (HT non-cancer), Resource use, minerals and metals (RU, minerals and metals). In Table 2, these ICs show relevant variations for BB polymers only. It is worth noting that, The Plastics LCA method recommends caution in interpreting LCA results for such ICs, especially in comparative studies, due to high uncertainty and lower robustness inherent in the underlying impact assessment methods. Such uncertainty can be up to 1-2 orders of magnitude (Nessi et al., 2021). For all of them, classified as global-scale effect ICs, both inventory spatialization and impact regionalization are

Table 6
Percentage contribution of the two most relevant spatialized elementary flows (both linked to Germany) within country-specific and RER datasets. While for FB polymers percentage contribution at country-specific level is reported as average, for BB polymers, for which only DE datasets are available, the percentage contribution in such DE datasets is reported.

		Arable, irrigated, intensive (regionalized, DE)	Arable, non-irrigated, intensive (regionalized, DE)	Total
HDPE	Average country-specific	30.59 %	13.84 %	44.44 %
	RER dataset	27.51 %	12.70 %	40.21 %
LDPE	Average country-specific	28.10 %	13.33 %	41.43 %
	RER dataset	43.57 %	22.61 %	66.19 %
LLDPE	Average country-specific	35.47 %	17.60 %	53.06 %
	RER dataset	27.43 %	12.63 %	40.06 %
PP	Average country-specific	30.56 %	13.79 %	44.35 %
	RER dataset	27.54 %	12.79 %	40.32 %
PLA	DE	63.33 %	0.78 %	64.12 %
	RER dataset	32.01 %	0.25 %	32.27 %
TPS	DE	98.19 %	0.67 %	98.85 %
	RER dataset	44.69 %	0.20 %	44.90 %

not implemented. As far as inventory regionalization is concerned, the following paragraphs are dedicated to each individual IC.

Freshwater Eutrophication (EUTR, fw). The calculated impact depends on two elementary flows associated with the “Inorganic emissions to freshwater” compartment in both PLA and TPS datasets. These are “Phosphate” and “Phosphorus”, of which “Phosphate” accounts for about 90 % in TPS and 85 % in PLA in the two (DE and RER) investigated datasets (Table 7). These elementary flows depend on the upstream phase of BB polymers' lifecycle in which fertilizers are used in agricultural activities (Gallego et al., 2010; Henryson et al., 2018) as well as on effluent wastes generated in starch production (Hottle et al., 2017).

Table 7 shows small variations between elementary flows that compose the impact of DE and RER datasets. For instance, Phosphate contributes for 91.28 % in DE dataset and 89.45 % in RER dataset for TPS, whereas its contribution is 85 % in DE dataset and 85.05 % in RER dataset for PLA. However, these variations may become more apparent when comparing datasets across different countries since the agricultural sector is particularly susceptible to regionalized data due to variations across space and time (Chaplin-Kramer et al., 2015). Presently, the shortage of available country-specific datasets poses a challenge in identifying such variations.

Human toxicity, cancer (HT, cancer) and non-cancer (HT, non-cancer). Regardless of dataset, the two ICs depend on elementary flows associated with “Heavy metal emissions to air”, “Heavy metal emissions to agricultural soil” compartments and, only for HT, cancer, “Heavy metal to freshwater” compartment. The most relevant elementary flows in HT, cancer are “Chromium”, “Mercury” and “Lead”, while those relevant in HT, non-cancer are “Lead”, “Mercury”, and “Cadmium”.

Table 7
Percentage contribution of the most relevant in elementary flows in DE and RER datasets available for BB polymers.

Elementary flows	TPS		PLA	
	DE	RER	DE	RER
Phosphate	91.28 %	89.45 %	85.00 %	85.05 %
Phosphorus	8.72 %	10.55 %	14.99 %	14.95 %

These findings are primarily attributed to the upstream and manufacturing stages of BB polymers, but it is not possible to distinguish which elementary flow depends on which phases. Indeed, the upstream stage regards the industrial agricultural production of BB feedstocks (e.g., corn, potato, sugar cane, sugar beet) which are grown using potentially toxic pesticides and fertilizers (Álvarez-Chávez et al., 2012). As for the manufacturing stage, the main contribution relates to the utilization of hazardous chemicals and hazardous additives in BB plastic production and processing (Álvarez-Chávez et al., 2012).

Resource use, minerals and metals (RU, minerals and metals). The calculated impact mainly depends on elementary flows associated with “Non-renewable elements” compartment, namely “Sulphur” and “Lead”. Of these, “Sulphur” provides major contribution, accounting for about 75–80 % in TPS datasets, and for about 55–60 % in PLA datasets.

These findings can be ascribed to the upstream and manufacturing stages of BB polymers. In particular, in the upstream stage a significant contribution is provided by agricultural practices entailing the utilization of sulphur-based pesticides. In the manufacturing stage, the main contribution concerns the utilization of sulphuric acid in BB plastic production and processing (Álvarez-Chávez et al., 2012).

3.3. *Cross-sectional discussion of the results analyzed under the second criterion and limitations of the study*

From the discussion in 3.2, a cross-sectional analysis of the results can be conducted, keeping in mind that, as anticipated in Section 2.2, a notable limitation of this study is that, out of the four available levels of regionalization (depicted in Fig. 1), information can only be reconstructed up to level 2, as all regionalized datasets in the MLC databases are aggregated. This aggregation prevents the direct linking of elementary flows to their specific sources, hindering detailed analysis and undermining the precision of impact assessment results. Direct access to the Master Database could potentially overcome this limitation. However, within the Sphera platform, access to this central archive is strictly limited to Data Team members and requires documented, signed permissions, along with designated read and edit rights (Sphera, 2022a). In light of these limitations, future research could benefit from exploring collaboration with database providers to enhance access to more disaggregated datasets.

Among the investigated ICs, three (i.e., *Ionizing Radiation* (IR), *Water Use* (WU), and *Land Use* (LU)) show differences between country-specific and RER datasets that can be explained by the energy supply (i.e., level 1 - by the differences in country-specific energy mix). For all the others (*Ozone Depletion* (OD), *Resource Use, minerals and metals* (RU, minerals and metals), *Human Toxicity, cancer* (HT, cancer) *and non-cancer* (HT non-cancer), and *Freshwater Eutrophication* (EUTR, fw)), differences in the environmental impacts calculated for country-specific and RER datasets cannot be explained by the energy supply and therefore are due to differences in other regional supply data (i.e., level 2). However, since these ICs are affected by high uncertainty and lower robustness inherent in the underlying impact assessment methods (Nessi et al., 2021), the analysis of the elementary flows did not allow to derive insightful information. Thus, the discussion was based on scientific literature only, when available (i.e., for RU, minerals and metals; HT, cancer; HT, non-cancer; EUTR, fw), and this is recognized as a limitation of this study. Overall, the analysis reveals significant variations in the investigated datasets and points out the need to build and make available more country-specific datasets to minimize the uncertainty around the use of RER datasets in LCA and, more broadly, to identify trends that could inform guidelines for using proxy data. Additionally, a much larger implementation of *inventory regionalization* should then be accompanied by *impact regionalization* at the LCIA level, as regional dynamics are made explicit through spatialized elementary flows if only regionalized CFs are available.

4. Conclusions

This study investigates the influence of choosing between generic and country-specific Life Cycle Inventory (LCI) datasets on the findings of LCA studies on the main FB and BB polymers produced in Europe, considering "1 kg of granulate polymer for packaging" as FU. The analysis was carried out using a selection of regionalized FB polymers (i.e., HDPE, LDPE, LLDPE, and PP) and BB polymers (i.e., PLA/starch, and TPS) datasets from MLC Databases, utilizing the EF 3.1 method and the LCA For Expert software.

The findings have revealed that site-specific datasets are frequently lacking or unevenly distributed. This issue is especially pronounced in the case of BB polymers. Although Europe has the largest availability of country-specific datasets, within the investigated database BB polymers remain significantly underrepresented. The absence of regional data necessitates reliance on generic datasets, which fail to accurately capture the environmental impacts specific to a given geographical area. As LCA serves as a decision-support tool, the use of generic data can lead to recommendations and actions that are ill-suited to the local context.

According to the first assessment criterion, the findings indicate that the burden-shifting implications associated with decisions to replace FB polymers with BB alternatives should not prioritize Climate Change as the sole critical factor. Currently, there is also a lack of a standardized approach for analyzing biogenic CO_2, complicating the assessment of the environmental impacts related to the use of BB materials. This highlights the need for improved data regionalization and a more nuanced understanding of biogenic carbon dynamics in future LCA studies. Moreover, a broader implementation of regionalization at the LCIA level is recommended. By employing regionalized characterization factors, local dynamics can be explicitly captured through spatialized elementary flows. This approach not only enhances the accuracy and relevance of LCA results but also solidifies the utility of LCA as a decision-support tool in environmental management and policy formulation.

The analysis according to the second assessment criterion revealed which ICs are mostly affected by the use of generic (i.e., RER) datasets. More specifically, *Ionizing Radiation, Land Use, Ozone Depletion,* and *Water Use* exhibited relevant variations for more than half of the country-specific datasets, for both FB and BB polymers. In addition to them, *Resource Use, minerals and metals, Human Toxicity, cancer and non-cancer,* and *Freshwater Eutrophication* showed relevant variations mainly for BB datasets. Moreover, while for *Ionizing Radiation*, *Water Use*, and *Land Use,* variations could be explained by differences in country-specific energy supply, for all the other ICs, differences in other regional supply data play an important role, as reported in previous scientific literature. Therefore, caution is recommended to LCA practitioners in relying on generic datasets, especially for impact categories such as *Ionizing Radiation, Land Use, Ozone Depletion*, and *Water Use*, which are highly sensitive to geographical variability. Unfortunately, the lack of transparency in how RER datasets are built currently limits in-depth analysis of the spatialization of elementary flows. Disclosing which spatialized elementary flows are mostly contributing to a specific RER dataset would advance the analysis of regionalization and spatialization in LCI. Meanwhile, site-specific datasets should be prioritized to enhance the accuracy and relevance of LCA results, although for LCI database developers expanding the availability of country-specific datasets is critical, especially for underrepresented regions and materials such as BB plastics.

It is important to recall that the study was conducted considering "1 kg of granulate polymer for packaging" as FU, to be able to deeply investigate the effects of the use of regionalized datasets on impact categories results, and therefore it is not useful to compare different packaging solutions. To assess environmental impacts of the whole life cycle of packaging solutions such as, for example, lightweight carrier bags, a different FU should be used (e.g., "To facilitate the transportation of purchased food and drinks to an average household for one year, from the store to the place of consumption") which would allow to consider e.g., the different mass of polymers used, the number of uses of each bag, and the different end of life treatment options.

It should also be noted that the analysis of both the occurrence of burden shifting and the influence of country-specific versus generic datasets are broadly applicable across various fields and product categories. Of course, the ICs to focus on could be different, depending on the materials or products under investigation, and the results of both analysis would highly depend on the available country-specific datasets.

Finally, as a concluding remark, a much larger implementation of *inventory regionalization* and impact regionalization at the LCIA level is recommended, as regional dynamics are made explicit through spatialized elementary flows if only regionalized CFs are available.

CRediT authorship contribution statement

Anna Carlesso: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Lisa Pizzol:** Writing – review & editing, Investigation. **Antonio Marcomini:** Funding acquisition. **Elena Semenzin:** Writing – review & editing, Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cesys.2025.100365.

Data availability

The data that has been used is confidential.

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