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RESEARCH AND ANALYSIS

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How do carbon footprints from LCA and EEIOA databases compare?

A comparison of ecoinvent and EXIOBASE

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Abstract

Life cycle assessment (LCA) and environmentally extended input output analysis (EEIOA) are two widely used approaches to assess the environmental impacts of products and services with the aim of providing decision support. Here, we compare carbon footprint (CF) results for products and services in the ecoinvent 3.4 cut-off and the hybrid version of EXIOBASE. While we find that there is good agreement for certain sectors, more than half of the matched products differ by more than a factor 2. Best fits are observed in the energy, manufacturing, and agricultural sectors, although deviations are substantial for renewable energy. Poorer fits are observed for waste treatment and mining sectors. Both databases have a limited differentiation in the service sector. Differences can, to some degree, be explained by methodological differences, such as system boundaries and approaches used to resolve multi-functionality, and data differences. The common finding that, due to incomplete economic coverage (truncation error), LCA-based CFs should be lower than EEIOA-based CFs, could not be confirmed. The comparison of CFs from LCA and EEIOA databases can provide additional insights into the uncertainties of CF results, which is important knowledge when guiding decision makers. An approach that uses the coefficient of variation to identify strategic database improvement potentials is also presented and highlights several product groups that could deserve additional attention in both databases. Further strategic database improvements are crucial to reduce uncertainties and increase the robustness of decision support that the industrial ecology community can provide for the economic transformations ahead of us. This article met the requirements for a gold-gold *JIE* data openness badge described at http://jie.click/badges.

KEYWORDS
carbon footprint, ecoinvent, environmentally extended input output analysis (EEIOA), EXIOBASE, industrial ecology, life cycle assessment (LCA)

1 | INTRODUCTION

Both life cycle assessment (LCA) and environmentally extended input–output analysis (EEIOA) are used to make environmental impact assessments of products and services. LCA focuses on specific products and services, and for this purpose, life cycle inventory (LCI) databases describe representative production processes (Finnveden et al., 2009; Hellweg & Canals, 2014). EEIOA focuses on product groups that typically cover everything consumed in an economy (e.g., Davis & Caldeira, 2010; Hertwich & Peters, 2009; Wiedmann et al., 2010). However, recently, LCAs have been used to assess GHG emissions for product groups covering everything consumed in the economy by pooling large numbers of LCAs (e.g., Nita et al., 2017; Sala & Castellani, 2019). At the same time, EEIOAs have become so detailed that they represent similar specific products as traditionally found in LCAs (e.g., Lenzen et al., 2013). Therefore, it has become possible to compare carbon footprints (CFs) with EEIOA and LCA at similar product detail.

Since EEIOA found application in the assessment of environmental impacts associated with the consumption of products and services, there has been an interest in comparing LCA results with EEIOA results. The general idea is that comparing the results of two different approaches to assess life cycle impacts gives us an idea of the absolute uncertainties in the results. Early work compared three steel production processes in the GaBi LCI database with Carnegie-Mellon University's EIO-LCA database (Hendrickson et al., 1997). Later work compared the ETH 96 LCA database and the MIET database (Mongelli et al., 2005) and the ecoinvent 2.1 database with the OpenIO database (Majeau-Bettez et al., 2011). Recent work compared the ecoinvent 3.2 and Agrifootprint v.2 databases to the hybrid version of EXIOBASE (v3.3.8) (Castellani et al., 2019). This last study demonstrates how the pooling of large numbers of LCAs and the disaggregated EEIOA databases can be used to calculate life cycle impacts of similar product groups. The authors compare the life cycle impacts of the total European household consumption for housing, mobility, food, household goods, and appliances. LCA-based CFs were found to be 15% lower than EEIOA-based CFs. Castellani et al. (2019) conclude that EEIOA and pooled LCA results converge in identifying the main areas of household consumption as key drivers of impact (i.e., food, mobility, housing, and energy using products), which is in line with previous findings by Tukker and Jansen (2006). Agez et al. (2020, 2021, 2020) have recently provided new methodology, data, and a code repository for the hybridization of ecoinvent and EXIOBASE, which may help to overcome truncation errors due to cut-offs in LCA. However, a study that compares the environmental impacts associated with all product groups as modeled in ecoinvent and EXIOBASE is missing so far.

The purpose of this article is to fill this gap by comparing the carbon footprints of products[1] between the ecoinvent and EXIOBASE databases at the highest possible product resolution. We are aware that one could argue that such a comparison is not valid due to differences in the definition and aggregation of products, the use of alternative data sources, or different modeling choices. Yet, our motivation is to conduct such a comparison for the practical reason that ecoinvent and EXIOBASE are increasingly used for the same purpose, that is, carbon footprinting of products and services, regardless of whether practitioners are aware of the underlying differences or not. Our main research questions are:

1. What is the sectoral coverage of ecoinvent and EXIOBASE and how does the level of product detail compare across sectors?
2. How do carbon footprints compare in both databases?

We then discuss systematic reasons for differences as well as potential implications for database improvements and the limitations of our study.

2 | DATA AND METHODS

2.1 | Overall approach

To conduct a comparison between LCI and EEIOA databases, we choose two frequently used databases: the ecoinvent database version 3.4 in its cut-off system model (Wernet et al., 2016) and the hybrid input-output table of EXIOBASE v3.3.18 (Merciai & Schmidt, 2018) following the by-product technology model (Suh et al., 2010). The hybrid version was chosen over the monetary version of EXIOBASE, since it expresses the products in physical units and the services in monetary units. This makes it easier to compare CFs across both databases, as ecoinvent uses physical units, and also reduces potential CF uncertainties in the comparison due to price fluctuation (Jakobs et al., 2021).

The overall approach consisted of four steps (see also Supporting Information S1, Figure S1): data preparation, matching, analyses, and interpretation. In the following sections, the first three steps are described. Interpretation consists of a discussion of systematic reasons for differences and implications of our findings, as well as conclusions and recommendations. The complete data, matching files, and code used in this paper are available on https://zenodo.org/record/6077868#.Yg9kR5Yo9WI.

2.2 | Data preparation

2.2.1 | Carbon footprint calculation

The carbon footprint of each product in EXIOBASE and ecoinvent is calculated per unit of product, for example, kg CO_2-eq. per kg or kg CO_2-eq. per MJ, and thus essentially represent carbon footprint intensities. For both databases, the IPCC, 2013 characterization factors (IPCC, 2013) for a

100-year time horizon have been used. In order to keep the characterization factors identical between the two databases, some characterization factors were removed for ecoinvent. This leads to a median and mean reduction of ecoinvent carbon footprints by 0.2% and 4%, respectively. Note that EXIOBASE does not have characterization factors for some substances, which are instead directly reported as CO_2-eq. (see Supporting Information S1, Table S2).

2.2.2 | Ecoinvent

The ecoinvent database distinguishes two types of activities (i.e., processes): transforming (production) activities and transferring activities (consumption mixes called markets) (Wernet et al., 2016). The general rule is that production activities source their inputs from markets. Although both types of activities can be regionalized, it is typically the production activities that are regionalized, while markets tend to be global (a notable exception being the energy sector). In addition to representing consumption mixes, markets in ecoinvent account for transportation and losses. However, typically the difference in environmental impact measured after production or at the market is small, since many markets contain only a single global producer, or group a number of equivalent producers from different geographies into a global market (again a notable exception being the energy sector). In order not to account for each product twice, that is, once after production and once at the market, we chose to exclude market activities from the comparison, giving priority to having a better regional resolution over environmental completeness. This means that for the compared ecoinvent products, the final transport step and potential product losses during this step are missing, while all other transport and losses of intermediates along the supply chain of products are included.

Further, rest-of-the-world (RoW) activities in ecoinvent were excluded from the comparison as their geographical scope does not match the geographical scope of the RoW regions in EXIOBASE (see also Section 2.3.2).

2.2.3 | EXIOBASE

Since many products in ecoinvent have a geographical scope of either global (GLO) or region Europe (RER), two aggregated regions were created with EXIOBASE based on the existing more detailed country classification, that is, GLO and RER, to enable a better matching of the databases. Additionally, products were classified according to the International Standard Industrial Classification (ISIC) section level classification that divides the economy into 21 sectors (United Nations, 2008), which enabled a high-level comparison of the sectoral coverage of both databases (see Section 2.4.1). Finally, we exclude EXIOBASE products that have a carbon footprint of zero in a given region as this means that they are not produced in this region.

2.3 | Matching

Three criteria were used to match datasets in the ecoinvent database to datasets in EXIOBASE. The first one is *product equivalency*. Here, we follow the idea that EXIOBASE is in general the more aggregated database, that is, the definition of a product in EXIOBASE is broader than that in ecoinvent (although exceptions may exist). For this reason, we associate, wherever possible, ecoinvent products with EXIOBASE products. This means that we perform a many-to-one matching, where several ecoinvent products can be matched to one EXIOBASE product, while an ecoinvent product can only be matched to exactly one EXIOBASE product. The second one is *geographical equivalency*. Here, we try to associate production regions in ecoinvent to those in EXIOBASE. The general logic applied was to identify exact matches, wherever possible, and otherwise search for an EXIOBASE region that contains an ecoinvent region. The third one is *unit equivalency*. In order to perform quantitative comparisons, for example, for product carbon footprints, the functional unit for both product systems needs to be comparable (e.g., kg to kg and not kg to Euro), and for weight, it was done on the basis of wet weight (data for the dry matter coefficients are provided as part of the general EXIOBASE data downloadable from exiobase.eu).

Due to the lack of a systematic product classification that enables a meaningful automatic matching of products of both databases, the matching of products was done manually to make matching at the highest level of detail possible.

2.3.1 | Products

We manually matched 2325 of 2851 products modeled in the ecoinvent database to 100 of the 164 products of EXIOBASE (e.g., *wheat production* to *Wheat* or *kiwi production* to *Vegetables, fruit, nuts*). The only exception was electricity, which could not be sufficiently distinguished by product name in ecoinvent (e.g., the product "electricity, high voltage" does not yield information about the power source, such as wind or gas). Here, we manually assigned 1987 ecoinvent activities to 12 EXIOBASE products (e.g., *electricity production, wind, 1–3MW turbine, onshore* to *Electricity by wind*).

2.3.2 | Regions

EXIOBASE covers the global economy through 43 countries and 5 RoW regions (Merciai & Schmidt, 2018). EXIOBASE's level of regional disaggregation is very high, that is, most products are produced in most regions. Ecoinvent also has global coverage (Wernet et al., 2016) and distinguishes 261 regions; however, the level of regional disaggregation is not very high; that is, most products are not produced across many regions. Ecoinvent also includes other regional constructs next to countries, such as UN regions and subregions (e.g., Region North America), provinces or states (e.g., for China, India, and Canada), and special constructs such as *Europe without Switzerland*.

For a small number of regions in ecoinvent, no perfect match could be found. This concerned the aluminum-producing regions, for which we assumed the respective RoW regions in EXIOBASE, as well as Region Asia, for which we assumed RoW Asia, and Region North America, for which we assumed the United States. For all other geographies, there was either an exact match (the 43 EXIOBASE countries, RER, and GLO) or a match where an EXIOBASE RoW region contained a regional activity in ecoinvent (e.g., a province).

2.3.3 | Units

In order to perform quantitative comparisons, corresponding datasets in ecoinvent and EXIOBASE had to have the same unit. The hybrid version of EXIOBASE distinguishes three units, that is, kg, MJ, and Euro, which represent 67.6%, 6.6%, and 25.8% of the number of products in the database, respectively. Ecoinvent distinguishes 17 different units, of which *kg* (38.8%) and *MJ* (9%) could be directly matched and *kWh* (32.7%) could be converted to MJ to provide an additional match (numbers represent the number of products in ecoinvent). Other important units in the ecoinvent database are *unit* (7.7%), m^3 (4.5%), *hour* (1.4%), *ton-km* (1.4%), *ha* (1.3%), and m^2 (1.3%). Since these units do not exist in EXIOBASE, ecoinvent products with these units could not be included in the comparison.

2.4 | Analyses

2.4.1 | Comparison of sectoral coverage

In order to answer RQ1, a higher-level classification of products was required. Multiple classification systems exist for structuring economic activities, for example, NACE, ISIC, and CPC. We chose the ISIC (United Nations, 2008), since it was already available for the ecoinvent database. For EXIOBASE, we manually added an ISIC classification at the "section level" (a broad classification of the economy into 21 sectors) for all products.

2.4.2 | Comparison of carbon footprints

In order to answer RQ2, comparisons between the carbon footprints of all matched products were made. In order to analyze this data, we used the following metrics and statistical measures.

Correlation

Spearman's rank order correlation is assessed for the matched ecoinvent-EXIOBASE results. Correlation coefficients can be calculated for any subset of the data, that is, to assess how all matched datasets compare or how specific products compare.

Relative deviation

LCA- and EEIOA-based CFs may differ in orders of magnitude depending on the product (e.g., 1 kg of steel is associated with much higher GHG emissions than 1 kg of wood). Therefore, a relative measure is required to compare the carbon footprint results of products in both databases. We use the relative deviation d_{rel} as defined in Equation (1), where $CF_{ecoinvent}$ and $CF_{exiobase}$ are the product carbon footprints in each database:

$$d_{rel} = \frac{CF_{ecoinvent} - CF_{exiobase}}{CF_{exiobase}} \quad (1)$$

The relative deviation thus describes how the ecoinvent CFs differ from EXIOBASE CFs in relative terms. Note that the scale of the relative deviation is not linear but consists of three parts, which can be interpreted as follows:

- *numbers greater or equal to 0*: If the impact assessment results are equal, the result of Equation (1) will be 0 (meaning no deviation). Positive numbers mean that ecoinvent results are higher than EXIOBASE results (e.g., 1 means twice the impact score, or +100%).

- *numbers between 0 and −1*: ecoinvent results are smaller than EXIOBASE results (e.g., −0.5 means 50% lower impacts and −0.99 means 99% lower impacts).
- *numbers below −1*: Impact assessment results have a different sign in both databases. Since ecoinvent does not have negative impact scores in the cut-off version, this is a result of the by-product technology model in EXIOBASE (substitution); see also Section 4.3.

Coefficient of variation

The coefficient of variation (CV) is a standardized measure of the dispersion of data. A high CV means a high dispersion of the data and the other way around. It is measured as the ratio of the standard deviation *std* over its *mean* as in Equation (2):

$$CV = \frac{std\,(CF)}{mean\,(CF)} \tag{2}$$

where *CF* represents the carbon footprints of a set of products in both databases. As described earlier, the matching has been made so that one or several ecoinvent products match exactly one product in EXIOBASE. Some sort of grouping is thus required to calculate a CV for EXIOBASE. We chose to calculate the CV for the product level, but across regions. By relaxing the geographical equivalency constraint, we obtain a reasonable sample size for EXIOBASE products (typically between 40 to 48, as most EXIOBASE products are produced in each region and anywhere from single digit numbers to several hundred for ecoinvent products). Therefore, regional and technological differences can both determine the CV of ecoinvent and EXIOBASE products.

For some products, one may expect low CVs due to a narrow product definition and small regional differences (e.g., *electricity by natural gas*), while for other products, one may expect high CVs due to a wider product definition (e.g., *chemicals nec*[2]) or important regional differences in production technology (e.g., *paddy rice* cultivation) or a combination of product and regional differences (e.g., *vegetables, fruits, and nuts*).

The CV of products in each database can be plotted against each other. Four quadrants can then be distinguished (as illustrated in Supporting Information S1, Figure S2): Both databases may contain low or high dispersion products (as expected). However, if a given product has a large dispersion in one database and a small one in the other, this indicates that one of the databases could be improved and that practitioners should make an informed decision concerning which database to use. For example, if ecoinvent shows a high dispersion and EXIOBASE a low dispersion for a given product, this could indicate that there are technological or regional differences that are not well captured in EXIOBASE.

3 | RESULTS

3.1 | Sectoral coverage of databases

Table 1 shows the sectoral coverage of ecoinvent and EXIOBASE at the ISIC section level (21 broad economic sectors). It can be seen that both databases have a similar scope, focusing on primary production and manufacture of basic products, as well as energy and transport services (sectors A-F and H). Other outputs of service sectors, such as retail, financial, insurance, educational, and health services are covered in an aggregated way in EXIOBASE or only partly in ecoinvent. It can be further observed that ecoinvent provides, with 4164 products, a much higher disaggregation at the product level (according to our definition of products that includes the information on the supplying process, see Section 1) than EXIOBASE with 164 products. However, EXIOBASE provides a much higher level of regionalization as most products are produced in most of the 48 covered world regions, while ecoinvent typically only includes a small number of regional products (a notable exception is the energy sector).

3.2 | Matching

Since both ecoinvent and EXIOBASE have global geographical coverage, a good matching was possible on the regional level: for all 48 EXIOBASE regions, a matching region was found in the ecoinvent database. However, matches were only found for 177 out of 257 regions in ecoinvent; 2 out of 3 EXIOBASE (kg and MJ) and 3 out of 17 ecoinvent units (kg, MJ, and by conversion kWh) could be matched. In total, we were able to match 74% of EXIOBASE and 81% of ecoinvent products based on units. On the product level, we were able to match 105 EXIOBASE products out of the total of 164; however, 22 of these had no matching unit; thus, 84 products were included in the final matching file. For ecoinvent, a matching product was identified for 3320 out of 4150 products; however, the number was reduced to 2084 after considering the geographical and unit equivalency constraints. Therefore, roughly half of the products in each database could be matched to the other. Overall, we obtained 4567 regional product matches (i.e., products from specific suppliers in specific regions in ecoinvent matched to products from specific regions in EXIOBASE, e.g., *electricity, high voltage|electricity production, wind, 1–3MW turbine, onshore|FR* matched to *Electricity by wind|FR*). Supporting Information S1, Table S1 summarizes the matching results.

TABLE 1 The sectoral coverage of the compared databases according to the section-level ISIC (rev 4) classification

		No regional disaggregation			With regional disaggregation		
Code	Section	ecoinvent	EXIOBASE	ratio	ecoinvent	EXIOBASE	ratio
A	Agriculture, forestry, and fishing	398	19	20.9	808	761	1.1
B	Mining and quarrying	135	15	9.0	284	437	0.6
C	Manufacturing	2059	48	42.9	3907	2185	1.8
D	Electricity, gas, steam, and air conditioning supply	343	17	20.2	3162	572	5.5
E	Water supply; sewerage, waste management	741	35	21.2	1504	1326	1.1
F	Construction	279	1	279.0	525	48	10.9
G	Wholesale and retail trade; repair of motor vehicles	10	4	2.5	18	192	0.1
H	Transportation and storage	151	7	21.6	248	336	0.7
I	Accommodation and food service activities	0	1	–	0	48	–
J	Information and communication	6	1	6.0	13	48	0.3
K	Financial and insurance activities	0	3	–	0	144	–
L	Real estate activities	13	2	6.5	200	96	2.1
M	Professional, scientific, and technical activities	2	2	1.0	4	96	0.0
N	Administrative and support service activities	26	1	26.0	85	48	1.8
O	Public administration and defense; compulsory social	0	1	–	0	48	–
P	Education	0	1	–	0	48	–
Q	Human health and social work activities	0	1	–	0	48	–
R	Arts, entertainment, and recreation	0	1	–	0	48	–
S	Other service activities	1	2	0.5	2	96	0.0
T	Activities of households as employers	0	1	–	0	46	–
U	Activities of extraterritorial organizations	0	1	–	0	0	–
	Total number	4164[a]	164	–	10760[a]	6671[b]	–

Note: The left side shows the numbers of unique products in EXIOBASE compared to unique product-activity combinations from ecoinvent without regional disaggregation, while the right side includes regional disaggregation. The ratios relate to the number of ecoinvent product–activity combinations per EXIOBASE product.

[a]Market activities have been excluded in order not to artificially increase the numbers for ecoinvent. Further, 45 ecoinvent processes have no ISIC classification (recycled content cut-off activities) and have also been excluded here.

[b]Not all EXIOBASE regions produce all products; therefore, this number is lower than if all 48 regions were to produce all 164 products (7872).

3.3 | Comparison of GHG emissions

3.3.1 | Overall correlation

A grand overview of the carbon footprints of the matched regionalized products is shown in Figure 1 (note the double logarithmic scale). Matches are grouped by ISIC sections, of which, after matching, only sections A-F and N remained. Vertical rows of data points may represent the situation where alternative suppliers (e.g., different production technologies) are available in ecoinvent for a product in EXIOBASE. Horizontal rows of data points may represent the situation where a product match was feasible for multiple regions, but where only the CF of the EXIOBASE product varied while the CF was approximately the same for each region in ecoinvent. The overall picture shows that we may expect order of magnitude deviations between the carbon footprints calculated with ecoinvent and EXIOBASE. The following sections analyze the differences in more detail.

3.3.2 | Relative deviation

The relative deviation between all matched products is shown in ascending order in Figure 2. The plot shows values for the relative deviation between −2 and 5. Lower and higher values are not shown in order to facilitate the readability of the figure. The observed minimum value is −25 and maximum value is 8.4×10^7. About 44% of all matches show deviations smaller than a factor 2 (i.e., where ecoinvent products have in between half to twice the impact of the corresponding EXIOBASE product). For about 29% of the matched datasets, ecoinvent CFs are at least twice as high,

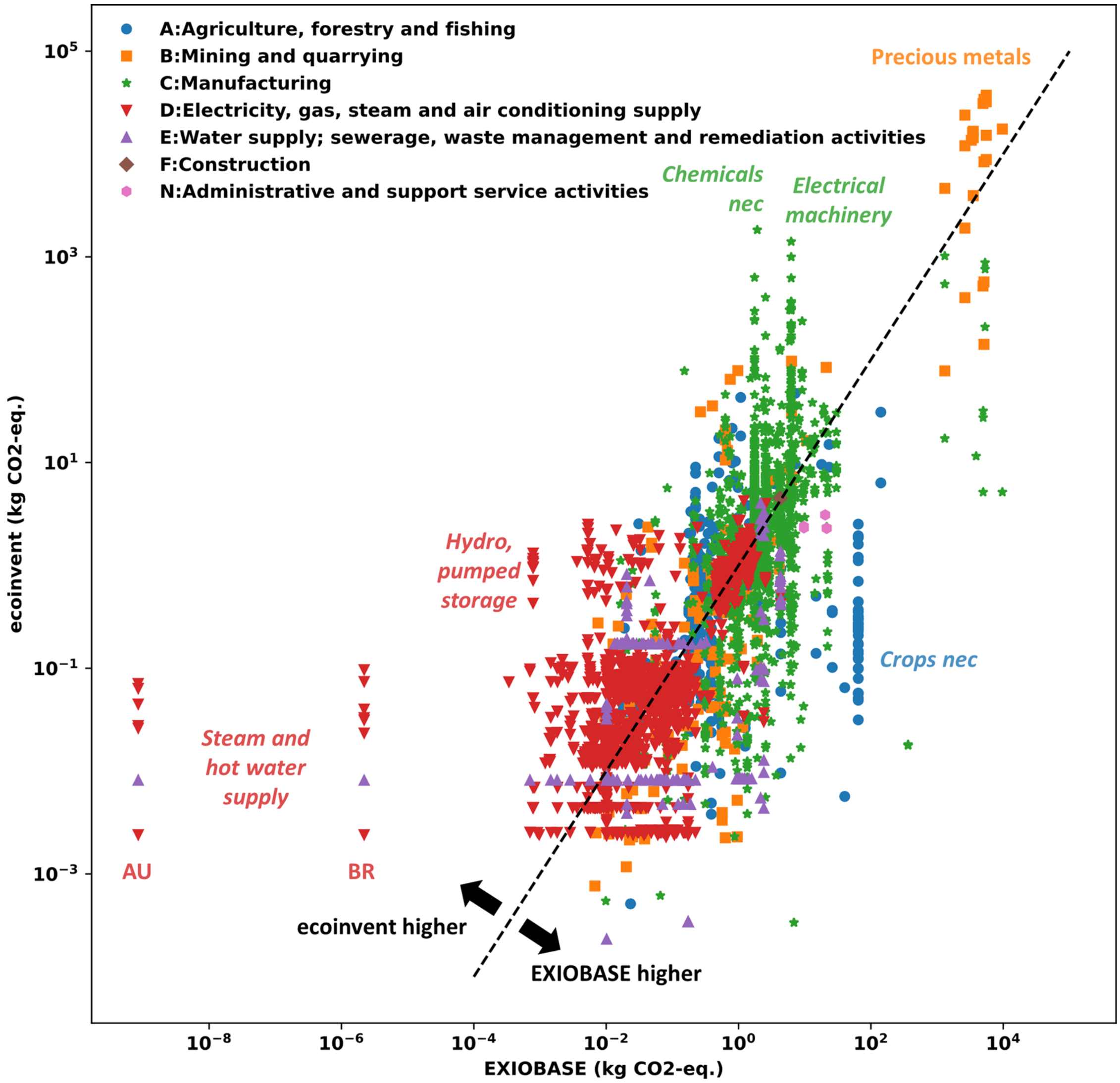

FIGURE 1 Comparison of carbon footprints in EXIOBASE and ecoinvent for matched products in kg CO_2-eq. Note that the functional unit depends on the specific product (it is either per kg, MJ or kWh [for electricity]) and that 49 products have been excluded from this comparison as their carbon footprint was negative in EXIOBASE (the logarithm for negative numbers is undefined). The dashed line represents the line of equality, that is, points on this line have equal CFs in both databases. The data behind this figure are provided in Supporting Information S2

and for about 24% of the matched datasets, the ecoinvent CFs are less than half of EXIOBASE CFs; 3% of matched datasets have no impact in ecoinvent. These are by-products of waste treatment processes, which by definition have no impact in the cut-off system model of ecoinvent as the waste treatment is fully allocated to the waste-producing activities (Wernet et al., 2016). This is handled differently in EXIOBASE, where a substitution approach is applied. The latter is responsible for the 1% of opposite sign impacts (benefits in EXIOBASE). The common finding that LCA results should be lower than EEIOA results due to truncation (Lenzen & Dey, 2000) is not confirmed here.

Figure 3 shows the relative deviation of the CFs of matched products per ISIC section level in the form of box plots. For the product classes with many matched products (A-E), we observe that the relative deviation can be large. For classes A (agriculture, forestry and fishing), C (manufacturing), and D (electricity, gas, steam and air conditioning supply), the median deviation is relatively small. CFs with ecoinvent are at average (median) 12% lower for class A, 9% lower for class C, and 16% higher for class D. CFs in classes B (mining and quarrying) and E (water supply, sewerage, waste management, and remediation activities) are at average 43% and 90% lower when assessed with ecoinvent. While we lack a compelling explanation for mining and quarrying, the substantially lower impacts of ecoinvent in class E, which is to a large extent dealing with waste treatment, can partly be explained by the use of the cut-off system model, which allocates all burdens of waste treatment to the waste producer and thus delivers co-products of waste treatment burden-free (Wernet et al., 2016). A meaningful comparison of classes F (construction) and N (administrative and support service activities) was not possible because of the small number of matched products.

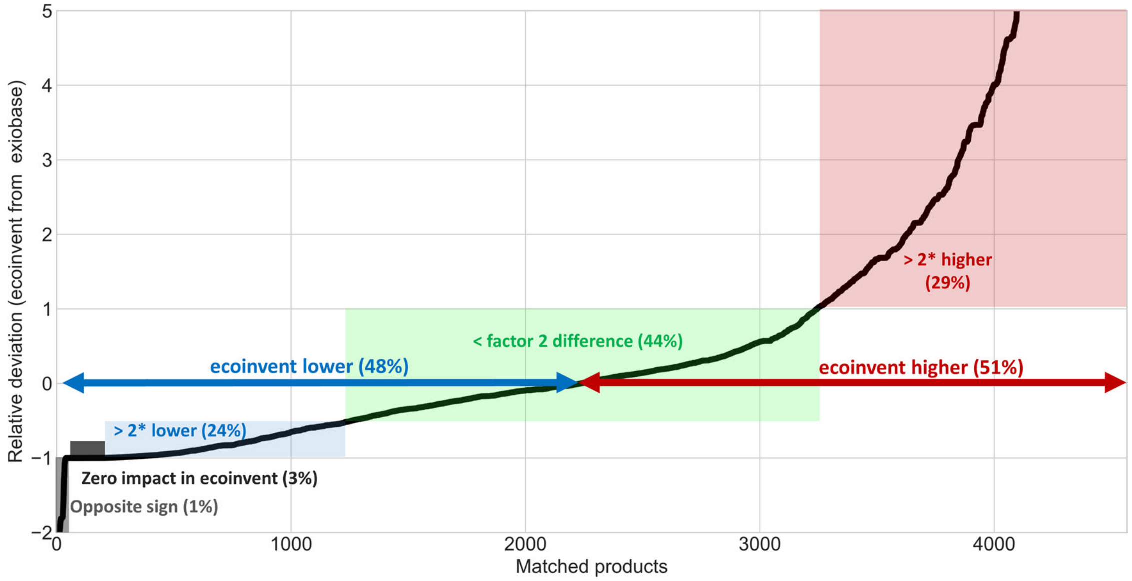

FIGURE 2 Relative deviation of the carbon footprints for all matched products (see Relative deviation on how to interpret the y-axis). The data behind this figure are provided in Supporting Information S2

FIGURE 3 Relative deviation of the carbon footprints for all matched products across International Standard Industrial Classification (ISIC) section levels. The number in the y-labels indicates the number of matches (18 products from ecoinvent could not be included in this comparison due to the missing ISIC section level information). The red line is where ecoinvent and EXIOBASE CFs are equal. Numbers smaller than −1 (grey line) are negative CF results in EXIOBASE. Boxplots: The boxes represent the quartiles 2 and 3, where the green line is the median. The whiskers extend to 1.5 times the interquartile range and outliers are shown as circles. For readability, the plot has been cut-off at +/− 10 as certain outliers are several orders of magnitude higher/lower. The data behind this figure are provided in Supporting Information S2

3.3.3 | Relative deviation by product and region

Figure 4 further disaggregates the relative deviation of the matched datasets on a regional level and by EXIOBASE product. While EXIOBASE covers most regions for all products, ecoinvent does so only for the energy sector (electricity and steam and hot water supply). For most other products, ecoinvent is limited to a small number of regions, often including Canada, Switzerland, China, Germany, and the United States, as well as GLO. The observations for Figure 3 are confirmed here, as beyond the energy and manufacturing sectors, a slight dominance of blue cells, meaning lower CFs in ecoinvent, can be observed, albeit with many exceptions. Within the power sector, the results for coal-, gas-, and oil-based electricity production match well. The results for renewables are mostly higher in ecoinvent. A clear regional pattern cannot be observed for the relative deviation. Instead, the differences between both databases seem to be more related to the products, and thus the underlying production technology and supply chains.

3.3.4 | Analysis of the electricity sector

Figure 5 shows a CF comparison for the electricity sector as it is represented in both databases at a relatively high level of technological and regional detail. The overall spearman correlation is 0.77. However, correlations for individual technologies are much lower (coal: 0.59, wind: 0.38, gas: 0.22,

FIGURE 4 Median relative deviation of carbon footprints in ecoinvent from EXIOBASE by EXIOBASE product (*y*-axis) and regions (*x*-axis). The colors relate to the value of the relative deviation: Blue means that ecoinvent CFs are lower and red means that ecoinvent CFs are higher. RoW EXIOBASE regions are: Asia and Pacific (WA), RoW America (WL), RoW Europe (WE), RoW Africa (WF), and RoW Middle East (WM). The number in the y-labels indicates the number of matches. The data behind this figure are provided in Supporting Information S2

petroleum and other oil derivatives: 0.18, hydro: −0.04, nuclear: −0.06, biomass and waste: −0.12, solar photovoltaic: −0.19). This confirms the observation that there is a good fit for fossil-based power generation, but not a good fit for renewables and nuclear.

To better understand the reasons for differences, we further analyzed this data for specific patterns (see also our annotations in Figure 5). Two factors seem to play an important role: regional and technological disaggregation. For example, in the case of *hydropower*, EXIOBASE shows only a small range of results, while ecoinvent shows large differences for, for example, reservoir or run-of-river versus pumped-storage hydropower plants (in pumped storage hydropower, larger CFs are due to the use of fossil-based electricity). In EXIOBASE, pumped hydropower is not specifically distinguished from conventional hydropower sector itself. The relatively high CFs associated with pumped hydropower may not be visible in EXIOBASE as long as the contribution of pumped hydropower to the overall output of the hydropower sector is small. Further, the CF of hydropower in general is driven to a large part by the construction of the plants and fugitive emissions from reservoirs, which are not included in EXIOBASE.

Another example is the EXIOBASE product *Electricity by biomass and waste*, for which two matching products in ecoinvent are highlighted in Figure 5: electricity from *biogas* and electricity from *wood chips*. We may first observe that the additional technological disaggregation in ecoinvent leads to different CFs depending on the feedstock that is used to generate electricity. This technological differentiation is not available in EXIOBASE. At the same time, we observe that there are considerable CF differences across EXIOBASE regions, while the CF of electricity from *biogas* is the

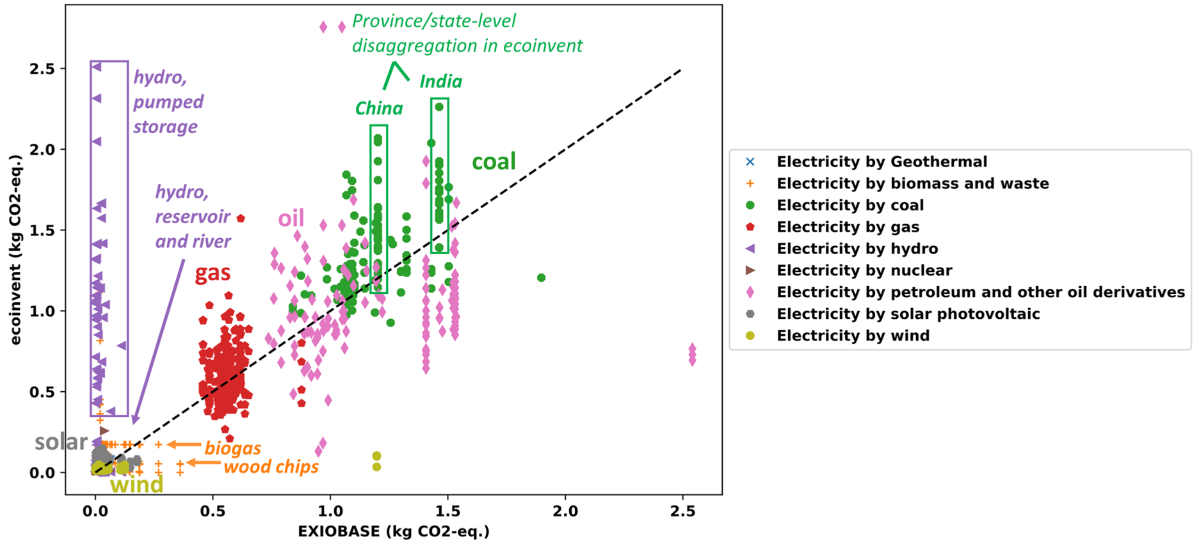

FIGURE 5 Carbon footprints per kWh of electricity in EXIOBASE and ecoinvent grouped by EXIOBASE products. Vertical lines of data points represent situations where multiple activities in ecoinvent are matched to a single regional product in EXIOBASE. This may be due to additional technological disaggregation (e.g., different hydropower technologies) or regional disaggregation (e.g., for China and India). Horizontal lines of data points reflect the situation where the results for an ecoinvent product are approximately the same across different EXIOBASE regions. The dashed line represents the line of equality; that is, points on this line have equal CFs in both databases. The data behind this figure are provided in Supporting Information S2

same for all regions. This indicates the accuracy of CFs for *electricity from biomass and waste* is limited in EXIOBASE by its level of technological disaggregation, while in ecoinvent, regional differences may not be fully accounted for. However, EXIOBASE does not always have a more detailed regional representation, as shown for *coal* power in China and India, for which data for individual sub-regions are available in ecoinvent, which makes a considerable difference for the respective carbon footprints. While regional and technological disaggregation may explain the observed differences partly, these may also be the result of more fundamental methodological or data differences (see Section 4.3).

3.3.5 | Comparison by coefficient of variation

Finally, we use the CV as a measure of the dispersion in each database at the product level without regional disaggregation (Figure 6). While both high- and low-dispersion sectors can be expected, significant disagreement in the level of dispersion between the databases may help to identify where further work may be necessary to improve the databases (for the concept, see also Supporting Information S1, Figure S2). Following this logic, the chemical products in the product group *Chemicals nec* would benefit most from further disaggregation in EXIOBASE as it has a dispersion value of 7 in ecoinvent but only 1 in EXIOBASE. This does not come as a surprise, as in our matching, we associated 494 different chemicals from a total of 648 supplying activities with this product group. Wind power on the other hand shows a dispersion value above 3.5 for EXIOBASE and well below 1 in ecoinvent, although ecoinvent distinguishes several onshore and offshore technologies. It is difficult to say whether the higher dispersion value in EXIOBASE is due to technological or regional differences as these cannot be distinguished here (see Coefficient of variation).

In general, it can be observed that the upper left quadrant is more populated than the lower-right one, which indicates that the level of technological detail covered in ecoinvent is a stronger driver for dispersion than the regional differences at the product group level in EXIOBASE. This is noticeable, for example, for agricultural products, such as *Vegetables, fruits, nuts* or *Cereal grains nec*, for which one might have expected stronger regional differences. It should be noted that the comparison of CVs can only provide indications and cannot replace a closer look at the technological, regional, or other reasons for differences (see Section 4.3).

4 | DISCUSSION

4.1 | Research questions

1. *What is the sectoral coverage of ecoinvent and EXIOBASE and how does the level of product detail compare across sectors?*

Since both databases have been set up with the goal to assess environmental impacts, they have a clear focus on the manufacture of important industrial products and corresponding raw material and energy supply chains with large direct emissions. Ecoinvent has a much more

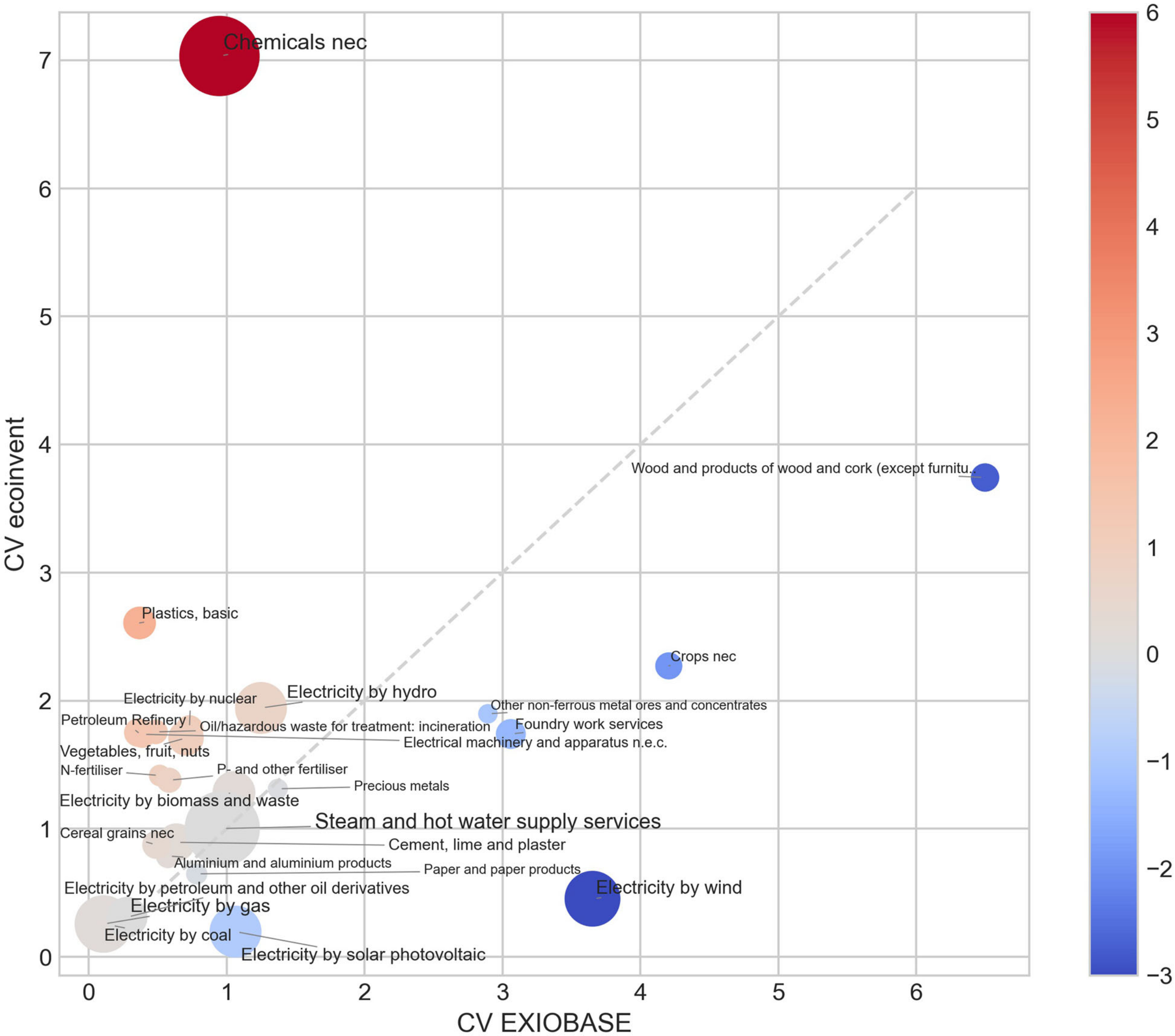

FIGURE 6 Coefficient of variation (CV) of the carbon footprint for matched products in ecoinvent and EXIOBASE. Circle size is proportional to the number of matched ecoinvent datasets (we only included EXIOBASE products where 30 or more matching ecoinvent products existed). The color scale represents the difference of CV (ecoinvent minus EXIOBASE); thus, red means the CV is higher in ecoinvent and hints at the need for further disaggregation in EXIOBASE. Blue has the opposite meaning. Products on the grey diagonal have equal CVs. The data behind this figure are provided in Supporting Information S2

detailed representation of technology (Table 1). At the extreme end, EXIOBASE distinguishes a single product group *chemicals nec*, while ecoinvent distinguishes 494 different chemicals that fall within this group. Another example is the product group *vegetables, fruits, nuts*, for which ecoinvent covers 70 different crop products. On the other hand, EXIOBASE has a higher degree of regionalization for most product groups (Figure 4). An exception is the energy sector, where both the technological and regional differentiations are higher in ecoinvent. Both databases have limited differentiation in the service economy, although it is more systematically included in EXIOBASE (Font Vivanco, 2020; Majeau-Bettez et al., 2011).

1. *How do carbon footprints compare in both databases?*

We found that roughly half of the matched products deviate in CF by less than a factor 2, a quarter of products have a CF of at least factor 2 smaller in ecoinvent, and another quarter of products have a factor 2 or higher CF in ecoinvent. The best fits are observed in the energy, manufacturing, and agricultural sectors (ISIC classes D, C, and A). A sector that is particularly well covered in both databases is the power sector. Interestingly, CFs related to fossil-based electricity are much more comparable than CFs for renewable and nuclear electricity. This indicates that there is large agreement whenever there are important direct GHG emissions and where capital infrastructure and supply chain GHG emissions play a smaller role. However, even for fossil-based electricity generation, there are considerable CF differences for specific technologies or regions (Figure 5).

TABLE 2 Summary of reasons for differences

Reason for differences	ecoinvent (cut-off model)	EXIOBASE (hybrid version)
Matching	Differences due to imperfect matching of products across both databases	
Methodology		
System boundaries and cut-offs (truncation)	Incomplete economic coverage (cut-offs); for example, tertiary sector is largely missing	By definition, complete system boundaries (see however limitations with regard to, e.g., temporal system boundaries and inclusion of capital goods)
Temporal system boundaries	Life cycle of a product	Snapshot for a reference year
Capital goods	Partially included (truncation)	Accounted for separately and thus not directly associated with CFs of product groups
Solutions to multi-functionality	Mix of allocation principles including economic allocation and the cut-off approach for waste treatment co-products	By-product-technology model (substitution)
Data		
Intermediate flows	Bottom-up unit process models from various data sources; higher product level differentiation than EXIOBASE	Top-down inter-industry monetary flows and international trade-flows; initial use of physical technical coefficients derived from LCIs but, eventually, influenced, for example, by data reconciliation and balancing
Elementary flows	Bottom-up unit process models with broader coverage than EXIOBASE	Extractions: based on the Global material flow database of the UN International Resources Panel. Emissions: calculated by multiplying activity levels (e.g., use of a specific energy carrier) with an emission factor (Merciai & Schmidt, 2018). Waste flows as a result of mass balance
Data age	Various reference years (specific to each unit process)	Specific reference year (here 2011)
Representation of average products	Aim in ecoinvent, but not always realized (often plant-specific data)	By definition, data relate to the average for an industry/product group
Characterization factors	No difference in this study	

The poorest fits are observed in the waste treatment and mining sectors (ISIC classes E and B). For waste treatment, this is due in part to the differences in the underlying methods to deal with multi-functionality (see Section 4.3). The largest spread is observed in the mining sector, which is not surprising as products range from low-CF materials, for example, sand, to high-CF materials, for example, gold. Product groups in EXIOBASE, such as *Other non-ferrous metal ores and concentrates*, may contain very different materials, and even seemingly narrow-enough product groups, such as *Precious metals*, still contain products with widely different CFs, for example, gold versus silver.

Although the material and energy flows of individual processes can be accurately measured, it is virtually impossible to validate if complex real-world supply chains are accurately represented in LCI and EEIOA databases and, therefore, how correct the calculated CFs really are. Yet, cross-comparisons as done here help to better understand where CF results tend to agree and where they do not. This is relevant information for deriving policy recommendations from LCA and EEIOA, as it provides additional information as to where uncertainties may be particularly high or low.

4.2 | Reasons for differences

Besides imperfect and potentially erroneous matching, differences in database methodology and data may have caused the observed differences in CFs (see overview in Table 2).

4.2.1 | Matching

Although both databases use international product classification systems, EXIOBASE uses NACE version 1.1 (2000) and ecoinvent uses ISIC rev. 4 (2008) as well as the Central Product Classification, an automatic matching of products was not possible due to the lack of a concordance table. Therefore, matching had to be done manually for several thousands of products and processes. This was a time-consuming step, also since often a look at the process descriptions was required to decide if a product match made sense. Even if corresponding product classifications were available, *product*-based matching has limitations. For example, matching *silver* in ecoinvent to *precious metals* in EXIOBASE seems to make sense, but besides matching *silver*, from a *silver mine*, it also leads to a match of *silver* from the *treatment of electronics scrap*, which should probably better be matched to a waste treatment process or excluded. Further, ecoinvent contains service activities that should not be matched with products in EXIOBASE, for example, *hot rolling, steel* provides the service of hot rolling as an input to the production of *steel, hot-rolled*, and only the latter should be matched to steel in EXIOBASE. Despite all efforts, it is possible that our matching contains imperfect or even nonsensical matches, which make the CF comparison seem worse than it should be. The development of a concordance file for ecoinvent and EXIOBASE that considers the obstacles mentioned in this paper would be desirable. Efforts in this direction have been made by Agez et al. (2020; 2021; 2020), but have not yet been used to test the consistency of CF results as done here.

4.2.2 | Specific database methodologies

Important *methodological differences* include, but are not limited to:

- System boundaries and cut-offs (truncation): EEIOA databases are thought to be more complete than LCI databases due to the fact that they cover the entire economy, while LCI databases are built bottom-up and may exclude certain parts of the modeled value chains (cut-offs), which is also known as the truncation error (Lenzen & Dey, 2000). For example, inputs from the service economy are often not included in LCI databases (Font Vivanco, 2019, 2020). This means that, in theory, CFs derived from EEIOA databases should be higher than those derived from LCI databases; however, we were not able to confirm this finding based on our comparison (e.g., Figures 2 and 3). In part, this may be explained by the differences in handling capital goods and temporal system boundaries, as discussed below.
- Temporal system boundaries: A fundamental difference is that in LCA the impacts of a product are modeled over its life cycle, while in EEIOA the impacts of a product group relate to a specific year. This difference may not matter for short-lived products, but it may lead to very different results for product groups where capital goods used in production are important. For example, investments and environmental interventions may be large when a hydropower plant is being constructed, but much lower in the years afterward. In LCA, the interventions related to the construction of the plant are distributed over its assumed lifetime, while in EEIOA, the interventions related to construction are recorded in the year the hydropower dam is built.
- Capital goods: Another fundamental difference is that in monetary EEIOAs, following national accounting rules, the production of capital goods in a single year is separately recorded as a final demand category gross fixed capital formation. This means that the environmental interventions associated with the production of capital goods used for productive purposes (e.g., factory buildings, technical installations, machinery) are not included in the calculated CFs. Although the use of capital goods could be connected to the supply chains of individual products (Södersten et al., 2018; Ye et al., 2021), this is not standard practice and was not the case in our comparison. Therefore, depending on the importance of capital goods in the supply-chain, CFs calculated with EEIOA could be lower than CFs calculated with LCA (Font Vivanco, 2019, 2020), which may explain some of the observed differences where capital goods are important, for example, for nuclear, photovoltaic, wind, or hydropower. For our hydropower example, this means that even if EEIOA were to take a life cycle perspective, the construction of the hydropower dam would not directly contribute to the CF of hydropower in standard EEIOA.
- Solutions to multi-functionality: We know from previous studies that the choices of transformation model in EEIOA (Heijungs & de Koning, 2019; Vendries Algarin et al., 2017) and allocation method in LCA (Azapagic & Clift, 1999; Guinée & Heijungs, 2007) can have a large influence on impact assessment results. While different approaches of dealing with multi-functionality contribute to CF differences in general, they also lead to some clearly identifiable effects. Ecoinvent uses, next to economic allocation, a cut-off approach, where environmental burdens from waste treatment are allocated to the waste producer and, consequently, waste treatment co-products have zero environmental burdens (3% of compared products) (Wernet et al., 2016). The by-product-technology model that is applied in the hybrid version of EXIOBASE, which is equivalent in LCA to a substitution approach (Suh et al., 2010), leads to negative CF results in EXIOBASE for certain multi-functional processes, for example, waste treatment, combined heat and power generation, or animal farming, which explain the opposite-sign results for about 1% of compared products (Figure 2).

4.2.3 | Data

Important *data differences* include, but are not limited to:

- Intermediate flows: Data for EEIOA and LCI databases are largely of different origin. LCI databases describe interlinked unit processes that are modeled bottom-up and in physical units. Multi-regional EEIOA tables follow a more top-down approach, which reconciles monetary flows between industries and countries based on data from statistical offices that follow specific accounting principles (SNA, 2009) and bilateral trade data provided by international institutes, for example, Comtrade (UNi). The reconciliation requires data balancing routines and, in some cases, additional aggregation or disaggregation of specific product groups (as the granularity is different across countries). For example, the different product groups for electricity in EXIOBASE are created by disaggregating a single electricity production sector based on data from national statistical offices and the International Energy Agency (IEA) (IEA, 2020). Data reconciliation, balancing, and other modification further affect the final CFs. There are also many specific differences in the data used to represent specific sector, which we cannot got into details here. For example, the aluminum industry has asserted that it uses cleaner-than-mix electricity for specific production sites. While this has been accounted for in ecoinvent, it is, to our knowledge, not accounted for in EXIOBASE, which means that aluminum products may have a higher CF for this reason. Finally, for specific sectors, there may also be important overlaps in the data sources; for example, data from the IEA are used for both databases, which may explain the particularly good fit for fossil-based electricity production.

- Elementary flows: Elementary flows are modeled bottom-up as part of the unit process models in LCA. Ecoinvent generally distinguishes more elementary flows than EXIOBASE, which could be a reason for slightly lower CFs in EXIOBASE, although we believe that the influence of this is small since EXIOBASE includes the most important greenhouse gases. Further, emission intensities are likely not the same, as different underlying data sources are used (Castellani et al., 2019). For example, in EXIOBASE (hybrid version), emissions from combustion are calculated by multiplying the use of fuels within activities by specific emission factors and the production of waste is determined by applying a mass balance within activities associated with lifetime functions of products.
- Data age: While data in EEIOA databases are specific to a reference year, data in LCI databases typically stem from a great variety of data sources with different reference years. Therefore, differences in CF may also be a result of different temporal scopes.
- Representation of average products: Both databases aim to represent data for average products; however, while this is the case by definition for EEIOA, unit processes in LCA do not always represent average processes, but instead the data from a specific plant. This may further contribute to the deviation of CF results.
- Characterization factors: Characterization factors can be excluded in this study as a reason for differences, as we used the same characterization factors for both databases.

4.3 | Strategic database improvements

The analysis of the sectoral coverage (RQ1) is obviously a good starting point to think about where the databases could be improved. Further, the CF comparisons (RQ2) provide information on the relative uncertainty of product CFs and, therefore, where database improvements could be most effective. Product groups containing a wide variety of products with very different environmental profiles are good candidates for further disaggregation (Majeau-Bettez et al., 2011), for example, *chemicals nec; vegetables, fruits, nuts;* and *plastics, basic*. In the ecoinvent database, specific products, such as electricity from biomass, could benefit from more region-specific data. Further regionalization of EXIOBASE, as shown for Chinese and Indian electricity (Figure 5), could also reduce uncertainties relating to CFs and other impact categories, for example, water and biodiversity (Cabernard & Pfister, 2021).

We also examined the possibility of using the coefficient of variation as a metric to identify which products in which database could benefit from further technological and regional disaggregation (see concept in Supporting Information S1, Figure S2). The results of the CV comparison (Figure 6) reaffirm the observations made earlier for specific products. Therefore, the CV comparison is, in principle, a suitable method to identify improvement potentials in each database. In addition to the *inter*-database metrics used in this work, *intra*-database analyses can provide additional insights for strategic improvements of LCI and EEIOA databases (Reinhard et al., 2016; Reinhard et al., 2019).

4.4 | Limitations and research opportunities

When we matched ecoinvent products to EXIOBASE product groups, we did not apply weighting factors to account for the different market shares of products in a product group (e.g., different types of hydropower in *Electricity by hydro*), as such data were not easily available. Thus, each ecoinvent product gets the same weight in the comparison regardless of whether it is a niche product or not. This represents a limitation for the presented correlations and relative deviation. However, we intentionally did not perform weighting to show the full dispersion of CF results across databases and to identify where practitioners can more safely use either database for a product CF calculation and where users should be cautious.

Some of the differences between the compared databases result, among others, as discussed, from differences in modeling choices such as dealing with multi-functionality. We recommend that future research tries a similar comparison for the monetary version of EXIOBASE with either the cut-off or the allocation at the point of substitution (APOS) versions of ecoinvent. We have tried this for this paper as well, but the general fit was not very good, probably because the data needed for translating between monetary and physical units were not good enough (we used ecoinvent production volumes), which is why we have not included this analysis in this manuscript. In fact, some of the observed differences in this paper's comparison may also be due to the conversion from monetary to physical unit as done when generating the hybrid EXIOBASE version. However, in the absence of knowing the "true" environmental impacts, it is very difficult to identify where improvements should take place.

Future research could extend the comparison of LCI and EEIOA databases to other impact categories, as greater differences have been observed for, for example, particulate matter, photochemical ozone formation, land use, and mineral resources (Castellani et al., 2019; Font Vivanco, 2020). In order to better understand the reasons for differences, such work could include contribution analyses (e.g., as in Steubing et al., 2016), to shed light into technological and geographical differences in the supply chain structure and potentially focus on specific sectors only to make the scope of such a comparison more feasible.

5 | CONCLUSIONS

The comparison of the ecoinvent and EXIOBASE (hybrid version) databases shows that there is still considerable disagreement in carbon footprint results. Despite good agreement for specific sectors, more than half of the matched products differ in CF by a factor greater than 2. This is not ideal, since both EEIOA and LCI databases are increasingly used to inform decision makers on the environmental performance of products and services, and depending on the database used, the conclusions, for example, the ranking of technologies, may be different. Reliable sustainability assessment approaches are essential for guiding the transition to more sustainable future economies. Efforts to further improve EEIOA and LCI databases are crucial to reduce uncertainties in the decision support that the industrial ecology community can provide. Such work should include efforts to further harmonize the methodologies and validate the results using all available data to shed more light on the real environmental impacts of products and services. The coefficient-of-variation approach and analyses presented here can provide additional information for identifying products and sectors that need particular attention, for example, renewables and chemicals.

An interesting result of our work is that the finding that LCA-based CFs are lower than EEIOA-based CFs due to truncation errors (Lenzen & Dey, 2000) could not be confirmed. Instead, CFs based on ecoinvent were in 51% of cases *higher* than EXIOBASE CFs for similar products. This result may be the consequence of some of the underlying differences in methodology and data of each database, as depicted in Table 2. For instance, while the LCA weakness of truncation is avoided by the inherent total economic coverage in EEIOA, an LCA approach is usually better positioned to include capital goods and the full product life cycle regardless of the time dimension (which is limited to 1 year in IOA).

Finally, when deciding which database to use, practitioners should not forget about the specific strengths of EEIOA and LCI databases. For example, LCA excels at the product level due to its fine-grained physical unit process models, while EEIOA is more suitable for larger scale national or regional analyses (see, e.g., Guinée et al. 2011 for further discussion). The observed CF differences may also remind practitioners that EEIOA and LCI databases remain models of reality and their results deserve careful interpretation.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available on Zenodo at https://www.doi.org/10.5281/zenodo.6077868 as well as on GitHub at https://github.com/bsteubing/ecoinvent-EXIOBASE-comparison.

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NOTES

[1] By *product*, we mean products and services in the LCA context and product groups in the EEIOA context. Note that although we typically assess the environmental footprint of products in LCA and EEIOA, we often use the term product with the meaning of "products of specific processes," such as *electricity, from a wind turbine* instead of just *electricity*. Therefore, in the context of this paper, when we talk about an ecoinvent product, we mean a product or service from a specific supplying process. However, when we talk about an EXIOBASE product, we mean a product group that may or may not include information about the supplying process, for example, *electricity by wind* or *wheat*. Note also, that this product definition does not include a geographical dimension. In order to distinguish products as defined before from "products in a given region," that is, with a geographical context, we call the latter *regional products*.

[2] *not elsewhere classified*

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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