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A near-real time daily European Power Consumption and Carbon Intensity Dataset (ECON-PowerCI)

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We present a near-real-time daily European Consumption-based Power Carbon Intensity Dataset (ECON-PowerCI), developed from the CarbonMonitor power production dataset for Europe. Spanning from January 2015 to December 2024, the dataset encompasses 35 European countries, with daily updates and a one-day latency. ECON-PowerCI provides consumption-based power carbon intensity at the national level, accounting for cross-border electricity net imports in the country of consumption. By integrating ENTSO-E (The European Network of Transmission System Operators for Electricity) data, ECON-PowerCI enables comprehensive analysis of carbon intensity trends shaped by cross-border transmissions, extreme weather events, and disruptions like the COVID-19 pandemic and geopolitical conflicts. This dataset facilitates in-depth study of the effect of cross-border electricity flows on national carbon footprints, providing insights for energy policy and climate resilience. The dataset also holds extensive research potential for power-related analyses and policy-making in Europe's interconnected power systems.

Background & Summary

Energy has emerged as a pivotal concern for European nations, engaged in phasing out coal and fossil fuels while facing geopolitical challenges such as higher gas prices since the war in Ukraine[1,2]. The region grapples with the dual challenges of maintaining energy security and adapting to the climate change that intensifies power demand while simultaneously affecting generation capacities[3]. Extreme events such as winter storms, heatwaves, drought exacerbate this dilemma with extreme cold temperature spiking the heating demand and potentially reducing the wind power generation due to the frozen turbines[4]. Conversely, extreme heat can amplify cooling demand, and may limit the operational efficiency of thermal power plants and solar photovoltaics[5–7]. Droughts can decrease the hydroelectric generation[8,9]. This critical issue is further complicated by societal upheavals — illustrated by fluctuating fuel costs and supply disruptions since the war between Russia and Ukraine—and behavioural shifts during global health crises like COVID-19 pandemic, prompting abrupt shifts in energy systems[10,11].

Developing high temporal resolution datasets for monitoring of power production and consumption is crucial for timely tracking of the security, resilience and sustainability of the European power system[12]. Previous datasets, with lower latency and coarse temporal resolution, falter in capturing the immediacy of power systems response to climate change and socioeconomic events[13–15]. The CarbonMonitor-Power database provides near-real-time daily and hourly power generation data, including total generation, source attribution and the carbon intensity of power generated[16]. It has been used in previous studies to understand the variations from

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daily periodical activities, weekends, seasonal cycles, regular and irregular events (i.e., holidays) and extreme events (e.g., COVID-19 pandemic, extreme hot/cold days)[3,17,18].

Nonetheless, with active cross-border power transmission between European countries, power generation is not in balance with power consumption at country scale[19]. According to the latest data from ENTSO-E (The European Network of Transmission System Operators for Electricity), the annual mean percentage of imported power relative to total power generation across 35 European countries ranges from 7.9% to 538.0%. Similarly, the annual mean exported power ratio to the total power generations varies from 0.48% to 157.1%. Cross-border electricity transmission extend beyond market regulated electricity sales costs; it also advances the pursuit of a more resilient, interconnected system capable of withstanding extreme events[20,21]. Numerous studies substantiate the premise that regional integration of power systems can be strengthened in the face of heatwaves, winter storms, droughts[22–24] during which the demand in an affected region can increase and requires more supply from inter-connected regions. Transmission within an interconnected network can serve as a mitigating solution, particularly when the surging demand outstrips available generations. For instance, reduced wind and solar resources in Great Britain could necessitate substantial power imports from France[25]. Conversely, when renewable power generations exceed demand within Germany, the surplus energy can be exported to the interconnected neighboring countries[26–28]. The expansive interconnected grid spanning Europe suggests that a comprehensive understanding of power dynamics requires data both on the power generated and the power consumed, the latter being not covered by the current CarbonMonitor-Power-Europe data.

To fill this gap, we developed the Carbon Transport and Equilibrium Model for European Electricity generation-transportation-consumption network as depicted in Fig. 1 to expand the CarbonMonitor-Power-Europe database by including cross-border transmission and power consumption. The expanded dataset provides country-level consumption-based power carbon intensity and power consumption data, with near-real-time update capacities and a latency of just one day. This significant enhancement enables us to attribute carbon emissions associated with power transmitted through interconnected power grids across European country borders. This updated database enhances our understanding of the environmental impact on Europe's power sector, alongside a more precise allocation of responsibility for carbon emissions associated with power consumption within each country.

Methods

Data acquisition. We compiled a dataset from 35 countries within the pan-European domain from ENTSO-E (https://transparency.entsoe.eu/). ENTSO-E encompasses nation-level actual electricity generation delineated by production type, observed electrical loads, cross-border electricity exchanges, and aggregated data on hydraulic reservoirs and pumped storage facilities. The 35 countries are Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Ireland, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Moldova, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. The raw data are collected at the highest temporal resolution —15-minute or 30-minute intervals, hourly, daily, or weekly intervals — depending on source availability.

Data preprocessing. Given noise, outliers and missing values in the raw data, the data filtering procedure follows a standard approach as described in Zhu *et al.*[16], summarized as follows: Firstly, we use the density-based clustering algorithm (DBSCAN) to filter out noise[29]. Secondly, manual processing was applied to evaluate whether abnormal values should be removed or retained. Some extreme values that coincide with periods marked by significant social disruptions (such as COVID-19 lockdowns) or natural disasters (like extreme hot/cold events and storms) are retained because these events have a real and abrupt effect on the power system. Finally, we filled the missing values with linear interpolation. We provided a quality flag ('Filtered' (F) for filled values and 'Normal' (N) for original values) to indicate the status of the values during the filling process. The proportion of "F" labelled data is 0.39% for generation, 1.75% for consumption, and 0.03% for cross-border transmission.

Table 1 presents the data statistics before and after preprocessing. This table details, for each country and each data type, the number and percentage of data points that were filtered out (due to missing values or outliers) as well as the number and percentage of data points that were imputed (filled in).

Consumption carbon intensity calculation. This section outlines the calculation of consumption-based power carbon intensity (as shown in Fig. 1). The development of the dataset involves four key steps. All the abbreviations have been summarized in Table 2.

Step 1: Calculating of the Country-Level Daily Carbon Intensity of Electricity Production

For each country, the daily carbon intensity of electricity production (CO_2 emission per unit of electricity generated) is calculated based on Eq. (1)[30]. The raw data includes 20 types of electricity production, grouped into 8 categories: coal, gas, oil, nuclear, hydro, wind, solar and other.

$$CI_{G,c} = \frac{\sum_{\alpha} G_{c,\alpha} Ef_{\alpha,c}}{\sum_{\alpha} G_{c,\alpha}} \tag{1}$$

$Ef_{\alpha,c}$ indicates the carbon emissions per MWh of electricity generated and varies based on the type of generation, natural resources, and technological levels in different countries. In this study, we adopt the carbon emission factors computed in previous research[16], which have been summarized in the Table 3. The fuel-specific

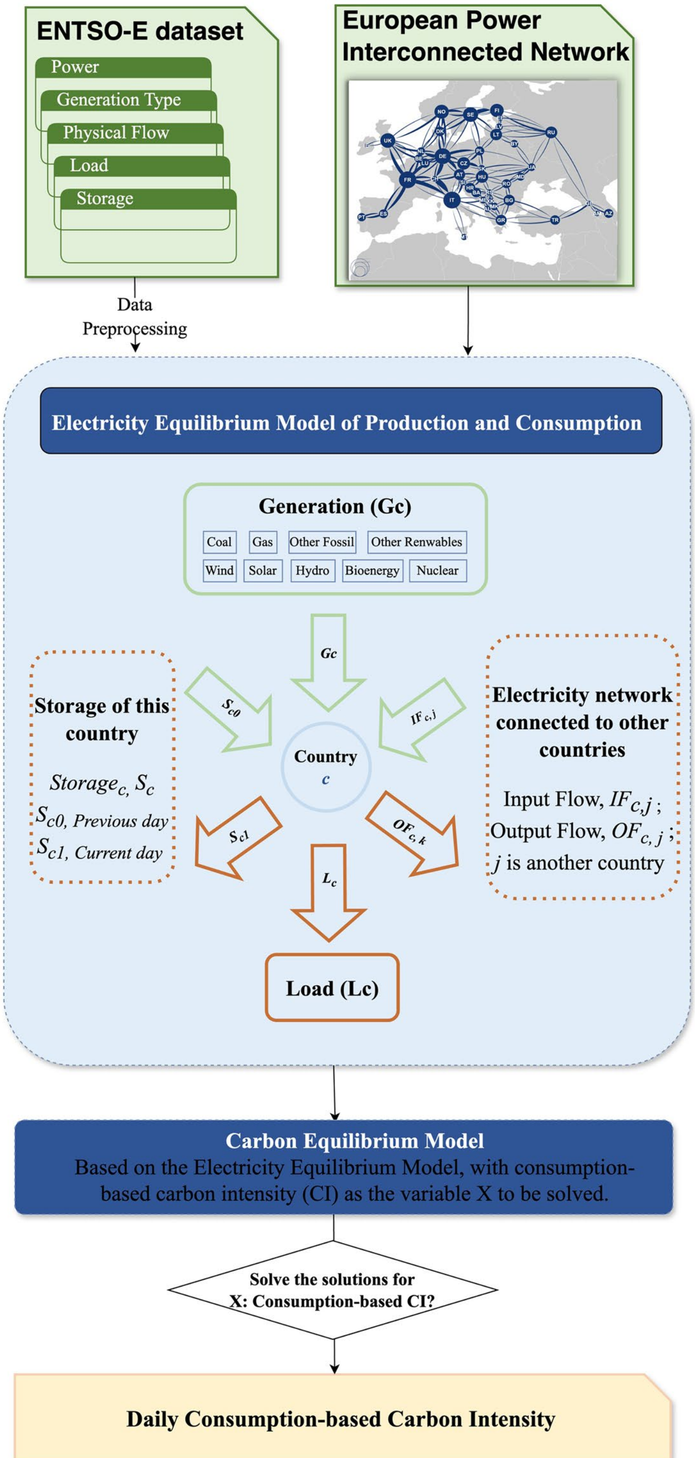

Fig. 1 Data acquisition and processing framework. Hourly updated data on power generation types, physical electricity flows between countries (imports & exports), load, and storage from the ENTSO-E website are downloaded and preprocessed. These data are used as inputs for the electricity equilibrium and carbon equilibrium models to produce a near-real-time, daily consumption-based power carbon intensity dataset for each country in the European power interconnected network (Methods).

emission factors are calculated as corrected emission factors based on IPCC emission factors corrected to baseline value (same baseline value applied in the first CarbonMonitor power emission dataset[31], with the following equation:

Country	Generation		Consumption		Transmission	
	Count	Percentage	Count	Percentage	Count	Percentage
Austria	7	0.19%	3	0.08%	10	0.05%
Belgium	8	0.22%	0	0.00%	0	0.00%
Bosnia and Herz.	12	0.33%	14	0.49%	0	0.00%
Bulgaria	7	0.19%	5	0.14%	0	0.00%
Croatia	21	0.57%	11	0.30%	5	0.03%
Czech Republic	22	0.60%	3	0.08%	11	0.08%
Denmark	4	0.11%	2	0.05%	0	0.00%
Estonia	10	0.27%	5	0.14%	5	0.05%
Finland	4	0.11%	3	0.08%	17	0.12%
France	14	0.38%	9	0.25%	1	0.00%
Georgia	1	0.03%	39	3.56%	0	0.00%
Germany	21	0.57%	3	0.08%	1	0.00%
Greece	15	0.41%	1	0.03%	4	0.02%
Hungary	18	0.49%	1	0.03%	11	0.04%
Ireland	11	0.30%	397	10.87%	0	0.00%
Italy	1	0.03%	5	0.14%	22	0.09%
Kosovo	4	0.11%	11	0.30%	0	0.00%
Latvia	18	0.49%	7	0.19%	9	0.08%
Lithuania	8	0.22%	9	0.25%	7	0.04%
Luxembourg	11	0.30%	9	0.25%	8	0.11%
Moldova	14	0.38%	358	19.93%	2	0.03%
Montenegro	1	0.03%	13	0.36%	5	0.03%
Netherlands	15	0.41%	4	0.11%	0	0.00%
North Macedonia	7	0.22%	132	3.61%	10	0.07%
Norway	39	1.07%	2	0.05%	0	0.00%
Poland	17	0.47%	4	0.11%	8	0.04%
Portugal	4	0.11%	11	0.30%	0	0.00%
Romania	5	0.14%	8	0.22%	5	0.03%
Serbia	59	1.62%	48	1.31%	3	0.01%
Slovakia	9	0.25%	1	0.03%	5	0.03%
Slovenia	7	0.19%	12	0.33%	3	0.02%
Spain	2	0.05%	3	0.08%	0	0.00%
Sweden	12	0.33%	3	0.08%	0	0.00%
Switzerland	3	0.08%	6	0.16%	1	0.01%
United Kingdom	20	0.55%	577	15.80%	0	0.00%

Table 1. Summary of Filtered and Imputed Data Points by Country and Data Type.

$$EF_{i,j}^{*} = EF_{j}^{IPCC} \times \frac{Emis_{i}^{2019-baseline}}{\sum(AD_{i,j}^{2019} \times EF_{j}^{IPCC})} \tag{2}$$

where $EF_{i,j}^{*}$ is the corrected emission factor used in this study, for country i and for fuel j. EF_{j}^{IPCC} is the IPCC emission factor for fuel j, $Emis_{i}^{2019-baseline}$ is the reference baseline total power emissions from country i in the year 2019. $AD_{i,j}^{2019}$ is the electricity generation for country i, fuel j in the year 2019.

Step 2: Develop an Energy Balance Model for Production and Consumption

According to the methods in a previous approach[17], we assume that electricity production and consumption for any given country c on any given day are balanced, as described in Eq. (3). The electricity equilibrium model applies to countries with available data on electricity generation, consumption, imports, and exports. Note that Eq. (3) includes no loss term, as the ENTSO-E Transparency Platform already accounts for transmission losses in each country's electricity consumption.

$$G_c + \sum_{i=1}^{m} I_{c,i} + S_{c,0} = L_c + \sum_{i=1}^{m} E_{c,i} + S_{c,1} \tag{3}$$

Here, G_c, $I_{c,i}$, L_c and $E_{c,i}$ are directly sourced from ENTSO-E, while $S_{c,0}$ and $S_{c,1}$ are estimated using weekly reservoir filling rates (MWh) from ENTSO-E, interpolated to daily resolution. m represents the total number countries that have electricity imports or exports with the specified country c. This is based on the dominance of

Abbreviations	Full name	Unit
c	Any given country.	
α	The different energy sources, here, Coal, Natural gas, Nuclear, Oil, Solar, Hydro, Wind, Other.	
G_c	The total electricity generation of country c on any given day.	MWh
$G_{c,\alpha}$	The electricity generation for α in country c.	MWh
$Ef_{\alpha,c}$	The carbon emission factor for type α in country c.	kg CO_2/MWh
$CI_{G,c}$	The production-based carbon intensity of electricity for country c.	kg CO_2/MWh
i	A set of all countries that engage in electricity cross-border transmission (imports or exports) with country c.	
$I_{c,i}$	The electricity imported by country c from country i on any given day.	MWh
$E_{c,i}$	The electricity exported by country c to country i on any given day.	MWh
$S_{c,0}$	The electricity reserve of country c before the start of the given day.	MWh
$S_{c,1}$	The electricity reserve of country c at the end of the given day.	MWh
L_c	The electricity consumption of country c on any given day.	MWh
$CI_{S,c,0}$	The carbon intensity of storage electricity for country c before the start of the given day.	kg CO_2/MWh
$CI_{L,c}$	The consumption-based carbon intensity of electricity for country c.	kg CO_2/MWh
$CI_{E,c}$	The carbon intensity of electricity exported by country c to other countries.	kg CO_2/MWh
$CI_{S,c,1}$	The carbon intensity of storage electricity for country c at the end of the given day.	kg CO_2/MWh

Table 2. List of Abbreviations.

Pumped Hydro Energy Storage (PHES), which accounts for 95–97% of global storage capacity and 99% of total energy storage[32,33].

Step 3: Develop a Carbon Intensity Balance Model for Production and Consumption

Building on the electricity equilibrium model in Eq. (3), we further constructed a model for the carbon intensity of production and consumption for each eligible country c.

$$G_c CI_{G,c} + \sum_{i=1}^{m} I_{c,i} CI_{L,i} + S_{c,0} CI_{S,c,0} = L_c CI_{L,c} + \sum_{i=1}^{m} E_{c,i} CI_{E,c} + S_{c,1} CI_{S,c,1} \tag{4}$$

Here, $CI_{G,c}$ denotes the generation-based carbon intensity of electricity for country c, while $CI_{L,c}$, $CI_{E,c}$, $CI_{S,c}$, and $CI_{S,c,1}$ represent the consumption-based carbon intensity, the carbon intensity of exported electricity, the carbon intensity of stored electricity before the start of the day, and the carbon intensity of stored electricity after the end of the day, respectively. The value of $CI_{G,c}$ is calculated based on Eq. (1).

We assume that, for a given country c, the consumption-based carbon intensity ($CI_{L,c}$) is equal to both the carbon intensity of exported electricity ($CI_{E,c}$) and the post-storage carbon intensity at the end of the day ($CI_{S,c,1}$). That is,

$$CI_{L,c} = CI_{E,c} = CI_{S,c,1} \tag{5}$$

Under this assumption, $CI_{L,c}$ (or equivalently $CI_{E,c}$ and $CI_{S,c,1}$) can be factored out from the right-hand side of Eq. (3), allowing the equation to be simplified into Eq. (6). The values of $CI_{L,c}$, $CI_{E,c}$, $CI_{S,c}$, and $CI_{S,c,1}$ are estimated by fitting Eq. (6) with publicly available energy flow and generation data from ENTSO-E.

$$\left(L_c + \sum_{i=1}^{m} E_{c,i} + S_{c,1}\right) CI_{L,c} - \sum_{i=1}^{m} I_{c,i} CI_{L,i} = G_c CI_{G,c} + S_{c,0} CI_{S,c,0} \tag{6}$$

Given that the carbon intensities of electricity consumption ($CI_{L,c}$), exported electricity ($CI_{E,c}$) and new electricity storage ($CI_{S,c}$) are identical values on any given day for any country c in the European interconnected power network (Fig. 1), we can express Eq. (6) in matrix form:

$$X = BA^{-1} \tag{7}$$

Where:

X denotes the unknown consumption carbon intensity of each country c.

$A \in R^{\mathrm{m}}$ *are defined as*:

$$b_j = G_j \cdot CI_{G,j} + S_{j,0} \cdot CI_{S,j,0}$$

$A \in R^{\mathrm{m}\times\mathrm{m}}$ *are defined as*:

Country	Coal	Gas	Oil	Hydro	Nuclear	Wind	Solar	Other renewables
Austria	820	1385	700	0	0	0	0	0
Belgium	820	777	700	0	0	0	0	0
Bosnia and Herz.	820	490	700	0	0	0	0	0
Bulgaria	1093	653	700	0	0	0	0	0
Croatia	990	591	700	0	0	0	0	0
Czech Republic	1309	782	1038	0	0	0	0	0
Denmark	1272	760	1008	0	0	0	0	0
Estonia	2758	1648	2186	0	0	0	0	0
Finland	1407	840	1115	0	0	0	0	0
France	1164	695	922	0	0	0	0	0
Georgia	820	490	700	0	0	0	0	0
Germany	1285	768	1018	0	0	0	0	0
Greece	1111	664	700	0	0	0	0	0
Hungary	1275	762	700	0	0	0	0	0
Ireland	948	566	752	0	0	0	0	0
Italy	1025	613	813	0	0	0	0	0
Kosovo	820	490	700	0	0	0	0	0
Latvia	820	677	700	0	0	0	0	0
Lithuania	820	3839	5093	0	0	0	0	0
Luxembourg	820	490	700	0	0	0	0	0
Moldova	820	490	700	0	0	0	0	0
Montenegro	820	490	700	0	0	0	0	0
Netherlands	1009	603	700	0	0	0	0	0
Norway	820	830	700	0	0	0	0	0
North Macedonia	820	490	700	0	0	0	0	0
Poland	1150	687	911	0	0	0	0	0
Portugal	885	529	700	0	0	0	0	0
Romania	1229	734	700	0	0	0	0	0
Serbia	820	490	700	0	0	0	0	0
Slovakia	1937	1157	1535	0	0	0	0	0
Slovenia	1072	640	700	0	0	0	0	0
Spain	965	577	765	0	0	0	0	0
Sweden	820	490	700	0	0	0	0	0
Switzerland	820	490	700	0	0	0	0	0
United Kingdom	1028	614	814	0	0	0	0	0

Table 3. Summary of Emission Factors of Each Country (in kg CO_2/MWh).

$$a_{j,k}=\begin{cases} L_j+\sum_{n=1}^{i}E_{k,j}+S_{k,1}, & j=k\\ -I_{j,k}, & j\neq k\end{cases}$$

j,*k* are the row and column indices in the matrix and then represent the corresponding country.

Solving Eq. (7) yields the daily consumption-based power carbon intensity for each European country ($CI_{L,c}$).

Calculation example: spain, france, portugal and italy on a hypothetical day. To clarify the calculation procedure, we provide a step-by-step example for Spain, France, Italy, and Portugal on a specific day. For simplicity, we assume a hypothetical interconnected power system that includes only these four countries. While real-world systems may involve more complex interconnections, this simplification does not affect the structure or logic of the calculation process described below.

1. Hypothetical Data Table

Suppose the following values (all energy units in MWh, carbon intensity in kg CO_2/MWh):

Country	Spain (ES)	France (FR)	Portugal (PT)	Italy (IT)
Generation (G)	10,000	12,000	5,000	8,000
Consumption (L)	11,000	10,500	5,500	8,500
Import (I) from others	PT → ES: 300 FR → ES: 1,000 IT → ES: 400	ES → FR: 1,100 PT → FR: 200 IT → FR: 700	ES → PT: 200 FR → PT: 900 PT → IT: 250	ES → IT:500 FR → IT: 600 PT → IT: 150
Export (E) to others	ES → PT: 200 ES → FR: 1,100 ES → IT: 500	FR → ES: 1,000 FR → PT: 900 FR → IT: 600	PT → ES: 300 PT → FR: 200 PT → IT: 150	IT → ES:400 IT → FR: 700 IT → PT: 250
Storage at Start (S_0))	500	400	300	600
Storage at End (S_1)	600	500	350	700
Generation CI (CI_G)	250	100	400	350
Initial Storage CI ($CI_{S,c,0}$)	270	120	410	340

2. Constructing the Matrix

EquationFor each country c:

$$\left(L_c + \sum_{i=1}^{m} E_{c,i} + S_{c,1}\right) CI_{L,c} - \sum_{i=1}^{m} I_{c,i} CI_{L,i} = G_c CI_{G,c} + S_{c,0} CI_{S,c,0}$$

Assembled for all four countries, this leads to a matrix formulation:

$$AX = B$$

where X is the vector of unknown consumption-based carbon intensities (specifically, $CI_{L,c}$ and $CI_{L,i}$. Matrix A captures the relationships among countries in the interconnected power system, including each country's electricity load (L_c), total electricity exports to other countries ($\sum_{i=1}^{m} E_{c,i}$), electricity storage at the end of the day ($S_{c,1}$), and electricity imports from other countries ($I_{j,k}$). Vector B represents the carbon emissions associated with both electricity generation and initially stored electricity, calculated as the products of electricity quantities and their respective carbon intensities.

The structures of matrix A and vector B are illustrated as follows:

2.1. Matrix A

Diagonal elements ($j = k$):

$$a_{j,j} = L_j + \sum E_{j,i} + S_{j,1}$$

Off-diagonal elements ($j \neq k$):

$$a_{j,k} = -I_{j,k}$$

In this case, they should be calculated and then get results as below.

- A(ES,ES): 11,000 + (200 + 1,100 + 500) + 600 = 13,400 (Total electricity consumption in Spain including load, export and storage.)
- A(ES,FR): −1,000 (FR → ES)
- A(ES,PT): −300 (PT → ES)
- A(ES,IT): −400 (IT → ES)
- A(FR,ES): −1,100 (ES → FR)
- A(FR,FR): 10,500 + (1,000 + 900 + 600) + 500 = 13,500 (Total electricity consumption in France including load, export and storage.)
- A(FR,PT): −200 (PT → FR)
- A(FR,IT): −700 (IT → FR)
- A(PT,ES): −200 (ES → PT)
- A(PT,FR): −900 (FR → PT)
- A(PT,PT): 5,500 + (300 + 200 + 150) + 350 = 6,500 (Total electricity consumption in Portugal including load, export and storage.)
- A(PT,IT): −250(IT → PT)
- A(IT,ES): −500(ES → IT)
- A(IT,FR): −600(FR → IT)
- A(IT,PT): −150(PT → IT)
- A(IT,IT): 8,500 + (400 + 700 + 250) + 700 = 10,550 (Total electricity consumption in Italy including load, export and storage).

	ES	FR	PT	IT
ES	13,400	−1,000	−300	−400
FR	−1,100	13,500	−200	−700
PT	−200	−900	6,500	−250
IT	−500	−600	−150	10,550

$$A = \begin{bmatrix} 13400 & -1,000 & -300 & -400 \\ -1,100 & 13,500 & -200 & -700 \\ -200 & -900 & 6500 & -250 \\ -500 & -600 & -150 & 10550 \end{bmatrix}$$

2.2. Vector B

$$b_j = G_j \cdot CI_{G,j} + S_{j,0} \cdot CI_{S,j,0}$$

- ES: $10,000 \times 250 + 500 \times 270 = 2,635,000$
- FR: $12,000 \times 100 + 400 \times 120 = 1,248,000$
- PT: $5,000 \times 400 + 300 \times 410 = 2,123,000$
- IT: $8,000 \times 350 + 600 \times 340 = 3,004,000$

$$B = \begin{bmatrix} 2,635,000 \\ 1,248,000 \\ 2,123,000 \\ 3,004,000 \end{bmatrix}$$

3. Solving for Consumption-Based Carbon Intensities

The matrix equation:

$$\begin{bmatrix} 13400 & -1,000 & -300 & -400 \\ -1,100 & 13500 & -200 & -700 \\ -200 & -900 & 6500 & -250 \\ -500 & -600 & -150 & 10550 \end{bmatrix} \begin{bmatrix} CI_{L,ES} \\ CI_{L,FR} \\ CI_{L,PT} \\ CI_{L,IT} \end{bmatrix} = \begin{bmatrix} 2,635,000 \\ 1,248,000 \\ 2,123,000 \\ 3,004,000 \end{bmatrix}$$

Solving the matrix equation yields the consumption-based carbon intensity for each country.

4. Result Interpretation

- Spain's consumption-based carbon intensity: ~223 kg CO_2/MWh
- France's consumption-based carbon intensity: ~132 kg CO_2/MWh
- Portugal's consumption-based carbon intensity: ~363 kg CO_2/MWh
- Italy's consumption-based carbon intensity: ~308 kg CO_2/MWh

In summary, Spain, Portugal and Italy show lower consumption-based carbon intensities compared to their generation-based values, while France shows higher values. This example demonstrates how the model accounts for electricity cross-border transmission, generation mix, and storage, and enables the calculation of country-specific, consumption-based carbon intensities on a daily basis.

Data Records

The dataset has been deposited to Zenodo[34] (https://doi.org/10.5281/zenodo.15987717). The dataset covers 3,653 days (from January 1, 2015, to December 31, 2024) for 35 countries. It contains a total of 113,247 records, each representing the daily consumption-based power carbon intensity (measured in kg CO_2/MWh) at the country level. Timestamps enable temporal identification by servers.

We provide a quality flag in the "FLAG" column to indicate the status of each value during the data filling process: "Normal" (N) for original values and "Filtered" (F) for filled values.

Due to limitations in the availability of original data, several countries exhibit gaps during certain time periods. We have listed the available data periods for these countries in Table 4. For simplicity, countries with complete data coverage from 2015.01.01 to 2024.12.31 are not listed in the table.

Technical Validation

This section presents an uncertainty quantifications, correlation analysis with the reference dataset, and a comparative analysis of our consumption-based carbon intensity dataset with the production-based carbon intensity dataset. We also examine the seasonality, interannual trends, variability, of consumption-based carbon intensity from ECO-PowerCI. In addition, we assess the robustness of the ECON-PowerCI dataset in capturing abrupt changes in carbon intensity during extreme weather events and geopolitical incidents.

Country	Start Date	Latest Date
Bosnia and Herz.	2017.03.01	2024.12.31
Croatia	2019.01.01	2024.12.31
Georgia	2022.01.01	2024.12.31
Italy	2016.01.01	2024.12.31
Kosovo	2021.09.01	2024.12.31
Luxembourg	2021.06.01	2024.12.31
Moldova	2020.02.01	2024.12.31
North Macedonia	2016.06.01	2024.12.31
Serbia	2017.01.01	2024.12.31
United Kingdom	2015.01.01	2021.05.31

Table 4. Data Availability Periods for Countries with Incomplete Coverage in the ECON-PowerCI Dataset.

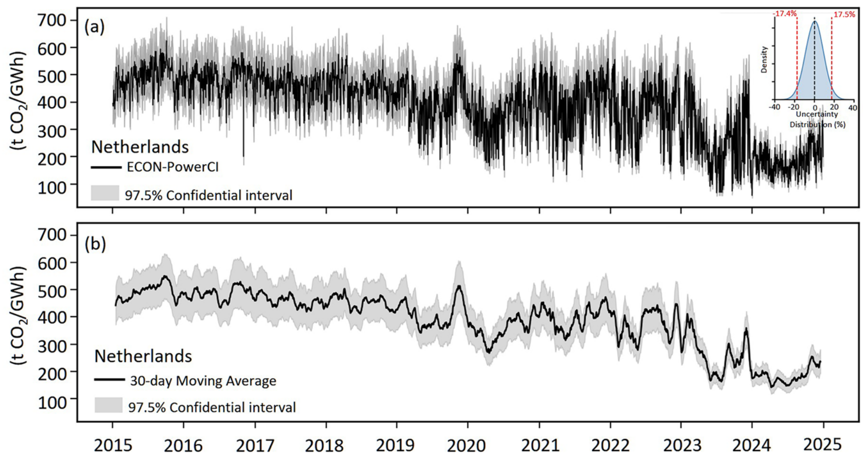

Fig. 2 Uncertainty characterization of the ECON-PowerCI dataset for the Netherlands. (**a**) Shows the daily temporal distribution of relative uncertainty, while (**b**) displays its 30-day moving average. The solid lines represent the original ECON-PowerCI consumption-based carbon intensity estimates; shaded regions denote the 97.5% confidence intervals. The inset plot presents the frequency distribution of relative uncertainty across the time series.

Uncertainties. To validate the reliability and accuracy of our dataset, comparative analysis with existing reference datasets is essential. However, publicly available datasets for consumption-based power carbon intensities calculations remain limited, especially those with comprehensive temporal and spatial coverage across European countries. Given this constraint, we conduct an uncertainty analysis based on Monte Carlo simulations.

The uncertainty of our dataset arises from various sources. According to the IPCC[35], potential sources of uncertainty include activity data, emission factors, data completeness, data availability, and measurement errors. Some of these uncertainties, such as measurement errors — whether random or systematic — are not quantifiable[36]. These may stem from inaccuracies in measurement, recording, transmission, or from approximated constants and parameters obtained from external sources[35], and are present throughout the carbon accounting process.

In this study, we focus on the uncertainty introduced by activity data, specifically electricity generation, which represents the most quantifiable uncertainty in ECON-PowerCI dataset. Electricity generation is one of the most important drivers of uncertainty in both emissions and carbon intensity estimations.

We applied Monte Carlo simulation, which is a technique recommended by the IPCC[35] to propagate the uncertainties from activity data and emission factors. The technique first assumes distributions (probability density function) for variable under consideration. In our study, we assume that electricity generation is the primary source of uncertainty and model it using a normal distribution[37]. The mean of its distribution is derived from actual generation data, while the standard deviation is defined by the coefficient of variation (CV) set at 10%. We then generate 100,000 random samples of electricity generation, resulting in 100,000 independent estimations of emissions[36]. These simulations yield a distribution of estimated consumption-based carbon intensity values for each country. From this distribution, key statistics such as the mean and confidence intervals are derived. Specifically, the 97.5% uncertainty range is calculated as the 97.5% confidence interval of the 100,000 simulated estimates, reflecting uncertainty in electricity generation and providing a credible range within which the true carbon intensity is likely to fall.

For illustration, Fig. 2 shows the 97.5% confidence interval (shaded in gray) for Netherlands. To isolate the uncertainty of each country, we simulate its uncertainty while holding other countries' data constant.

Country-specific results indicate that the 97.5% confidence intervals of consumption-based carbon intensity are, for example, as follows: Austria (−4.7% to +5.6%), Belgium (−16.0% to +16.2%), Bulgaria (−4.1% to +4.4%), Czech Republic (−17.3% to +17.3%), Denmark (−16.8% to +16.9%), Finland (−6.5% to +7.6%), France (−9.4% to +9.8%), Germany (−19.2% to +19.2%), Hungary (−12.6% to + 13.2%), Latvia (−7.9% to +8.5%), Lithuania (−10.3% to+10.4%), and the Netherlands (−17.4% to +17.5%).

Comparisons with reference data. We compared our dataset with a reference database (consumption-based carbon intensity provided by Electricity Map (https://www.electricitymap.org)) over the overlapping period from 2017 to 2024. The reference dataset uses a flow-tracing methodology[38] to track the origin of electricity, primarily based on the ENTSO-E database, which is consistent with the data source used in ECON-PowerCI. Previous studies using Electricity Map data have demonstrated its reliability[39,40]. Overall, the results show that our data generally agree well with the reference dataset at both annual and monthly scales (Fig. 3). For the multi-year average consumption-based carbon intensity, the ECON-PowerCI database shows good agreement with the reference dataset for most countries ($R^2 = 0.78$). For multi-monthly averages, there is also strong consistency, with R^2 values ranging from 0.76 to 0.85, and most countries distributed closely along the 1:1 line. The inter-annual variability (as indicated by the error bars) further demonstrates that the agreement between the two datasets remains within a reasonable and acceptable range (Fig. 3). These results indicate that, in aggregate terms, the consumption-based carbon intensities provided by ECON-PowerCI are broadly consistent with the reference dataset.

However, two countries, Montenegro and Estonia, show notably higher values in ECON-PowerCI compared to the reference. This discrepancy mainly stems from differences in the emission factor calculations used for these countries. For coal, gas, and oil in EU countries, Electricity Map applies a thermal power plant-level matching approach, directly linking verified emissions with actual generation, which enables more transparent and higher-resolution carbon intensity signal[41]. ECON-PowerCI applies emission factors of 820, 490, and 700 kg CO_2/MWh (coal, gas, oil) for Montenegro and 2758, 1648, and 2186 for Estonia, whereas Electricity Map reports 820, 490, and 650 for Montenegro, and significantly lower values of 1097, 530, and 885 for Estonia. This highlights that ECON-PowerCI could potentially benefit from incorporating more precise plant-level emission factors and country-specific power system efficiencies.

Flow-tracing methodology (as implemented by Electricity Maps) provides a physically detailed attribution of carbon intensity by tracing electricity flows from each generator to consumer zones across the transmission network[42]. This method can even account for loop-flows and regional imports/exports, capturing the actual electricity mix available in each region. In contrast, our methodology adopts a more data-parsimonious, pragmatic framework that avoids the need for granular mapping of generation sources to flows or complex grid simulations. This simplification improves computational efficiency and transparency, making it especially suitable for near-real-time scientific and policy-oriented analyses. Moreover, in alignment with the mission of the Carbon Monitor platform—an international initiative providing the first science-based, regularly updated daily CO_2 emission estimates—our dataset is fully open and comprehensively documented, significantly improving reproducibility and utility over existing tools like Electricity Maps.

Comparisons of daily production-based and consumption-based power carbon intensities. Our near-real-time daily carbon intensity dataset for electricity consumption can be used for analyzing daily and seasonal dynamics of consumption-based carbon intensity across various countries. Typically, consumption-based power carbon intensity, which accounts for cross-border electricity exchanges, differs from production-based carbon intensity, which considers only domestic power generation (Fig. 4). These differences can be attributed to varying socio-economic factors and active cross-border transmissions.

For instance, Italy exhibits lower consumption-based power carbon intensity due to its substantial imports of less carbon intensive electricity from France (accounting for an annual average ratio of 7.5%) and Switzerland (0%)[43]. Hereafter, percentages are annual averages. Despite fossil fuels accounting for around 41.88% of Italy's electricity production, its consumption-based power carbon intensity is mitigated by these cleaner energy imports. On the other hand, France, despite having a low carbon domestic electricity generation profile—with only 7.5% derived from fossil fuels—displays a higher consumption-based power carbon intensity than production-based carbon intensity. France exports significant clean electricity to the United Kingdom, Spain, Germany, Italy, and other countries while also importing electricity from neighboring countries, many of which are more reliant on fossil fuels (62.0%, 68.9%, 89.1%, 32.8%, 43.4%, 56.2% power generated from fossil fuels for interconnected UK, ES, LU, BE, DE, IT, respectively). This results in a slight increase in France's consumption-based power carbon intensity, with an annual mean rise of 5 t CO_2/GWh (Fig. 4). Germany, with a relatively high reliance on fossil fuels for electricity production, imports nuclear power from France. As a major electricity exporter within the EU, Germany's consumption-based power carbon intensity is lower than its production-based intensity. Similarly, Spain's consumption-based power carbon intensity is reduced compared to its production-based intensity, partly due to its significant electricity imports from France's clean energy sources[44]. Meanwhile, Poland (85.7% of power generated from fossil fuels), which relies heavily on fossil fuels generated electricity, generally shows a lower consumption-based power carbon intensity after taking lower carbon cross-border power transmissions into consideration. The annual mean differences between production-based and consumption-based power carbon intensities underscore the impact of interconnected cross-border transmissions.

These comparisons illustrate the critical differences between consumption-based and production-based power carbon intensities, highlighting the significance of cross-border electricity exchanges. By factoring in these exchanges, we can more accurately assess the carbon intensity of electricity consumed within each country,

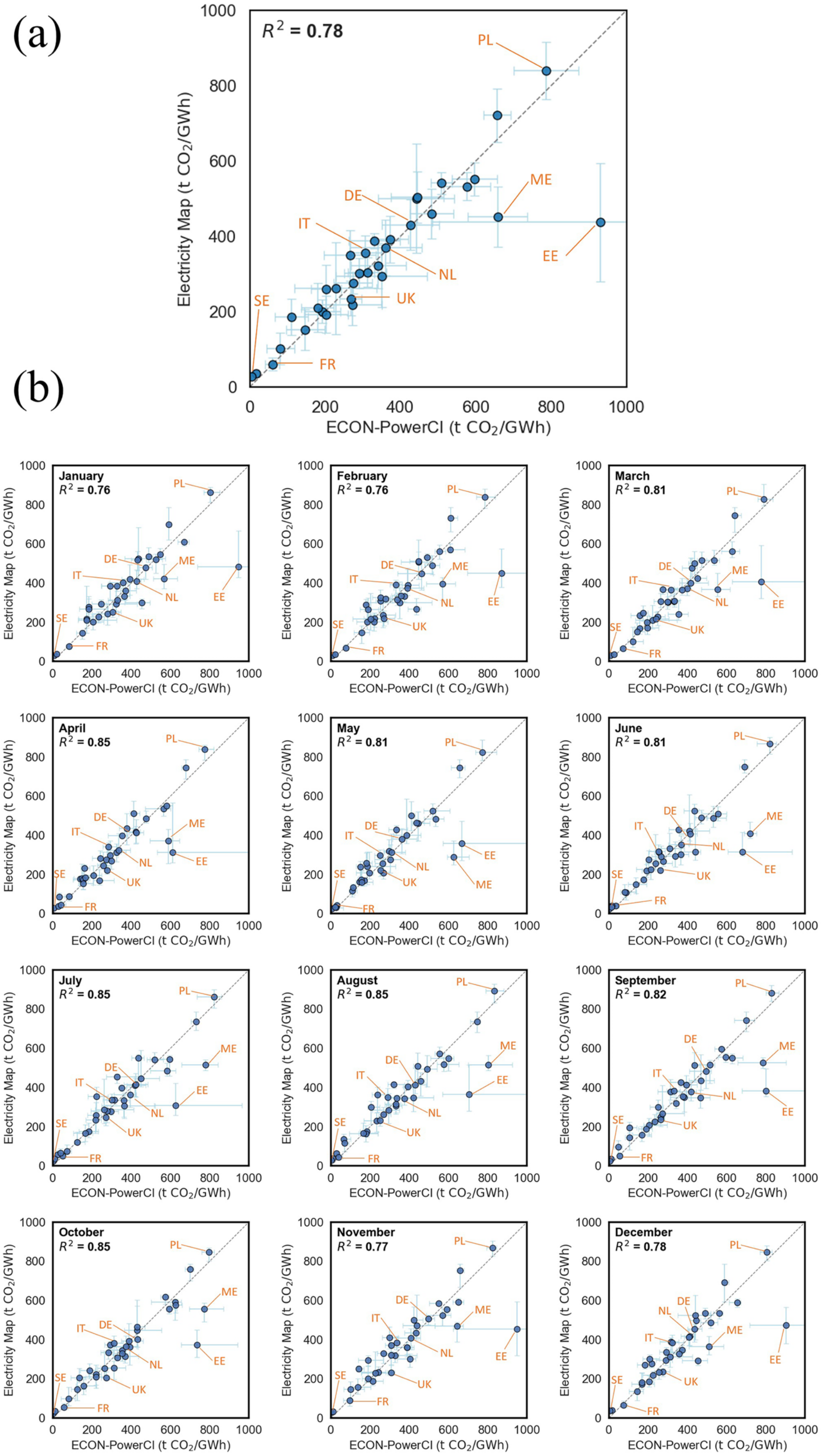

Fig. 3 Comparisons with reference data. This figure presents a comparison between ECON-PowerCI and the reference dataset (consumption-based carbon intensity from Electricity Map.This figure presents a comparison between ECON-PowerCI and the reference dataset (consumption-based carbon intensity from Electricity Map. Panel (**a**) shows the multi-yearly averages, while Panel (**b**) displays the multi-monthly averages. Horizontal and vertical error bars indicate the standard deviations for ECON-PowerCI and Electricity Map, respectively, for the period 2017–2023. For clarity, not all labels are displayed to avoid overlapping.

revealing the interconnected nature of Europe's power systems and the influence of imports and exports on national carbon footprints.

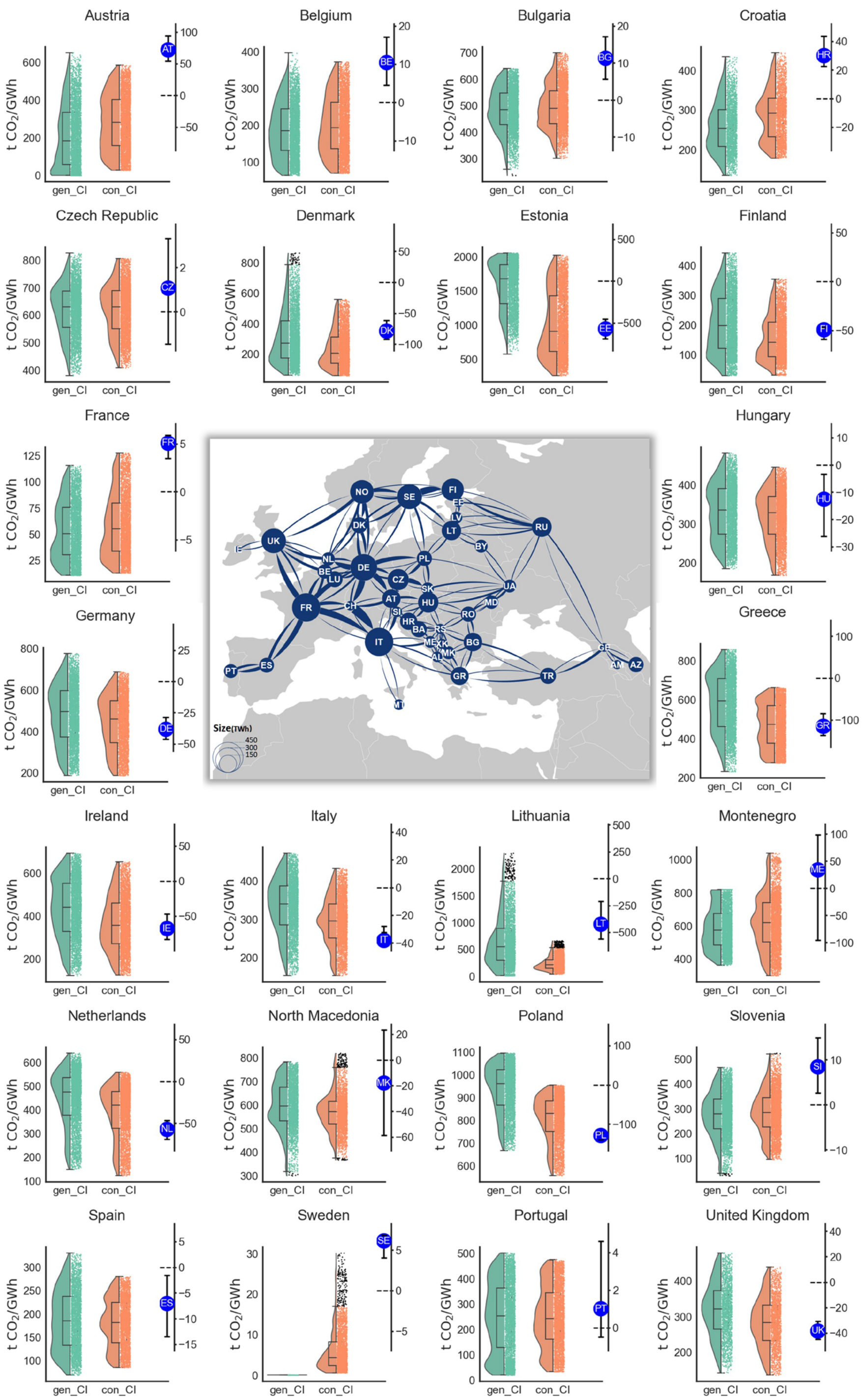

Fig. 4 Consumption-based Power Carbon Intensity for European Countries. This figure illustrates the interconnected power network within European countries. The arrows and lines indicate the average import or export of electricity during the period from 2015 to 2023. The size of each marker reflects the annual average of import and export for each country. The thicker end of each arrow denotes the exporting country, while the thinner end points to the importing country. All arrows are unidirectional, showing the direction of cross-border electricity flow from exporter to importer. Surrounding the map, boxplots compare the production-based carbon intensity (gen_CI) with the consumption-based power carbon intensity (con_CI) for selected European countries. In each boxplot, the central line shows the median value, the box edges mark the 25th and 75th percentiles (interquartile range, IQR) and the whiskers extend to 1.5 times the IQR. Individual data points are displayed as dots, while the probability density distribution is shown alongside each boxplot for reference. Data points beyond the whiskers are classified as outliers (black dots). The inset plots highlight the annual mean difference between consumption-based and production-based power carbon intensities (con_CI minus gen_CI), shown as a blue dot with the country abbreviation. The upper and lower whiskers represent the range from the 25th to the 75th percentile. These inset plots emphasize the impact of cross-border electricity transfers on carbon intensity, illustrating the tendency after accounting for these cross-border power transmission.

Limitations. One limitation of the ECON-PowerCI is its daily temporal resolution, which may overlook important sub-daily dynamics in electricity systems. Electricity generation, consumption, and cross-border flows exhibit substantial intraday variability. For example, surplus renewable electricity, particularly from solar PV, is often exported during midday hours when solar output peak[28]. Conversely, evening peak demand periods may coincide with increased reliance on fossil-fuel-based generation[45]. These intraday dynamics are not captured in the present daily consumption-based carbon intensity estimates. If an hourly-resolution dataset is developed, it will enable a more detailed characterization of short-term variations in consumption-based carbon intensity and provide deeper insights into diurnal energy and carbon flow patterns.

Another limitation lies in the use of fixed emission factors for thermal power generation. While this choice ensures consistency with previous Carbon Monitor products, it does not account for variations in power plant operations, technology vintages, or fuel quality across countries and over time. For instance, emission factors may change during ramping events due to declining thermal efficiency and differ across plants with varying technologies and ages in each country. Additionally, the carbon content and combustion efficiency of fuels, such as coal, natural gas, and oil, can vary significantly by country, depending on sourcing practices and regulatory standards[46].

If dynamic and country-specific emission factors that better reflect operational and technological differences are incorporated, it will be possible to include plant-level characteristics, fuel composition data, and load-dependent efficiency curves where available.

The dataset does not incorporate dynamic and country-specific emission factors that capture operational and technological heterogeneity. Specifically, information on plant-level characteristics, fuel composition data, and load-dependent efficiency curves is not included. The absence of these factors may limit the accuracy of emission estimates for individual plants or regions where such variations are substantial.

Furthermore, while this dataset currently focuses solely on CO_2 emissions, we acknowledge that other emission species—such as methane (CH_4), nitrous oxides (N_2O), sulfur dioxide (SO_2), and particulate matter (PM)—are also important contributors to climate change and air pollution.

Data availability

The dataset has been deposited to Zenodo[34] (https://doi.org/10.5281/zenodo.15987717).

Code availability

The codes for producing the datasets are available publicly from: https://doi.org/10.5281/zenodo.16934373.

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Author contributions

W.Z., B.Z. and G.Q. designed the study. S.Z., W.Z. and B.Z. designed the methods. S.Z. and W.Z. conducted the main data processing and model developments. W.Z. and S.Z. led the writing with input from all co-authors. All authors contributed to the conception and design of the research, including algorithm developments, data interpretation and quality control. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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