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CARBON FOOTPRINTING

Increasing temporal resolution in greenhouse gas accounting of electricity consumption divided into Scopes 2 and 3: case study of Germany

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Abstract

Purpose As renewable energy sources (RES) experience short-term variability, electricity greenhouse gas (GHG) emissions also fluctuate. Increasing temporal resolution in electricity emissions accounting allows capturing these fluctuations. However, existing time-resolved models either neglect indirect impacts, adopt a generation perspective, or are based on non-public country-specific data. We provide an approach for calculating time-resolved GHG emission factors (EFs) of electricity consumption based on open access data for European countries and examine the temporal variability of German EFs.

Methods Time-resolved electricity GHG EFs are calculated within the framework of attributional life cycle assessment (LCA) with up to quarter-hourly resolution. The approach involves top-down calculation of annual combustion emissions, validation and scaling of time-resolved electricity generation data, as well as calculation of inland consumption EFs for each interval throughout a year. The EFs are divided by the stages of net generation, consumption by hydro-pumped storage (HPS), and transmission and distribution (T&D) losses, as well as Scopes 2 and 3, enabling GHG Protocol Corporate Standard-compliant reporting. The approach is exemplarily applied to Germany and its transmission system operator zones at quarter-hourly resolution for the years from 2017 to 2020 to investigate the relation between grid mix composition and temporal variability of EFs.

Results and discussion The annual average EF of the German consumption mix, encompassing direct and upstream emissions, declined from 499 (2017) to 377 g CO_2e/kWh (2020), while quarter-hourly variability increased by 12%. Neglecting upstream emissions and intermediate steps between generation and consumption in Germany in 2020 resulted in an underestimation of 13% on an annual level, while quarter-hourly Scope 3 EFs reached up to 100 g CO_2e/kWh. On a sub-national level, annual average EFs varied between 157 g CO_2e/kWh (TenneT zone) and 505 g CO_2e/kWh (50Hertz zone) in 2020. Temporal variability is the greatest in electricity systems with both fossil-fuel and renewable capacity sufficient to dominate short-term electricity generation. At an advanced level of RES integration, the fluctuations of EFs start declining, as demonstrated by the TenneT case.

Conclusion An increased temporal resolution in electricity emissions accounting can enhance a posteriori LCA results' accuracy during the energy transition phase. The provided EFs link the life cycle-based perspective with time-resolved emissions accounting. With increasing reliance on RES, indirect emissions, including those related to energy storage, will gain in significance. The next step should focus on integrating physical cross-border electricity exchanges to complete the consumption perspective, as well as examining practical implementation to other countries.

Keywords Carbon footprint · Emission factors · Energy transition · Greenhouse gas (GHG) protocol · Open access data · Temporal variability

1 Introduction

The energy sector is the largest contributor to climate change, accounting for 76% of global emissions in 2018 (WRI 2021). Furthermore, almost a quarter of energy-related greenhouse gas (GHG) emissions is assigned to power generation (IEA 2021a). To achieve the net-zero emission target by 2050, electricity-related emissions will have to exhibit the fastest decline among all sectors, despite the continuously growing electricity demand (IEA 2021a). This can be achieved primarily through an increasing share of renewable energy sources (RES) in the electricity grid mix, supported by increased energy storage capacity.

Electricity generation from renewables is subject to weather-dependent temporal fluctuations (Denholm and

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Hand 2011), which indirectly affects short-term (i.e., hourly or sub-hourly) GHG emissions of produced electricity. Consequently, GHG emissions from electricity consumption can vary drastically depending on the time of electricity use, e.g., as shown by Messagie et al. (2014), Roux et al. (2016), Kopsakangas-Savolainen et al. (2017), Kono et al. (2017), and Pereira and Posen (2020). These GHG emissions can be reduced through optimizing the timing of electricity usage, which requires quantification of time-resolved GHG emissions per kWh expressed through emission factors (EFs).

Time-resolved EFs can be utilized for different purposes, which determines the methodological framework for their calculation, as discussed in Soimakallio et al. 2011. Part of the recent literature aims at determining marginal time-resolved EFs within the consequential approach, e.g., for optimizing smart charging (Huber et al. 2021) and data center operation (Dandres et al. 2017) or for designing heating systems (Roux et al. 2017). Another group of approaches adopts the attributional perspective, quantifying location-based emissions either through electricity system modeling (e.g., Deane et al. 2014; Victoria and Gallego-Castillo 2019; Portolani et al. 2022) or retrospectively based on historical data (e.g., Kono et al. 2017; Clauß et al. 2019; Marrasso et al. 2019; Unnewehr et al. 2022), which is the focus of this paper. Retrospective approaches can be applied to enhance the accuracy of historical emissions estimates as well as for providing insights to initiate strategies for reducing electricity-related GHG emissions, e.g., in households and companies (Kopsakangas-Savolainen et al. 2017), when charging electric vehicles (Rupp et al. 2019; Baumann et al. 2019), within the context of buildings (Roux et al. 2016; Clauß et al. 2019; Beloin-Saint-Pierre et al. 2019) as well as for establishing demand-based carbon dioxide (CO_2) pricing (Stoll et al. 2014; Milovanoff et al. 2018).

Calculating location-based GHG electricity emissions poses several methodological challenges with regard to system modeling choices. First, it should be differentiated between the generation and consumption accounting perspectives. The latter involves several intermediate stages after the gross generation, including own use by power plants, physical cross-border electricity exchanges (further referred to as "exchanges"), consumption by hydro-pumped storage (HPS), as well as transmission and distribution (T&D) losses (ENTSO-E 2015). However, electricity exchanges are often the only element that is considered to model the difference between the two perspectives (Milovanoff et al. 2018; Tranberg et al. 2019; Schram et al. 2019; Agora Energiewende 2020). The consumption by HPS as well as T&D losses are rarely explicitly incorporated into electricity emissions models (e.g., being included in Spork et al. 2015; Roux et al. 2016), although these might have an increasing influence on the GHG intensity of consumed electricity with an increasing reliance on RES (Pimm et al. 2021). Thus, the GHG EFs of consumed electricity should reflect all intermediate steps between the point of generation and consumption.

The second issue refers to the inclusion of indirect emissions according to the life cycle principle (ISO 2006a). Electricity-related emissions can be classified into direct emissions released during fuel combustion (Scope 2) and indirect upstream and downstream emissions arising along the electricity supply chain (assigned to Scope 3), e.g., during fuel extraction or power plant construction (WRI and WBCSD 2004). The inclusion of indirect emissions is required by the frameworks of both attributional Life Cycle Assessment (LCA) and product carbon footprinting, while it is optional for most organizational carbon accounting standards (Holzapfel et al. 2023). The ISO 14040/44 (ISO 2006a, b), ISO 14067 (ISO 2018a), and the GHG Protocol Product Standard (WBCSD and WRI 2011) demand the inclusion of all life cycle emissions, while in the GHG Protocol Corporate Standard (WRI and WBCSD 2004) and ISO 14064 (ISO 2018b) the inclusion of indirect (Scope 3) emissions is optional. Most electricity emissions accounting models adopt the operational perspective (Hamels et al. 2021) and thereby omit emissions associated with upstream and downstream activities. While these models can be used for calculating direct emissions, they are not directly applicable, e.g., within the GHG Protocol Corporate Standard if Scope 3 emissions are considered.

Finally, the general issue of data availability in EFs calculation becomes especially pronounced with increasing temporal resolution. Existing approaches therefore have to rely on country-specific or non-publicly available data, limiting their applicability (Hamels et al. 2021). Hence, a calculation approach for time-resolved electricity EFs based on a uniform open access data might be favorable. For instance, several approaches comply with the life cycle perspective and fully or partly adopt the consumption perspective; however, they are designed based on country-specific parameters, such as Pereira and Posen (2020) for the province of Ontario, Spork et al. (2015) for Spain, and Messagie et al. (2014) for Belgium. The European Network of Transmission System Operators for Electricity (ENTSO-E) platform provides data for a large number of European countries with the temporal resolution up to 15 min (ENTSO-E 2022a). The online tool "Electricity Maps" represents a successful implementation example of ENTSO-E data electricity exchanges (Electricity Maps 2022). However, the historical time-resolved values that they provide are not publicly available. Furthermore, published approaches based on ENTSO-E data often neglect upstream emissions (Marrasso et al. 2019; Braeuer et al. 2020; Unnewehr et al. 2022; Agora Energiewende 2023) and thus do not comply with the life cycle perspective requirement or rely on ecoinvent-datasets (Roux et al. 2016; Kono et al. 2017; Vuarnoz and Jusselme 2018;

Clauß et al. 2019; Beloin-Saint-Pierre et al. 2019; Schram et al. 2019). These ecoinvent-based approaches provide one aggregated estimate for Scopes 2 and 3 and are thus not applicable for emissions reporting under the GHG Protocol Corporate Standard (WRI and WBCSD 2004).

To our knowledge, no methodology exists on the fine temporal resolution level, which simultaneously addresses the following identified shortcomings: (i) incomplete representation of the consumption perspective; (ii) neglection of indirect GHG emissions and thus an incomplete life cycle perspective; (iii) use of non-universal, country-specific or not publicly available source of electricity raw data; and (iv) option for division by Scopes 2 and 3 in line with the GHG Protocol Corporate Standard.

This paper aims to fill these gaps by providing an approach for calculating time-resolved GHG emission intensity of electricity consumption within the framework of attributional LCA based on the ENTSO-E data (ENTSO-E 2022a). Thereby, the temporal resolution level is determined by the country-specific granularity data provided by ENTSO-E and might vary between 15-min, 30-min, and hourly intervals. Further, the developed approach allows deriving separate EFs for each stage of the electricity supply system from the consumption perspective according to ENTSO-E (2015), except for the stage of electricity exchanges (as elaborated in Section 2.2). This allows division of electricity-related emissions between Scopes 2 and 3, which enables more consistent reporting under the GHG Protocol Corporate Standard (WRI and WBCSD 2004). The presented approach is applied to an example of Germany between 2017 and 2020. The derived EFs are used to analyze the quarter-hourly temporal variability in the context of energy transition, which represents the second goal of the paper. For this purpose, a finer regional analysis is adopted at the level of independent transmission system operator (TSO) zones, representing systems with different degrees of RES integration.

In the following sections, the data and method for deriving EFs are presented (see Section 2), followed by the results at the annual (see Section 3.1) and quarter-hourly (see Section 3.2) resolution levels, interpretation, and critical reflection on the approach (see Section 4), and finally, a conclusion (see Section 5).

2 Data and method

This section provides a method description for calculating time-resolved electricity consumption EFs that respects the key requirements of ISO 14067 (ISO 2018a) and the GHG Protocol Corporate and Product standards (WRI and WBCSD 2004, 2011). The attributional LCA approach is adopted, meaning that average EFs are derived for each time interval. Raw data on electricity generation is obtained from ENTSO-E (ENTSO-E 2022a). The calculation is done on a quarter-hourly (15 min) basis, which corresponds to the finest temporal data resolution provided by the ENTSO-E. The method is exemplarily applied to Germany for the years 2017, 2018, 2019, and 2020. In addition, EFs for the four German TSO zones (50Hertz, Amprion, TenneT, and TransnetBW) are derived to investigate the effect of spatial grid mix differences on the sub-national level (ENTSO-E 2023). These differ in their extent of RES adoption, which provides insights into temporal fluctuations at different grid mix compositions.

The system boundary starts with upstream activities prior to electricity generation and ends at the point of electricity supply to the end-consumer. The consumption perspective is represented by gross generation, own use, pumping consumption, and T&D losses. Emissions from electricity exchanges are not included due to significant data gaps in the "Cross-border physical flows" dataset (ENTSO-E 2022b), e.g., 16% in 2017 compared to the annual value reported in "Energy Balances" (eurostat 2022a). Filling these data on the fine temporal resolution level would require assumptions on country of origin, timing of import, and the GHG intensity of imported flows, without possibility of validation through statistics. Thus, inland electricity consumption serves as the reference point for the EFs calculation and is further referred to as *consumption*.

The methodology consists of two subsequent steps, as illustrated in Fig. 1: calculation of the annual combustion emissions (Section 2.1) and calculation of time-resolved electricity EFs (Section 2.2).

2.1 Calculation of annual combustion emissions

2.1.1 Data preparation

Combustion emissions (direct emissions) are estimated in a top-down approach (see Section 2 of Supplementary Information (SI), based on annual statistics on fuel consumption for electricity generation. This data is obtained from "Energy Balances" ([nrg_bal_c]) for each combustible energy product, further referred to as *fuel type* (f), according to the classification adopted by Eurostat (2022a). Both autoproducer and main activity producers per definition from energy statistics (UNSD 2018) are considered. All parameters from "Energy Balances" (Eurostat 2022a) serving as background data and involved in the following calculations are described in Table S1 of SI.

The total annual fuel transformation input for electricity generation comprises fuel input to electricity plants, CHP plants, and own use in the energy sector. To estimate the amount of combustible fuel consumed by CHP plants

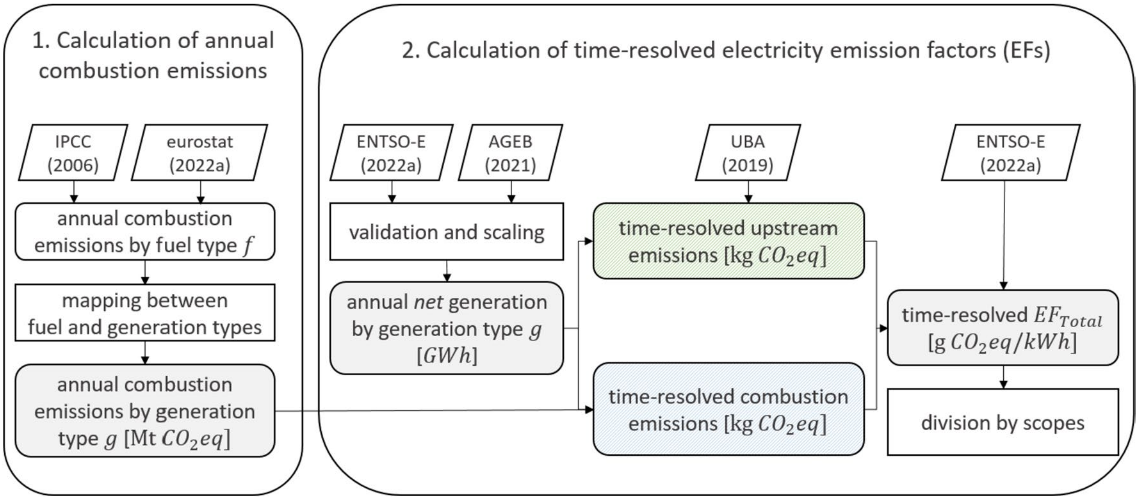


Fig. 1 Simplified illustration of the applied method

specifically for electricity generation, the fixed-heat-efficiency approach is adopted (IEA 2021b). Thereby, a constant heat conversion rate of 90% for CHP plants is assumed.

"Energy Balances" provides one aggregated value for *own use* in the electricity generation process without the differentiation between the fuel types. Therefore, the amount of each fuel type f consumed by electricity plants ($\mathrm{Ownuse}_{ele,f}$) is calculated based on the amount of gross electricity generated from a specific fuel type ($\mathrm{Eleoutput}_{gross,f}$) in relation to the total energy output from that fuel, as follows from Eq. (1).

$$\text{Own use}_{ele,f} = \text{Own use} * \frac{\text{Ele output}_{gross,f}}{\text{Ele output}_{gross,f} + \text{Heat output}_{gross,f}} \quad (1)$$

2.1.2 Direct emission calculation

In the second step, direct CO_2, methane (CH_4), and nitrous oxide (N_2O) combustion emissions resulting from gross generation are calculated following the approach of International Energy Agency (IEA 2021b). This is done by multiplying the annual transformation input for electricity generation, estimated in the previous step, with the "default emission factors for stationary combustion in energy industries" (combustion EFs) provided by Intergovernmental Panel on Climate Change (IPCC 2006). These combustion EFs represent the average non-country-specific fuel composition, which may underestimate or overestimate actual emissions. The decision to adopt the average combustion EFs is intended to provide a uniform solution for all countries reporting to ENTSO-E. Both data sources, Eurostat (2022a) and IPCC (2006), follow the same classification system (UNSD 2018), which allows direct mapping of transformation input flows by fuel type and combustion EF. Direct combustion emissions are calculated separately for each GHG as a product of fuel input and the corresponding combustion EF.

Total inland combustion emissions are obtained by summing up combustion emissions over each fuel type. Finally, CO_2, CH_4, and N_2O emissions are converted to CO_2 equivalent (CO_2eq) values using global warming potentials (GWP) for a 100-year time horizon from the fifth assessment report of IPCC (2015). Direct emissions from biomass and renewable waste are available for reporting, but are not included in the EFs calculation according to the ISO 14064 (ISO 2018b) and the GHG Protocol Standard (WRI and WBCSD 2004).

2.1.3 Mapping of fuel types and generation types

In the third step, the fuel-specific emission classification is replaced by the ENTSO-E technology-based classification by generation types (g) (ENTSO-E 2022a). This is done to enable a later calculation of time-resolved electricity EFs based on the generation type classification adopted by ENTSO-E. The mapping is done by aggregating fuel-specific emissions to larger groups that correspond to the equivalent ENTSO-E generation types (UNSD 2018). Thereby, fuel-specific annual emission results (E_f) are translated into annual emissions per generation type (E_g). A list of matching fuel types and generation types can be found in Table S2 of SI.

2.2 Calculation of time-resolved electricity EFs

The calculation of time-resolved electricity EFs is based on annual combustion emissions derived in Section 2.1. The procedure is illustrated in Fig. 2 and is explained in the following sections step-wise.

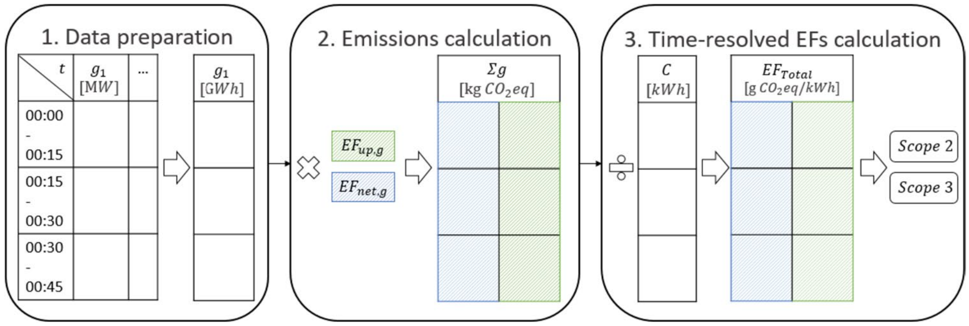


Fig. 2 Illustration of the process of calculating time-resolved electricity EFs on the quarter-hourly level. The blue color symbolizes direct emissions resulting from fossil fuel combustion, and the green color represents the upstream emissions arising along the electricity supply chain

2.2.1 Data preparation

Raw data for calculating time-resolved emission factors is obtained from the ENTSO-E dataset "Aggregated generation per type" (16.1.B&C), corresponding to inland net electricity generated (gross electricity generation without own use by plants) (ENTSO-E 2022a). Quarter-hourly values are expressed in [MW] and are first converted to [GWh] for each generation type and every 15-min interval. The dataset contains a formal error, due to the shifts between Central European Time (CET) and Central European Summer Time (CEST), which results in eight duplicated intervals of 15 min per year (2 am and 3 am). After eliminating the duplicates, quarter-hourly values per generation type are summed up over each time interval of a year to derive annual net generation from each generation type.

Despite the finest available data resolution, the incompleteness of the underlying dataset has been pointed out by several authors (European Commission 2017; Hirth et al. 2018; Buyle et al. 2019; Marrasso et al. 2019). In the case of Germany, around 9% of the total electricity supply is not included due to the differences in classification systems (ENTSO-E 2015). Additionally, a part of the German fossil gas plants is not covered by the "Actual generation per type" dataset (EC 2017). Therefore, to validate raw data for Germany, quarter-hourly values provided by ENTSO-E are aggregated to the annual level and compared with the annual values published in two external data sources: "Net electricity generation" by Energiebilanzen e.V. (AGEB 2021) and "Statistical Factsheet" (ENTSO-E 2019). The priority is given to the national source AGEB (2021) as it provides more complete data, despite the different classification system. A comparison of aggregated raw data with the "Statistical Factsheet" indicates data gaps in the categories "Fossil Gas" and "Fossil coal-derived gas." However, "Fossil coal-derived gas" is not presented in the classification adopted by AGEB (2021) and thus cannot be verified by this source. Thus, both categories are further merged to "Fossil Gas."

Next, scaling factors are obtained for each generation type using the approach by Agora Energiewende (2020). Thereby, the corrected annual *net* generation value is divided by the sum of quarter-hourly ENTSO-E values over a year. An example of data validation and calculation of scaling factors for Germany in the year 2018 is demonstrated in Table S3 of SI.

2.2.2 Time-resolved emission calculation

Time-resolved combustion and upstream emissions are calculated by multiplying scaled electricity generation values by generation type for each 15-min interval of a year with the corresponding annual average EF. Annual average EFs are derived for the stage of net electricity generation ($\mathrm{EF}_{\mathrm{net},g}$), since the electricity data from ENTSO-E refers to net generation. These factors are calculated by dividing annual combustion emissions per generation type (E_g) by the corresponding annual amount of net generation output ($\mathrm{Eleoutput}_{\mathrm{net},g}$) according to Eq. (2).

$$\mathrm{EF}_{\mathrm{net},g} = \frac{E_g}{\mathrm{Ele\ output}_{\mathrm{net},g}} \tag{2}$$

The annual upstream emissions are calculated in a top-down approach by using EFs per generation type ($\mathrm{EF}_{\mathrm{up},g}$) adopted from UBA (2019). A complete list of generation types extended by renewables and nuclear, as well as corresponding upstream EFs, is provided in Table S4 of SI. Additionally, it includes a description of the procedure for calculating upstream EFs for categories not addressed by UBA. The EFs of pumping consumption and T&D losses do not require a separate emissions calculation, since no actual emissions occur at these stages. The respective EFs are derived based on combustion emissions as explained in Section 2.2.3.

Scaled quarter-hourly net electricity generation values per generation type are multiplied with $\mathrm{EF}_{\mathrm{net},g}$ and $\mathrm{EF}_{\mathrm{up},g}$ to calculate combustion and upstream emissions, respectively. The obtained values are summed up over generation types, resulting in two values for every 15-min interval—$E_{15\mathrm{min,d}}$ for total direct emissions and $E_{15\mathrm{min,up}}$ for total upstream emissions, according to Eq. (3).

$$E_{15\mathrm{min,d/up}} = \sum_g \mathrm{Ele}_{15\mathrm{min},g} * \mathrm{EF}_{\mathrm{net/up},g} \tag{3}$$

2.2.3 Time-resolved electricity EFs calculation

Electricity consumption EFs are estimated separately for combustion and upstream emissions as a ratio of that emissions to the amount of consumed electricity. To provide a reference for consumption EFs calculation, the amount of electricity supplied to the end-consumer every 15 min of a year is first derived (C). This is done by taking scaled net generation values, subtracting the amount of electricity consumed by HPS (P) and adjusting by the percentage of electricity losses in the T&D processes (L), as demonstrated by Eq. (4).

$$C = (\text{Ele output}_{net} - P) * (100\% - L) \tag{4}$$

Besides the upstream life cycle emissions, HPS causes direct emissions by consuming electricity, which means that the total amount of direct emissions remains constant. Data on consumption by HPS is included in the "Actual Generation per Type" dataset (ENTSO-E 2022a) and has undergone scaling together with the net generation values in Section 2.2.1. Thereby, the approach does not consider how electricity stored in HPS impacts the GHG emission intensity of EFs during the time interval when stored electricity is released.

Due to data limitations, T&D losses are assumed to be stable over 1 year. The respective annual values are derived from "Energy Balances" under the code "DL" (Eurostat 2022a). The T&D loss factor L is obtained by dividing the annual losses by the amount of electricity in the network after pumping consumption ($\text{Eleoutput}_{net} - P$). This value represents an annual average percentage of electricity lost in the network and can be applied for each time interval.

For each 15-min interval, the sum of direct ($E_{15min,d}$) and indirect emissions ($E_{15min,up}$) divided by electricity consumption (C) yields EF_{Total}, which corresponds to the total life cycle emissions per kWh from the consumption perspective, excluding electricity exchanges. This factor is further divided according to the stages of electricity supply system for allocating emissions between direct (Scope 2) and indirect emissions (Scope 3), as illustrated in Fig. 3. The GHG Protocol requires reporting emissions from net generation, T&D, and the upstream activities separately when purchasing electricity (WRI and WBCSD 2004). However, emissions associated with consumption by HPS are not explicitly mentioned there (WRI and WBCSD 2004; WRI 2011). We decided to derive a separate factor for consumption by HPS because energy storage cannot be explicitly classified either as generation or consumption due to its specific function (EC 2020).

As a result of dividing EF_{Total}, Scope 2 is represented by the net electricity generation factor (EF_{net}), which refers to the combustion emissions released during the generation process, and Scope 3 by the remaining three factors—ΔEF_P, ΔEF_L, and EF_{up}. Within Scope 3, EF_{up} represents actual upstream emissions from electricity generation. In contrast, ΔEF_P and ΔEF_L, representing downstream emissions, correspond to the share of combustion emissions allocated to the amount of electricity lost during pumping consumption and T&D, respectively. Formulas for deriving each of the factors can be found in Section 3 of SI.

3 Results

The following section illustrates the results of the EFs calculation for Germany and its TSO zones from 2017 to 2020. The results are represented on annual (Section 3.1) and quarter-hourly (Section 3.2) resolution levels to investigate the potential results deviation when increasing the temporal granularity. Additionally, quarter-hourly results aggregated to a monthly level are provided in Section 4 of SI.

3.1 Annual resolution

3.1.1 Annual average results

The total results for the annual average EFs comprising direct and upstream emissions (EF_{Total}) on the country level and for each TSO zone from 2017 to 2020 are shown in Fig. 4. Detailed results can be found in Table S8 of SI. Within the studied period, the average emission intensity of the German consumption mix, comprising direct and upstream emissions, declined by a quarter from 499 to 377 g CO_2e/kWh. This is mainly due to the increasing share of RES, which expanded from 27 to 37% of the total electricity production on the country level (Fig. 5). The share of fossil fuels declined by 15% in total from 2017 to 2020. In particular, electricity generation from hard coal and lignite experienced a decline by 39% and 54%, respectively, equivalent to the saving of 92.9 Mt direct CO_2e emissions.

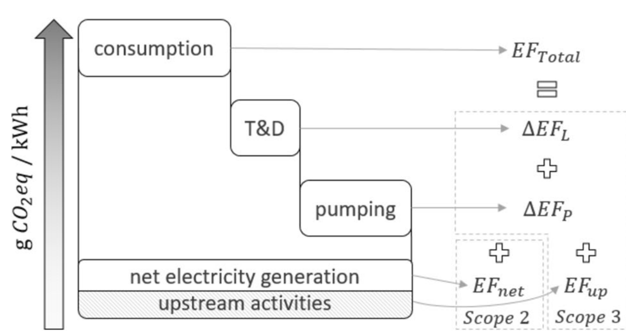


Fig. 3 Principle of dividing EF_{Total} into separate factors by Scopes 2 and 3 based on WRI and WBCSD (2004). As a part of net generated electricity is consumed by pumping and T&D processes on its way to consumers, the GHG intensity of electricity flow increases over the electricity supply system

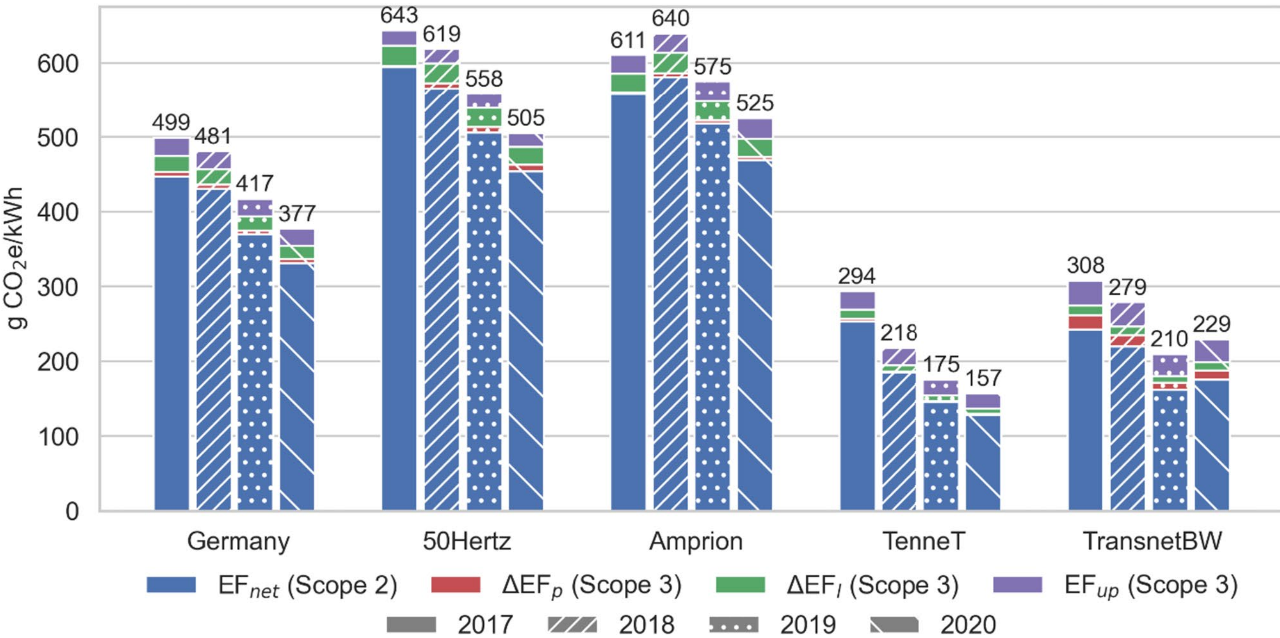


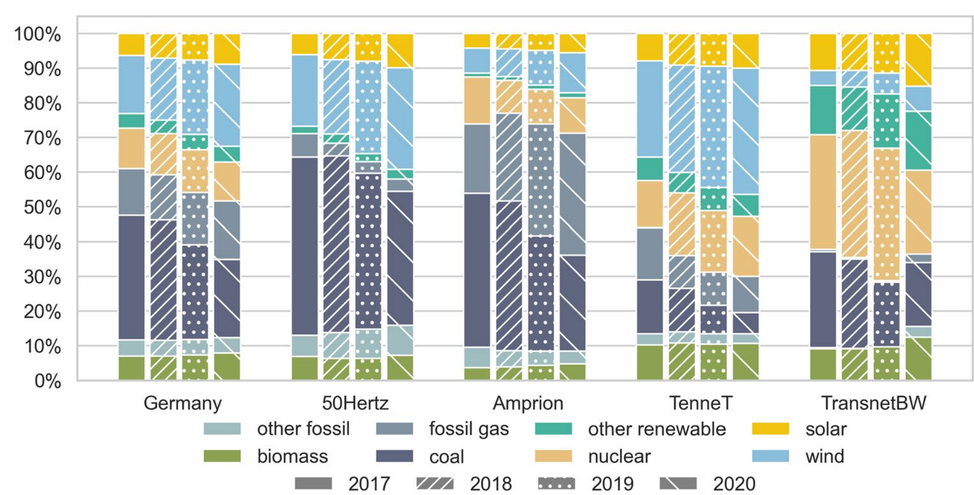
Fig. 4 Annual average consumption EFs for Germany and its TSO zones from 2017 to 2020 divided into net generation (EF_{net}), pumping consumption (ΔEF_P), T&D losses (EF_l), and upstream (EF_{up}). Single EFs are differentiated by colors and the years by hatches. The annotated values correspond to EF_{Total}

At the level of single TSO zones, the result differs significantly as a result of the differing grid mix compositions (Fig. 5). Between 2017 and 2020, the annual average EF_{Total} in Amprion and 50Hertz was around a third higher than the national average. In particular, Amprion was the zone with the highest annual GHG emission intensity per kWh after 2018. As the zone with the lower share of RES in its grid mix, it also showed the slowest reduction in EF_{Total} of 14% over the studied period. The reason is the high reliance on coal due to the mining activity in the region of North Rhine-Westphalia, covering 37% of the installed capacity of coal-fired electricity generation in Germany (UBA 2022).

Similarly, the relatively high GHG intensity of 50Hertz electricity is mainly due to the brown coal combustion. Lignite remained the main energy source in the zone between 2017 and 2020, causing around 70% of the annual direct GHG emissions. This translates into the relatively slow EF_{Total} decline by 18% (Fig. 4), despite the significant reduction in electricity generation from fossil fuels and the expansion of RES. In particular, electricity generation from fossil gas and hard coal declined by 57% and 70%, respectively. However, this reduced their share in the grid mix only by 10%.

Among the TSO zones, the highest GHG intensity reduction of 47% and the lowest EF_{Total} was observed in the TenneT TSO zone. Over the four years, the difference between TenneT's and the national EF_{Total} increased from 41 to 58%. This is mainly due to the quick expansion of offshore capacity (+ 70% between 2017 and 2020), while reducing coal-fired electricity generation by 9% (ENTSO-E 2022c).

Fig. 5 Annual grid mix composition based on net generation in Germany and its TSO zones between 2017 and 2020 based on ENTSO-E (2022a). Generation technologies are differentiated by colors and the years by hatches



The TransnetBW zone exclusively operates in the region of Baden-Württemberg, with the second-largest capacity for coal-fired electricity generation in Germany (UBA 2022). Yet, its grid mix contained the smallest share of fossil fuel electricity (19–29%) and had around 40% lower GHG intensity per kWh than the national average from 2017 to 2020. In particular, TransnetBW had the largest share of electricity generated from nuclear power in its grid mix (11%) compared to the other zones during the studied period. The shutdown of the nuclear power plant Philippsburg 2 in 2019 resulted in a net capacity loss of ca. 5% compared to the prior year (ENTSO-E 2022c). This was partly compensated by the rise of electricity generation from fossil gas from 237 to 1062 GWh (ENTSO-E 2022c), thereby increasing the average EF_{Total} in the zone by nearly 10% in 2020.

3.1.2 Quarter-hourly variability

Figure 6 illustrates the distribution of quarter-hourly values around their statistical mean in Germany and its TSO zones between 2017 and 2020. The underlying results, including quarter-hourly mean EF_{Total}, standard deviation (SD), and the minimum and maximum quarter-hourly values, can be found in Table S8 of SI.

Over the studied years, the range of the quarter-hourly values shifted towards a lower GHG intensity per kWh (Fig. 6). At country level, the quarter-hourly variability of EF_{Total}, measures by the SD, has increased by 12% over the studied period (2017: SD = 109.14; 2020: SD = 122.42), accompanied by a declining annual average value (Fig. 4). A rising temporal variability is also observed in Amprion (2017: SD = 85.95; 2020: SD = 128.36), and *50Hertz* (2017: SD = 144.56; 2020: SD = 172.98), with the latter zone showing the highest increase by 39% among all TSO zones.

In contrast, quarter-hourly variability in the TenneT zone showed a declining trend between 2017 (SD = 115.95) and 2019 (SD = 77.28), followed by a slight increase in the year 2020. During the 4-year period, coal and fossil gas were replaced by RES in the electricity grid mix almost linearly (Fig. 5). Based on previous years, it would be expected that the quarter-hourly variability would decrease further in 2020. The opposite development suggests that an increase in quarter-hourly variability in 2020 was caused by external factors, such as weather anomalies and COVID-19-related restrictions, as elaborated in Section 4 of SI.

Results for TransnetBW between 2018 and 2020 indicate a relatively stable temporal variability in GHG intensity (Table S8 of SI). The electricity grid mix in 2017 and 2018 had an almost identical composition, supporting this hypothesis (Fig. 5). Despite fossil fuels partially replacing nuclear power in 2020, quarter-hourly emissions variability remained almost unchanged in this zone (2019: SD = 117.00; 2020: SD = 121.39).

While TenneT and TransnetBW have similar annual average and mean of quarter-hourly values (Fig. 6), quarter-hourly variability of their EF_{Total} varies substantially. In particular, the range of quarter-hourly values in the TransnetBW zone in 2020 was 1.8 times larger compared to that in the

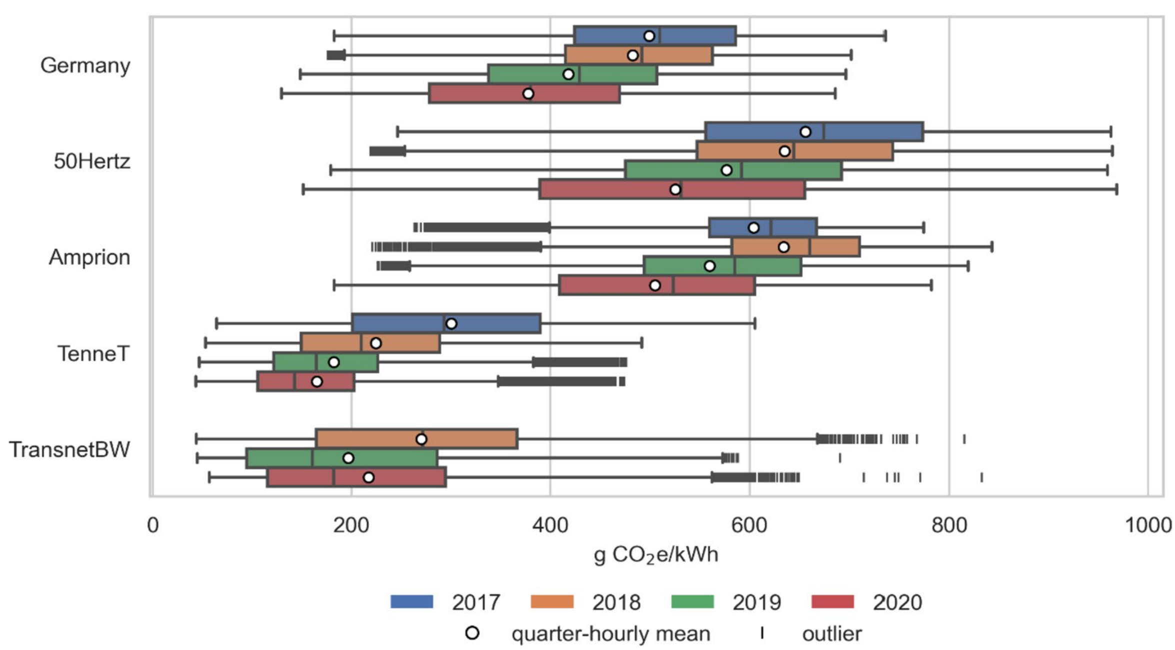


Fig. 6 Development of the quarter-hourly EF_{Total} between 2017 and 2020 in Germany and its TSO zones. The data for the TransnetBW zone in 2017 is excluded due to data gaps on a quarter-hourly level

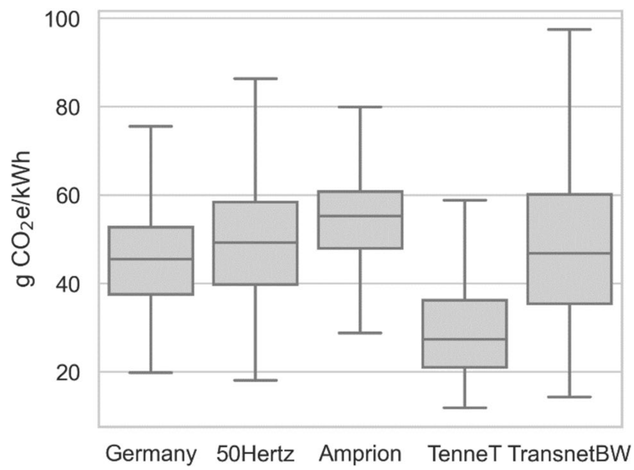


Fig. 7 Distribution of quarter-hourly Scope 3 (indirect) emissions per kWh consumed electricity in Germany and its TSO zones in 2020

TenneT, with the absolute difference reaching 345 g CO_2e/kWh at the upper end. In 2020, both zones had the highest short-term GHG intensity when coal dominated their grid mix. Meanwhile, only 6.07% of electricity generated in the TenneT zone originated from coal, and 18.51% in the TransnetBW zone (Fig. 5).

Scope 3 (indirect) emissions The temporal variability of quarter-hourly Scope 3 (indirect) emissions by year follows a similar trend as EF_{Total} over the four years (Fig. 6) and thus is not illustrated separately. The differences in quarter-hourly distribution of Scope 3 emissions per kWh by zone, excluding statistical outliers, are exemplarily shown on the example of the year 2020 in Fig. 7. The underlying values can be obtained from Table S7 of SI.

At the country level, the mean of quarter-hourly Scope 3 share from the EF_{Total} increased marginally from 10.48 to 12.94% from 2017 to 2020. A decline in the annual average EF_{Total} offset this growth, resulting in a decrease in Scope 3 emissions from ca. 51 to 46 g CO_2e/kWh. The range of quarter-hourly values stayed nearly stable over the four years, shifting to the lower range by less than 2 g CO_2e/kWh.

In both TSO zones dominated by fossil fuels—50Hertz and Amprion—the annual trends were almost identical. Their share of Scope 3 emissions was around 10% from EF_{Total}, accounting for around 53 and 55 g CO_2e/kWh, respectively, in 2020. Despite similar mean values, the quarter-hourly variability of Scope 3 emissions differed considerably. Over the four years, the range of Scope 3 EFs grew by 22% in the 50Hertz zone, compared to an 8% growth in the Amprion zone. In 2020, the range of quarter-hourly values in the 50Hertz zone was 2.57 times larger than in Amprion.

In the remaining TSO zones, TenneT and TransnetBW, the mean of quarter-hourly Scope 3 emissions in 2020 made up almost 20% and 28% from EF_{Total}, respectively. TenneT's Scope 3 emissions per kWh were the lowest of all TSO zones, with nearly 29 g CO_2e/kWh in 2020. This is primarily due to a high share of ofshore wind power, which has one of the lowest upstream emissions per kWh according to the proposed method, but also the lowest ΔEF_P and ΔEF_l among the zones (Fig. 8a, b).

While the mean of EF_{Total} in the TransnetBW zone is considerably lower than those in 50Hertz and Amprion, the absolute Scope 3 emissions were nearly as high as in these TSO zones, reaching 52.34 g CO_2e/kWh in 2020. This is due to the highest relative share of HPS in its grid mix among the zones, resulting in the largest range of quarter-hourly ΔEF_P values (Fig. 8a). It should be pointed out that ΔEF_P indicates the share of electricity generated from HPS from the grid mix and not the absolute amount of electricity consumed in the pumping process (P), which is obviously the largest at the country level.

In 2020, the EF attributed to T&D losses (ΔEF_l) showed highest quarter-hourly variability in the 50Hertz zone, while

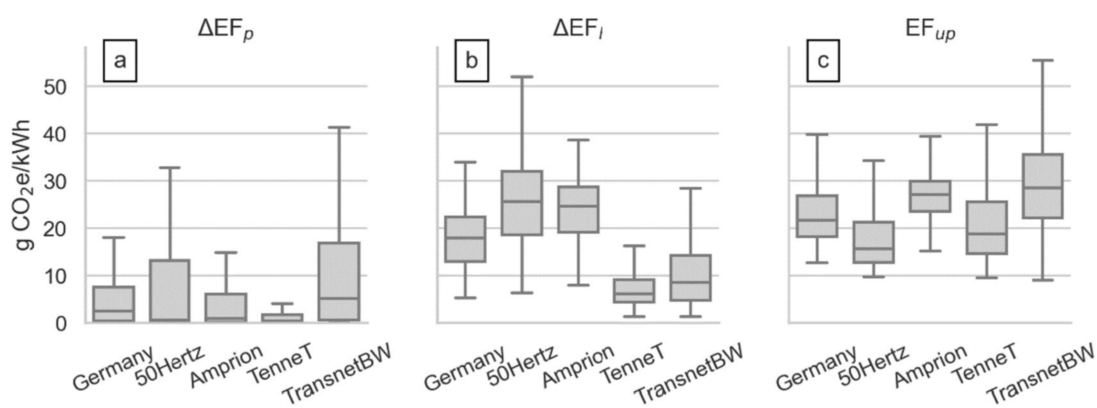


Fig. 8 Distribution of quarter-hourly Scope 3 (indirect) emissions per kWh consumed electricity attributed to pumping consumption **a**, T&D losses **b**, and upstream emissions **c** in Germany and its TSO zones in 2020

the lowest range is observed in TenneT (Fig. 8b). This correlates with the quarter-hourly variability of EF_{Total} in these zones (Fig. 6) and is linked to the calculation methodology, whereby ΔEF_l is estimated as a fixed percentage from EF_{Total}. Thus, temporal variability of ΔEF_l is determined by that of EF_{Total}.

The highest quarter-hourly variability of the upstream emissions (EF_{up}) in 2020 was demonstrated by the TransnetBW zone (Fig. 8c). Over the 4-year period, the annual mean of EF_{up} remained nearly constant at the country level, while the quarter-hourly value range has increased from 24.28 g CO_2e/kWh in 2017 to 31.48 g CO_2e/kWh in 2020. Among the TSO zones, TransnetBW showed both the highest quarter-hourly variability and highest annual mean value, with the highest value reaching 62.75 g CO_2e/kWh and the annual mean of 29.5 g CO_2e/kWh in 2020. Contrary to this, the smallest range of quarter-hourly values in 2020 was observed in the Amprion zone (15.15–43.40 g CO_2e/kWh), although the annual means of TransnetBW and Amprion are nearly equal.

3.2 Quarter-hourly resolution

Figure 9 displays the daily trend of electricity EFs divided by the stages of electricity supply for Germany and its TSO zones using the mean of quarter-hourly values during the winter and summer season of 2020. The winter season includes the months from January to March and from October to December, and the summer season months from April to August.

EF_{Total}: from 2017 and 2020, the daily trend during the winter season was relatively stable with the range of EF_{Total} mean values within 10–11% from the annual average, e.g., daily range of 48 g CO_2e/kWh at the annual average of 480 g CO_2e/kWh. This is explained by a relatively stable electricity generation from wind throughout the day, which accounted for about 40% of net generation on average. During summer season, a larger temporal variability is observed: in 2020, the daily range of quarter-hourly values reached 141 g CO_2e/kWh on average. This is due to a combination of a high share of solar energy during daylight hours, replacing fossil generation, and a low share of renewables at night. In particular, wind generation was almost twice as low as in summer, while electricity consumption is only slightly lower than in winter. This requires compensation by fossil sources when solar energy is not available, resulting in higher EFs during summer nights compared to winter. As a result of an increased solar generation capacity, the daily range of mean EF_{Total} increased from 28% in 2017 to 36% in 2020 at the country level.

ΔEF_P: in this approach, the EF for the HPS consumption stage is determined by the amount of electricity consumed in this process (P) (Eq. S2 of SI). Thus, ΔEF_P is not equal to zero only when the upper water reservoir is being charged. This occurs mainly during the night hours when electricity demand is relatively low and surplus generation capacity is available, with the peak around 4 am (Fig. 9). From 2017 to 2020, the annual mean value has declined from 6.47 to 5.40 g CO_2e/kWh at the country level. The mean value of ΔEF_P during the night peak was around 16 g CO_2e/kWh in winter and 18 g CO_2e/kWh in summer. However, single quarter-hourly values, in particular during the summer season, reached up to 46 g CO_2e/kWh in 2020. TransnetBW showed the highest HPS reliance among the TSO zones, resulting in a greater ΔEF_P over the studied years. During the night peak, quarter-hourly values made up over 20% from EF_{net} on average. In particular, the mean value of ΔEF_P during the night peak reached 40.99 g CO_2e/kWh in the summer and 46.82 g CO_2e/kWh in the winter season of 2020. Moreover, statistical outliers for quarter-hourly ΔEF_P happened to be higher than EF_{net} during time intervals when pumping consumption was larger than the amount of generated electricity.

EF_l: the share of electricity consumed at the T&D stage is assumed to be equal at the country level and for each TSO zone and is determined by the amount of generated or consumed electricity according to this method. For this reason, the share of ΔEF_l from EF_{Total} is roughly identical among each TSO zone over 1 year and on the quarter-hourly level, making up around 5%. Thus, ΔEF_l generally shows the same behavior as EF_{Total}, resulting in a higher temporal variability during summer and relatively stable emissions' intensity during winter.

EF_{up}: the share of EF_{up} from EF_{Total} does not change significantly over a course of a day. Similar to the other EFs, its quarter-hourly variability is prone to seasonal changes. In the summer of 2020, the value varied approximately between 5 and 14% from EF_{net}, which corresponded to the range between ca. 20 and 34 g CO_2e/kWh. In the winter season, the upper range value shifted down to ca. 8%. In both cases, the daily maximum is achieved during the midday.

4 Discussion

In this section, the findings are first interpreted with regard to the goals of the approach and study, as well as discussed in light of energy transition (Section 4.1). Second, the results are validated at the annual resolution level through a comparison with existing publications (Section 4.2). The final section reflects on the limitations of the approach and study, while also providing recommendations for a further development (Section 4.3).

4.1 Results interpretation

The primary goal of the proposed approach is to enable time-resolved calculation of GHG emissions of consumed

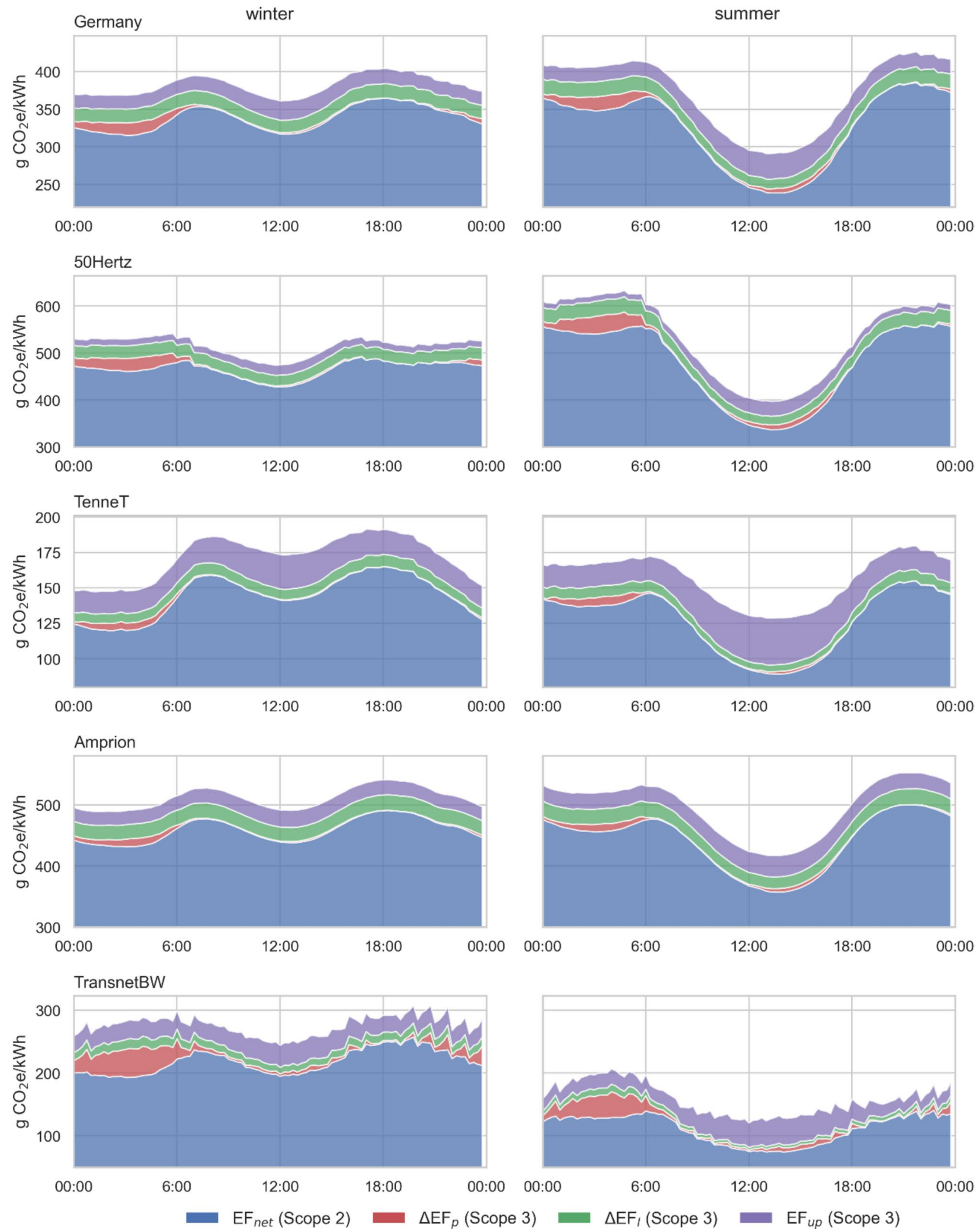


Fig. 9 Mean of quarter-hourly electricity consumption EFs divided into net generation (EF_{net}), pumping consumption (ΔEF_P), T&D losses (ΔEF_l), and upstream emissions (EF_{up}) for Germany and its TSO zones in 2020, aggregated by season. Winter season corresponds to the periods Jan–Mar and Oct–Dec, and summer season to Apr–Sep

electricity based on open access data. Additionally, this paper aims to evaluate the impact of energy transition on the temporal variability of electricity EFs on the example of Germany. For this reason, the analysis is expanded by the TSO control zones. It should be noted that the division by control zones is merely administrative, and the choice of utilized energy carriers is not geographically restricted. This explains the presence of the offshore wind power in the Amprion's grid mix, although the coastal area is not included in the physical borders of the zone. Thus, results per TSO zones provided here exclusively serve as example of energy systems with different level of RES adoption.

The results show a clear dependency between the installed capacity of intermittent energy sources and the extent of temporal variability of electricity EFs. For instance, the range of quarter-hourly values in 50Hertz zone compared to Amprion in 2020 was 1.36 times larger in the case of EF_{Total} and 2.57 times larger when considering Scope 3 emissions only (Tables S7 and S8 of SI). This can be linked to the differences in the installed capacity of intermittent energy sources, which constituted 56% and 34% of the total capacity in 50Hertz and Amprion in 2020, respectively (ENTSO-E 2022c). As a consequence, during this period, almost 40% of the 50Hertz's electricity was obtained from wind and solar, compared to 17% in the Amprion zone (Fig. 5). The temporal variability of the quarter-hourly generation mix in the 50Hertz zone was higher than in Amprion due to low-carbon energy sources dominating the grid mix in the short term, leading to larger fluctuations of the overall electricity GHG emission intensity.

Comparing temporal variability in the TenneT and TransnetBW zones raises a further question regarding the sensitivity of EF_{Total} to the share of coal-derived electricity in the grid mix. In 2020, *TransnetBW's* grid mix had a threefold greater coal-derived electricity share than *TenneT's* (Fig. 5). This possibly explains why the quarter-hourly variability of EF_{Total} in the TenneT zone was 1.8 times lower than in TransnetBW (Fig. 6). This observation, together with the annual development of *TenneT's* grid mix composition and quarter-hourly variability (Table S8), suggests that the temporal variability starts declining at a certain level of RES integration. Nevertheless, the example of TenneT as an advanced energy system shows that external factors can affect the temporal variability contrary to the expected trends, as elaborated in Section 3.1.2. Future work should identify the conditions at which fossil fuel shares can be counterbalanced by non-emitting sources by conducting a sensitivity analysis.

Stages of pumping consumption and T&D are rarely explicitly covered by electricity emission models. From 2017 to 2020, T&D losses accounted for around 7.5% of *gross* generation in Germany in total (eurostat 2022a). With an increasing reliance on RES, these processes will gain in significance for several reasons. First, an increasing share of RES in the grid mix, operating in low-voltage ranges, will cause short-term fluctuations in transmission losses (Finke 2014). This can be confirmed by the observed correlation between the quarter-hourly variability of ΔEF_l and EF_{Total} (Section 3.1.2), as well as the increasing distribution of quarter-hourly ΔEF_l values over the four years (Figure S3, b).

Second, energy storage technologies (EST) will be required to provide flexibility to the power system. Currently, HPS represents the most mature EST and makes up over 90% of the installed energy storage capacity in the EU (EC 2020). At the country level, both the annual mean ΔEF_P and the range of quarter-hourly values showed a slightly declining trend over the course of 4 years (Table S6 of SI). In 2020, the daily peak of the national ΔEF_P was almost three times lower than in the TransnetBW zone. Thus, it can be argued that the inclusion of this stage is of less importance for regions with a low reliance on HPS, such as Germany. However, ΔEF_p remained nearly constant while EF_{Total} declined by around a quarter during the 4-year period at the country level (Table S6 of SI). This means that excluding ΔEF_p will lead to a greater underestimation of electricity GHG intensity while the share of RES grows.

A possible explanation for a non-growing ΔEF_p is the fact that HPS was being operated in Germany close to its capacity limit (ENTSO-E 2022c, a). However, an additional storage capacity will be required in a long term to ensure sufficient grid flexibility. This will involve HPS expansion as well as the integration of Power-to-X technologies and stationary batteries (EC 2020). This not only underscores the importance of separate accounting for HPS-related emissions but also implies the need to potentially extend ΔEF_p to an EF incorporating all EST losses at a certain point.

4.2 Comparison to existing literature

A comparison of results to existing studies is only possible to a limited extent because of the differences in the calculation approaches, such as exclusion of electricity exchanges and choice of combustion factors databases. Nevertheless, the annual combustion emissions, consumption EFs comprising direct emissions only, as well as EF_{net} for the years 2018 and 2019 can be compared to external sources.

The results obtained in this work are slightly lower compared to the annual direct CO_2 emissions and inland consumption EFs calculated by UBA (2021), with the difference under 4% for each year (Table S9 of SI). The reason for that is an underestimation of the annual CO_2 emissions through the default energetic fuel content from IPCC (2006) instead of country-specific values as applied by

UBA (2021). Given the fact that CO_2 emissions make up 99% of the GHG emissions in the fuel combustion process, this conclusion should be plausible for the results in CO_2e.

A study by Wörner et al. (2019) provides both EF_{net} and EF_{Total} for Germany in 2017, calculated in a similar approach. While the EF_{net} is identical to the one calculated in this work, we estimate the EF_{Total} to be lower by 16% (594 vs. 498.69 g CO_2e/kWh). The reason for that cannot be determined because of the missing details on the calculation of the upstream emissions. The EF_{net} for 2018 obtained in this work lies between the values calculated by top-down and bottom-up approaches by Unnewehr et al. (2022).

The presented approach provides an advantage of deriving EFs solely based on open access data provided by ENTSO-E without relying on specific LCA databases for addressing indirect emissions, e.g., as required by methodologies by Roux et al. (2016), Kono et al. (2017), and Clauß et al. (2019). The use of non-country-specific combustion EFs enables application to many European countries. A methodological contribution addressing both of these factors was proposed by Unnewehr et al. (2022) from the generation perspective, similarly to the studies by Marrasso et al. (2019) and Braeuer et al. (2020). The suggested approach makes a step towards representing the *consumption* perspective by including energy losses along the electricity supply chain. However, it does not incorporate physical electricity exchanges, as elaborated in Section 4.3.3, contrary to existing models which consider imports but do not comply with the above-mentioned criteria (e.g., Vuarnoz and Jusselme 2018; Baumann et al. 2019). Finally, none of the known models allows a straight-forward division of temporally resolved EFs by Scopes 2 and 3. The limitations of the approach, their implications, and suggested solutions are discussed in detail in Section 4.3.

4.3 Limitations and further research needs

4.3.1 Scaling

Aggregating time-resolved ENTSO-E data on electricity generation to the annual level results in a lower value than that reported by national sources. This is not only the result of a specific German classification scheme pertaining to certain electricity generation pathways, as elaborated in Section 2.2.1, but also due to non-systematic reporting issues leading to several missing quarter-hourly data entries. To restore these data, scaling is done based on aggregated annual values reported by national sources. Thereby, a constant scaling factor for each generation type is applied without considering the actual available generation capacity during each time interval.

Scaling factors obtained at the country level are applied at the level of TSO zones without alteration. This is due to the fact that TSO zones do not report on their annual electricity generation in the Energy Balances format. As a result, the sum of aggregated annual values by zone is slightly higher than the amount of electricity generated at the country level. Nevertheless, the difference made up less than 0.1% of total net generation for each of the studied years. The highest deviation was observed for biomass in 2019, which reached 1.57%.

The underlying ENTSO-E dataset for Germany has been evaluated by Hirth et al. (2018) as one of the most complete ones available on the platform. According to our calculation, the data gap on an annual basis varied between 9 and 11% between 2017 and 2020. It is assumed that such a low amount of electricity evenly distributed by each 15-min interval over a year does not significantly impact the result. Nevertheless, further research should be conducted to validate this hypothesis.

4.3.2 Division of Scope 3 EFs by electricity supply stages

Time-resolved Scope 3 EFs in the TSO zones can be higher than that at the country level, although electricity generated in these zones sums up to the amount generated at the country level. For instance, the ranges of quarter-hourly ΔEF_P and EF_{up} values in 2020 were larger in the *TransnetBW* zone than in Germany (Fig. 8). Such a counterintuitive result can be explained by the calculation method, which implies the dependence of these factors on the share of electricity consumed by the respective processes (e.g., consumption by HPS in case of ΔEF_P) from the amount of generated (or consumed) electricity.

As an example, EF_{up} is calculated as the ratio of the upstream emissions to the amount of consumed electricity (C). Thus, EF_{up} can be lower in the zones where the absolute upstream emissions are higher, but the consumption is lower. This can be demonstrated for a particular 15-min interval when the highest EF_{up} in 2020 in TransnetBW zone was observed (21.06.2020 13:15), reaching 62.75 g CO_2e/kWh. During the same time, the absolute upstream emissions in the *Amprion* were higher by 73.6 t CO_2e, but the EF_{up} was nearly 23 g CO_2e/kWh lower than in *TransnetBW*. Thus, the results for EF_{up} in the different TSO zones cannot be compared because EF_{up} does not directly correlate with the absolute amount of upstream emissions. This limitation applies to each of the Scope 3 EFs.

Another limitation of the approach is that it does not account for emission delays through HPS. For a more realistic modeling, one should track specific time intervals for when electricity is stored in and released from HPS, respectively. Thereby, the EF during the time interval when stored electricity is released should also incorporate the emission intensity of the electricity at the point when it was consumed by HPS. The data adopted in this approach does not allow for a clear differentiation of such intervals. However, integrating emissions delay through HPS, e.g., via external modeling, would enhance the approach.

Finally, ΔEF_P and ΔEF_I cannot be applied separately from each other for estimating emissions of the corresponding processes, as they are calculated based on attributed shares of combustion emissions and are intended for use in conjunction with the Scope 2 EF (EF_{net}) to complete the consumption perspective.

4.3.3 Exclusion of electricity exchanges

Electricity imports can significantly affect the national electricity generation mix, depending on the carbon intensity of the exchanged flows (Moro and Lonza 2018; Clauß et al. 2019; Tranberg et al. 2019). To reduce uncertainties associated with modeling transboundary electricity flows, the decision to integrate electricity exchanges in the EFs should be based on the share of imported electricity in the grid mix and the GHG intensities of the exchanged flows (Ryan et al. 2016).

In the case of the German grid mix, the decision to exclude electricity exchanges can be justified by their low effect on the national EF, both on the annual level, as estimated by Moro and Lonza (2018) and UBA (2021), and at the hourly resolution (Tranberg et al. 2019). This is possibly due to the relatively low proportion of imports compared to domestic generation, and the interplay of carbon intensities of imported flows. From 2017 to 2020, the share of annually imported electricity relative to the gross generation increased from 4 to 8% (eurostat 2022a). Around 85% of 2020 imports originated from France (27%), the Netherlands (18%), Denmark (13.5%), Switzerland (15.5%), and Austria (11%) (eurostat 2022b). Thereby, only imports from the Netherlands had a slightly higher annual GHG intensity compared to Germany, with a difference declining from 51 to 19 g CO_2e/kWh from 2017 to 2020 (EEA 2022). The other four countries demonstrated significantly lower GHG intensities, reducing the average German EF on the annual basis (EEA 2022). Despite Poland's higher GHG intensity due to coal reliance, its contribution to Germany's annual import mix was around 0.1% (eurostat 2022b).

However, at a finer resolution level, the impact of these CO_2-rich inflows and of electricity exchanges overall might still be significant. For instance, time intervals with a recording high share of RES in 2020 were linked to an increase in electricity imports from countries with a lower reliance on RES compared to Germany (Halbrügge et al. 2022). Furthermore, a high hourly correlation between the GHG intensities of generated and imported electricity flows does not rule out the possibility of potential outliers during specific time intervals. Finally, an increasing amount of electricity imported to Germany suggests a reduced result precision when neglecting electricity exchanges. Therefore, integrating those exchanges, e.g., by means of flow tracing, is crucial when further developing the approach.

A major challenge in calculating time-resolved electricity EFs for exchange partners pertains to data gaps on the short-scale or when a country is not represented by ENTSO-E (e.g., Switzerland). By harmonizing the quality and temporal granularity of country-specific ENTSO-E dataset and restarting the publication of annual statistics in the form of "Statistical factsheets" (ENTSO-E 2019), effort to incorporate electricity exchanges would be significantly reduced.

4.3.4 Applicability to other countries

One of the goals of this approach is to enable the calculation of EFs for European countries in a harmonized manner. In this study, the approach was illustrated on the example of Germany, and its applicability to other countries represented by ENTSO-E has not been practically tested. Given the differences in the completeness of country-specific datasets available on that platform, it might be more challenging to fill data gaps for time-resolved intervals for countries, such as Italy, for which around half of time-resolved entries are missing (Hirth et al. 2018).

The utilization of average combustion EFs derived from IPCC (2006) allows a uniform estimation of direct emissions without aligning differing classification systems. However, it might compromise the accuracy of estimates by disregarding regional variations, such as fuel content and technological efficiency. In the case of Germany, derived annual emissions did not differ significantly from the official values (Table S9 of SI). However, it might be beneficial to validate country-specific annual combustion emissions before calculating EFs.

The influence of electricity exchanges can further limit the applicability of the approach to other countries, while electricity inflows are not incorporated in the model. As mentioned in Section 4.3.3, this might be of lesser relevance for countries in which the GHG intensity of imported flows does not differ significantly from the national generation intensity and the reliance on import is low. For instance, while this condition is met for Germany, this is not the case for Austria, where electricity imports increase the national generation intensity by nearly a factor of three (Tranberg et al. 2019).

Furthermore, the choice of interval rate (quarter-hourly, half-hourly or hourly) for calculating the EFs is limited by the granularity level provided by ENTSO-E for each country. Currently, hourly resolution represents the most frequent option, which has implications for including electricity exchanges. To ensure time-consistent EFs calculation, the granularity level of data on electricity generation and cross-border flows should be the same for each of the countries participating in exchanges. As of now, this condition can be met only at the hourly resolution and requires aggregation of sub-hourly values.

Another obstacle is that the most recent edition of “Statistical factsheets” by ENTSO-E, providing annual net generation values for scaling, dates back to 2018 (ENTSO-E 2019). Thus, an additional source after 2018 is required for each country. As evidenced by the absence of the category “Fossil coal-derived gas” in the German statistics, national inventories may use a different classification system than that used by ENTSO-E. An alignment of different classification systems for electricity generation technologies might increase uncertainty. Thus, an updated “Statistical Factsheet” series would significantly contribute to harmonized GHG emission calculation across European countries. Independent of the country-specific completeness of the ENTSO-E data, a more sophisticated solution for filling the data gaps under consideration of the actual generation capacity and daytime is required for reconstructing a realistic time series.

4.3.5 General limitations

The proposed approach is designed specifically for greenhouse gas accounting and covers direct and upstream electricity-related emissions, which implies limitations for the use of derived EFs. First, the EFs do not include emissions associated with downstream activities and thus cannot be directly used in ISO-compliant carbon footprinting for products (ISO 2018a). Nevertheless, the approach can be extended by adding a separate factor representing downstream emissions, which would complete the life cycle perspective.

Another limitation of this study and the carbon footprinting in general refers to the focus on GWP as a single impact category. The proposed approach is designed specifically for GHG accounting, which implies the potential risk of burden shifting to other impact categories, e.g., when applied for GHG mitigation strategies. Thus, the use of carbon footprint results in decision-making should involve an analysis of multiple impact categories to allow for a holistic environmental assessment and identification of trade-offs between those, as stated in ISO 14067 (2018a).

Further, the EFs calculation covers direct emissions of three GHGs (CO_2, CH_4, and N_2O), whereas the GHG Protocol Corporate Standard states that all gases listed in the Kyoto Protocol should be included (WRI and WBCSD 2004; WRI 2011). This is due to the adoption of the IPCC combustion factors (IPCC 2006), which are limited to these three gases for combustion activities, but allow a consistent calculation of direct emissions for any country.

Finally, the underlying data for the performed analysis could be impacted by economic or climatic conditions, potentially leading to biases in observed trends. These impacts were accounted for by using net generation data instead of installed capacity for deriving EFs. The trend evaluation links the changes in EFs with the changes in the amount of renewable energy having been generated in reality, independent of what caused these changes. Mentioned impacts are therefore believed to be of low significance if not stated otherwise.

5 Conclusion

Integration of RES in energy systems can lead to increased temporal variability in electricity GHG emissions when combining renewable and fossil energy sources during the intermediate stage of energy transition. A higher temporal resolution in electricity emissions accounting, along with the inclusion of indirect emissions and consumption perspective, can enable more accurate estimates of electricity-related environmental impacts. We provide a novel approach for estimating GHG emissions of electricity consumption at a quarter-hourly resolution level following the life cycle perspective and using open access data, with ENTSO-E as a foundation. The approach allows for a division of time-resolved electricity EFs into direct (Scope 2) and upstream (Scope 3) emissions.

The results emphasize the importance of including upstream emissions as well as the intermediate steps between generation and supply to the end-consumer, despite their low share at the annual resolution level. As long as energy sources with vastly different GHG emission intensities are present in a grid mix, it should be expected that electricity EFs will exhibit high temporal variability. Hence, the importance of increasing temporal resolution in electricity emissions accounting remains especially relevant as long as fossil fuels contribute to electricity generation.

The next step should focus on the practical implementation of the approach to other countries, as well as integrating time-resolved electricity exchanges to complete the consumption perspective. Harmonizing the reporting scheme to ENTSO-E among the countries and relaunching annual statistics would facilitate the approach’s application and reduce its uncertainties.

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Data availability The data that support the findings of this study are included in the Supplementary Information. Further, the Python code used to generate the complete datasets and figures, as well as input files, is available on GitHub (https://github.com/darblz/time-resolved_GHG_EFs).

Declarations

Conflict of interest The authors declare no competing interests.

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