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RESEARCH

Carbon intensity of electricity: a systematic methodological and quantitative review

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Abstract

The carbon footprint of electricity is a critical metric for climate policy and corporate sustainability reporting, yet its quantification is hampered by a lack of methodological consensus and a fragmented evidence base. This fragmentation reflects a central debate in industrial ecology regarding the consistency and comparability of life-cycle-based emission factors across different modelling paradigms. This study addresses this gap by performing a systematic, quantitative comparison of electricity emission factors from a wide range of authoritative sources, including process-LCA databases (Ecoinvent), environmentally extended input–output tables (EXIOBASE, EMERGING, EORA, GLORIA, GTAP), primary agency data (IEA), and others. We harmonize technology taxonomies and GHG characterization factors to compare technology-level and national-level emission factors for the EU and the US. Our findings indicate that, for technology-specific emission factors, there is a moderate level of agreement regarding direct operational emissions (direct carbon intensity). However, we observe substantial and systematic variation when it comes to full life-cycle carbon intensity. These discrepancies propagate to national-level estimates, where a country's calculated carbon intensity can significantly vary, solely based on the data source chosen. This paper provides a useful reference to deconstruct and understand such divergences. We operationalize these findings into a set of practical selection criteria that enable analysts and decision-makers to make transparent and context-appropriate choices. We conclude that a more transparent and critical approach to sourcing emission data is fundamental to the credibility of carbon accounting and the broader energy transition.

Keywords Carbon intensity · Electricity · Emission factors · Systematic review · Corporate sustainability accounting · Industrial ecology

1 Introduction

The generation of electricity constitutes a substantial portion of global greenhouse gas (GHG) emissions. Around one quarter of worldwide GHG emissions can be attributed to electricity and heat production, as stated by (Lamb et al., 2021) and confirmed by observing this metric from environmentally extended input–output (EEIO) tables: in 2015, they accounted for 26% according to EXIOBASE (Stadler et al., 2021) and for 31% according to FIGARO-E3 (EC JRC, 2024). From EEIO databases, it is also possible to state that the contribution of power production to the total carbon footprint of any marketed commodity ranges between 5 and 30% (see Supplementary Information 1, SI1). Concurrently, the pace of electrification across economic sectors is accelerating rapidly (EMBER, 2025c). In this context, electricity plays a pivotal role in climate policies and emissions disclosure frameworks, spanning both voluntary schemes [e.g., (ESRS Voluntary Sustainability Reporting Standards for SMEs under the European Sustainability Reporting Standards Framework, 2025)] and binding regulations, such as EU's Corporate Sustainability Reporting Directive (European Parliament and Council, 2022), Carbon Border Adjustment Mechanism (European Commission, 2025) or the California's Senate Bill 253 in the US (California State Legislature, 2023).

This evolving context is driving an increasing number of companies to measure and report emissions associated with their operations. In particular, emerging regulations require firms to assess their carbon footprint and to report

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emissions related to purchased electricity (Scope 2 emissions, i.e., emissions associated with companies' energy supply), emphasizing the need for accurate and reliable emission factors for consumed electricity, typically following standardized approaches, like the GHG Protocol (World Resource Institute, 2011). Moreover, implicit assumptions about the quantification of national electricity mixes add uncertainty and significantly influence the calculation of Scope 3 emissions (e.g., those emissions occurring across the value chains). Indeed, as corporations reporting total GHG inventories must evaluate both Scope 2 and Scope 3, they frequently introduce systemic inconsistencies by employing disparate data sources and conflicting hypotheses for each scope, despite electricity's pervasive and dominant impact across the entire value chain.

(Davis et al., 2025) show that 25.8% of 10,867 reporting companies in 2023 used spend-based approaches, typically relying on input–output sources. Among those specifying the method, 75% adopted single-region EEIO models, implicitly assuming domestic technologies. This leads to applying domestic electricity and emission intensities to imported goods, thereby underestimating the often higher carbon intensity of global supply chains.

Despite the critical importance of electricity in climate mitigation strategies, there is currently no universally agreed methodology, nor a universally accepted reference source, for estimating the carbon intensity per kWh of electricity. Instead, several authoritative sources—including the Intergovernmental Panel on Climate Change (IPCC) assessment reports (ARs), life cycle assessment (LCA) databases (Ecoinvent, 2025), international agencies such as the International Energy Agency (IEA, 2024b), widely cited commercial solutions by scientifically reputable sources, such as Electricity Maps (Electricity Maps, 2025) and input–output tables such as EXIOBASE (Stadler et al., 2018) or CEDA (Watershed, 2025), widely utilized both in the academic and corporate sustainability contexts—often report misaligned values for the environmental impact of electricity production. Previous works highlighted how the absence of harmonized protocols can lead to divergent estimates: differences in standards and reporting conventions generate substantial discrepancies in GHG estimates, resulting in notable variation among published grid emission factors, despite considering the same technology and/or the same geographical boundary (Hawkes, 2010; Pehl et al., 2017; Turconi et al., 2013). Moreover, in many cases, even high-resolution databases yield misleading results as they often embed outdated electricity supply mix data. Electricity data in the most commonly utilized life cycle databases typically suffer from a significant time lag—averaging between 4 and 8 years—in accurately representing the current state of national power mixes, although the frequency of publication and updates has increased in recent years (Olindo et al., 2021). Such variability arises from several scientific and methodological factors, including the definition of system boundaries [e.g., direct combustion emissions only vs. broader upstream and downstream coverage through life-cycle approaches ("Ecoinvent", 2025; Asdrubali et al., 2015; Barros et al., 2020; National Renewable Energy Laboratory, 2021)], assumptions about electricity mix composition and plant efficiencies, and choices regarding marginality [i.e., consequential vs. attributional approaches (Beltrami et al., 2025; Ryan et al., 2016)]. Additional drivers are the selection and resolution of input data, encompassing not only geographic and technological detail but also temporal resolution, as power grids become increasingly heterogeneous with high penetration of renewable generation (Blizniukova et al., 2023; Khan, 2019). Examples range from physically grounded but narrow-boundary approaches, such as process-based LCA (P-LCA), and monetary input–output approaches, or hybrid datasets like EXIOBASE Hybrid (Merciai & Schmidt, 2021), that are more internally consistent from a modeling standpoint but less granular.

1.1 Objective and contribution

Our study maps the main families of sources, used both at academic and corporate level, that estimate the direct and life-cycle carbon intensity of electricity, undertaking a systematic, methodologically transparent comparison focusing on EU27 countries and the US.

To ensure commensurability, all series are harmonized and aligned to a shared technology taxonomy. Results are presented at technology and national-mix level under both direct and indirect emissions perspectives.

While previous research has explored discrepancies within subsets of electricity carbon footprint studies, such as P-LCA meta-reviews or EEIO database comparisons, no prior work has provided an integrated, cross-paradigm assessment that aligns EEIO, P-LCA, and agency-based datasets under a harmonized taxonomy and GWP framework.

The performed cross-source comparison is also intended to provide a practical compass for analysts and decision-makers in navigating a fragmented evidence base, clarifying what each source measures, when it is most appropriate, and how boundary choices and methodological assumptions shape results. Comparative findings are translated into selection criteria and reporting conventions that support deliberate, defensible choices (i.e., whether for policy appraisal, procurement, or corporate disclosure) so that users can select sources consciously instead of arbitrarily.

2 Literature review

We analyzed 39 studies published after 2013 to identify the main methodological challenges in quantifying emissions from electricity generation, mainly distinguished on three key levels of complexity: (i) the quantification of emissions factors (EFs) for specific generation technologies; (ii) the aggregation of these into grid-level intensities; and (iii) the comparison of results from fundamentally different modeling paradigms, such as P-LCA and EEIO models. Before presenting the literature review, we introduce the terminology adopted throughout the article.

2.1 Terminology

A primary obstacle to comparing emission data is inconsistent terminology. To ensure clarity, we distinguish between two key emissions factors based on system boundaries. We define "direct carbon intensity" (DCI) as the operational emissions from generating 1 kWh of electricity (equivalent to Scope 1 for a power producer). In contrast, we use "life-cycle carbon intensity" (LCCI) as a generic term for any emission factor that goes beyond DCI. However, term "life-cycle" is still somewhat ambiguous because different sources draw system boundaries in different ways, sometimes including upstream processes (e.g., fuel extraction, plant construction) and downstream impacts (e.g., transmission and distribution losses). A synonym of LCCI is "carbon footprint intensity" (Steubing et al., 2022), since the term "carbon footprint" refers to the total amount of GHG emissions attributable to a commodity or activity.

Furthermore, a crucial methodological divide, central to the following review, is the distinction between attributional and consequential (or marginal) modeling. Attributional CIs allocate the total emissions of a grid across all consumed electricity, answering the question: "What is the average intensity of the electricity mix?". Consequential CIs, instead, estimate the change in system-wide emissions resulting from a change in demand, answering: "Which power plant will operate to meet an additional kWh of consumption?". For this article, we focus on national-scale attributional CIs, since they represent the common ground across multiple applications, including corporate carbon footprint. Consequential approaches, on the other hand, are more suitable when the objective is to provide behavioral or price signals for short-term applications, such as daily or weekly operations (e.g., smart charging), requiring dedicated databases and tools (Merciai et al., 2025).

2.2 Technology-specific emission factors

The foundational challenge in electricity carbon accounting lies in the wide availability and heterogeneity of published emission factors for individual generation technologies. Comprehensive reviews by (Khan, 2019) and (Barros et al., 2020) systematically documented this issue, identifying the primary drivers of divergence: inconsistent system boundaries, methodological choices, and different geographical or technological assumptions. Earlier works, such as (Turconi et al., 2013) and (Asdrubali et al., 2015), conducted thorough comparisons of LCA analyses' results for different technologies, demonstrating how even subtle analytical choices can yield significantly different results (e.g., variations exceeding a factor of 10 for renewable technologies in Turconi et al., while harmonized data in Asdrubali et al. show maximum differences of 500%). A vast body of literature exists performing LCAs of specific electricity technologies, such as the parametric analysis of nuclear power by (Gibon & Hahn Menacho, 2023) and the work of (Raadal et al., 2016) on offshore wind turbines. Other studies, like (Hertwich et al., 2015), perform environmental impact analysis for various technologies through the same methodology, in this case scenario-based hybrid LCA.

The lack of comparability created a clear need for standardized benchmarks. In response, major institutional efforts emerged to harmonize these values. The National Renewable Energy Laboratory's (NREL) work on establishing statistical ranges (Asdrubali et al., 2015) and the IPCC's provision of harmonized emissions ranges (Schlömer et al., 2014) have become cornerstone references in the field (Clauß et al., 2019; Unnewehr et al., 2022). These IPCC values, alongside its widely used combustion factors and methodological guidelines (Blizniukova et al., 2023; Scarlat et al., 2022), provide a crucial, authoritative starting point for analysis. However, they represent technology-level potentials, and the next layer of complexity arises when aggregating them to model real-world, interconnected electricity grids.

2.3 Grid-level emission factors

Moving from individual plants to national grids introduces a further layer of methodological complexity. While some studies employ top-down approaches using aggregated national statistics on emissions and generation (Unnewehr et al., 2022), the prevalent methods are "bottom-up," building upon technology-specific factors. Even within this dominant category, significant variability exists: (Bertolini et al., 2025) compared six different EF-based methods for Italian electricity zones, finding a 12% spread between minimum and maximum average EFs in the North zone alone, and underscoring that no single approach is universally applicable.

(Ryan et al., 2016) systematically mapped 32 methodological approaches, classifying them into "Empirical Data and Relationship Models" (including simple EFs, commercial exchanges, and statistical relationship models) and "Power System Optimization Models". Their US case study showed that the choice of method alone could alter the CI for vehicle charging by up to 68%, a variation often larger than geographic location. Their subsequent recommendations (Ryan et al., 2018) highlight the pivotal distinction between attributional and marginal EFs: studies on cross-border electricity trade (Beltrami et al., 2025) show that marginal generation technologies in highly interconnected European markets often diverge substantially from the average mix, with spatially resolved marginal factors (Sarhan et al., 2023) enabling more granular locational analysis.

A more computationally intensive class of methods addresses cross-border carbon accounting through flow-tracing algorithms. Tranberg et al. (2019) and Schäfer et al. (2020) applied these techniques across the EU, revealing significant discrepancies between a country's production-based and consumption-based carbon footprints. For instance, nations with large low-carbon generation shares, such as Slovakia and Austria, see their consumption footprints increase due to electricity imports from higher-emission neighbors like Poland and Czech Republic (Tranberg et al., 2019). By incorporating high temporal resolution and explicit trade modeling, these studies demonstrate substantial sub-monthly variations in grid CI. Such time-resolved, flow-tracing approaches enable a more accurate allocation of emissions from producers to final consumers, providing valuable data for actors who can control their electrical loads (Clauß et al., 2019; Messagie et al., 2014).

2.4 Divergences in foundational databases

A final and fundamental source of variation stems from the databases used to model background economies and supply chains. Practitioners must often choose between two distinct paradigms: bottom-up P-LCA databases and top-down, economy-wide EEIO tables. The fundamental differences between these approaches have long been recognized in the debates on completeness and truncation errors: Suh et al. (2004) demonstrated that system boundary selection in LCA significantly affects results, with IO-based approaches capturing a broader economic scope that process-based inventories systematically truncate. Majeau-Bettez et al. (2011) further quantified these truncation and aggregation issues, showing that P-LCA databases tend to underestimate impacts due to incomplete upstream coverage. A comparative work by Steubing et al., (2022) directly addressed this issue by matching product carbon footprints between Ecoinvent and EXIOBASE. Despite both sources being used for similar purposes, the results showed significant discrepancies, with over half the matched products exhibiting footprint differences greater than a factor of two. While concordance was better for fossil energy and manufacturing, the discrepancies for electricity from renewable sources were particularly pronounced, driven by differing regional and technological disaggregation.

The comparison highlighted fundamental trade-offs: the comprehensive economic coverage of EEIO tables appears to be counterbalanced by the more detailed inclusion of capital goods and multi-year timeframes in P-LCA. This tension is further analysed by Henriques and Sousa (2023), who show for electricity generation that EEIO-based assessments tend to provide systematically higher impacts than P-LCA, advocating for hybrid options to leverage the strengths of both paradigms. This claim has been strongly supported by Hagenaars et al. (2025), while Perkins and Suh (2019) provide empirical evidence that hybridization can improve accuracy by combining the completeness of IO boundaries with the detail of process data.

However, results can vary even within the same paradigm. A comparison of four major multi-regional input–output databases by Moran and Wood (2014) found that while the underlying economic structures were broadly similar, divergences in CIs were primarily driven by the satellite environmental accounts used for GHG emissions. Crucially, they demonstrated that harmonizing these satellite accounts alone could reduce the divergence between major economies' footprints to under 10%. This finding underscores that both high-level modeling choices (P-LCA vs. EEIO) and low-level data compilation decisions contribute significantly to the fragmented evidence base that practitioners currently face.

2.5 Research gap identification

Ultimately, the body of analysed studies leaves the practitioner facing a series of critical, yet unresolved, methodological forks in the road. In the context of corporate carbon footprint assessment, established protocols such as the GHG Protocol prescribe an annual perspective. Within this temporal scope, the attributional approach represents the standard methodological choice. Nevertheless, an analyst must choose not only a set of technology-specific EFs, but also an aggregation method, and, at an even more fundamental level, a foundational database paradigm (P-LCA or EEIO) adopting the most accurate EF for a defined region and year. Our literature review demonstrates that each of these choices is highly influential yet offers no clear guidance on how to navigate them in concert. While individual studies have illuminated specific points of friction, the cumulative impact of these discrepancies remains unquantified in a single, harmonized framework. Addressing this requires moving from isolated comparisons to a systematic, multi-source confrontation.

3 Methods

Our analysis performs a comprehensive comparison of CIs drawn from a curated selection of widely used data sources, grouped into four main categories: EEIO tables, P-LCA databases, primary data from international agencies, and secondary data from literature harmonization projects. A detailed summary of these sources, including their reference years, scope, and key methodological characteristics, is provided in Table 1.

3.1 EEIO databases

The EEIO databases considered in this study are: EXIOBASE, in two distinct versions, the hybrid Supply-Use Table (SUT) format (v3.3.18, data year 2011) (Merciai & Schmidt, 2021) and the more recent (v3.10.2) monetary Input–Output Table (IOT) format (Stadler et al., 2025); GLORIA (v0.60, SUT format) (ielab, 2026); EMERGING (v199.82) (Huo et al., 2026); EORA26 (v199.82) (Lenzen et al., 2013) and the WIOD format of GTAP (v11) (Aguiar et al., 2022). The GTAP project also provides electricity price data for each region, as detailed in Sect. 3.4.

3.2 P-LCA databases

Ecoinvent, as the most utilized process-based database in industrial ecology, is a critical component of our analysis. Due to licensing constraints on publishing direct results, we leverage the data made available by the comparative study of Steubing et al. (2022), which reports carbon footprints from Ecoinvent v3.4 (cut-off system model) with regional information removed.

3.3 Agencies' primary data

We include the authoritative International Energy Agency (IEA) emission factors for combustion technologies. The IEA provides country-specific DCIs for 1990–2023. As this data is licensed, our figures will not show these series. Two versions of IEA DCIs are provided, differentiated by assumptions regarding the allocation of emissions from combined heat-power (CHP) plants: "Electricity only" assumes all CHP plant emissions are attributed to electricity generation, while "CHP" assumes a portion of the emissions is allocated to heat, resulting in a lower DCI (IEA, 2024a). One peculiarity of IEA factors is that they do not exclude CO_2 emissions of biogenic origin, as suggested by the IPCC guidelines (Eggleston et al., 2006).

3.4 Secondary and harmonized data

To include influential reference values, we incorporate several sources: the IPCC, we use the benchmark technology-level carbon intensities reported by Working Group III in AR5 from 2014 (IPCC, 2014); the harmonized LCA emission estimates from (NREL, 2021) release. Finally, we consider Electricity Maps, a widely used platform providing real-time electricity flow data (Electricity Maps, 2025). The values considered are their declared, static emission factors for each region (Electricity Maps, 2024), which are themselves derived from a combination of other key sources, including IPCC AR5 and (UNECE, 2021) reports. We also include sources that provide ready-to-use, country-level CIs. From the European Commission's Joint Research Centre (JRC), we include their dataset providing both direct "emissions intensity" (DCI) and "lifecycle emissions intensity" (LCCI) for EU27 countries (Bastos et al., 2024). Since JRC data covers EU countries only, the DCI for US is obtained from (eGRID, 2023). From EMBER, we use their "Carbon emissions intensity" data, which represent LCCIs (EMBER, 2025a, 2025b).

3.5 Data harmonization and processing

To enable a robust and fair comparison across the selected sources, a multi-step harmonization protocol was applied to align technology definitions, GHG characterization factors, and analytical scope.

First, a common technological taxonomy was established. The diverse electricity generation categories reported in each source were mapped and consolidated to a common level of aggregation; details are documented in Supplementary Information SI1.

Second, all emission factors were standardized to a consistent climate metric. We express all results in terms of Global Warming Potential (GWP) over a 100-year horizon, employing the characterization factors from IPCC AR5, following what is done by similar works (Steubing et al., 2022), and since CIs from the same version of the report are utilized in our analysis (IPCC, 2014).

The processing of EEIO databases was conducted using MARIO (Tahavori et al., 2023), an open-source Python package for input–output analysis. Within this framework, a critical distinction was made between activity-based and commodity-based footprints. DCI is defined only at the activity level, as environmental accounts are linked to industry outputs. The LCCI of the electricity commodity, however, is calculated following the industry-based technology assumption (United Nations, 2018), by weighting the intensity of each electricity production activity, including those that are not power plant technologies (e.g., industries producing from PV rooftops), on their market share. This modeling approach is particularly relevant for capturing the effects of cogeneration, as detailed in Supplementary Information SI1.

3.6 Derivation of grid electricity emission factors

To assess the impact of different data sources at a national level, we calculated grid-level emission factors for each EU

Table 1 Data sources considered in this study with versioning or publication year, detailing the acronym adopted henceforth, the data reference year, availability of region-specific data for EU and US, the type of emission factors analyzed and on which GHG substance, methodological treatment of co-production processes, data type, and source references

Data source and publication year (or version)	Acronym	Data year	Detail on US and EU	Carbon intensity analyzed	GHGs included	Handling co-products	Data type and unit	Reference
EXIOBASE Hybrid SUT v3.3.18	EXIO Hybrid	2011	✓	direct, life-cycle	CO_2, N_2O, CH_4, SF_6, HFCs	Industry-based	EEIOT, physical	Merciai and Schmidt (2021)
Ecoinvent v3.4 via Steubing et al	Ecoinvent			life-cycle	CO_2, N_2O, CH_4, SF_6, HFCs	Cut-off	P-LCA, physical	Ecoinvent (2025) and Steubing et al. (2022)
IEA emission factors per plant 2024	IEA (CHP) IEA (ele)	1990–2023	✓	direct	CO_2, N_2O, CH_4	Electricity and heat CHP/Electricity output only	Primary data, physical	IEA (2024b)
Electricity Maps, 2025	Electricity Maps		✓	direct, life-cycle	Generic $CO_{2\text{-eq}}$		Secondary data, physical	Electricity Maps (2024)
NREL harmonization 2021	NREL		x	life-cycle	Generic $CO_{2\text{-eq}}$		Secondary data, physical	NREL (2021)
IPCC AR5 WG3 (Annex III)	IPCC		x	direct, life-cycle	Generic $CO_{2\text{-eq}}$		Secondary data, physical	Schlömer et al. (2014)
EXIOBASE IOT ixi/pxp v3.10.2	EXIO ixi EXIO pxp	1995–2024	✓	direct, life-cycle	CO_2, N_2O, CH_4, SF_6, HFCs	Industry-based technology assumption	EEIOT, monetary	Stadler et al. (2025)
EMERGING v2.2	EMERGING	2015, 2018, 2021, 2023	✓	direct, life-cycle	Generic $CO_{2\text{-eq}}$	Industry-based technology as	EEIOT, monetary	Huo et al. (2026)
EORA26 v199.82	EORA	1990–2023 (open access -2017)	✓	direct, life-cycle	CO_2, N_2O, CH_4	Industry-based technology as	EEIOT, monetary	EORA (2026) and Lenzen et al. (2013)
GLORIA v0.60	GLORIA	1990–2025	✓	direct, life-cycle	CO_2, N_2O, CH_4,CO, SF_6, HFCs	Industry-based technology as	EEIOT, monetary	ielab (2026)
GTAP 11	GTAP	2004, 2007, 2011, 2014, 2017	✓	direct, life-cycle	CO_2, N_2O, CH_4,CO, SF_6, HFCs	Industry-based technology as	EEIOT, monetary	Aguiar et al. (2022)
EMBER, 2025a, 2025b, 2025c	EMBER	2000–2024	✓	Life-cycle	Generic $CO_{2\text{-eq}}$		Secondary data, physical	EMBER (2025b)
JRC CoM	JRC	1990–2021	EU only	direct, life-cycle	CO_2, N_2O, CH_4		Secondary data, physical	JRC (2024)
eGRID summary tables	eGRID	2018–2023	US only	direct	CO_2, N_2O, CH_4		Secondary data, physical	eGRID (2023)

Extended version in Supplementary Information SI2 country and the US as the weighted average of the technology-specific EFs from a given data source, with the weights determined by that country's annual electricity generation mix. The electricity supply mix data was obtained from the ENTSO-E Transparency Platform for EU countries (ENTSO-E, 2025) and from the eGRID database for the US (eGRID, 2023). Consistent with the comparative objective of the analysis, we limited our calculations to EFs from electricity generated within national borders, as, according to Table 6.2 of the GHG Protocol Scope 2 guidelines, national production-based factors are an accepted and adopted option for corporate carbon footprint (World Resource Institute, 2023). Moreover, production-based factors represent the necessary foundation for deriving accurate consumption-based factors.

It should be noted that, since EXIOBASE Hybrid only provides data for 2011, we did not compute the CI as the table's electricity commodity, but rather as the weighted average CI of electricity generation activities, as described in the previous paragraph. This was done to avoid including the impact of any other activities that produce electricity as a co-product, to ensure that electricity supply mixes were the same as for IPCC and NREL results.

3.7 Emission factors from economic databases and conversion to physical units

In practice, compiling a corporate carbon footprint compliant with frameworks like the GHG Protocol typically relies on economic databases for Scope 3.1 emission factors, given the scarcity of primary data (Davis et al., 2025). While Scope 2 emissions are generally assessed using physical sources, electricity often drives a significant portion of the overall impact, necessitating consistent integration across all footprint elements. Consequently, this comparison includes monetary databases to evaluate their viability as a single, unified data source for comprehensive corporate carbon accounting. As mentioned, we analyzed CIs from EXIOBASE, available in monetary IOT format in its latest 3.10.2 version, from which we derived the CI of electricity, by aggregating all electricity production sectors into one, therefore weighting the CIs according to the generation shares included in the IOT. We followed the same procedure both for the product-by-product (pxp) and industry-by-industry (ixi) tables. Other EEIO tables directly provide one unique sector for electricity production: we extracted CIs from EMERGING, EORA, GLORIA, and GTAP (see Table 1 for more details). The values obtained are emissions per monetary unit, in basic prices. The comparison with CIs in physical units is possible through the conversion with the regional price of electricity provided by GTAP; since those prices are available, for recent years, only for 2017 and 2023, those are the years selected for the comparative analysis in Sect. 4.3.

3.8 Benchmark definition

Regarding the DCIs in physical units, IEA data were used as the reference benchmark, given their primary-data status and their widespread institutional authority. Given that the CI of a product depends on a wide range of factors that we have explicitly addressed, it is not meaningful to define a single benchmark. Instead, we compare the various sources by examining their relative deviations.

4 Results

4.1 Technology-specific emission factors comparison

Our cross-source comparison highlights significant variability in the estimation of electricity EFs. Even for DCIs where methodological alignment might be expected, the sources exhibit substantial divergences rather than a clear consensus. Moreover, the picture for LCCIs shows wide-ranging disagreement and methodological heterogeneity, especially for renewable technologies.

The analysis of DCI for fossil fuel generation (Fig. 1a, where IEA values are not reported due to license limitations) demonstrates a higher consensus than the corresponding LCCI. For coal-fired power, the spread between medians, meaning the relative difference between minimum and maximum median, is 36%; for oil, the spread is 52%, and for natural gas it is 116%. For LCCIs, instead, the defined spread ranges from 101 to 631%. This suggests that, when the analytical scope is restricted to direct combustion emissions, estimates from different providers tend to be more comparable, although non-trivial discrepancies may persist.

However, a critical exception immediately highlights a primary source of confusion: the treatment of biogenic CO_2 in biomass-based electricity. The IEA reports DCI values for biomass that can exceed 2000 gCO_2eq/kWh, in stark contrast to other sources that report near-zero direct, non-biogenic emissions. This enormous discrepancy stems from a single accounting choice: IEA includes direct CO_2 emissions in its factors even if they are of biogenic origin (IEA, 2024a), a practice contrary to IPCC guidelines (Eggleston et al., 2006), which consider such emissions to be carbon–neutral within the energy system's carbon cycle. This example is a stark illustration of how a differing interpretation of accounting rules, even for direct emissions, can lead to a result that is orders of magnitude different and potentially misleading for policy or reporting purposes.

In contrast to the DCI analysis, the comparison of LCCIs reveals larger disagreements across nearly all technologies (Fig. 1b and c). For renewables, where the intensity is dominated not by operational but by manufacturing and decommissioning emissions, the choice of data source becomes critical. For example, the reported LCCI for hydroelectric power in Ecoinvent, and the maximum of the range reported by IPCC, are substantially higher than in any other source, a result (Steubing et al., 2022) attribute to the inclusion of diverse plant types and fugitive reservoir emissions. Similarly, for nuclear power, the LCCI from Electricity Maps is less than half the median reported by the IPCC and falls below the minimum range of the NREL harmonization project. These discrepancies underscore that once the analytical boundary expands beyond the smokestack into the complexities of the full supply chain, any semblance of consensus vanishes, leaving the user in a landscape of highly variable data.

4.2 Systematic differences between EEIO and P-LCA databases

Across the wide variability of LCCI data, a clear and actionable pattern emerges: the choice between a P-LCA and an EEIO database is not neutral. Our results show that the EEIO database EXIOBASE Hybrid consistently yields the highest or among the highest LCCI values for nearly every technology analyzed.

This effect is highly visible for conventional generation technologies (Fig. 1b). For natural gas, the medians for IPCC and NREL align on 490 gCO_2eq/kWh, Electricity Maps' range is tightly concentrated around 529 gCO_2q/kWh (coefficient of variation of only 10%), and Ecoinvent has a broader span with a median of 598 gCO_2eq/kWh. The median LCCI from EXIOBASE Hybrid, instead, reaches 780 gCO_2eq/kWh. This relatively high value can be attributed to the use of the hybrid EEIO framework, which captures the full range of transactions along the value chain, including services typically excluded from process-based LCA approaches. In addition, the industry-based technology assumption, combined with the treatment of blast furnace gas as an input to the power sector, indirectly activates the steel industry, thereby inflating the intensity. Despite these methodological effects, process-based studies in the recent literature analyzing the liquefied natural gas supply chain report estimates of a similar magnitude (Howarth, 2024). The pattern is even more pronounced for coal: the entire distribution of LCCI values from EXIOBASE Hybrid lies above the third quartile of NREL, IPCC, and Electricity Maps, effectively creating a separate, higher-impact class of results. Even Ecoinvent provides 26% of values below EXIOBASE Hybrid's lower whisker and 60% of values below its first quartile.

This effect persists, and in some cases is amplified, for renewable technologies (Fig. 1c). For wind power, all medians fall within the narrow range of 11–23 gCO_2eq/kWh; EXIOBASE Hybrid's distribution is significantly higher and wider, with outliers surpassing 150 gCO_2eq/kWh. Similarly, for geothermal energy, EXIOBASE Hybrid's median LCCI is 53% higher than the value reported by the IPCC and Electricity Maps.

This systematic difference is not an error, but a direct consequence of the fundamentally different analytical boundaries of the two paradigms, as explored in the literature review.

Across the sources compared here, EEIO-based LCCI estimates are generally higher than process-LCA-based estimates within our matched sample of electricity technologies and national mixes. We do not interpret this pattern as evidence that EEIO results are necessarily closer to ground truth. Rather, the gap reflects differences in modelling architecture, including broader system boundaries and reduced truncation of upstream services and capital in EEIO, vs. greater technological specificity but potentially narrower boundaries in P-LCA. The magnitude and even direction of the gap may also depend on aggregation, multifunctionality assumptions, data vintage, and the geographical representation of supply chains.

4.3 National grid emission factors

The methodological divergences identified at the technology level directly propagate to the calculation of national grid emission factors, leading to a wide range of potential carbon intensity values for any given country. Analyzing the computed DCIs, the difference between minimum and maximum estimates, relative to the IEA reference value, ranges between 72 and 730% for 2017 (Fig. 2a), and between 38 and 612% for 2023 (Fig. 2c). This confirms that even for direct emissions, the methodological landscape is far from settled. When grouping databases by original unit (monetary vs. physical), a consistent pattern emerges: monetary-based sources tend to yield lower DCI estimates, a trend that is particularly pronounced for the year 2017, in which more than 90% of the minimum values across technologies are attributable to a monetary source. It should be noted, however, that monetary EFs are inherently mediated by electricity prices: a higher price assumption would allocate the same quantity of GHG emissions to a smaller electricity output, thereby resulting in a higher DCI estimate.

In examining the LCCI (Fig. 2b and d), it is observed that the spread (difference between minimum and maximum) of monetary-derived data is systematically wider than that of physical sources: on average, the range is approximately 150% larger for monetary than for physical databases in

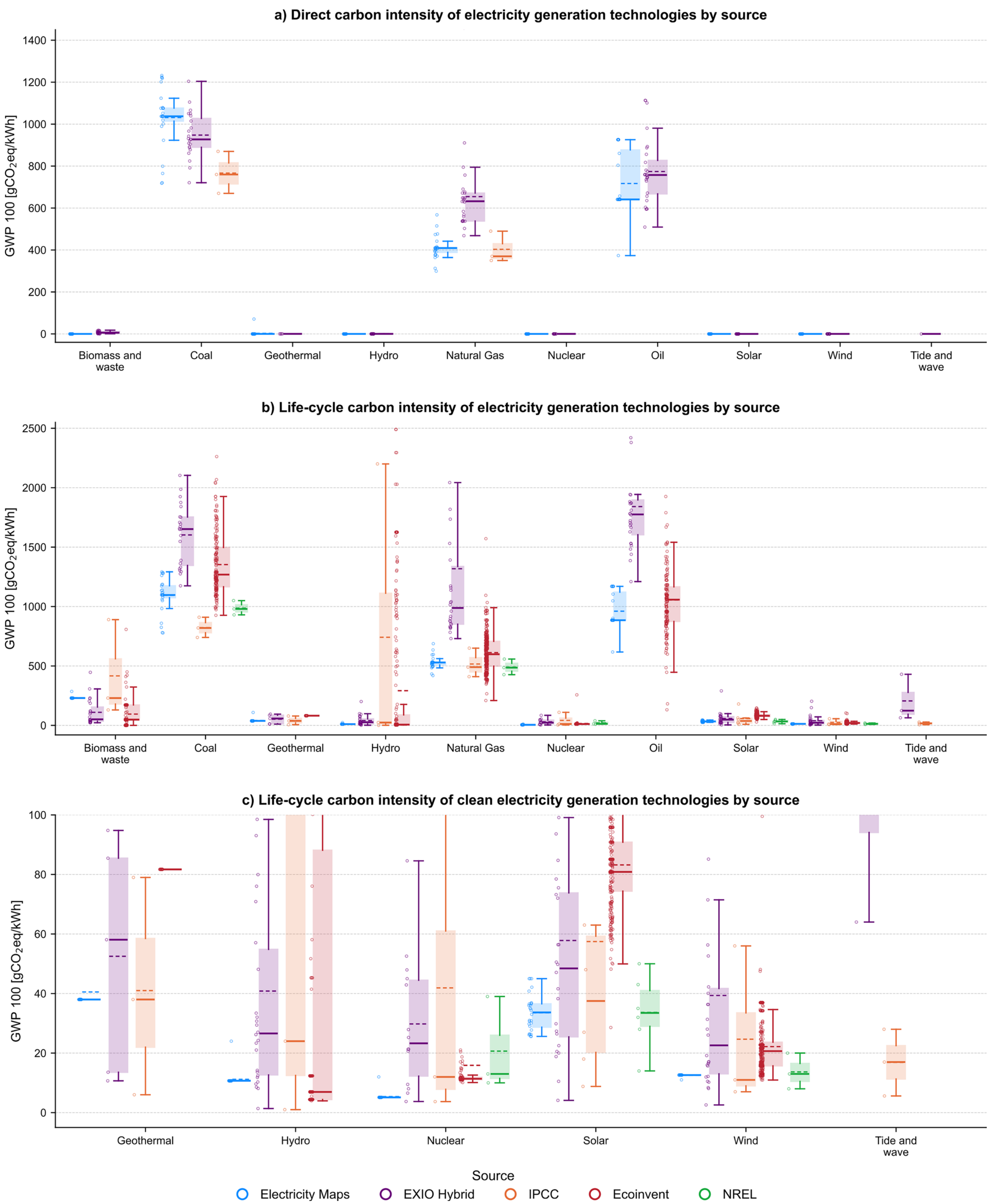

Fig. 1 Physical-unit emission factors of electricity generation technologies by source for EU27 and US (gCO_2eq/kWh). From top to bottom: **a** direct carbon intensities; **b** life-cycle carbon intensities of all technologies (vertical axis limited to 2500 gCO_2eq/kWh, full figure in Supplementary Information SI1); **c** focus on life-cycle carbon intensities of clean technologies. Each box spans the interquartile range (IQR), with the central line and dashed line indicating the median and mean, respectively; whiskers extend to the most extreme values within 1.5 × IQR, with quartiles computed using linear interpolation. The data for Fig. 1 can be found in Supplementary Information SI2

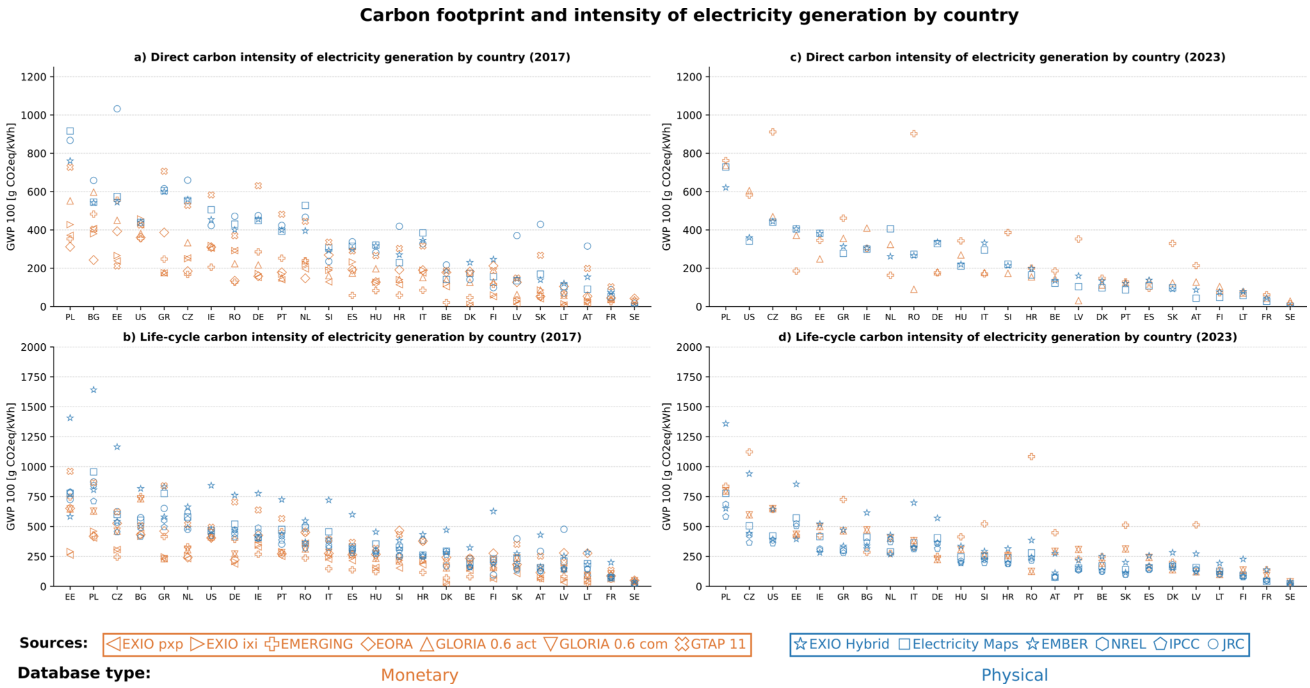

Fig. 2 Physical-unit direct **a** and **c** and life-cycle **b** and **d** carbon intensity of electricity generation at the national level by country (gCO_2eq/kWh) for 2017 (a and b) and 2023 (c and d). Different colors identify the original unit of measure in which data was provided: physical (mass of emissions per physical unit of energy), monetary [mass of emissions per monetary unit of energy, converted using GTAP prices (Aguiar et al., 2022)]. The countries Cyprus, Malta, and Luxembourg were not represented due to the absence of data for numerous sources. The data for Fig. 2 can be found in Supplementary Information SI2

2017. Furthermore, for the 2017 LCCI values, monetary sources fall below the country-level median in 60–100% of cases (except GTAP 11, which does so in only 12% of countries), whereas physical sources exceed the median in 64–92% of countries (except for IPCC-based values, only 32%). The hybrid EXIOBASE estimates, computed here in combination with respectively the 2017 and 2023 ENTSO-E electricity mix, stand above the country median in 96% of cases; moreover, for 20 out of 28 countries, this source reports the highest LCCI value in 2017, and for 13 out of 28 in 2023.

5 Discussion

This study set out to provide a practical compass for navigating the fragmented evidence on electricity's carbon intensity. Our results move beyond simply confirming the existence of discrepancies: by systematically examining them, we can translate our findings into a set of guiding principles. The core conclusion is that an optimal data source does not exist; the "best" choice is contingent on the user's specific application and analytical goals.

The first critical decision point for any analyst concerns the analytical scope: reporting direct emissions (DCI) vs. full life-cycle impacts (LCCI). Our analysis reveals a moderate consensus for the DCI of fossil fuels, suggesting that for straightforward applications like basic Scope 2 reporting, relying on primary data from sources like the IEA provides a widely accepted foundation. However, even within this consensus, our findings on biogenic carbon accounting warn that differing guideline interpretations can yield very different results, demanding user vigilance.

When the scope extends to LCCIs, the choice of modeling paradigm becomes the central strategic consideration. We consolidated a systematic yet typical "paradigm effect," where EEIO databases tend to yield higher LCCIs than P-LCA sources. This pattern should not be interpreted as evidence of closer agreement with ground truth, but rather because of broader system boundaries and reduced truncation in EEIO models. This is not an error, but a feature that can be leveraged. If an analyst's objective is a conservative, upper-bound estimate that captures the broadest economic context (e.g., in a corporate risk assessment), then the use of an EEIO database is a defensible choice. Moreover, the EEIO framework is, in our view, the only approach that enables a comprehensive assessment of a company's carbon footprint while allowing for a systematic and coherent allocation of Scope 3 emissions. If, conversely, the goal is comparability with standard product LCAs or Environmental Product Declarations (EPDs), which predominantly use process-based data, selecting an LCA-based source is necessary to ensure methodological consistency.

A final, crucial distinction lies between physical and monetary units. Our analysis of monetary emission factors revealed a higher spread of values for monetary databases, and we highlight that the obtained EFs are inherently mediated by the price of electricity. This renders their uncritical use for formal reporting highly problematic. While convenient for high-level screening where accountability data is readily available, their application must be approached with extreme caution. Whenever accuracy is a priority, physical factors based on actual consumption (in MWh) should be the default and preferred method. However, for corporate carbon accounting, the key question is not which paradigm is "truer", but which data infrastructure enables coherent, repeatable annual inventories. In practice, mixing Scope 3.1 estimates based on monetary tables that are several years out of date with electricity factors drawn from heterogeneous physical sources is hard to justify, especially when electricity can explain a large share of the footprint. This motivates the advantages of a centralized, integrated, regularly updated framework that uses physical data where feasible and monetary proxies where necessary, while preserving internal consistency across scopes and categories, and is complemented by primary data whenever available.

To make these discrepancies concrete, consider a 10 MWh electricity bill corresponding to 1600 EUR (basic price, 2023) in Italy. Utilizing the presented monetary and physical factors, the maximum total GHG emissions are 3 times the minimum value, with a difference of 4 tCO2eq in the considered year, a spread that underscores how methodological choice dominates results and why transparent reporting is non-negotiable.

Ultimately, all these decisions are bound by one unbreakable rule: the imperative of radical transparency. Given that a country's calculated footprint can vary dramatically based on the data source, any reported EF must be accompanied by a clear citation of the underlying source and version. This is the minimum requirement for enabling reproducibility and allowing the audience to understand the context and limitations of the presented figures. These principles are summarized in Table 2 as a practical guide for practitioners.

5.1 Conclusions

The carbon intensity of electricity is not a single, fixed value, but a context-dependent figure shaped by deliberate methodological choices. This study has systematically dissected the impact of those choices, mapping the landscape of divergence from technology-level data to national averages and monetary factors. By transforming these quantitative findings into a practical set of guiding principles, we have provided the tools for analysts, companies, and policymakers to move from arbitrary data selection to conscious, evidence-based choices. These conclusions, however, must be viewed considering the study's methodological boundaries. Our analysis was intentionally focused on a production-based perspective and limited to attributional models to ensure a fair comparison of the underlying data sources. This highlights two critical avenues for future research: first, integrating flow-tracing algorithms to extend this comparative analysis to consumption-based footprints, and second, performing an equally systematic comparison of consequential (marginal) EFs, which is essential for guiding policy on demand-side management and grid decarbonization. It is important to note that the GHG Protocol is already moving toward an update of the Scope 2 Guidance, with increasing emphasis on the temporal and geographical granularity underpinning low-carbon electricity claims. While this represents a relevant advancement, particularly for market-based accounting, it only partially addresses the challenges highlighted in this study, which primarily concern the consistency and comparability of emission factors across data sources and methodologies. In parallel, the joint effort between GHG Protocol and ISO to establish a harmonized standard represents a significant step forward in enhancing comparability. Nonetheless, these initiatives on their own may prove insufficient. Without more reliable primary data, clear and definitive guidance on temporal and spatial granularity (including an explicit and unique indication on the treatment of imports and exports), robust residual-mix methodologies where applicable, a more precise delineation between location- and market-based accounting, and systematic documentation of sources and versions, significant discrepancies are likely to persist. In essence, while stricter rules are essential, the ultimate quality of Scope 2 reporting will continue to depend on rigorous data and uncompromising transparency.

Ultimately, in a rapidly decarbonizing context—and amid polarized views on sustainability regulation—credibility in climate policy and corporate reporting depends on transparent data sourcing and clear communication of analytical boundaries. A practical way to support this credibility is to anchor inventories in a centralized and regularly updated reference dataset, applied consistently over time and complemented by integrated primary data to progressively enable more robust hybrid assessments.

Table 2 Decision framework for selecting electricity emission factor sources

Use cases	Recommended data type	Rationale and key considerations
Territorial electricity benchmarking / producer-side analysis	Production-based DCI or LCCI in physical units from primary or official sources	Use when the question concerns electricity generated within a territory. Suitable for producer-side benchmarking and comparability with generation statistics. Not ideal for end-use footprints where imports/exports materially alter the delivered mix
Scope 2 location-based accounting	Consumption-/delivery-oriented DCI in physical units; production-based factors only as a proxy when better consumption-based data are unavailable	Prefer in highly interconnected or import-dependent grids. Always disclose whether the factor is production- or consumption-based, together with its data year and treatment of imports/exports
Scope 2 market-based accounting	Supplier-specific or residual-mix DCI in physical units	Use only for contractual claims that meet Scope 2 quality criteria. This should be explicitly flagged as outside the main quantitative comparison in the present paper
Scope 3 category 3 (fuel- and energy-related activities, incl. upstream electricity and T&D losses)	Physical LCCI of electricity (kgCO2e/kWh), using average-data, supplier-specific, or hybrid factors	Align with the chosen Scope 2 basis. Explicitly state whether transmission and distribution losses are included. Monetary factors are not appropriate once kWh are known
Corporate Sustainability Disclosure, Hot spotting	EEIO databases (e.g., EXIOBASE)	Appropriate when expenditure data dominate and many categories or suppliers must be covered. Prefer multiregional models when supply chains are international (Davis et al., 2025) Use to identify hotspots, then refine material categories with hybrid or supplier-specific/physical data
Comparability with product LCAs or EPDs	P-LCA databases (e.g., Ecoinvent)	Ensures methodological consistency with the dominant approach in product-level studies. Disclose cut-off rules, multifunctionality assumptions, capital goods treatment, geography, and data vintage
Rapidly evolving grids / time-sensitive applications	Freshest year-matched physical factors; where relevant, sub-annual/hourly or near-real-time datasets	If the data lag exceeds ~ 2–3 years, or the grid mix is changing quickly, run a sensitivity analysis or triangulate with a more recent source. Temporal and spatial representativeness should weigh as much as source authority

6 Summaries:

Supplementary Information S1: This supporting information provides additional details on data sources, harmonization procedures, and robustness checks adopted in the article. It includes extended results on electricity generation emissions, methodological notes on harmonization across databases, details on the construction of the boxplot visualization and a comparison of EXIOBASE intensities by commodity and activity. Further sections report national carbon intensities, treatment of monetary databases, and a worked example of company-level electricity footprints. These materials support the reproducibility of the analysis and illustrate the implications of methodological choices for reported emission factors.

Supplementary Information S2: This supporting information provides the values of carbon intensity by technology from the considered sources, and results of computations to obtain factors for country electricity generation. Summaries of statistical analysis are reported for each intensity indicator. "Data sources's details" extends Table 1 of the article.

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Data availability The data that supports the findings of this study are available in the online resources of this article. Restrictions apply to the availability of IEA data, which were used under license for this study. Data are available at https://www.iea.org/data-and-statistics/data-product/emissions-factors-2024. Ecoinvent data used for the study were not directly extracted from Ecoinvent database but from the supporting materials of Steubing et al. (2022), published as open access material under CC-BY-NC 4.0 license. The utilization and dissemination of data from the GTAP database is permitted: the application in fact encompasses a single commodity and 28 geographical regions. The code used to manipulate MRIOT tables, obtain results and plot the figures is available in this GitHub repository https://github.com/eNextHub/electricity-carbon-footprint.

Declarations

Conflict of interest The authors declare no competing interests.

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