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Towards Standardized Grid Emission Factors: Methodological Insights and Best Practices (Electronic Supplementary Information)†

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1 Theoretical Background

Grid EF can be calculated at different steps along the conversion chain from the power plant to the plug. The following illustration (Figure 1) provides an overview of these conversion steps.

Primary energy (PE) in the form of e.g., wind, solar radiation or lignite is converted in generators/power plants into gross electricity production (GEP) and waste heat (conversion losses). After subtracting the electrical energy these generators need for e.g., powering its own pumps (auxiliary consumption), the result is net electricity production (NEP). This is the amount of electrical energy fed into the grid. Gross electricity consumption (GEC) is NEP minus electricity exports to, and plus imports from, neighboring regions (e.g., countries, bidding zones); and minus the losses occurring from cycling grid storage (e.g., pumped hydro). Finally, after subtracting the grid losses due to transformation and distribution, the result is net electricity consumption (NEC).

Going from left to right, the EF referenced to each of these stages necessarily grows larger (with the exception of electricity trade - this may have the opposite effect under certain circumstances). The total amount of emissions (numerator) remains the same, while the amount of electrical energy (denominator) decreases.

2 Extended State of Research

This section expands on the literature review covered in the main article.

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2.1 Scope and Retrieval Process

The review of the literature is aimed at identifying any studies that meet the following criteria regarding the studies' content:

- ELECTRICITY FOCUS: Discusses electricity-related emissions (not emissions related to other forms of energy, e.g., heat)
- CONSUMER FOCUS: Focuses on emissions primarily from a consumer perspective (not from the producer perspective, i.e. power plant or grid operators)
- CLIMATE FOCUS: Focuses on GHG emissions and/or climate change impact (extending the scope to other types of emissions/impact is acceptable if climate change impact/GHG emissions are included)
- METRIC MATCH: Assesses emissions on the basis of an indicator which relates emissions to the amount of electricity produced, i.e. an EF (and discusses not only e.g., total emissions)
- TRANSPARENCY: Transparently documents most or all (i.e. more than half of the) methodological choices made in calculating emission factors
- ACCOUNTING PERSPECTIVE: Focuses on average (not marginal) EF
- GRID SCALE: Assesses emissions within interconnected electricity systems and markets of significant scale, typically national grids (excluding e.g., off-grid, micro-grid or island grid cases)
- REAL SETTING: Assesses emissions of real, existing electricity systems and markets, using real world data and realistic assumptions (excluding fictional grid setups)
- RETROSPECTIVITY: Assesses past emissions (not projections of possible future emissions)

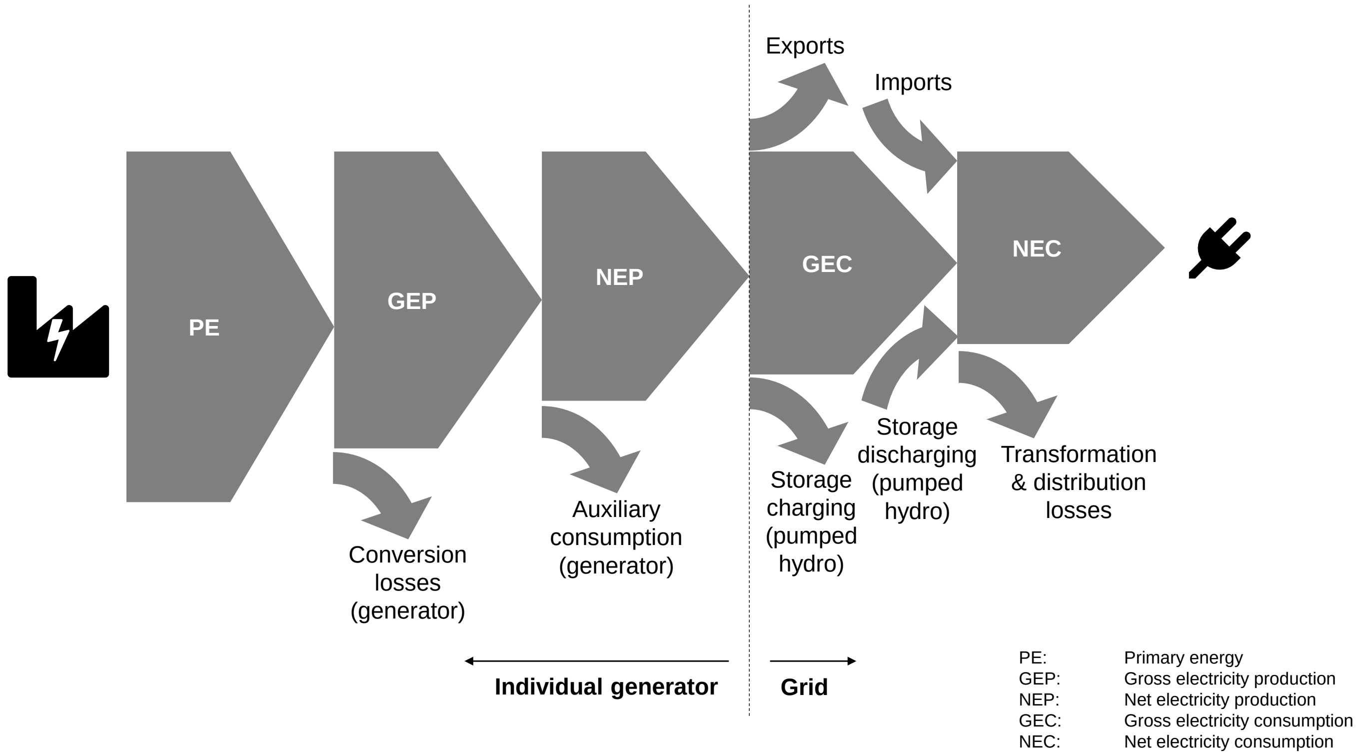


Fig. 1 Energy conversion steps from the power plant to the plug, inspired by ENTSO-E[1]

Additionally, the references have to meet these formal requirements to be included in the review:

- Only peer-reviewed journal articles
- Primary research (no review articles)
- Must be cited at least once
- At least one citation from authors other than the study authors

In the literature retrieval process, we used various combinations of relevant key-words (e.g., “emission factor”, “electricity”, “average”, “grid”) in literature search engines and software tools, primarily Google Scholar and ResearchRabbit. From initially discovered references, we then conducted an upstream- and downstream-search, i.e. we reviewed the citing and citing literature for relevant articles. We also looked through articles of the same author to uncover further relevant studies.

2.2 Detailed Literature Review of Methodological Aspects

The following paragraphs briefly describe each methodological aspect reviewed in the literature review of the main article. Furthermore, they summarize the findings of studies where the impacts of each aspect are quantified. An emphasis lies on studies that quantify the effect for Germany, as this is the focus of our own investigation.

Where impacts are quantified, we compare grid EF for two (or more) choices regarding a methodological aspect. We list the resulting grid EF for each choice, and calculate the absolute (*Abs.dif.*) and relative difference (*Rel.dif. (%)*) between them using the equations $Abs.dif. = (EF_{choice2} - EF_{choice1})$ and $Rel.dif.(\%) = Abs.dif./EF_{choice1}$.

2.2.1 Impact Metric

describes the metric used to assess the global warming/climate change impact per kWh of electricity. In order to fully define an impact metric, one needs to specify the impact assessment model used. An impact assessment model shall contain information on which substances it includes, the characterization factors used to evaluate their impact, and the time period over which their impact is assessed.

Most studies use GWP as a metric to calculate climate impact, and only a few[2–10] rely on just CO_2. In two studies, CO_2 and GWP (CO_2e) appear to be mixed together and used interchangeably[11,12]. Some studies assess environmental impact besides climate change, either on the basis of the amount of substances (e.g., CH_4) emitted, or relying on impact assessment methodologies used in LCA[8–10,13–21]. Most studies use the IPCC impact assessment models to calculate the resulting climate impact, while a few rely on other impact assessment models, namely CML[22,23], EF3.0[24], GREET[25], IMPACT2002+[13,17,21], ReCiPe[26] and TRACI[16]. These "other" impact models, however, employ the IPCC models as well[27], so it is safe to say that the IPCC models dominate impact assessment. Not all studies explicitly state which impact assessment model they use[11,12,28–35]. To highlight the impact of short-lived GHG such as methane, one study[36] assesses both the impact over 20 years (GWP20) and over 100 years (GWP100), with the GWP20 values being 15 to 20% higher than the GWP100 values. In the same study, the authors conduct a probabilistic estimate of the amount of emissions emitted per source and for the characterization factors of the substances emitted using probability density functions, to account for the inherent uncertainty surrounding these parameters.

Of all reviewed studies, only one assesses both CO_2 and CO_2e emissions [34]. The authors do not specify which impact assessment model (characterization factors) they use to calculate CO_2e emissions. In the following Table 1, we assume these to represent GWP100, as it is the most common indicator used in impact assessment models. Pereira and Posen [36] also provide different impact metrics, consisting of a comparison of GWP20 and GWP100 as well as a probabilistic estimate of different characterization factors for non-CO_2 substances. Unfortunately, the detailed data is locked behind a paywall, and thus is not included in the quantitative analysis in Table 1.

For the case of Germany, the study reports a +1.9 to +5.9% relative difference (+9 to +33 g/kWh) between CO_2 and GWP100 EF. The relative and absolute differences are larger for EF that include multiple life cycle stages (LC) than those that only cover the operational stage (OP).

2.2.2 System Boundaries

describe the life cycle stages included in calculating the EF of a generator or a set of generators. In general, one can distinguish between the plant life cycle and the fuel life cycle. For the purpose of this review, we only distinguish between operational (OP) and life cycle (LC) system boundaries. As per the definition used in this study, LC boundaries differ from OP boundaries in that they cover at least one additional life cycle stage, i.e. an upstream and/or downstream stage from the fuel and/or plant life cycle.

Several studies limit their assessment to operational emissions [2,6,8–10,12,20,29,35,37,38]. The other studies consider life cycle emissions to a different extent, including e.g., fuel upstream emissions [3–5,7,19,25,39,40], fuel upstream emissions and the plant life cycle [13–16,21,23,24,28,31,32,36,41] or the complete fuel and plant life cycle [17,18,22,26,30,42–45]. One study distinguishes between operational (combustion) emissions, upstream and downstream emissions, which are again split up into fuel extraction and power plant construction (upstream) and T&D as well as pumping losses (downstream), respectively [46].

For two studies [47,48], it is unclear which life cycle stages are included. These studies draw the generator-specific EF from the 2021 IPCC Special Report on Renewable Energy (SRREN) [49], which provides aggregate EF values based on a review of LCA studies. The qualifying criterion regarding system boundaries in the IPCC SRREN report states that two or more life cycle stages must be covered, so the EF reported by Stoll *et al.* and Fiorini and Aiello are considered LC EF. Nilsson *et al.* combine the aggregate values from the IPCC SRREN report with values from the IEA (which covers operational and fuel upstream emissions). Schwabeneder *et al.* appears to mix system boundaries, reporting operating emissions only for renewables and nuclear, and adding fuel upstream emissions for all other generation technologies. Tranberg *et al.* reports two separate EF, one including the operational stage and the fuel upstream stage, and the other adding the plant upstream stage to it. Similarly, Wörner *et al.* provides an EF based on only operational emissions, and one which additionally includes both fuel and plant upstream emissions.

Studies which calculate EF with different system boundaries, keeping all other aspects constant, are required to quantify the effect that using different system boundaries has on the results. Only four of the studies we review do so [33,34,44,45]. Unfortunately, two of those studies only provide plots without the underlying data that could be used for a comparison [44,45]. Data from the remaining two studies [33,34] is documented in Table 2 to quantify the system boundary effect. From the study by Tranberg *et al.*, only the countries with the largest and smallest relative effect, and Germany (as it is the same country assessed by Wörner *et al.*) are selected. The system boundaries are documented for the lower and higher bound of the EF range, which describes the EF resulting from applying those system boundaries.

At the low end, Tranberg *et al.* find no difference between OP emissions and emissions considering more LC stages for the case of Poland. This is not entirely plausible, since the coal-heavy generation mix of Poland should generate at least some upstream plant and feedstock emissions. Perhaps this fact can be explained by a combination of using average European data instead of country-specific data and numerical (rounding) errors. At the high end, Wörner *et al.* finds a relative difference of up to 13.2% between OP and LC emissions for Germany. Across studies and calculation methods, the relative difference between OP and LC EF for Germany is in the range of 2.2 to 13.2%.

2.2.3 Co-generation of Heat

describes the co-production of electricity and other products, usually heat and/or steam, within the same plant. Since these co-products provide a value to their users, one can argue that the emissions from these co-generation plants should be allocated to both their electricity and their heat (steam) output. Different principles exist to decide on how exactly this allocation is to be implemented, based e.g., on economic value, energy or exergy content of the outputs [3]. Alternatively, using a substitution approach, one can calculate the emissions created when using alternative heat (or steam) sources, and subtract these emissions from the co-generating plant's emissions to receive the emissions for producing electricity only [45]. The share of generators that participate in co-generation within a set of generators, the share of primary energy converted to electricity vs. other products, and the method used to allocate generator emissions to the various outputs all have an impact on the resulting EF of the electricity produced.

Few studies mention co-generation at all [3,4,17,18,22,28,30,34,40,45,46,51]. Soimakallio and Saikku provide the only study with a detailed assessment of the impact that allocation methods have on the resulting EF. Jean-Nicolas Louis, Antonio Caló, Eva Pongrácz, Kauko Leiviskä distinguish between co-generation of heat and power (CHP) for district heating and for industrial use, and when generation is driven by demand for electrical power and when by demand for heat. Kopsakangas-Savolainen *et al.* list CHP plants as a separate type of generator technology, but do not disclose how they arrive at their estimate of an electricity EF for CHP plants.

Table 1 Impact metric effect in the literature, based on data from Wörner *et al.* [34] Values in EF-columns are in g CO_2(e)/kWh. All values are for Germany, 2017

Perspective	Sys. bound.	EF_{CO_2}	EF_{GWP100}	Abs.dif.	Rel.dif. (%)
Production	OP	439	448	+9	+2.1
Production	LC	479	507	+28	+3.8
Consumption	OP	515	525	+10	+1.9
Consumption	LC	561	594	+33	+5.9

OP: Operational; LC: Life cycle

Table 2 System boundary effect in the literature. Values in EF-columns are in g CO_2(e)/kWh

Study	Region	EF_{OP}	EF_{LC}	Abs.dif.	Rel.dif. (%)
[33]	DE[a]	643	657	+14	+2.2
[33]	EU28[a]	440	446	+6	+1.4
[33]	PL[a]	1030	1030	0	0
[33]	SE[a]	39.3	42.3	+3.0	+7.7
[34]	DE[b]	439	479	+40	+9.1
[34]	DE[c]	448	507	+59	+13.2
[34]	DE[d]	515	561	+46	+8.9
[34]	DE[e]	525	594	+69	+11.6
[46]	DE[f]	354	377	+23	+6.5

OP: Operational; LC: Life cycle
[a]Low voltage mix; [b]Production-based & CO_2; [c]Production-based & GWP100; [d]Consumption-based & CO_2; [e]Consumption-based & GWP100; [f]Germany, 2020, EF_{up} and EF_{Total};

Vuarnoz and Jusselme use allocation by exergetic content, as do Munné-Collado *et al.*, for those countries where data is available (BG, DE, NL). Baumann *et al.* consider co-generation of heat in the plant dispatch model they use to calculate EF, but do not specify how exactly. Similarly, Baumgärtner *et al.* appear to provide details on how they consider CHP plants, but the details are available only in the supplementary material that is locked behind a paywall. Wörner *et al.* allocate all emissions from CHP to electricity, knowing that this may lead to an overestimation of electricity-related emissions. Braeuer *et al.* supposedly to do the same, as they state that some outliers in their data from the high end may be explained by the fact that CHP plant emissions are allocated to electricity only. Scarlat *et al.* consider CHP plant emissions using a substitution approach (as is used by the IEA). They calculate the amount of emissions that would have been generated if the heat from CHP plants had been produced in heat-only plants with an efficiency of 85-90%, and subtract these emissions from the CHP plant emissions. Unnewehr *et al.* allocate emissions based on free allowances of emission certificates for heat generation under the European Emission Trading Scheme (ETS). Blizniukova *et al.* employ the IEA method ("fixed-heat-efficiency approach").

Multiple studies probably implicitly consider CHP plants via the data that they use (e.g., the unit processes for CHP units in the Ecoinvent LCA database [52] without explicitly stating whether and how they allocate emissions [5,13,15–17,19–21,23,25,26,28,33,40,42,44].

To assess the impact that co-generation allocation methods have on the resulting EF, we use data by Soimakallio and Saikku, as it is the only study in our review quantifying this effect. We select seven countries from the list of OECD countries with various shares of electricity generation originating in CHP plants ("CHP share") and absolute levels of grid EF. We document the range of EF for each of these countries when using each of the two different allocation methods applied in the study, allocation based on energy content of the co-products (EN) and all emissions allocated to the electrical energy ("Motivation electricity" / EL100: 100% of emissions allocated to electricity). All values are from the latest year documented in the study (2008) and use production-based EF only, to avoid confounding effects from electricity trading. The results are documented in Table 3.

For Denmark, with a relatively high CHP share of 81%, the EF estimate almost doubles when using a different allocation method. Finland's EF estimate exhibits a very similar behavior, yet from a lower baseline. Poland, with a much higher CHP share of 98%, but compared to Denmark and Finland also a much higher absolute EF to begin with, the allocation method only shifts the estimate by about one third. The biggest influence of the allocation method (in relative terms) can be observed with Sweden, even though its CHP share is only 10%—mostly due to the baseline effect, with Sweden having a very low grid EF of 15 (53) g CO_2/kWh. As expected, for countries with a low CHP share (Mexico and Norway), the CHP allocation method has little impact on the grid EF. For Germany, with a CHP share of 13%, the CHP allocation method can change the resulting grid EF by 9.9-11.4% (production-/consumption-based).

2.2.4 Auto-producers

are generators which do not feed into the electrical grid, but instead exclusively supply one consumer (e.g., an industrial facility) with electricity. Depending on whether the underlying dataset contains auto-producer generation and/or emission data, they may be included in grid EF calculations.

Only five studies address the issue of auto-producers [25,41,42,46,51]. In their first study, Clauß *et al.* compare two scenarios, one in which auto-producers are included in the dataset, and one in which they are excluded [41]. They find that for the case of Norway, removing auto-producers reduces the resulting EF noticeably in three out of five bidding zones. In their second study, they only consider scenarios without auto-producers [42]. Colett *et al.* consider the emissions from on-site generators in their aluminum smelting case study. Unnewehr *et al.* estimate the emissions from auto-producers based on the emissions profiles of main-activity producers. Blizniukova *et al.* include both auto-producers and main-activity-producers in their assessment. Unfortunately, none of these study quantifies the effect of removing auto-producers from the dataset on the resulting grid EF.

Table 3 Co-generation effect in the literature, based on data from Soimakallio and Saikku [3] (year 2008). Values in EF columns are in g CO_2/kWh

Country	CHP share (%)	EF_{EN}	EF_{EL100}	Abs.dif.	Rel.dif. (%)
DE[a]	13	547	601	+54	+9.9
DE[b]	13	525	585	+60	+11.4
DK[a]	81	351	663	+312	+88.9
FI[a]	36	185	316	+131	+70.8
MX[a]	0	566	566	0	0
NO[a]	0	3	4	+1	+33
PL[a]	98	902	1229	+327	+36.3
SE[a]	10	15	53	+33	+253

[a]Production-based; [b]Consumption-based;

2.2.5 Auxiliary Consumption

describes the amount of electricity used by generators for supporting their own operations (e.g., to power pumps). By subtracting auxiliary consumption from gross electricity production (GEP), one receives the net electricity production (NEP).

Nine studies in total address auxiliary consumption[3,5,22,29,31,34,45,46,51], using a simple calculation step consisting of subtracting the auxiliary consumption from GEP. One of these studies quantifies the effect that this subtraction has for multiple (primarily European) countries[45]. The findings for a selection of these countries are summarized in Table 4.

Table 4 Auxiliary consumption effect in the literature, based on data from Scarlat *et al.*[45] Values in EF-columns are in g CO_2e/kWh

Region	EF_{GEP}	EF_{NEP}	Abs.dif.	Rel.dif. (%)
DE	390	410	+20	+5.1
EE	571	659	+88	+15.4
SE	33	33	0	0
EU27	296	310	+14	+4.7

GEP: Gross electricity production; NEP: Net electricity production

The results show the for the EU27 states, auxiliary consumption increases the grid EF on average by 4.7%. For a country like Estonia, with a comparatively high share of auxiliary consumption, the increase may be as high as 15.4%, while the opposite is true of Sweden (no change). For Germany, the influence of the auxiliary consumption (5.1%) is close to that of the EU27-average (in relative terms).

2.2.6 Electricity Trading

is the exchange of electricity between different regions (e.g., countries, bidding zones), typically in return for money. It separates the net electricity production (NEP) within a grid from the gross electricity consumption (GEC) within that same grid. Note that, unlike depicted in Figure 1, losses from storage cycling are not included at this point. They are covered in a paragraph further down.

The approaches that take into account electricity trading fall into two categories: 1) simple, first order trading (SFOT) approaches[2–5,14,17–19,21,24,25,30,32,34,36,38,40,45,47,50,53] and 2) approaches based on multi-regional input-output (MRIO) models[6,7,12,20,23,33,37,39,41,42]. SFOT approaches only consider direct neighbors of the region of interest, the amount of electricity traded with these neighbors, and the EF of these neighbor regions. MRIO approaches (sometimes also referred to as "network-based" or "flow-tracing" approaches) rely on networks and graph theory, where regions are nodes with a specific generation and load, and the connections between regions are edges with specific, bidirectional flows. The MRIO networks include more regions than just the direct neighbors of the region of interest, and therefore-unlike SFOT models-consider higher-order effects as well (e.g., transit flows from region A via region B to region C). Like SFOT models, MRIO models may be based on data with different temporal resolution levels.

Table 5 contains data on all studies that provide both EF_{NEP} and EF_{GEC}, thus allowing for an analysis that electricity trade has on the resulting grid EF. The table lists the regions covered by these studies, the method (SFOT or MRIO) used to calculate the EF, the production- (EF_{NEP}) and consumption-based EF (EF_{GEC}), and the absolute and relative difference between the two. For each study, we list minimum, mean and maximum values.

The table illustrates that in every single study, trade has a moderating effect on the grid EF, i.e. the minimum values are higher and the maximum values are lower after accounting for electricity trade. In some cases, the maximum differences (both absolute and relative) between EF_{NEP} and EF_{GEC} can be very high (e.g., for de Chalendar *et al.*[20]). This typically occurs when regions have little electricity generation compared to the amount of electricity traded with neighboring regions, and when the domestic grid EF (EF_{NEP}) differs a lot from the grid EF of its neighbors. In these instances, these outliers may have an impact not just on the maximum, but also on the mean grid EF (as is the case e.g., for de Chalendar *et al.*[20]).

For Germany, which is of special interest for this study, the influence of trade on the grid EF is moderate. Most authors find that trade reduces the grid EF, including Soimakallio and Saikku (-22 absolute / -4.0% relative difference), Qu *et al.* (-20 / -4.3%) and Tranberg *et al.* (-10 / -1.9%). On the contrary, Scarlat *et al.* detect the trade increases the German grid EF (+12 / +2.9%). This may be due to different time periods covered by the studies, or due to other methodological differences.

2.2.7 Storage Cycling

losses are the difference between the amount of electrical energy used for charging and the amount generated from discharging a grid-connected storage (e.g., a pumped hydro plant). Storage cycling losses complement electricity trading, in the sense that both together comprise the step from net electricity production (NEP) to gross electricity consumption (GEC).

A total of 17 studies consider the losses due to grid storage cycling[3,14–17,19,22,24,26,33,34,40–42,45,46,51]. For some studies, it is

Table 5 Electricity trading effect in the literature. Listed are the minimum (min), mean and maximum (max) values for the production-based emission factor (EF_{NEP}-does not include trade), and the consumption-based emission factor (EF_{GEC}-does include trade). Further listed are the absolute (Abs.dif.) and relative (Rel.dif. (%)) differences between these two values

Study	Regions	Method	Value	EF_{NEP}	EF_{GEC}	Abs.dif.	Rel.dif. (%)
	51		min	0	143	-104	-38.5
[2,a]	US	SFOT	mean	169	191	+21.5	+209
	States		max	291	250	+174	+8233
	25		min	3	6	-109	-31.1
[3,b]	OECD	SFOT	mean	408	419	+10.5	+54.6
	Countries		max	902	880	+167	+1113
	6		min	398	408	-123	-12.4
[39,c]	CN	MRIO	mean	810	795	-14.7	-1.2
	Regions		max	1197	1171	+36	+4.4
	30		min	219	265	-162	-12.4
[6,d]	CN	MRIO	mean	674	672	-1.3	+1.2
	Provinces		max	947	947	+229	+41.4
	137		min	0	0	-790	-49.8
[7,d]	World	MRIO	mean	452	451	-1.5	+48.7
	Countries		max	1587	1169	+391	+4340
	66		min	0	0	-208	-36.0
[20]	US	MRIO	mean	389	392	+3.0	+2088
	BA		max	1034	1003	+409	+681 029
	9		min	7	9	-145	-56.0
[42]	Scandinav.	MRIO	mean	115	83	-31.3	+22.2
	BZ		max	461	316	+9.0	+114
	27		min	11	16	-171	-38.7
[33]	European	MRIO	mean	459	455	-3.7	+6.9
	Countries		max	994	947	+161	+82.4
	42		min	19	24	-187	-28.4
[45,e]	European	MRIO	mean	376	426	+50.2	+28.9
	Countries		max	1101	1101	+236	+253

SFOT: simple, first order trading approach; MRIO: multi-regional input-output approach; BA: balancing area; BZ: bidding zone;
[a] in MtC/GWh; [b] for year 2008; [c] boundary 3; [d] network method; [e] net electricity production;

not clear which efficiencies (losses), EF or share of electricity they assume for pumped hydro[3,19,22,34,45,51]. Two studies indicate only the share of electricity contributed by pumped hydro[16,26], but not the losses or EF they assume. Two other studies assume an efficiency of 70% for pumped hydro[14,24]. Baumgärtner *et al.* list efficiencies and losses, but they are in the supplementary information that is hidden behind a paywall. Six studies list the EF used for electricity coming from pumped hydro plants[15,17,33,41,42,46].

Since it is not always clear how these EF for pumped hydro are used in calculating grid EF, it is worth noting that if done incorrectly, double-counting may occur. The electricity used in pumping mode (storage charging) has already been accounted for in gross/net electricity production. Only the difference between the electricity used for storage charging and the electricity generated from storage discharging (pumping losses) should be accounted for, not the total amount of electricity discharged. Depending on how EF for pumped hydro (e.g., from the Ecoinvent database) factor into grid EF calculations, the resulting grid EF may be too high. For example, Kono *et al.* uses an EF for pumped hydro in Germany of 951.52 g CO_2e/kWh, which is higher than the grid-average. If this EF is used for pumped hydro just like the EF for all other sources (e.g., biomass, wind, coal), without considering double-counting, the resulting grid EF is too high.

Only one study quantifies the effect of pumped hydro losses, listed in table 6. It shows that for Germany (the only country assessed in the study), the losses make up consistently 1.2-1.3 % of the total EF.

Table 6 Effect of pumped hydro storage losses in the literature, from Blizniukova *et al.*[46]. The values refer to EF_{Total} (EF_{wP}) and EF_{Total} - ΔEF_P (EF_{woP}) for Germany in the Supplementary Information of the study

Year	EF_{woP}	EF_{wP}	Abs.dif.	Rel.dif. (%)
2017	493	499	+6	+1.2
2018	475	481	+6	+1.3
2019	412	417	+5	+1.2
2020	372	377	+5	+1.3

2.2.8 Transformation & Distribution

describe the conversion of electricity from one voltage level to another, and the transmission from producers to consumers. These steps are accompanied by dissipation of heat to the environment, i.e. losses. Following the logic illustrated in Figure 1, T&D losses separate gross electricity consumption (GEC) from net electricity consumption (NEC). In our review, we assume that study authors who do not mention T&D losses in their study do not consider them.

T&D losses are typically calculated using a fixed value that can be derived e.g., from the difference between generation and load (possibly including trade). Most studies considering grid losses fall into this category[2,3,5,10,15,24,29–31,34,40,46]. Some studies differentiate between losses in different regions (e.g., countries)[2,17,25,33,35,37] or at different grid voltage levels[16,23,45].

Table 7 summarizes the findings from those studies that quantify T&D losses. The losses are identical to the relative difference between EF_{GEC} and EF_{NEC}.

Table 7 Effect of transformation and distribution (T&D) losses in the literature

Study	Region	T&D losses (%)
Mills and MacGill 2017	AU	10
Li *et al.* 2013	CN	2
Kono *et al.* 2017	DE	4
Baumgärtner *et al.* 2019	DE	3.9
Rupp *et al.* 2019	DE	4.15
Blizniukova *et al.* 2023	DE	4.4-4.9
Milovanoff *et al.* 2018	EU	$1.9\text{-}2.9^{T}$
Fleschutz *et al.* 2021	EU	3.8-15.3
Roux *et al.* 2016	FR	3^{T} / 6^{D}
Papageorgiou *et al.* 2020	SE	1.97^{HV} / 0.3^{MV} / 3.12^{LV}
Mehlig *et al.* 2022	UK	7.5
Jiusto 2006	US	8.5-10.5

^{T}Transformation; ^{D}Distribution;
^{HV}High voltage; ^{MV}Medium voltage; ^{LV}Low voltage.

A review of the studies that quantify the contribution of grid losses to the EF show that these losses lie in the range of 1.9 to 15.3% (see Table 7). The two% losses for the Chinese grid stated by Li *et al.* appear relatively low, and probably only include transformation losses (without distribution losses), even though the study does not state this explicitly. In the European cross-country study by Fleschutz *et al.*, Finland features the lowest grid losses (3.8%), and Serbia the highest (15.3%). Studies that distinguish losses by voltage levels or between transmission and distribution grid losses show that low voltage/distribution grid losses tend to be higher than high voltage/transmission grid losses[14,23]. However, this assessment rests on sparse data. T&D losses in Germany are in the range of 3.9-4.9%[15,31,35,40,46], and 2.1% for losses in the high-voltage grid only[17].

2.2.9 Temporal Resolution

describes the temporal reference frame used to calculate a temporally averaged EF. The length of the reference frame depends primarily on the user needs and the temporal resolution of the available data needed for EF calculation. Most of the studies included in our review calculate hourly EF, while some rely on a coarser resolution of one year[2,3,6,7,25,37,39,45], and others on finer resolutions of up to 30 minutes[29,38,53] or even 15 minutes[31,34,46]. Some studies that include multiple countries in their analysis harmonize data by choosing the lowest temporal resolution available for all countries of interest[17,35,44].

Several studies contain EF at multiple temporal resolution levels. They allow for an assessment of the impact that the choice of temporal resolution has on the resulting EF, as documented in Table 8. All but one study compare yearly (y) and hourly (h) resolution levels, while Kono *et al.* additionally provides monthly (m) EF. We limit our comparative assessment in this study to the coarsest (yearly, EF_y) and finest (hourly, EF_h) spatial resolution level.

Table 8 provides an overview of all studies that quantify the effect that changing the temporal resolution of the grid EF has on the resulting emissions. It lists the effect that changing the temporal resolution from annual to hourly has on the electricity consumer's electricity-related GHG emissions. Besides the temporal resolution, all else remains constant (e.g., no change in the consumer load profile). The relative difference is calculated by dividing the difference between the emission results at an hourly resolution and the results at an annual resolution by the results and an annual resolution. The table contains all study results from the literature review that allow for such a quantiative comparison.

Table 8 Temporal resolution effect in the literature. The relative difference describes the change in GHG emissions when applying an hourly instead of an annual grid EF.

Study	Region	Rel.dif. (%)
[14]	France	+36
[28]	Finland	-5.7
[17]	Spain	-28
[17]	France	-2.6
[18]	Austria	+6.2
[18]	France	-4.9
[18]	Switzerland	+5.0
[19]	Switzerland	+69
[21]	Canada, Ontario	+2.8
[10]	United Kingdom	+4.2
[24]	Spain	-7.6

The largest relative difference can be observed for the study by Beloin-Saint-Pierre *et al.*, who find that the temporal resolution effect can increase emissions by 69% for the case of Switzerland. The smallest effect is observed by Milovanoff *et al.* for the case of France, with an emission reduction of 2.6%. No study quantifies the effect for the case of Germany.

2.2.10 Other Methodological Aspects

for calculating grid EF besides those mentioned above exist as well. Most importantly, the choice of spatial[5,6,12,20,25] and technological resolution[9,12,20,35,51] stand out.

The spatial resolution describes the geographical reference frame chosen for calculating a grid EF. The most typical spatial resolution is that of a country, but it is also possible to calculate a grid EF for a state, a province, a region, a bidding zone, a balancing area, a grid region or a continent. Colett *et al.* discuss this choice in detail, including the (dis)advantages for each reference frame, and develop their own approach that spans several spatial resolution levels ("Nested approach"). Due to the grid topology in most places with interconnected grids, there is no "right" choice for choosing a spatial resolution level. Usually, the spatial resolution level is determined by the data availability-most data is available at country level. Due to this fact, and since data on how the spatial resolution influences grid EF, we do not pursue this aspect any further in our study.

The technological resolution describes the level of differentiation between individual generators (power plants). The most common technological resolution is one where all generators are grouped together by the type of primary energy input (e.g., wind, coal, biomass). Some further distinctions are often made, e.g., between offshore and onshore wind, or between hard coal and lignite. However, at this "generator type" level, no distinction is made between individual generators. Therefore, e.g., all hard coal fueled power plants and offshore wind turbines are lumped together into a homogeneous mass. A notably higher level of technological resolution is the "generator" level. At this level, each generator has individual technical aspects that influence the final result. These aspects may include different efficiencies due to age or different emissions due to the fuel type used (example: different chemical compositions of lignite used in East and West German lignite power plants [54]). We do not include an investigation on the technological resolution in our study, mostly because the data needed for such an assessment is sparse, and because the effort is relatively high.

Besides the spatial and technological resolution, there are several other methodological niche aspects not covered by our review. These aspects are either covered only in very few studies, their impact on emission accounting results is deemed negligible, the data availability to consider these aspects is insufficient, or a combination of these circumstances applies. Some of these aspects include the ramping (up/down) of generators [9,40], the age of generators [42], the operational restrictions of power plants (e.g., minimum load [17]) and the uncertainty regarding the characterization factors of the different greenhouse gases [36].

2.3 Extended Summary of the Literature Review

Table 9 summarizes which methodological aspects are considered in previous studies.

3 Extended Methodology

This section expands on the methodology and data covered in the methodology section of the main article.

3.1 Extended Methodology: Input Data

3.1.1 ENTSO-E Data

ENTSO-E provides data on the *Aggregated Generation per Type (AGPT)*, i.e. the net electricity production per individual energy carrier/generation technology [55] at a temporal resolution of up to 15 minutes. At the same temporal resolution, ENTSO-E also documents *Physical Flows (PF)*, i.e. the flow of electrical energy between bidding zones/countries [55].

3.1.1.1 Aggregated Generation per Type (AGPT). The data downloaded from the ENTSO-E Transparency Portal (e.g., via FTP client) is available at a monthly resolution. The datasets for the four years of interest (2019-2022) are merged together into one combined dataframe. A filter is applied to the dataframe to limit it to the data and locations of interest (Germany and its neighboring countries). The data is then interpolated to 15 minute time steps, to take into account e.g., data gaps. The method chosen for the interpolation is "forward fill", i.e. a missing entry will be filled with the last available entry for that location and production type (type of generator). A plausibility check ensures that the total sum of the numerical data did not change too much with the interpolation step.

3.1.1.2 Physical Flows (PF). The data manipulation steps for PF are identical to those for AGPT. Only the flows from and to Germany are considered.

3.1.2 Eurostat Data

Eurostat provides annual data on primary energy (PE) input, gross electricity production (GEP) and net electricity production (NEP), electricity imports and exports, inputs and outputs from pumped hydro storage and distribution losses (from T&D). We assume Eurostat to be more accurate than ENTSO-E data, due to reasons listed e.g., in studies by Hirth *et al.* and Wörner *et al.* [34,56]. In some cases, we therefore used it to normalize the annual sums of high resolution data from ENTSO-E.

All data from Eurostat is freely available on the Eurostat website. We use the `xlsx` data format, but they can also be downloaded as `csv` or `tsv` files.

3.1.2.1 Primary Energy Demand (PE). The dataset contains the PE demand for main-activity producers (MAP) and autoproducers (AP). These can be separated into electricity-only (EL) generators and combined heat and power (CHP) units. The data is filtered for years (2019-2022), location (Germany) and production types of interest (those that are potentially relevant for Germany). *NaN* values are replaced with zeros. If for any combination of year and production type a PE value does not exist, it is added as a zero value.

3.1.2.2 Gross Electricity Production (GEP). The dataset contains the GEP for main-activity producers (MAP) and autoproducers (AP). These can be separated into electricity-only (EL) generators and combined heat and power (CHP) units. Furthermore, it contains data on gross heat production (GHP) for CHP units (both MAP and AP). The data manipulation steps for GEP (& GHP) are identical to those for PE.

3.1.2.3 Net Electricity Production (NEP). The dataset contains the NEP for main-activity producers (MAP) and autoproducers (AP). These can be separated into electricity-only (EL) generators and combined heat and power (CHP) units. The data manipulation steps for NEP are mostly identical to those for PE and GEP. The dataset differs primarily in that it uses different (fewer) categories for production types for NEP than for both PE and GEP. Therefore, these categories need to be matched.

3.1.2.4 Imports and Exports. The dataset contains the amount of electricity traded within Europe. The data is filtered for the years (2019-2022) of interest, and for imports and exports to and from Germany.

3.1.2.5 Pumped Hydro (Storage Cycling). The dataset for the electricity input into pumped hydro storage (charging) comes from Eurostat. It contains data for both pure and mixed plants. Both pure and mixed plants' input are added together into one single column. The other data manipulation steps for are identical to the other Eurostat datasets (filter etc.).

The dataset for the electricity output from pumped hydro storage (discharging) also comes from Eurostat, and is included in the NEP dataset (pumped hydro being a production type within that dataset). The date for pumped hydro is separated from the rest of the NEP data and manipulated similarly to the pumped hydro input.

Table 9 Summary of methodological aspects in primary research articles. The count indicates how many studies addressed a specific aspect or which choice is made with respect to that aspect. A checkmark (✓) indicates that an aspect is addressed, a dash (-) that it is not

Metric	Sys. bound.	Co-gen.	AP	Aux.	Trade	Stor.	T&D	Temp.res.
14 CO_2	13 OP	3 EL100	5 ✓	9 ✓	31 ✓	17 ✓	24 ✓	8 y
34 GWP100	37 LC	1 EN	43 -	39 -	17 -	31 -	24 -	34 h
1 GWP20		2 IEA						6 <h
		2 EX						
		6 other						
		35 -						

AP: auto-producers; T&D: transformation & distribution losses; GWP: global warming potential; OP: operational; LC: life cycle; EL100: all emissions allocated to electricity; EN: allocation by energy content; IEA: allocation method used by the International Energy Agency; EX: allocation by exergy;

3.1.2.6 Distribution Losses (T&D). The dataset on the distribution losses due to transformation and distribution (T&D) contain all losses in Europe. The data manipulation steps for NEP (& GHP) are identical to the other Eurostat datasets (filter etc.).

3.1.3 UBA Data

The German Umweltbundesamt (UBA)-the German Federal Environmental Agency-provides emission factors per individual production type (EF_{PE}), referenced to its primary energy content[57]. In addition, it publishes reference efficiency values for electricity and heat generation (eta_ref), which are used for emission allocation in CHP units.

3.1.3.1 Emission Factor per Production Type. The data is extracted from the report "Emissionsbilanz erneuerbarer Energieträger" (2020) by the Umweltbundesamt[57]. It contains CO_2, CH_4 and N_2O upstream and operational EF per production type (e.g., biomass, wind onshore etc.), referenced to the PE input. They are mapped to the production type categories used by Eurostat. For those categories for which the UBA reference does not provide an EF, the EF of similar energy carriers are used. These assumptions are documented in (ref Excel UBA comments).

3.1.3.2 Reference Efficiencies The UBA provides reference efficiencies of 0.4 for electricity production and 0.8 for heat production, which are used in the UBA allocation method ("Finnish Method") for allocating emissions to electricity and heat in CHP units. These values are used in the calculation steps on cogeneration of heat for the UBA allocation method[57].

3.1.4 IPCC Data

The Sixth IPCC Assessment Report (AR6)[58] provides characterization factors (CF) used to calculate the global warming potential (GWP) of various greenhouse gases. In our assessment, we include CO_2, CH_4 and N_2O. The IPCC AR6 CF are listed in Table 10.

Table 10 Characterization factors for different impact metrics, from the IPCC AR6[58]

Substance	Impact metric		
	CO_2	GWP20	GWP100
CO_2	1	1	1
CH_4	0	81.2	27.9
N_2O	0	273	273

3.1.5 Further Notes on Input Data

All the input data can be found in `1_data\1_raw` in the folder structure for the code and data accompanying this article, organized by data source (e.g., Eurostat).

3.2 Extended Methodology: Mapping

3.2.1 NEP to GEP Categories

The NEP dataset distinguishes between fewer production type categories than the GEP (and the PE) dataset. We want to use the more detailed GEP set of categories. To do so, we match the data as listed in Table 11.

The NEP values matched to the GEP categories are calculated using the logic from Equation 1:

$$NEP_{xj} = \frac{GEP_{xj}}{\sum_{i=1}^{n} GEP_{xi}} \cdot NEP_y \tag{1}$$

Where NEP and GEP are the values for net and gross electricity production, respectively. y is the NEP category that encompasses all GEP categories $x_1 ... x_n$. n is the total number of GEP categories, and j is a specific GEP category of interest ($j \in [1...n]$).

Besides mapping NEP to GEP values, we also add values for net heat production (NHP). Eurostat does not provide these data, so we assume the NHP to be identical to GHP.

The calculation steps for mapping NEP to GEP categories are documented in section `1.2.2.1 Map NEP to PE/GEP categories` of the Jupyter Notebook attached to this study. The GEP and NEP data required for the calculations in Equation 1 are provided by Eurostat, as described in Section 3.1.2.

3.2.2 Eurostat Data to ENTSO-E Categories

This section describes how Eurostat data is mapped to ENTSO-E production type categories.

3.2.2.1 Generation. Eurostat provides data on PE, GEP, NEP, and ENTSO-E on NEP (at a higher temporal resolution than ENTSO-E - named *Aggregated Generation per Production Type, AGPT*). These two entities, however, do not use the same categories when describing fuels/energy carriers. Eurostat uses the Standard International Energy Product Classification (SIEC) scheme, while ENTSO-E uses a proprietary type of classification. Table 12 indicates how both categorization schemes are matched with one another.

The matching of categories is done in the same manner as the matching of NEP and GEP categories, as described in Section 3.2.1. The only difference is that (unlike for matching NEP and

Table 11 Mapping Eurostat NEP data to GEP categories

NEP category	GEP category
Hydro + Tide, wave, ocean	Hydro
Geothermal	Geothermal
Wind	Wind
Solar	Solar photovoltaic Solar thermal
Nuclear fuels and other fuels n.e.c.	Nuclear heat
Combustible fuels + Other fuels n.e.c. - heat from chemical sources + Other fuels n.e.c.	Anthracite Coking coal Other bituminous coal Sub-bituminous coal Lignite Coke oven coke Gas coke Patent fuel Brown coal briquettes Coal tar Manufactured gases Peat and peat products Oil shale and oil sands Natural gas Oil and petroleum products (excluding biofuel portion) Primary solid biofuels Charcoal Pure biogasoline Blended biogasoline Pure biodiesels Blended biodiesels Pure bio jet kerosene Blended bio jet kerosene Other liquid biofuels Biogases Non-renewable waste Renewable municipal waste

GEP categories) for Eurostat and ENTSO-E categories, two type of matching logics apply: one-to-many (e.g., "Natural gas" –> "Fossil Gas", "Other") and many-to-one (e.g., "Anthracite", "Other bituminous coal" –> "Fossil Hard coal"). One-to-many matching is done in the same manner as described in Equation 1. Many-to-one matching is even simpler, as the values for two categories that are combined into one are simply added together.

Note that the Eurostat values include only electricity from main-activity producers (MAP), as it is assumed that the same is true for ENTSO-E data. The mapping logic depicted in Table 12 is applied to PE, GEP and NEP, so that all of these datasets are organized according to the same categories of fuels/energy carriers.

The calculation steps for mapping Eurostat data to ENTSO-E categories are documented in section `1.2.2.2 Map NEP, GEP and PE to ENTSO-E categories` of the Jupyter Notebook attached to this study. The PE and GEP data required for the mapping steps described above are provided by Eurostat, as described in Section 3.1.2. The NEP data, mapped to GEP categories, comes from the previous mapping step described in Section 3.2.1. The ENTSO-E categories are provided by ENTSO-E, as described in Section 3.1.1.

3.2.2.2 Imports and Exports. The annual data for imports and exports provided by Eurostat does not match the annual sums of the high resolution data for physical flows (PF) by ENTSO-E, which tracks cross-border flows. Since we assume Eurostat data to be more accurate than ENTSO-E data, i.e. better representing the actual electricity trade between countries (bidding zones), we scale the ENTSO-E PF data to the Eurostat data on imports and exports.

We first sum up the ENTSO-E PF data by year. Then, we calculate the ratio of Eurostat annual import (export) flow to ENTSO-E annual PF (per year). Finally, we multiply this ratio with the high resolution PF data, to result in corrected PF data.

The calculation steps for scaling ENTSO-E import and export data to Eurostat values are documented in section `1.2.2.3 Map (scale) imports & exports` of the Jupyter Notebook attached to this study. The annual data are provided by Eurostat, as described in Section 3.1.2. The hourly data are provided by ENTSO-E, as described in Section 3.1.1.

3.2.3 UBA Emission Factors to ENTSO-E Categories

The UBA emission factor input data is categorized by Eurostat categories. To map it to ENTSO-E categories, we use a similar method (and the same mapping logic) as described in Section 3.2.2. For all many-to-one mappings, the mapping of UBA emission factors from Eurostat to ENTSO-E categories follows the following logic (see Equation 2):

$$EF_{PE,y} = \frac{\sum_{i=1}^{n}(PE_{xi} \cdot EF_{PE,xi})}{\sum_{i=1}^{n} PE_{xi}} \tag{2}$$

Table 12 Mapping Eurostat data to ENTSO-E categories

Eurostat category	ENTSO-E category
Anthracite Other bituminous coal	Fossil Hard coal
Coking coal Sub-bituminous coal Lignite Coke oven coke Gas coke Patent fuel Brown coal briquettes Coal tar Peat and peat products	Fossil Brown coal/Lignite
Manufactured gases	Fossil Coal-derived gas
Oil shale and oil sands Oil and petroleum products (excluding biofuel portion)	Fossil Oil
Natural gas	Fossil Gas Other
Hydro	Hydro Run-of-river and poundage Hydro Water Reservoir
Geothermal	Geothermal
Wind	Wind Offshore Wind Onshore
Solar photovoltaic Solar thermal	Solar
Tide, wave, ocean	Marine
Primary solid biofuels Biogases Renewable municipal waste Other liquid biofuels	Biomass
Charcoal Pure biogasoline Blended biogasoline Pure biodiesels Blended biodiesels Pure bio jet kerosene Blended bio jet kerosene	Other renewable
Non-renewable waste	Waste
Nuclear heat	Nuclear

Where EF_{PE} is the emission factor referenced to primary energy for a certain production type, and PE is the primary energy input for a certain production type. y is the ENTSO-E category that encompasses all Eurostat categories $x_1 ... x_n$. n is the total number of Eurostat categories that make up the ENTSO-E category y.

For one-to-many mappings, the case is simpler: EF_{PE} for the (many) ENTSO-E categories is identical to the (one) Eurostat category.

The calculation steps for mapping UBA emission factors to ENTSO-E categories are documented in section `1.3.2 Map (Eurostat -> ENTSO-E)` of the Jupyter Notebook attached to this study. The UBA emission factors following the Eurostat categorization scheme are provided by the UBA, as described in Section 3.1.3. The ENTSO-E categories are provided by ENTSO-E, as described in Section 3.1.1. The PE data following the Eurostat categorization scheme are provided by Eurostat, as described in Section 3.1.2.

3.2.4 Other Data Mapping & Manipulation Aspects

Some other relevant aspects of input data manipulation that come before the actual calculation step are listed here.

3.2.4.1 Missing UBA EF. The UBA does not provide EF for all Eurostat categories (production types). For some production types, the emission factor had to be estimated. Details are listed in the column labeled "reference, comment" in the input file `ef_pe.xlsx`.

3.2.4.2 Diverging CF. The UBA uses characterization factors (CF) from the Fifth IPCC Assessment Report (AR5)[59]. In our own calculations, we use more recent CF from the Sixth Assessment report[58]. Therefore, our calculated GWP100 values differ slightly from those calculated in the UBA report[57].

3.2.4.3 Biomass EF. The UBA calculates individual EF for sub-production types of solid, liquid and gaseous biomass-based electricity production[57]. We summarize them into aggregated EF for solid, liquid and gaseous biomass-based electricity production, using CF from the IPCC AR6[58]. More details can be found in the input data file `ef_pe_biopower.xlsx`. The resulting aggregated EF are used in `ef_pe.xlsx`.

3.3 Extended Methodology: Calculations

3.3.1 Generator Level

The calculations at the generator level address the methodological aspects *Impact metric*, *System boundaries*, *Co-generation of heat*, *Auxiliary consumption* and *Auto-producers*.

3.3.1.1 Impact Metric. In a first step, the EF from UBA are transformed to reflect the chosen impact metric (CO_2, GWP20, GWP100). An EF that reflects a specific impact metric is calculated as follows (eq. 3):

$$EF_m = \sum_i (CF_{i,m} \cdot EF_{PE,i}) = CF_{CO_2,m} \cdot EF_{PE,CO_2} + CF_{CH_4,m} \cdot EF_{PE,CH_4} + CF_{N_2O,m} \cdot EF_{PE,N_2O} \quad (3)$$

Where EF_m is the EF for the impact metric m, $CF_{i,m}$ is the characterization factor for a substance i and impact metric m, and $EF_{PE,i}$ is the emission factor referenced to the primary energy content of the fuel/energy carrier for a substance i.

CF for substances other than the three listed above exist as well[58]. However, they are not used, since the UBA reference lists EF only for CO_2, CH_4 and N_2O. The characterization factors for the impact metrics CO_2, GWP20 and GWP100 are listed in Table 10.

The impact metric calculation steps are documented in section `2.1 Impact metric` of the Jupyter Notebook attached to this study. The EF_{PE} data that is used here is the result of the mapping process as described in Section 3.2.3. The CF data is provided by the IPCC, as described in Section 3.1.4.

3.3.1.2 System Boundaries. An EF can reflect the system boundaries of choice: operational (OP), upstream (UP) or life cycle (LC) emissions. They relate to one another as described in Equation 4

$$EF_{LC} = EF_{OP} + EF_{UP} \quad (4)$$

Where EF_{LC} is the life cycle EF, EF_{OP} the operational EF and EF_{OP} the upstream EF.

In section `2.2 System boundaries` of the Jupyter Notebook attached to this study the system boundaries calculation steps are documented. The EF data that is used here is the result of the previous calculation step on impact metrics.

3.3.1.3 Co-generation of Heat. For all generation units that produce not only electricity, but also heat (which is used e.g., for district heating), one has to decide how to allocate the emissions to each of these outputs. Multiple methods exist for allocating emissions in combined heat and power (CHP) units. The emission factor for a set of generators, consisting of both electricity-only (EL) and CHP units, is calculated as follows (see Equation 5):

$$EF_{GEP} = \frac{EF_{PE,EL} \cdot PE_{EL} + x \cdot EF_{PE,CHP} \cdot PE_{CHP}}{GEP_{EL} + GEP_{CHP} + y} \quad (5)$$

Where EF_{GEP} is the EF for a set of generators, consisting of both EL and CHP units, referenced to the gross electricity production (GEP) from that set of generators. $EF_{PE,EL}$ is the EF of the EL units within that set, referenced to the primary energy (PE) input, and $EF_{PE,CHP}$ is the EF of the CHP units within that set, referenced to the PE input. PE_{EL} is the amount of PE going into EL units within that set, and PE_{CHP} is the amount of PE going into CHP units within that set. GEP_{EL} is the GEP from EL units, GEP_{CHP} is the GEP from CHP units. GHP is gross heat production (from CHP units only). x and y are variables that depend on the allocation method, and are listed in Table 13.

Table 13 Variables x and y, to be applied to Equation 5, for different allocation methods

Method	x	y
EL100	1	0
TH100	0	0
EN	$\frac{GEP_{CHP}}{GEP_{CHP}+GHP}$	0
EX	1	$(1-\frac{T_0}{T}) \cdot GHP$
IEA	$1-\frac{GHP}{eta_{th,iea}}$	0
UBA	1	$\frac{eta_{el,uba}}{eta_{th,uba}} \cdot GHP$

$eta_{th,iea}$: reference efficiency for heat producer, IEA method (= 0.9);
$eta_{el,uba}$: reference efficiency for electricity producer, UBA method (= 0.4);
$eta_{th,uba}$: reference efficiency for heat producer, UBA method (= 0.8);
T_0: reference surrounding temperature (assumed to be 282 K);
T: reference CHP output temperature (assumed to be 363 K);

The allocation calculation steps for co-generation of heat are documented in section `2.3 Co-generation of heat` of the Jupyter Notebook attached to this study. The EF_{PE} data that is used here is the result of the previous calculation step on system boundaries. The PE and GEP (GHP) data that is used here is the result of the mapping process described in Section 3.2.2. The reference efficiencies eta_i are provided by the UBA[57] and the IEA[60]. T and T_0 are based on assumptions.

3.3.1.4 Auxiliary Consumption. The first part of the changes/losses along the path from gross electricity production (GEP) to net electricity consumption (NEC)-auxiliary consumption of generators-occurs at the generator-level, while the other losses/changes (electricity trading, storage cycling losses, T&D losses) occur at the grid level. Due to this fact, they are addressed in a separate sub-section (3.3.2) of the methodology description.

An EF considering auxiliary consumption, and thus referenced to net electricity production (NEP), is calculated as described in Equation 6:

$$EF_{NEP} = \frac{GEP \cdot EF_{GEP}}{NEP} \quad (6)$$

Where EF_{NEP} is the EF referenced to NEP, GEP is the GEP, EF_{GEP} is the EF referenced to NEP, and NEP is the NEP.

The calculation steps for considering auxiliary consumption are documented in section `2.4 Auxiliary consumption` of the Jupyter Notebook attached to this study. The EF_{GEP} data that is used here is the result of the previous calculation step on co-generation of heat. The GEP and NEP data that is used here is the result of the mapping process described in Section 3.2.2.

3.3.1.5 Auto-producers. Depending on the scope and goal of an assessment, one may want to include auto-producers (AP) into the calculation of a grid EF or exclude them. A grid EF for a grid with both main-activity producers (MAP, connected to the grid) and AP (not connected to the grid) is calculated as follows (see Equation 7):

$$EF_{GEP,a} = \frac{GEP_{MAP} \cdot EF_{GEP,MAP} + x \cdot GEP_{AP} \cdot EF_{GEP,AP}}{GEP_{MAP} + y \cdot GEP_{AP}} \tag{7}$$

Where $EF_{GEP,a}$ is the EF for a set of generators consisting of both MAP and AP units, referenced to the GEP from that set of generators, for an auto-producer rule a (see below). $EF_{GEP,MAP}$ is the EF of only the MAP within that set, referenced to the GEP. $EF_{GEP,AP}$ is the EF of only the AP within that set, referenced to the GEP. GEP_{MAP} is the GEP by MAP, and GEP_{AP} is the GEP by AP. x and y are variables that depend on the auto-producer rule, and are listed in Table 14.

Table 14 Variables x and y, to be applied to Equation 7, for different auto-producer rules

Rule	x	y
MAPonly	0	0
APem	0	1
APen	1	0
MAP&AP	1	1

MAPonly: emissions and electricity from main-activity producers only,
APem: emissions from all generators, electricity from main-activity producers only,
APen: emissions from main-activity producers only, electricity from all generators,
MAP&AP: emissions and energy from all generators;

For calculating an EF referenced to NEP instead of GEP, all the instances of GEP in Equation 7 have to be replaced with NEP.

The calculation steps for considering auto-producers are documented in section `2.5 Auto-producers` of the Jupyter Notebook attached to this study. The EF$_{GEP}$ data that is used here is the result of the previous calculation step on auxiliary consumption. The GEP data that is used here is the result of the mapping process described in Section 3.2.2.

3.3.2 Grid Level

This section describes the calculations at the grid level, which address the methodological aspects *Temporal resolution*, *Electricity trading*, *Storage cycling* and *Transformation & distribution*. From here on, the EF calculated refer to the grid mix, while the EF in Section 3.3.1 refer to individual production types.

3.3.2.1 Temporal Resolution. At the transition from generator to grid level, the decision is made which temporal resolution is required for the grid EF. The EF per production type is assumed to remain constant within a year, while the grid EF changes with the production shares of the individual production types. These shares change much more frequently. Therefore, the temporal resolution is introduced at this point, at the transition from production type to grid EF. Equation 8 describes how the temporal dimension is included in EF calculation:

$$\begin{aligned} EF_{HR} = \frac{EM_{HR}}{GEP_{HR}} = \frac{\sum_i EM_{HR,i}}{\sum_i GEP_{HR,i}} = \\ \frac{\sum_i (GEP_{HR,i} \cdot EF_{HR,i})}{\sum_i GEP_{HR,i}} = \frac{\sum_i (GEP_{HR,i} \cdot EF_{LR,i})}{\sum_i GEP_{HR,i}} \end{aligned} \tag{8}$$

Where EF_{HR} is the high resolution grid EF, EM_{HR} are the high resolution grid emissions, GEP_{HR} is the high resolution GEP summed up across all production types i, $EM_{HR,i}$ are the high resolution emissions from production type i, $GEP_{HR,i}$ is the high resolution GEP from production type i, $EF_{HR,i}$ is the high resolution EF for production type i, and $EF_{LR,i}$ is the low resolution EF for production type i. As noted above, $EF_{LR,i}$ and $EF_{HR,i}$ are assumed to be identical.

For calculating an EF referenced to NEP instead of GEP, all the instances of GEP in Equation 8 have to be replaced with NEP.

In section `2.6 Temporal resolution` of the Jupyter Notebook attached to this study, the temporal resolution calculation steps are documented. The EF$_{LR,i}$ data that is used here is the result of the previous calculation step on auto-producers. The GEP data that is used here is a combination of the high resolution energy data provided by ENTSO-E (see Section 3.1.1) and the mapping process described in Section 3.2.2.

3.3.2.2 Electricity Trading. An EF that considers electricity trading effectively starts out with a production-based EF, subtracts the carbon flows out of the region of interest, and adds the carbon flows into the same region. The carbon flow is calculated from the production-based grid EF for the region of origin multiplied with the amount of electricity transferred from the region of origin to the destination region. The result is a consumption-based EF, which can be calculated as described in Equation 9:

$$\begin{aligned} EF_{CONS} = \frac{EM_{CONS}}{GEC} = \frac{EM_{DOM} + EM_{IMP} - EM_{EXP}}{GEP_{DOM} + IMP - EXP} = \\ \frac{EF_{DOM} \cdot GEP_{DOM} + \sum_n (EF_{DOM,n} \cdot IMP_n) - EF_{DOM} \cdot \sum_n EXP_n}{GEP_{DOM} + \sum_n IMP_n - \sum_n EXP_n} \end{aligned} \tag{9}$$

Where EF_{CONS} is the consumption-based grid EF for a region of interest, EM_{CONS} are the total, consumption-based emissions from the region of interest, GEC is the gross electricity consumption within the region of interest, EM_{DOM} are the domestic, production-based total emissions within the region of interest, EM_{IMP} are the imported emissions into the region of interest, EM_{EXP} are the exported emissions from the region of interest, GEP_{DOM} is the domestic gross electricity production within the region of interest, IMP is the amount of electricity imported into the region of interest, EXP is the amount of electricity exported from the region of interest, EF_{DOM} is the domestic, production-based grid EF for the region of interest, $EF_{DOM,n}$ is the production-based grid EF for neighbor region n, IMP_n is the amount of electricity imported into the region of interest from neighbor region n and EXP_n is the amount of electricity exported to the neighbor region n from the region of interest. $EF_{DOM,n}$ can be calculated just like EF_{DOM}, following the previous steps described in this methodology section-but replacing the GEP values with those of the neighbor region.

Note that this method only considers influences on the EF of a region from direct neighbors. Knock-on effects, such as imports/exports from/to second-order neighbors, are not taken into account (SFOT approach, see Section 2.2.) Note also that the results differ depending on the temporal resolution of choice. If the variables in Equation 9 are calculated at an hourly level, the resulting EF will be different from one calculated based on annual variables, as the temporal variability of the grid EFs, generation and imports/exports is "smoothed out". In our calculations, we consider trade at a high temporal resolution (15 minutes).

For calculating a consumption-based grid EF referenced to NEP instead of GEP, all the instances of GEP in Equation 9 have to be replaced with NEP.

The electricity trade-related calculation steps are documented in section `2.7 Electricity trading` of the Jupyter Notebook attached to this study. The EF_{DOM} data that is used here is the result of the previous calculation step on the temporal resolution. The GEP data that is used here is a combination of the high resolution generation data (AGPT) provided by ENTSO-E (see Section 3.1.1) and the mapping process described in Section 3.2.2. The high resolution import and export data (EXP_n and IMP_n) is a combination of the high resolution trade data (PF) provided by ENTSO-E (see Section 3.1.1) and the mapping process described in Section 3.2.2.

3.3.2.3 Storage Cycling. To calculate an EF that reflects gross electricity consumption within a grid, the cycling losses of grid storage (pumped hydro) have to be considered. Equation 10 describes how this EF is calculated:

$$EF_{grid,PH} = \frac{GEP_{grid} + PH_{in}}{GEP_{grid} + PH_{out}} \cdot EF_{grid} \tag{10}$$

Where $EF_{grid,PH}$ is the grid EF with consideration of pumped hydro storage, GEP_{grid} is the GEP within that grid, PH_{in} is the amount of electricity consumed by pumped hydro plants (charging), PH_{out} is the amount of electricity produced by pumped hydro plants (discharging), and EF_{grid} is the grid EF without considering pumped hydro storage.

Note that the results differ depending on the temporal resolution of choice. If the variables in Equation 10 are calculated at an hourly level, the resulting EF will be different from one calculated based on annual variables, as the temporal variability of the grid EFs, generation and imports/exports is "smoothed out". In our calculations, we consider pumped hydro storage cycling at a low temporal resolution (yearly).

The pumped hydro storage cycling calculation steps are documented in section `2.8 Storage cycling (pumped hydro)` of the Jupyter Notebook attached to this study. The EF_{grid} data that is used here is the result of the previous calculation step on electricity trading. The GEP data that is used here is the result of the mapping process described in Section 3.2.2. The data on pumped hydro input and output (PH_{in} and PH_{out}) are provided by Eurostat, as described in Section 3.1.2.

3.3.2.4 Transformation & Distribution. In a final calculation step, the EF is transformed to reflect the dissipation losses from transformation and distribution in the grid. It is calculated as described in Equation 11:

$$EF_{NEC} = \frac{GEC}{NEC} \cdot EF_{GEC} = \frac{GEC}{GEC - L_{TD}} \cdot EF_{GEC} \tag{11}$$

Where EF_{NEC} is the grid EF referenced to the net electricity consumption (NEC), GEC is the gross electricity production, NEC is the net electricity consumption, EF_{GEC} is the grid EF referenced to the net electricity consumption (GEC, not including T&D losses), and L_{TD} are the relative transformation and distribution (T&D) losses.

The T&D calculation steps are documented in section `2.9 Grid losses (T&D)` of the Jupyter Notebook attached to this study. The EF_{GEC} and GEC data that is used here is the result of the previous calculation step on storage cycling. on distribution losses (L_{TD}) are provided by Eurostat, as described in Section 3.1.2.

4 Extended Results

This section expands on the results described in the results section of the main article.

4.1 Extended Results: Data Sampling

All violin plots in this study plot a sample of 10% of the full dataset of 323 149 824 data points, i.e. 32 314 982 data points. The sample data is drawn randomly from across all rows (time steps) and columns (ways to calculate a grid EF). We plot only a sample of the data, and not the full dataset, to reduce computational burden. The full dataset takes up around 2.5 GB of storage space (`pickle` file format). In some instances, we ran into limits with respect to working memory on a computer with 16 GB RAM when trying to plot the full dataset. To ensure that others can replicate our work, we decided to reduce the computational burden by relying on a sample of the full dataset for plotting.

To ensure that the sample dataset represents the full dataset well, we compare key statistical indicators for both, and calculate the relative difference. Comparing the mean, median and standard deviation of the full dataset and the sample dataset, the relative difference between them is 0.0045%, 0.0053% and 0.0047%, respectively. We deem these differences to be small enough to be acceptable.

4.2 Extended Results: Individual Effects

4.2.1 System Boundaries

In Figure 2, the effect of varying the system boundaries is plotted. The choices for the system boundaries are *Operational (OP)* and *Life Cycle (LC)*. The displayed values represent the mean for each choice, and the relative difference between the mean for a specific choice and the mean for the reference choice (in this case, *OP*).

Figure 2 indicates that when disaggregated by year, a *LC*-EF is on average 13.8-16.7% larger than a *OP*-EF. This observation matches our expectations, since a *LC*-EF covers more emission sources than a *OP*-EF. The variation of the effect between years, which is smallest in 2022 (13.8%) and largest in 2020 (16.7%),

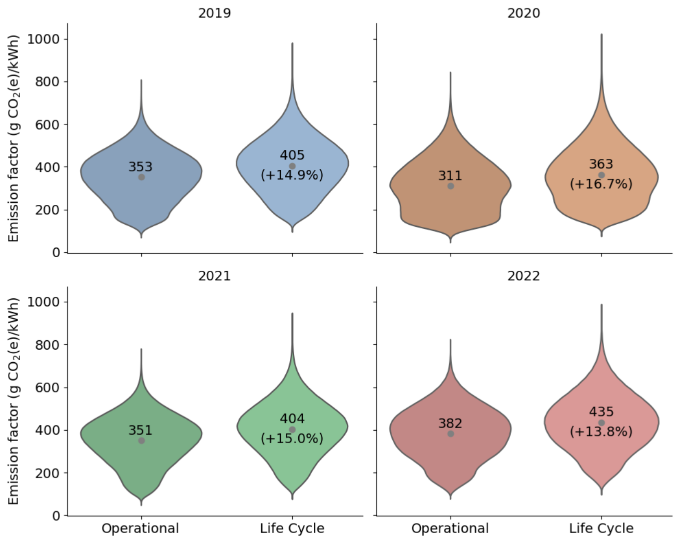


Fig. 2 System boundary effect, disaggregated by year-the distribution of grid EF values for the system boundaries *Operational* and *Life Cycle* and the years 2019-2022. Labeled are the mean values for all data points, and the relative difference of the mean compared to the mean of the first impact metric (*Operational*), for each year individually.

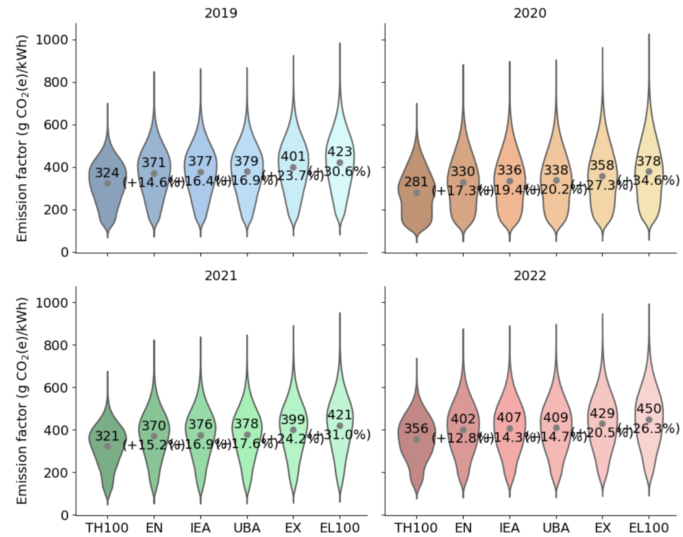


Fig. 3 Co-generation of heat allocation effect, disaggregated by year-the distribution of grid EF values for the allocation methods *TH100*, *EN*, *IEA*, *UBA*, *EX*, and *EL100* and the years 2019-2022. Labeled are the mean values for all data points, and the relative difference of the mean compared to the mean of the first allocation method (*TH100*), for each year individually.

may be explained by the baseline effect. While the absolute difference between the *OP*-EF and the *LC*-EF is larger in 2022 than in 2020 (53 vs. 52 g/kWh), the relative difference is smaller in 2022 than in 2020 due to the higher baseline value in 2022 compared to 2020 (382 vs. 311 g/kWh).

4.2.2 Co-generation of Heat

In Figure 3, the effect of varying the allocation method for CHP units is plotted. The choices for the allocation method are *100% to heat (TH100)*, *By Energy Content (EN)*, *IEA Method (IEA)*, *UBA Method (UBA)*, *By Exergy Content (EX)* and *100% to Electricity (EL100)*. The displayed values represent the mean for each choice, and the relative difference between the mean for a specific choice and the mean for the reference choice (in this case, *TH100*).

Figure 3 indicates that when disaggregated by year, a *EN*-EF is on average 12.8-17.3% larger than a *TH100*-EF, a *IEA*-EF is on average 14.3-19.4% larger than a *TH100*-EF, a *UBA*-EF is on average 14.7-20.2% larger than a *TH100*-EF, a *EX*-EF is on average 20.5-27.3% larger than a *TH100*-EF, and a *EL100*-EF is on average 26.3-34.6% larger than a *TH100*-EF.

The variation across years of the absolute values and the relative differences have already been discussed in the main article. The consistent ranking of the allocation methods, with *TH100* yielding the lowest values, and *EL100* yielding the highest values, match our expectations based on the internal logic of the allocation methods. *TH100* is an extreme case which allocates all emissions from CHP plants to the heat and no emissions to the electricity that these plants produce. Naturally, this will yield relatively low electricity-EF for a fleet of generators that contains CHP plants. The opposite is true of the *EL100* method: all CHP emissions are allocated to the electricity produced, and none to the heat. The *EN* method yields relatively low electricity-EF, since it treats both heat and electricity as equal, irrespective of the fact that electricity is a more "valuable" form of energy, and typically has a lower conversion efficiency than heat when produced from a chemical energy carrier (e.g., coal). The *IEA* and the *UBA* method are both substitution methods that do consider the differences between conversion efficiencies. They take into account reference efficiencies for alternative methods of either producing heat ($\eta_{ref,th} = 0.8$ for UBA, 0.9 for IEA) or electricity ($\eta_{ref,el} = 0.4$ for both UBA and IEA), and subtract these emissions for alternative heat / electricity production processes from the total CHP plant emissions. The small difference between the *UBA* and the *IEA* values can be explained by the different $\eta_{ref,th}$ values employed by these methods. The *EX* method assesses the value of the two outputs of CHP plants, heat and electricity, based on the exergy of the output streams. The exergy of electricity is equal to one, while the exergy of heat depends on the both the temperature of the CHP heat output and the temperature of the environment. In this study, we assume the former to be 363 K (90°C) and the latter 282 K (9°C). The exergy of the heat output increases when the difference between the two values increases, which would mean a higher heat output temperature or a lower environmental temperature. An increase of the exergy of the heat output leads to decrease of the respective electricity-EF: the higher the "value" (=exergy) of an output, the larger the emission share assigned to it.

4.2.3 Auxiliary Consumption

In Figure 4, the effect of considering auxiliary consumption is plotted. The choices for considering auxiliary consumption are *Without Auxiliary Consumption (w/o AC)* and *With Auxiliary Consumption (w AC)*. The displayed values represent the mean for each choice, and the relative difference between the mean for a specific choice and the mean for the reference choice (in this case, *w AC*).

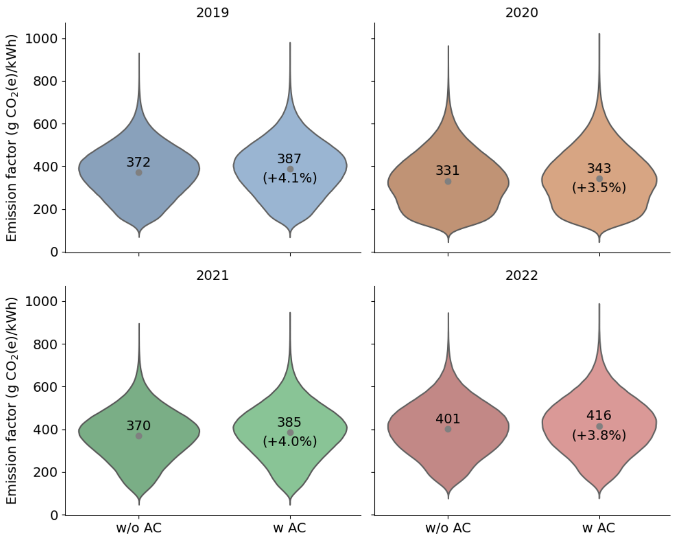


Fig. 4 Auxiliary consumption effect, disaggregated by year-the distribution of grid EF values for EF without (*w/o AC*) and with auxiliary consumption (*w AC*), and the years 2019-2022. Labeled are the mean values for all data points, and the relative difference of the mean compared to the mean of the first EF (*w/o AC*), for each year individually.

Figure 4 indicates that when disaggregated by year, an EF *w AC* is on average 3.5-4.1% larger than an EF *w/o AC*. This effect meets our expectations—if more losses are included, then the resulting EF is higher.

4.2.4 Auto-producers

In Figure 5, the effect of considering auto-producers is plotted. The choices for considering auto-producers are *Electricity & Emissions from MAP only (only MAP)*, *Electricity from MAP, Emissions from MAP & AP (AP emissions)*, *Electricity from MAP & AP, Emissions from MAP (AP energy)* and *Electricity & Emissions from MAP & AP (MAP&AP)*. The displayed values represent the mean for each choice, and the relative difference between the mean for a specific choice and the mean for the reference choice (in this case, *only MAP*).

Figure 5 indicates that when disaggregated by year, an *AP emissions*-EF is on average 10.8-14.4% larger than a *only MAP*-EF, an *AP energy*-EF is on average 7.1-10.5% smaller than a *only MAP*-EF, and a *MAP&AP*-EF is on average 0.2-0.8% smaller than a *only MAP*-EF.

It appears worth noting that *AP emissions* and *AP energy* are cases of incorrect data matching. Normally, one would either consider both electricity and emissions from auto-producers (*MAP&AP*), or omit them (*only MAP*). Considering only one of the two, electricity or emissions, may however happen in cases where datasets don't match. One might e.g., calculate a grid EF from an emission dataset which contains both MAP and AP, and an electricity dataset which contains only MAP. Since this case cannot be entirely ruled out in practice, we include them in our assessment.

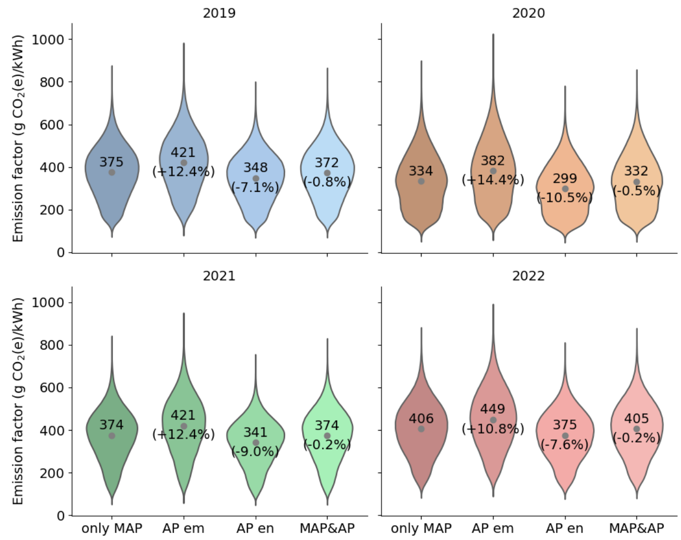


Fig. 5 Auto-producer effect, disaggregated by year-the distribution of grid EF values for different auto-producer inclusion rules *only MAP*, *AP emissions*, *AP energy*, *MAP & AP*, and the years 2019-2022. Labeled are the mean values for all data points, and the relative difference of the mean compared to the mean of the first rule (*only MAP*), for each year individually.

4.2.5 Electricity Trading

In Figure 6, the effect of considering electricity trade is plotted. The choices for considering electricity trade are *Without Trade (Production)* and *With Trade (Consumption)*. The displayed values represent the mean for each choice, and the relative difference between the mean for a specific choice and the mean for the reference choice (in this case, *Production*).

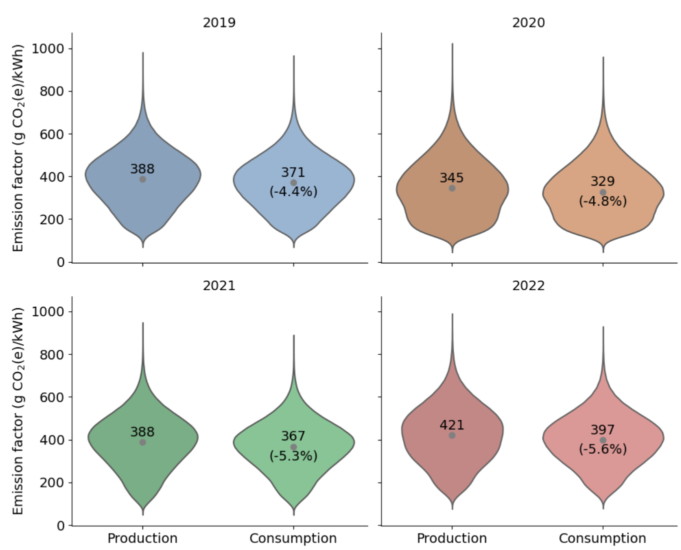


Fig. 6 Electricity trade effect, disaggregated by year-the distribution of grid EF values for the perspectives *Production* and *Consumption*, and the years 2019-2022. Labeled are the mean values for all data points, and the relative difference of the mean compared to the mean of the first allocation perspective (*Production*), for each year individually.

Figure 6 indicates that when disaggregated by year, a *Consump-*

tion-EF is on average 4.4-5.6% smaller than a *Production*-EF.

These results indicate that either Germany exports more electricity than it imports, that the exported electricity has a higher EF on average than the imported electricity, or both. To shed more light on this aspect, Figure 7 depicts the net electricity (left) and emission (right) flow balance for the years 2019-2022.

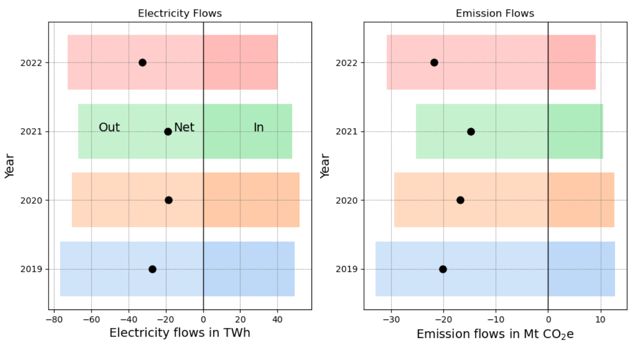


Fig. 7 Trade balance.

Both the net electricity and net emission flow balance is negative for every year depicted. The ratio of outflows (bars to the left of the vertical line at zero) to inflows (bars to the right) is higher for the emission flows than for electricity flows, indicating that the exported electricity was on average more emission-intensive than the imported electricity.

4.2.6 Storage Cycling

In Figure 8, the effect of considering pumped hydro storage cycling is plotted. The choices for considering pumped hydro storage cycling are *Without Pumped Hydro (w/o PH)* and *With Pumped Hydro (w PH)*. The displayed values represent the mean for each choice, and the relative difference between the mean for a specific choice and the mean for the reference choice (in this case, *w/o PH*).

Figure 8 indicates that when disaggregated by year, an EF *w PH* is on average 0.4-0.6% larger than an EF *w/o PH*. Just as with auxiliary consumption (cf. section 4.2.3), this effect meets our expectations—if more losses are included, then the resulting EF is higher.

4.2.7 Transformation & Distribution

In Figure 9, the effect of considering transformation & distribution (T&D) losses is plotted. The choices for considering T&D losses are *Without T&D losses (w/o TD)* and *With T&D losses (w TD)*. The displayed values represent the mean for each choice, and the relative difference between the mean for a specific choice and the mean for the reference choice (in this case, *w/o TD*).

Figure 9 indicates that when disaggregated by year, an EF *w TD* is on average 5.4-5.6% larger than an EF *w/o TD*. Just as with auxiliary consumption (cf. section 4.2.3) and storage cycling (cf. section 4.2.6), this effect meets our expectations—if more losses are included, then the resulting EF is higher.

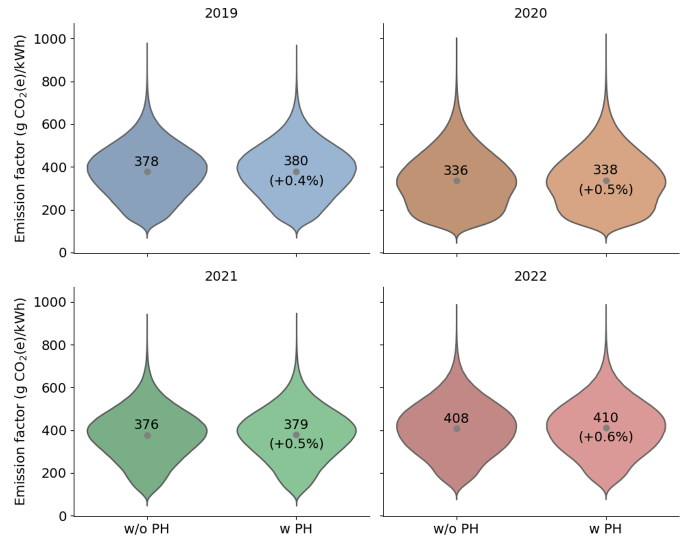


Fig. 8 Storage cycling effect, disaggregated by year-the distribution of grid EF values for EF without (*w/o PH*) and with pumped hydro storage cycling (*w PH*), and the years 2019-2022. Labeled are the mean values for all data points, and the relative difference of the mean compared to the mean of the first EF (*w/o PH*), for each year individually.

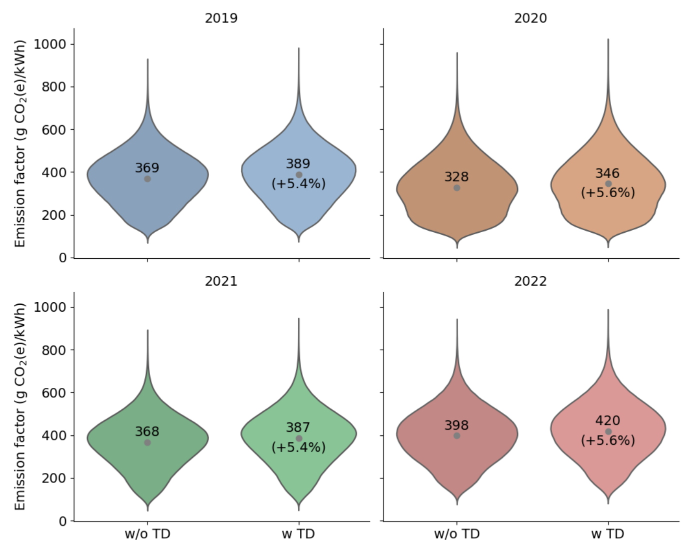


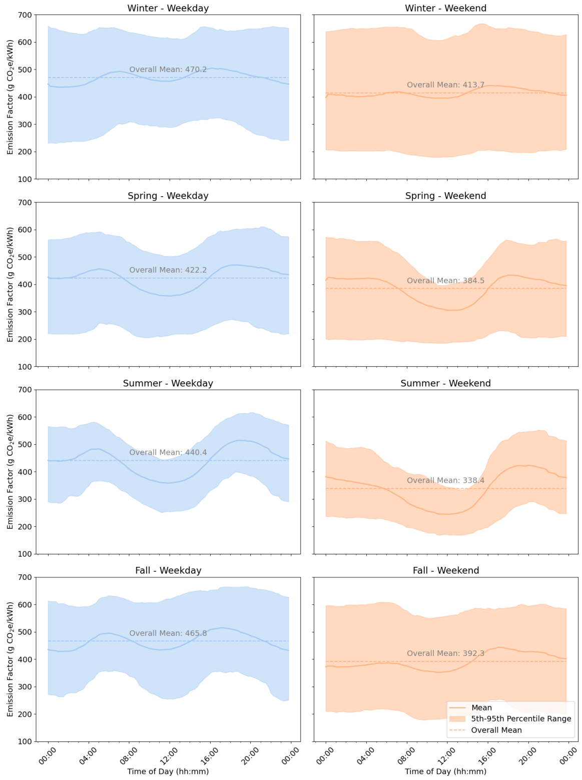
Fig. 9 Transformation & distribution (T&D) effect, disaggregated by year-the distribution of grid EF values for EF without (*w/o TD*) and with T&D losses (*w TD*), and the years 2019-2022. Labeled are the mean values for all data points, and the relative difference of the mean compared to the mean of the first EF (*w/o TD*), for each year individually.

4.2.8 Temporal Resolution

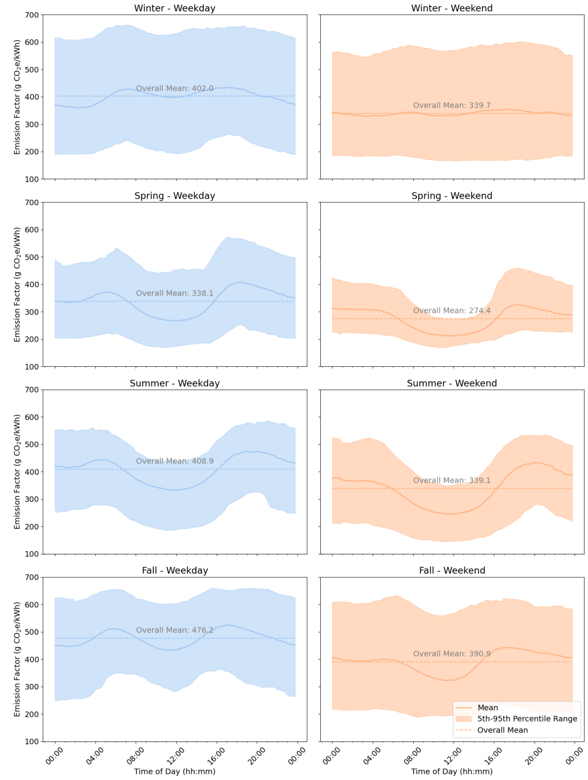
4.2.8.1 Grid EF Temporal Trends. Figure 10 depicts the grid EF by day type, season, and time of day for the years 2019-2022 (2021 is also covered in the main article).

Various possible explanations exist for the grid EF patterns described in the main article.

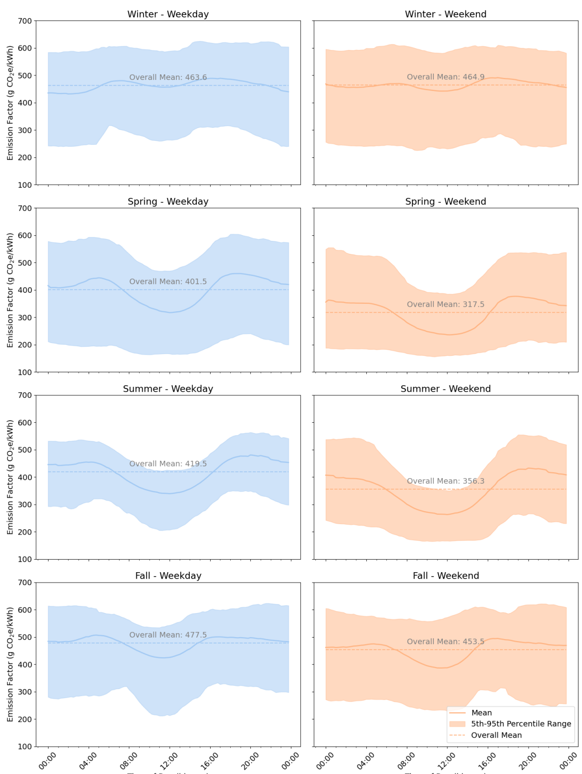
The relatively high grid EF in the morning and evening correlate with an overall high level of electricity production and consumption during those times. Besides hydro pumped storage plants, it is mainly fossil power plants (especially hard coal and



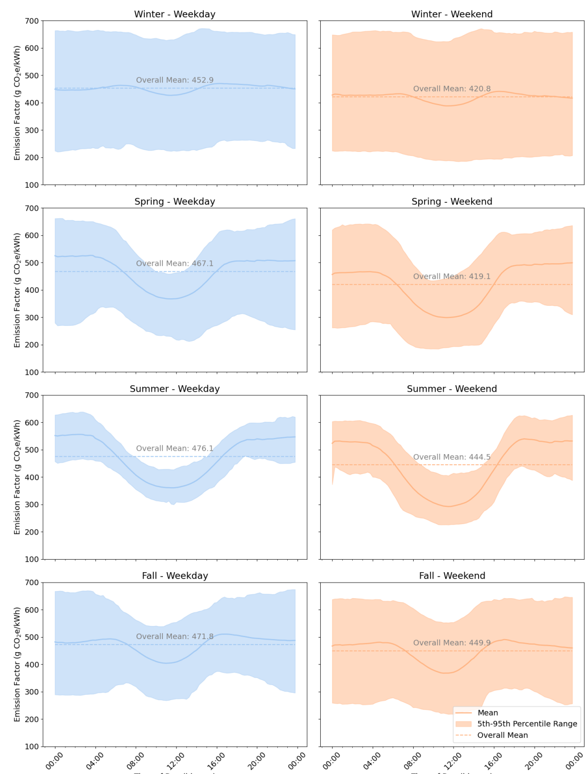
(a) 2019



(b) 2020



(c) 2021



(d) 2022

Fig. 10 Grid EF by day type, season, and time of day for the years 2019-2022. The solid line represents the mean value for specific time points (e.g., 12:00 h), day type (e.g., weekday), and season (e.g., Summer). The shaded area delineates the range between the 5th and 95th percentiles of the data, highlighting the distribution's variability and indicating where 90% of the values lie for the given time and year. The dashed line represents the overall mean, i.e., the daily mean for a given day type and season.

natural gas) that increase their output to meet the increased electricity demand during those peak hours. Likewise, when demand recedes (e.g. during night), these fossil plants reduce electricity production, thus lowering the grid EF. The relatively low grid EF at noon benefits from the large share of solar PV production during those times.

Part of the reason that the 'nightly dip' can barely be observed in 2022 may be twofold: 1) the Russian invasion of Ukraine during that year and the subsequent energy crisis that unfolded, and 2) the shutting down of nuclear reactors in Germany. Skyrocketing natural gas prices in Germany, which until then procured most of its gas from Russia, led to a change in the power plant merit order, so that natural gas plants ran less often, and hard coal plants ran more often. Since the latter are more emission intensive than the former, an electricity mix that relies more on hard coal at the expense of natural gas results in an increase of the grid EF. In addition, three German nuclear power plants went offline on December 31st, 2021. The lack of nuclear base load, and natural gas based generation being replaced by hard coal based generation, may explain the relatively high grid EF at night during 2022 compared to previous years.

The grid EF drop around noon that varies with the season is most likely primarily due to solar PV production. Lower demand on weekends (which include public holidays) may explain why the grid EF is lower than on weekdays. As long as there is no curtailment, generation from renewables is comparable for weekdays and weekends, meaning that less emission-intensive fossil generation is required to meet residual demand on weekends, resulting in a lower grid EF. Since the share of renewable generation is relatively low in the Winter compared to other seasons, this effect may be less pronounced then (or may even be non-existent, as for the year 2021 shown here). The narrower range between the 5th and the 95th percentile during the Summer may indicate that more solar PV generation reduces variability of the grid EF. This could be due to the remaining, non-solar generation exhibiting less variability with respect to its emission intensity. The more low-emission solar PV is included in the generation mix, the less residual generation (e.g., from natural gas or hard coal, both with notably different emission intensities) can impact the overall grid EF.

4.2.8.2 Correlation Analysis. The grid EF does not only correlate with the time of day, day type, season, and year, but also with overall electricity generation. Figure 11 depicts a correlation of generation intensity and grid EF for the years 2019-2022. Generation intensity describes overall generation (AGPT, cf. section 3.1.1) normalized to the maximum overall generation, resulting in values between 0.3 and 1. The grid EF is the recommended configuration discussed in the main article.

The plot indicates that with every year, the two variables become increasingly correlated. While the distribution is almost random in 2019, the Spearman R is -0.52 and the Pearson R -0.51 in 2022. The slope of the regression line also decreases continuously from year to year.

For a more detailed analysis of temporal trends, figure 12 depicts the correlation of generation intensity and grid EF for the years 2019-2022 by day type (weekday, weekend) and season (Winter, Spring, Summer, Fall).

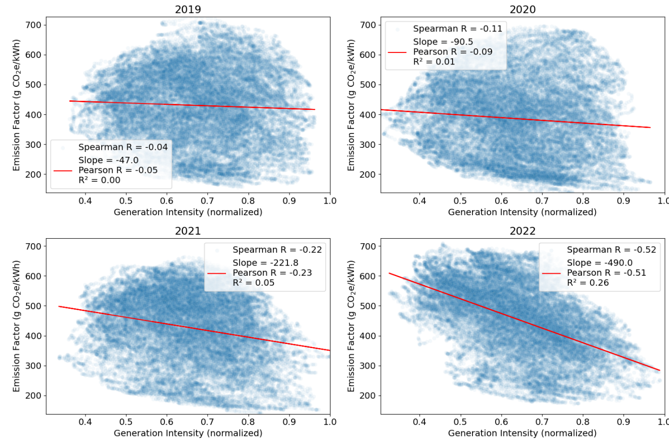


Fig. 11 Correlation analysis for generation intensity and grid EF for the years 2019-2022. The Spearman R indicates the degree to which the data can be represented by a strictly monotonous function, while the Pearson R indicates the degree to which the data can be represented by a linear function (in both cases, 0 describes no representation at all, and -1 or 1 a perfect representation).

The plots illustrate that the two variables tend to correlate more strongly on weekends than on weekdays, and more strongly during Spring and Summer than during Fall and Winter. The difference between the Pearson R and Spearman R is relatively small across all time periods, indicating that a linear regression line (in red) represents the data similarly well as a strictly monotonous function (not plotted).

Finally, to illustrate differences throughout the course of a typical day, figure 13 depicts the correlation of generation intensity and grid EF for the years 2019-2022 by time of day.'Night' is defined as the time from 00:00 h to 04:00 h, 'Morning' from 04:00 h to 11:00 h, 'Afternoon' from 11:00 h to 18:00 h, and 'Night' from 18:00 h to 00:00 h.

The differentiation by time of day does not reveal any notable patterns. The correlation between generation intensity and grid EF is relatively weak overall (for both the Pearson and the Spearman Rank correlation), and strongest in the year 2022.

5 Extended Discussion

This section expands on the discussion covered in the main article.

5.1 Extended Validation

5.1.1 Extended Validation: Official Sources

Possible explanations for the relative differences between grid EF calculated in this study and those provided by official sources include differences in characterization factors used (from IPCC AR6[58] for this study, AR5[59] by the official sources). Also, all three official institutions assume zero emissions from the operational phase for renewable energy sources, while in this study, they are larger than zero. As the only institution, the UBA includes the emissions from flue gas desulfurization[61].

An interesting effect that can be observed, and discussed in the main article discussion, is that the consumption-based EF by the UBA is larger than the comparable production-based EF, while for our own calculations, the opposite is true. This can be traced back to the way the UBA considers electricity trade: if we understand it correctly, the consumption based-EF is mere correction of the production-based EF using the net trade balance. The actual grid EF of the neighboring countries our not taken into account. Our approach, which we consider more sophisticated than the UBA approach (yet less sophisticated than the MRIO approaches discussed in Section 2.2), does not only account for the net trade balance, but additionally takes into account the grid EF of the neighbors from which electricity is imported (and vice versa). Thus the opposing trends: for the UBA, electricity trade leads to a higher German grid EF, in our calculations, it leads to a lower EF.

5.2 Extended Recommendations

5.2.1 Extended Recommendations: Grid EF Calculation

Referenced to all possible ways of calculating a grid EF with the methodology we propose, the recommended configuration (set of choices) is closer to the high end (see Figure 14). About 21.1-26.3% of the possible grid EF are larger than the recommended value, while the rest is smaller. The recommended configuration is therefore neither an extreme one nor the most typical (it's not around the median).

5.3 Limitations

Despite our best efforts to contribute in a comprehensive, complete and consistent manner to the standardization and harmonization of grid EF for Scope 2 emission accounting, some shortcomings remain. Besides some aspects already mentioned in the methodology section of the main article (e.g., omitting the technological and spatial resolution), more caveats apply to this study. We briefly list them here, distinguishing between general limitations and limitations that are specifically relevant for certain methodological aspects.

5.3.1 General Limitations

Our study only covers Germany throughout the years 2019-2022. The results and conclusions may differ for other locations and time periods due to the different composition of the underlying energy system.

Also, we only assess the environmental impact with respect to GHG emissions. While this is the only aspect relevant for corporate GHG accounting and reporting, other types of impacts from electricity production and consumption (e.g., resource depletion, water use, impact on biodiversity) are of similar importance and should not be neglected.

Our calculations are based on primary-energy referenced EF for specific production types from UBA[57]. However, other approaches exist as well, such as the two approaches demonstrated by Unnewehr *et al.* that are based on total emission data from the European Emissions Trading System (ETS) and the UNFCCC national emissions inventory, respectively. Since the data sources are unlikely to match completely, the outcome will differ between approaches.

The mapping process described in the methodology section of the main article, which we include because of non-matching data categories, is likely to introduce some error. If the data providers were to use matching data categories, this could be avoided.

Additionally, for some production types, the primary-energy referenced EF are not provided by the data sources and had to be guessed (see Section 3.1.3). Furthermore, these EF are only applicable to Germany, and refer to the year 2020. For other countries and years, these EF are probably not the best representation of the operational and upstream emissions of the production types in question.

5.3.2 Aspect-specific Limitations

The following limitations apply to specific methodological aspects and choices covered in this study.

5.3.2.1 Impact Metric. The GWP values used in this study are based on the CF from the IPCC AR6[58], and will therefore differ from other publications that rely on EF from the IPCC AR5[59]. A more detailed analysis could also take into account probabilistic instead of deterministic CF, as demonstrated by Pereira and Posen[36].

5.3.2.2 System Boundaries. While we only distinguish between operational and life cycle (operational & upstream) emissions, one could go further and distinguish between the feedstock and the infrastructure life cycle, as well as the up- and downstream emissions.

5.3.2.3 Co-generation of Heat. We cover six different allocation methods to account for electricity and heat co-generation in CHP units. However, there are several more that could be included, and no consensus appears to exist which one is the "correct" or most suitable one. The reference efficiencies used by the UBA (0.8 and 0.4) may be considered quite low for state-of-the-art heat and power generators. The temperature levels assumed for the allocation by exergy (T_0: 282 K, T: 363 K) are probably not entirely unrealistic, but should be verified and/or varied using a sensitivity analysis in future studies.

5.3.2.4 Auxiliary Consumption. There are no limitations of this study with respect to auxiliary consumption that we are aware of.

5.3.2.5 Auto-producers. Our definition of auto-producer rests on the assumption that these units do not feed electricity into the grid. We did not find information about this in our data sources. Should this assumption be wrong, then the calculations based on this assumption should be reviewed and updated.

5.3.2.6 Temporal Resolution. We only assess the temporal resolution levels of 15 minutes and one year. Additional, intermediate resolution levels may provide further relevant insights. Also, as mentioned in the main article's discussion, 15 min data may not be available in every region, especially outside of Europe and North America.

5.3.2.7 Electricity Trading. Our approach, while perhaps more sophisticated than the one used by the UBA (see main article's discussion section), is based on the SFOT approach, not on the more complex (and probably more accurate) MRIO approach. This means that our study only considers electricity exchange with direct neighbors, but ignores additional, network-wide interactions.

5.3.2.8 Storage Cycling. The method to calculate virtual emissions for the electricity flows going into and coming out of pumped hydro storage units in this study is a simplified one. It assumes a constant grid EF for these electricity flows, instead of calculating a grid EF at a higher temporal resolution. Should the inflows and outflows occur at times when the grid EF is systematically higher or lower than the annual average grid EF, this approach will introduce an error.

5.3.2.9 Transformation & Distribution. Similarly, our calculation of T&D losses does not temporally (or spatially) disaggregate losses in the grid. Also, the losses at different voltage levels of the grid are not analyzed separately.

5.4 Future Work

Besides the obvious opportunities for future work, i.e. addressing the limitations mentioned in Section 5.3 (to the extent possible), we want to briefly highlight some additional promising avenues for research and applications.

To find out if and how it applies to a different context, we would welcome it if researchers were to use the methodology demonstrated in this study for calculating grid EF for other countries and time periods. Some data sources may have to be adjusted (e.g., for the primary-energy referenced EF[57]). The results could be compared to the grid EF calculated by official institutions (IEA, EEA, national institutions).

Another interesting approach would be to engage in a type of global sensitivity analysis (GSA). While in this study, we only investigated single effects in isolation, it may be worth mapping the entire solution space more systematically. Existing approaches from mathematics[62,63], some of which have been already applied to life cycle assessment[64–66], may be a good starting point. The findings may e.g., provide additional insight into how individual aspects (effects) interact with one another.

Moving away from research, and towards application, it may be worth developing a user interface (UI) for the methodology. This UI could e.g., be an interactive, browser based solution which requires no installations by the user. This UI would lower the barriers to using the methodology and applying it to Scope 2 emission accounting.

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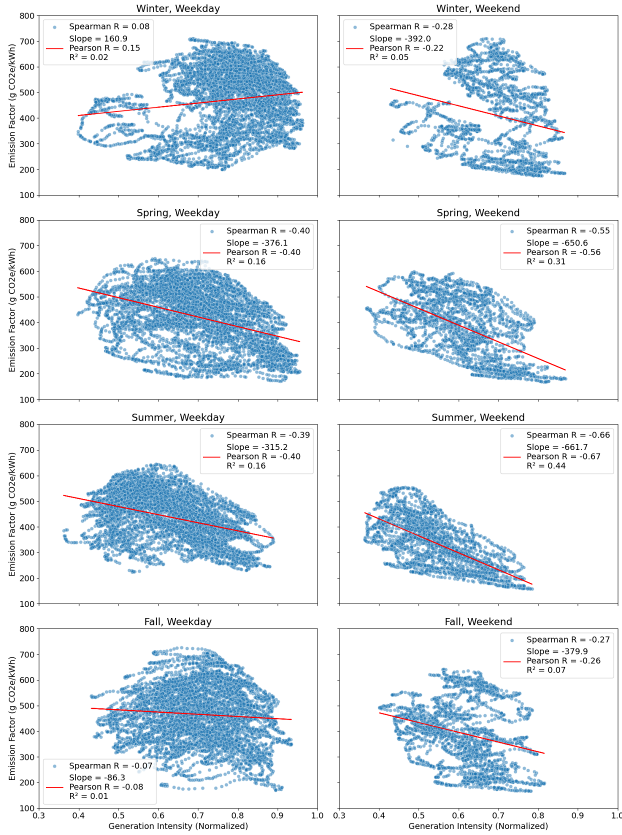

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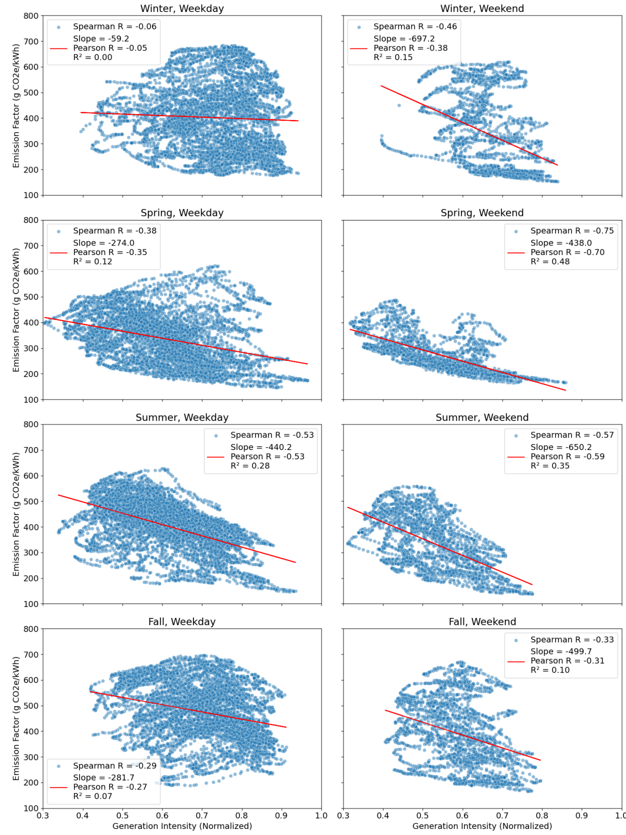

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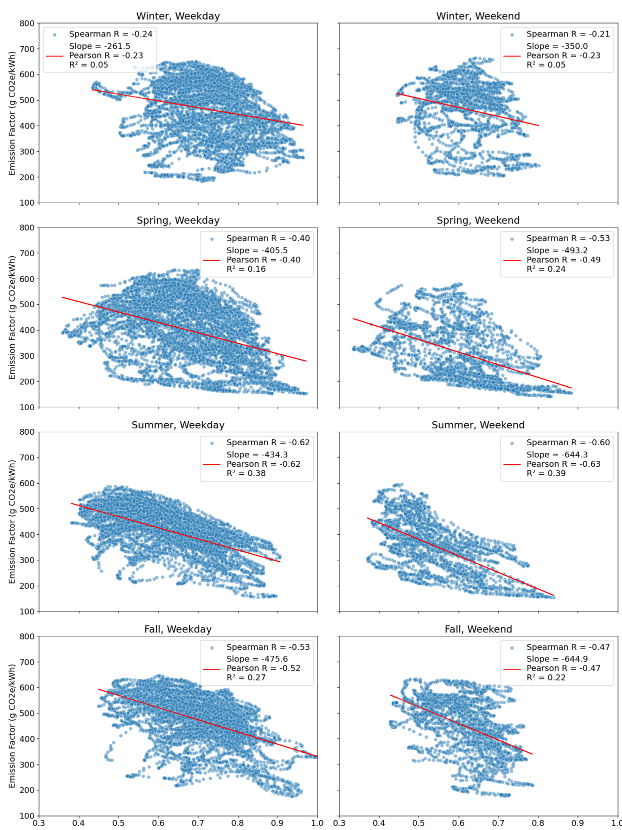

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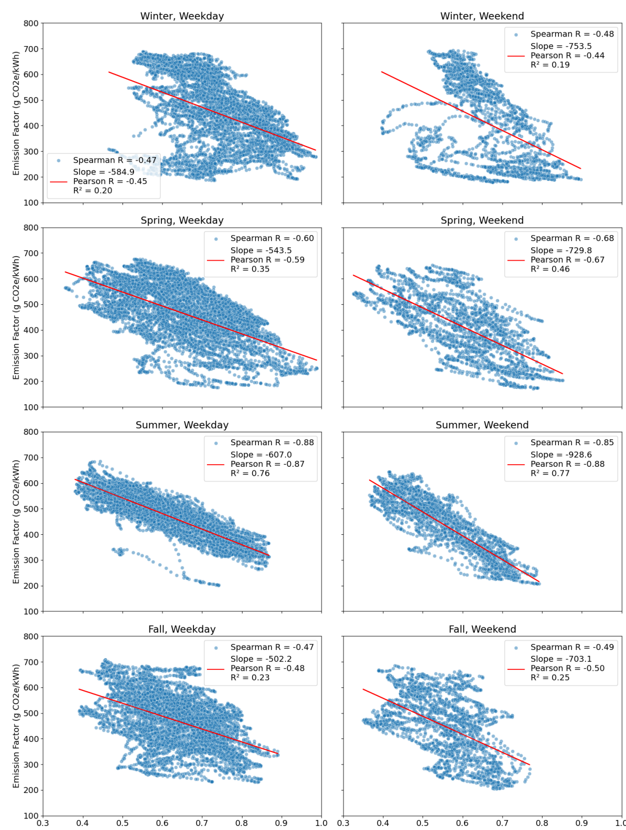

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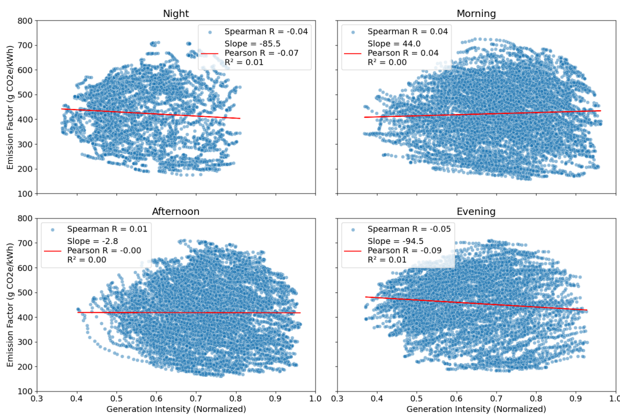
Fig. 12 Correlation analysis for generation intensity and grid EF by day type and season for years 2019-2022. The Spearman R indicates the degree to which the data can be represented by a strictly monotonous function, while the Pearson R indicates the degree to which the data can be represented by a linear function (in both cases, 0 describes no representation at all, and -1 or 1 a perfect representation).



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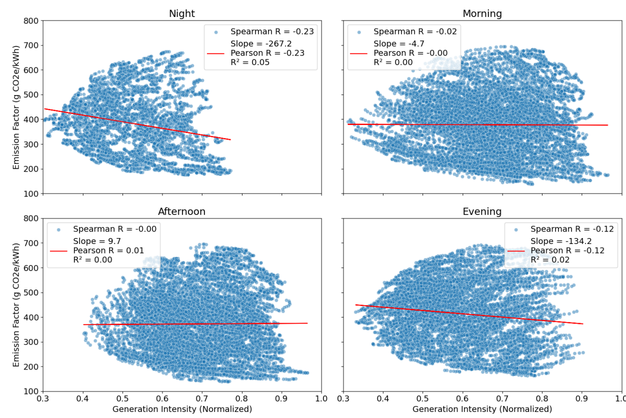

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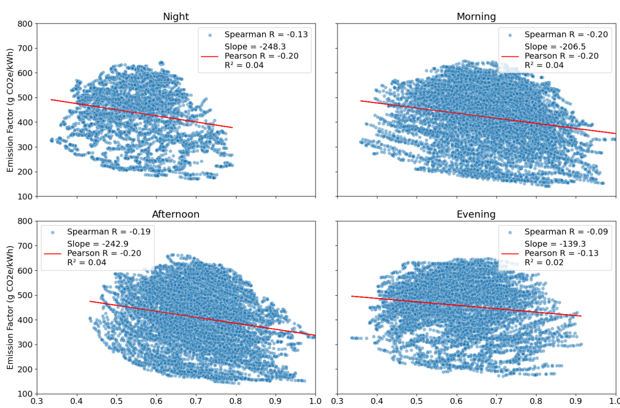

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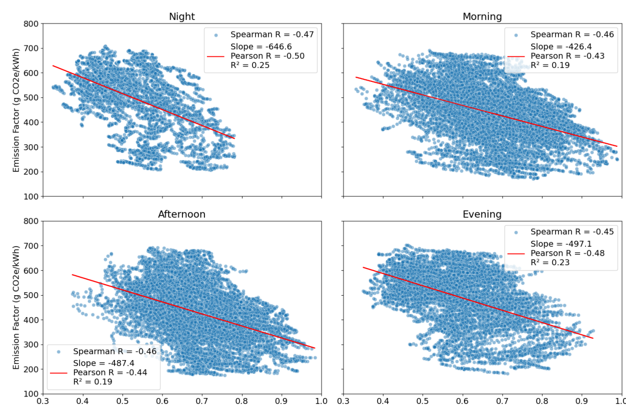

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Fig. 13 Correlation analysis for generation intensity and grid EF by time of day for years 2019-2022. The Spearman R indicates the degree to which the data can be represented by a strictly monotonous function, while the Pearson R indicates the degree to which the data can be represented by a linear function (in both cases, 0 describes no representation at all, and -1 or 1 a perfect representation).

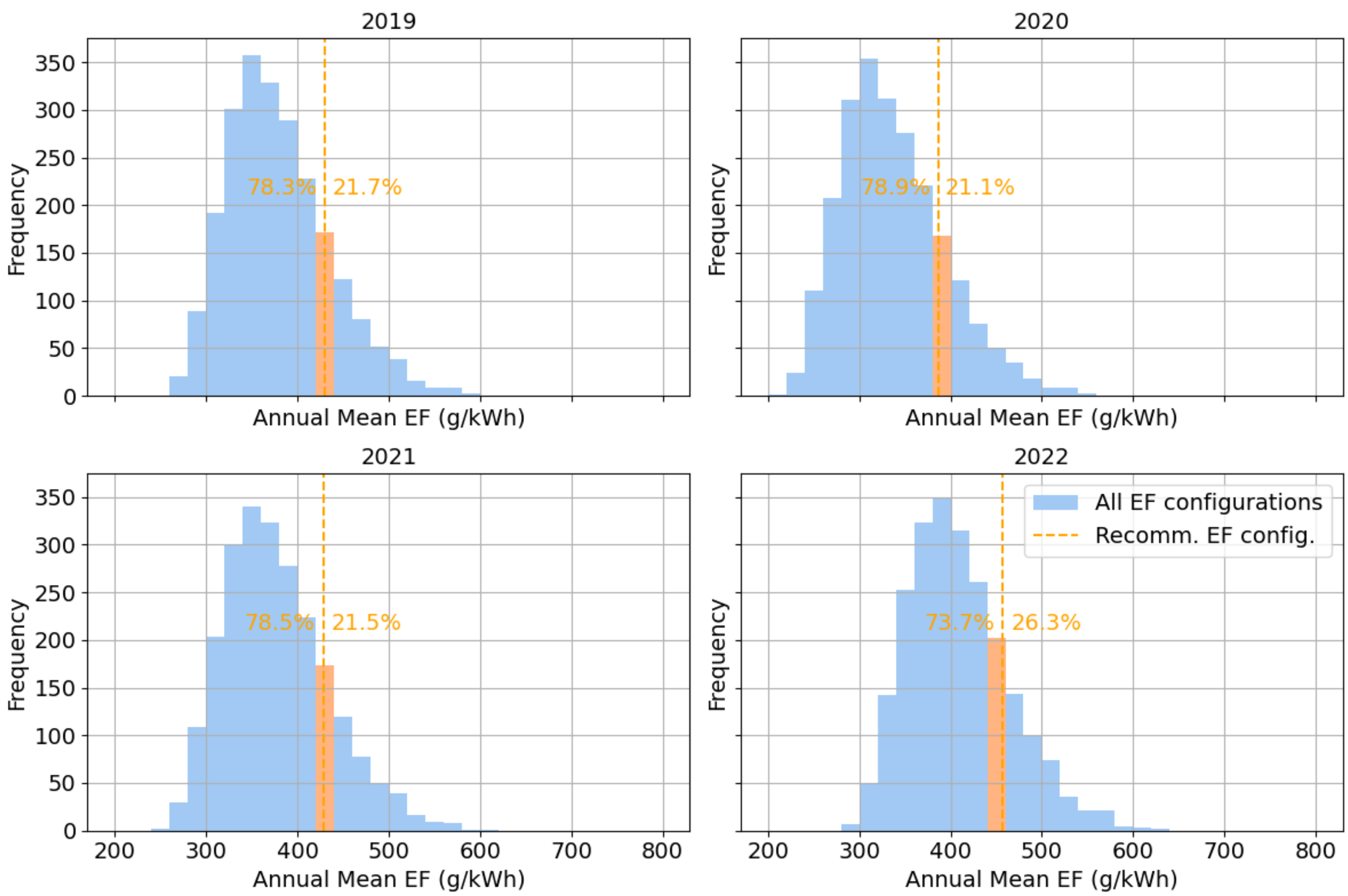

Fig. 14 Annual mean of the recommended grid EF configuration (orange) compared to the annual means of all possible grid EF configurations (blue), by year. The recommended configuration is the one described in the discussion section of the main article. The percentages in the plot indicate the relative share of the 2304 configurations which result in a lower (left of the orange vertical line) and higher (right) annual mean EF than the recommended configuration.