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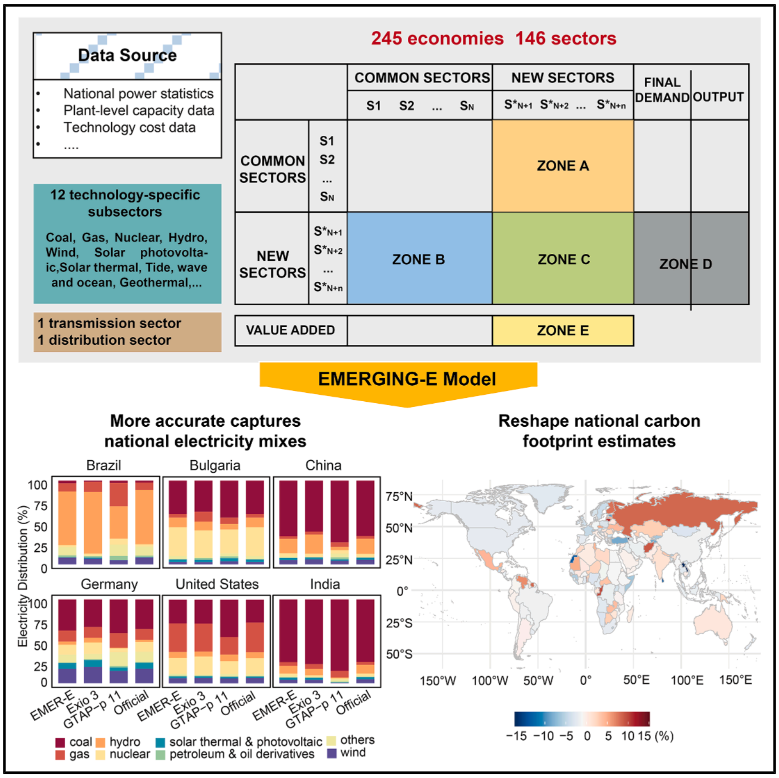
EMERGING-E: A global multi-regional input-output model with renewable electricity disaggregation

Graphical abstract



Highlights

- We establish EMERGING-E, a multi-regional input-output model disaggregating electricity
- EMERGING-E better captures national electricity mixes than existing databases
- Electricity disaggregation shifts national carbon footprints by up to ±15%
- EMERGING-E advances clean energy transition assessment across global supply chains

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In brief

Electricity generation drives fossil fuel use and CO_2 emissions across global supply chains, yet existing MRIO databases misrepresent power systems. We present EMERGING-E, a global MRIO covering 146 sectors and 245 economies, with technology-specific electricity disaggregation that better captures national power mixes and improves analysis of clean energy transitions worldwide.

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EMERGING-E: A global multi-regional input-output model with renewable electricity disaggregation

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SCIENCE FOR SOCIETY Multi-regional input-output (MRIO) models are a key tool for examining socioeconomic activity and environmental impacts across global supply chains. Because electricity generation accounts for a large share of fossil fuel use and CO_2 emissions, a more detailed representation of electricity is essential for analyzing changes in electricity generation structure and the role of renewable technologies. Here, we develop EMERGING-E, an MRIO model covering 146 sectors and 245 economies that separates electricity into one transmission sector, one distribution sector, and 12 technology-specific generation subsectors. Compared with the existing electricity-disaggregated MRIO databases, EXIOBASE 3 and GTAP-Power 11, EMERGING-E more closely reproduces officially reported national electricity mixes. Our results show that EXIOBASE 3 and GTAP-Power 11 tend to overestimate fossil-fuel-based generation, especially coal and gas, while also misrepresenting renewable sources such as hydropower and wind. Electricity is a fundamental input across supply chains, so misrepresenting its structure can affect assessments of socioeconomic and environmental impacts across the entire supply chain. Accounting with EMERGING-E shows that electricity disaggregation shifts national consumption-based carbon footprints by up to ±15%, increasing in some fossil-intensive economies and decreasing in cleaner-energy economies. EMERGING-E therefore provides a more robust and transparent basis for sustainability assessment and for energy and climate governance.

SUMMARY

Multi-regional input-output (MRIO) models trace socioeconomic and environmental performance along complex global supply chains. However, the electricity sector, a major source of fossil fuel consumption and CO_2 emissions, remains insufficiently disaggregated in MRIO databases, hindering assessment of power generation structural change and renewable technology reforms, especially in emerging economies. Here, we establish EMERGING-E, an MRIO model covering 146 sectors across 245 economies, which disaggregates the electricity sector into one transmission sector, one distribution sector, and twelve technology-specific subsectors. Validation against officially reported country-level power generation mixes reveals that EXIOBASE 3 and GTAP-Power 11 tend to overestimate fossil-fuel-based generation (particularly gas and coal) and misrepresent renewables such as hydropower and wind power. By contrast, EMERGING-E aligns closely with official data, improving the accuracy of national electricity generation structures. EMERGING-E enables robust, transparent, and science-based assessments of energy transitions to help guide effective energy and climate governance across global supply chains.

INTRODUCTION

The multi-regional input-output (MRIO) database is a crucial tool for analyzing the complex interactions and impacts of resource use and environmental consequences within global supply chains.[1] The MRIO table reveals the economic and technological links between sectors in different regions, which allows researchers to trace the flow of resources and emissions across different regions and sectors, providing a comprehensive picture of global production and consumption patterns.[2] One of the most critical sectors within this framework is electricity production, which is responsible for a significant portion of global fossil fuel consumption and CO_2 emissions. Specifically, electricity production accounts for 32% of total fossil fuel use and 41% of energy-related CO_2 emissions.[3] This substantial impact underscores the importance of understanding and optimizing the electricity sector's role within the global supply chain to mitigate environmental consequences.

According to data from the International Energy Agency (IEA), if global fossil fuel power generation could achieve the current best efficiency levels (as determined by technical feasibility), there could be substantial energy savings and emission reductions.[4] Coal-fired power generation, in particular, has the most significant potential, with each percentage point increase capable of reducing CO_2 emissions by many millions of tonnes over a unit's operational lifetime.[5] Electricity generation from fossil energy sources remains the largest contributor to global greenhouse gas emissions, especially in emerging economies.[6] Nearly 40% of the world's primary energy is consumed for power production, with coal still accounting for approximately 40% of global electricity generation.[7] The expansion of clean technologies, such as photovoltaic (PV) power generation, will help reduce the direct greenhouse gas emissions from the power sector.[8] Due to economic interactions in the global market, this transformation of the power structure will not only influence domestic socioeconomic development but also drive indirect energy consumption and greenhouse gas emissions across non-energy sectors worldwide.[9] Therefore, it is evident that accurately representing the supply relationships of the electricity sector and the various power generation technologies in the MRIO model is crucial. Such accurate representation is essential for understanding the implications of power generation structures for national carbon reduction strategies and clean technology reforms.[10]

Among existing MRIO databases, only EXIOBASE and GTAP-Power disaggregate the electricity sector based on generation technologies, using different methods. EXIOBASE separates power generation from utilities and breaks it down into technologies such as coal, gas, hydro, wind, and solar. It relies on a combination of supply-use tables, life cycle inventory databases, and energy data from models such as GEM-E3 to construct generic coefficients, which are then adjusted to generate country-specific input structures accounting for fuel substitution and co-production effects.[11,12] On the other hand, GTAP-Power follows a cost-driven bottom-up approach within the GTAP-computable general equilibrium (CGE) modeling framework. It disaggregates electricity output into base-load and peak-load technologies, using micro-level data on fuel use, capital costs, and operation and maintenance (O&M) expenses to derive levelized input costs.[13] Updates in GTAP-Power 11 further incorporate transmission and distribution cost data and extend the scope to include heat generation for 80 countries.[14,15] Both methods depend on assumptions and parameters derived from associated CGE models (e.g., GEM-E3 and GTAP), which are often unavailable in emerging economies, making them less suitable for disaggregating the electricity sector in the EMERGING MRIO model.

To accurately capture the evolution of the electricity sector and evaluate the potential of different technologies, here we adopted the advanced disaggregation approach proposed by Sören Linder[16] to disaggregate the electricity sector in the EMERGING MRIO model, creating the EMERGING-E MRIO model. This model divides the electricity sector into one transmission sector, one distribution sector, and 12 subsectors representing different power plant technologies (such as subcritical coal, hydro, etc.). We analyze the electricity generation mix across 9 specific economies using the EMERGING-E MRIO, EXIOBASE 3, and GTAP-Power 11 databases and validate the results by comparing them with each country's officially reported electricity mix. We also investigate differences in carbon accounting across the three databases by comparing CO_2 emission intensities of different electricity generation types and the associated production- and consumption-based carbon emission structures across these 9 economies. To evaluate the effects of electricity sector disaggregation, we compare national and sectoral consumption-based emissions between the EMERGING-E and the original EMERGING MRIO models in 2018 (see more details on validation method and comparative results in Notes S1–S4 and Figures S1–S4). Furthermore, to further quantify uncertainty in the EMERGING-E model and in consumption-based environmental footprints derived from it, we conduct a two-stage uncertainty assessment. We first apply a Monte Carlo framework to assess uncertainty in key parameters underlying the EMERGING-E electricity disaggregation, reporting 95% confidence intervals for fossil fuel generation shares and consumption-based value added across 245 economies (see more details in Note S5). We then perform an analytical uncertainty propagation analysis for 2018 consumption-based carbon footprints to attribute total uncertainty to emission intensities, the Leontief inverse matrix, and final demand (see more details in Note S6).

RESULTS

Method summary

The EMERGING model builds on the foundational principles of comprehensive coverage and timely updates.[17] It utilizes economic data from 245 nations, with a special focus on emerging economies, and employs a modular approach to compile MRIO tables. To further enhance its capabilities, the EMERGING-E model includes a new module specifically for electricity disaggregation, providing detailed insights into power generation and distribution. We divide the MRIO table compilation process into ten modules (see breakdown below) and adopt corresponding compilation procedures according to the data source and the economy. The methods and standards for the first eight modules—excluding the electricity and validation modules—are consistent with those established in our previous EMERGING model (for detailed methodology, see the EMERGING methodology paper[17]). Figure 1 shows the main framework of the EMERGING-E MRIO tables compilation.

Initially, we gather essential data, including bilateral trade information, macroeconomic indicators such as input-output (IO) data, and details on sectoral output and value added, collectively referred to as the data module. The trade module is the core of developing a detailed time series of MRIO tables, enriched with high-resolution regional data and annually updated bilateral

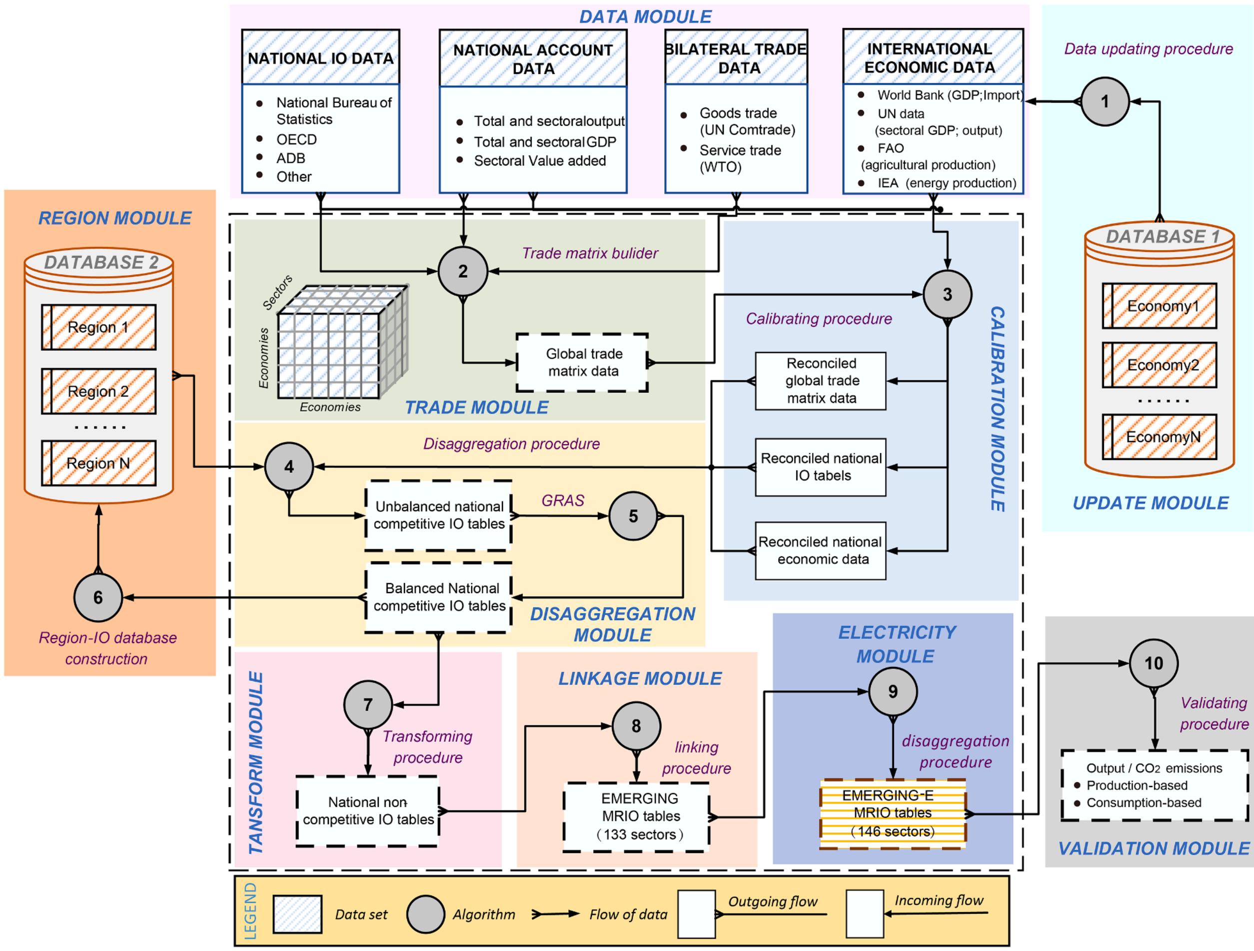

Figure 1. Framework of EMERGING-E model

The EMERGING-E model is built using a modular framework comprising ten modules. The electricity disaggregation approach is implemented in the electricity module, and validation is carried out in the validation module.

trade data for both exports and imports. We utilize this module to forge economic linkages between countries, creating a three-dimensional matrix that encompasses 245 economies and 133 sectors annually. For the reconciliation module, we gather original economic data from multiple sources, each with unique statistical properties, to maximize the utilization of each country's statistics. Before compiling this information, we employ World Bank data to standardize and reconcile diverse raw economic data across different economies. In the disaggregation module, we utilize the trade matrix created in the trade module, which includes detailed bilateral trade flows, to construct national competitive input-output tables (IOTs) consistent across 133 sectors. Where complete IO data are unavailable, we estimate regional IOTs using weighted averages of national IOTs from the same region, which are then refined in the disaggregation module using the regional IOTs as a basis.

Following this, the transformation module converts competitive IOTs into national non-competitive IOTs for each economy. These are then integrated into a comprehensive MRIO table via the linkage module. Next is the electricity module; we use this module to further divide the electricity sector into 14 electricity-related subsectors (see more disaggregation details in the methods).

The final step involves validating the EMERGING-E MRIO tables through the validation module, where we assess the share structure of electricity sectors' output and compare it against other databases to evaluate their precision and comparability. For individual and timely updates of data for specific economies, the initially collected raw data are stored in database 1. For newly released economic data not present in database 1, we update this database and revise the existing MRIO tables through the update module.

The electricity sector classification in EMERGING-E adopts the classification standard of EXIOBASE 3, which is divided into a total of 14 electricity sectors (see Table 1). This can also match the IEA's power-type classification, which includes 1 transmission, 1 distribution sector, and 12 subsectors representing different types of technology in power plants (subcritical coal, hydro, etc.). The 245 economies and 146 sectors of EMERGING-E MRIO are listed in Tables S1 and S2. A detailed description of the methods for splitting the electricity sector within the electricity module in EMERGING-E is shown in the methods section.

Table 1. Electricity sector classification in EMERGING-E

Code	Sector
97	production of electricity by coal
98	production of electricity by gas
99	production of electricity by nuclear
100	production of electricity by hydro
101	production of electricity by wind
102	production of electricity by petroleum and other oil derivatives
103	production of electricity by biomass and waste
104	production of electricity by solar photovoltaic
105	production of electricity by solar thermal
106	production of electricity by tide, wave, ocean
107	production of electricity by geothermal
108	production of electricity nec
109	transmission of electricity
110	distribution and trade of electricity

Resource description

To disaggregate the electricity sector and construct EMERGING-E, multiple data sources were integrated. Annual electricity output by generation technology was collected from the IEA,[18] while transmission and distribution investment shares were obtained from the Energy Information Administration,[19] Eurostat,[20] IEA, World Bank,[21] and national energy agencies. Levelized cost of electricity generation (LCOE) data were sourced from the IEA,[22] supplemented by public energy investment data from the International Renewable Energy Agency[23] when necessary. Data on a mix of the regional installed capacity of point-source power plants were derived from the World Electric Power Plants (WEPP) database. Original input-output data were taken from the EMERGING MRIO database.[17] Detailed information on data sources can be seen in the methods section.

Technical validation

To verify the accuracy of the electricity sector structure in the EMERGING-E database, we compared the 2018 electricity sector output structure for 9 specific economies: three developed economies with their own regional industrial structure data (the United States, Japan, and the United Kingdom), three emerging economies with such data (China, Brazil, and Bulgaria), and three economies without their own regional data (Hungary, Germany, and India). For each economy, we compared the 2018 electricity sector output structure derived from EMERGING-E MRIO (2018), EXIOBASE 3 v.3.9.5 (2018), and GTAP-Power 11 (2017) against official national statistics based on actual generation mixes published by relevant energy authorities (see Table S3). To ensure comparability and remove the influence of inflation, all monetary values were converted to constant 2015 prices using producer price indices (PPIs) based on seven price categories from the UN National Accounts Main Aggregates Database.[24]

Overall, the results show that both EXIOBASE 3 and GTAP-Power 11 tend to overestimate fossil-fuel-based generation, particularly gas and coal (see Figure 2). EXIOBASE 3 overstates gas shares in economies such as Bulgaria and Japan, while GTAP-Power 11 significantly overestimates coal use in China and India. Both databases also show inconsistencies in representing renewables—for instance, EXIOBASE 3 overestimates hydro in Brazil, while GTAP-Power 11 underestimates wind in Brazil and Germany. In contrast, EMERGING-E closely matches official statistics and provides a balanced representation of national electricity mixes across all nine economies examined, including those with and without their own regional electricity data, highlighting its robustness and broad applicability.

In Brazil, official data show that hydropower accounts for approximately 64.7% of the electricity mix. GTAP-Power 11 significantly underestimates this share, reporting just 38.5%, while overestimating natural gas at 27.9% compared to the official 9.0%. EXIOBASE 3, by contrast, overstates hydropower at 73.5%. EMERGING-E closely aligns with the official figures, accurately reflecting both the dominant role of hydropower and the contribution of gas.

In Bulgaria, official statistics indicate that coal and nuclear power each contribute around 39.8% and 34.4% to the national electricity mix, respectively. GTAP-Power 11 overestimates the role of coal, assigning it nearly 44.2%, while underestimating hydro at just 6.5% compared to the official 11.6%. EXIOBASE 3, on the other hand, inflates the share of gas to 11.7%, despite official data placing it below 4.3%. EMERGING-E offers a more balanced and accurate representation, closely mirroring the actual shares of coal, nuclear, and renewables in Bulgaria's power structure.

In China, official statistics confirm that coal remains the primary energy source, accounting for 66.2% of total electricity generation. However, GTAP-Power 11 overestimates coal, reporting it at 73.8%, while significantly underestimating hydro energy, reporting it at just 3.8% compared to the official 18.2%. EXIOBASE 3 also misrepresents China's energy mix, particularly by overreporting the hydro share at 22.8%. In contrast, EMERGING-E aligns well with the official data, accurately reflecting the dominance of coal while maintaining a balanced representation of renewables.

In Germany, official data show that coal and gas contribute around 35.4% and 12.9% of the electricity mix, respectively, while renewables, mainly wind, account for over 17.2%. GTAP-Power 11 overestimates coal at 40.4% and underrepresents wind at 14.6%. EXIOBASE 3 overstates hydro at 5.6% compared to the official 2.6%. EMERGING-E closely aligns with the official mix, accurately reflecting Germany's strong reliance on renewables.

In Hungary, official data indicate that nuclear energy dominates the electricity mix at 49.1%, followed by gas at 22.7%. GTAP-Power 11 underestimates nuclear at 32.9% and overestimates gas at 27.9%. EXIOBASE 3 also significantly inflates gas to 33.6%, about 50% higher than the official figure. In contrast, EMERGING-E provides a balanced representation, closely matching the official shares of nuclear and gas in Hungary's electricity mix.

In India, official data show that coal dominates the electricity mix at 74.5%, while gas and hydropower contribute 3.6% and 10.5%, respectively. GTAP-Power 11 overestimates coal's

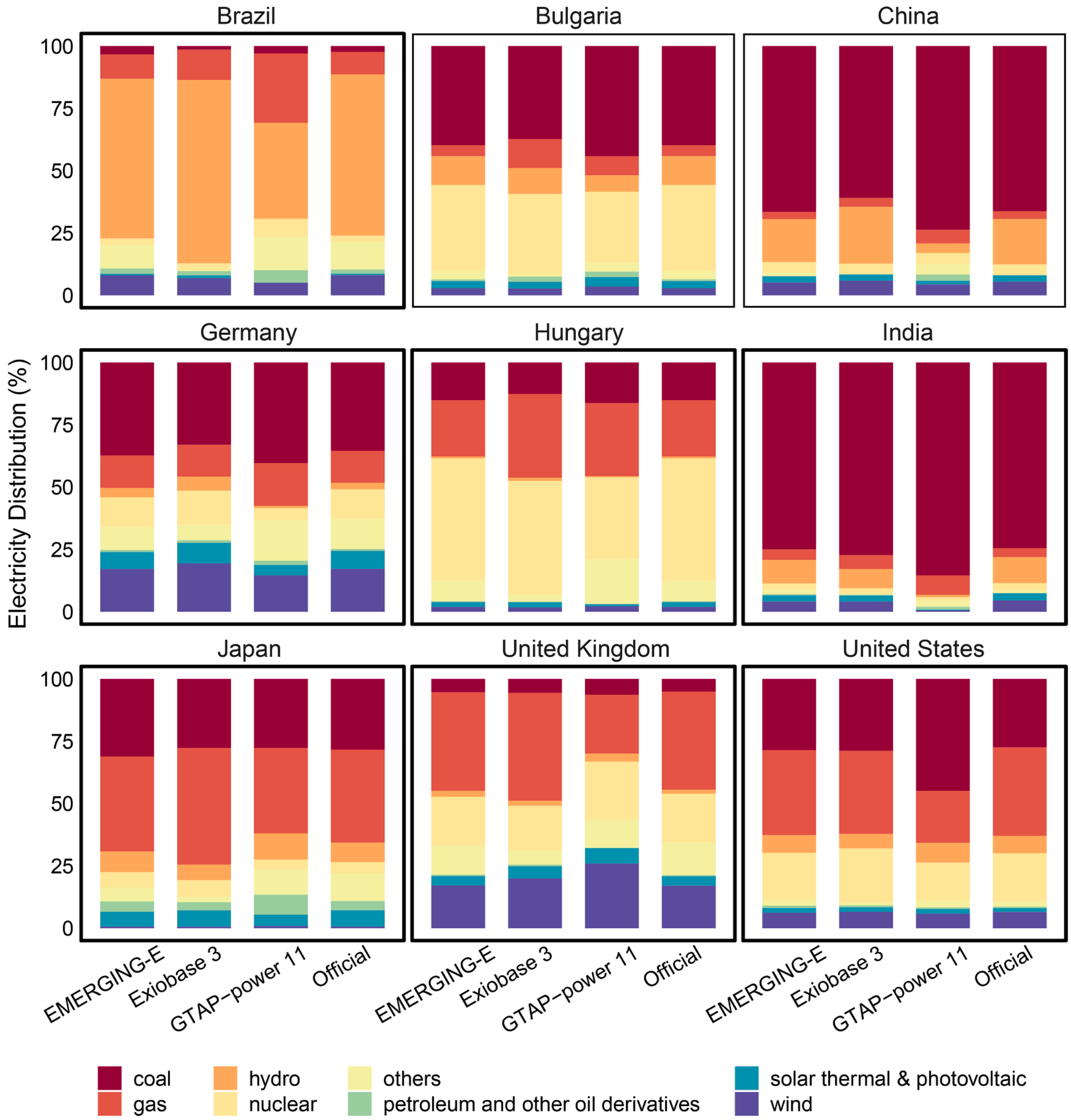

Figure 2. Electricity generation mix comparison for nine selected economies in 2018 between three MRIO databases' official statistics
Electricity generation mixes in 2018 are shown for Brazil, Bulgaria, China, Germany, Hungary, India, Japan, the United Kingdom, and the United States. Each image compares EMERGING-E, EXIOBASE 3, and GTAP-Power 11 with official statistics. Stacked bars indicate the percentage share of each generation technology in total electricity output, with colors representing different generation technologies.

share at 85.4% and also overstates the role of gas, assigning it 7.9%. EXIOBASE 3 similarly inflates gas to 5.7%. Both databases underestimate wind energy, and GTAP-Power 11 severely underrepresents hydropower at just 0.9%. In contrast, EMERGING-E closely aligns with official data, accurately capturing India's coal-heavy mix and the growing contribution of renewables.

In Japan, official data show that gas and coal account for 37.4% and 28.3% of the electricity mix, respectively, with nuclear at 4.7% and the remainder from renewables such as hydropower, wind, and solar. EXIOBASE 3 notably overestimates both nuclear (6.8%) and gas (46.8%) while underrepresenting renewables. GTAP-Power 11 also inflates petroleum-based generation at 7.9%, compared to the official 3.7%. In contrast, EMERGING-E closely aligns with the official mix, accurately capturing Japan's balanced and transitional electricity structure.

In the United Kingdom, the official electricity mix reflects a significant shift toward gas (39.4%) and renewables, with wind power contributing nearly 17.1% and coal reduced to below 5.0%. However, GTAP-Power 11 underestimates gas's presence, assigning it around 23.5%, and overstates wind power at 25.9%. EXIOBASE 3 also overestimates wind energy's share, placing it at 20.0%. EMERGING-E provides a closer match to the official statistics.

In the United States, official data show that natural gas dominates with a 35.5% share, followed by coal at 27.5%, then nuclear at 19.3%. GTAP-Power 11 overstates coal's contribution, placing it at 44.9%, while underestimating the share of gas at 20.9%. EXIOBASE 3 slightly overstates hydropower at 7.9% compared to the official 7.0% and underrepresents gas at 33.4%. EMERGING-E captures the primary energy sources well and also reflects the structure of renewable energy.

Limitations

Our study aims to establish a new framework for electricity sector disaggregation within MRIO models. Due to data limitations—particularly in emerging economies—many economies lack detailed regional sectoral statistics, necessitating the use of approximations in our approach. Currently, only 19 economies have access to regional-level output data. For the remaining economies, we estimate the input demand from other economic sectors to the newly disaggregated electricity subsectors in the Z matrix (intermediate transaction matrix) using average technical coefficients derived from their respective continental groupings. These regionally aggregated structures serve as regional prototypes that guide the disaggregation process in the absence of subnational data. Future research shall aim to continue integrating higher-quality national-level regional sectoral output data as they become available, ensuring regular updates to the EMERGING-E database and further improving its accuracy.

DISCUSSION

Comparison with existing methods and knowledge

Electricity sector disaggregation in the MRIO model construction faces persistent challenges in data availability and regional specificity. While existing models provide broad global coverage, they often overlook the diversity of national electricity structures, especially in data-scarce emerging economies. EMERGING-E overcomes these limitations by integrating national statistics with point-source power plant data, enabling a more representative and practical modeling approach. This section outlines EMERGING-E's advantages over existing MRIO models and its potential for advancing research on clean energy transitions and sustainability policy. Although the collected data do not cover all economies comprehensively, the uncertainty analysis indicates that our disaggregation approach is relatively robust under varying data conditions. The results show that most economies exhibit narrow uncertainty ranges, generally within 2%, while small island states and data-scarce economies that rely on regional averages display comparatively wider intervals, with 95% confidence intervals reaching 20%–30% in some cases (see Note S5 and Table S5). In addition to validating the EMERGING-E database through systematic comparisons with other MRIO datasets and officially published national statistics, we quantify uncertainty in consumption-based carbon footprints derived from the EMERGING-E MRIO model by applying an analytical uncertainty propagation framework to all 245 economies for 2018. This analysis yields economy-specific uncertainty ranges and enables the identification of dominant uncertainty contributors among emission intensities, the Leontief inverse matrix, and final demand. The results show that dominant uncertainty sources differ systematically across economies (see Note S6 and Table S6).

Advanced nature of the EMERGING-E model

EMERGING-E represents a methodological advancement in MRIO model construction by integrating nationally reported electricity output data with point-source power plant information to disaggregate the electricity sector into 14 electricity subsectors. Unlike existing models, including EXIOBASE 3[11] and GTAP-Power 11,[13] that rely heavily on generalized coefficients or extensive life cycle datasets, EMERGING-E achieves high accuracy with a leaner, more transparent data foundation—making it especially suitable for data-scarce emerging economies. Comparative analyses across 9 major economies show that EMERGING-E provides a more accurate and consistent representation of national electricity and carbon structures than GTAP-Power 11 and EXIOBASE 3. GTAP-Power 11 overestimates coal-based generation by 7.6% in China and 10.9% in India, while EXIOBASE 3 overstates hydropower in Brazil by 8.8% and gas in Japan by 9.4%. In contrast, EMERGING-E closely matches official generation data. This demonstrates its strength in capturing national electricity structures and reinforces its role as a critical supply chain analysis tool and data foundation for understanding electricity system evolution and supporting future low-carbon energy transitions in emerging economies.[25]

To enhance the methodological transparency and comparability of the cross-database assessment, we further compared production- and consumption-based CO_2 emission intensities and emission structures across the three databases. EMERGING-E and GTAP-Power 11 show similar magnitudes and ranking patterns across power types, while EXIOBASE 3 consistently reports higher values, particularly for coal and gas, reaching 0.022 and 0.012 tCO_2 USD^{-1} compared with 0.010 and 0.007 tCO_2 USD^{-1} in EMERGING-E. From the emission account structures on the production side, EMERGING-E aligns more closely with EXIOBASE 3 in countries such as China, India, and the United States, where coal accounts for 93.7% and 94.2% in China, while showing better agreement with GTAP-Power 11 in countries such as Japan and Hungary, where gas contributes 48.3% in EMERGING-E and 42.8% in GTAP-Power 11 for Japan. For the consumption side, China and Germany show strong consistency across all three databases. EMERGING-E aligns with EXIOBASE 3 in the United States, where gas accounts for 50.3% and 51.5%. In contrast, EMERGING-E is closer to GTAP-Power 11 in countries such as Japan, India, and the United Kingdom; for example, in the United Kingdom, gas contributes 56.4% in EMERGING-E and 54.4% in GTAP-Power 11 (see more details in Notes S1–S3 and Figures S1–S3).

Implications for renewable power system management

The EMERGING-E model provides a high-resolution and nationally grounded data and analytical foundation for supporting the transition to clean power systems.[26] By accurately capturing technology-specific electricity generation, it enables detailed assessments of resource dependencies and carbon footprints via the supply chain.[27] We compared national and sectoral consumption-based carbon emission footprints between the 2018 EMERGING-E and the original EMERGING MRIO models (see more details in Note S4 and Table S4). The results show that electricity disaggregation changes national footprints by up to ±15%, increasing in fossil-intensive economies such as India

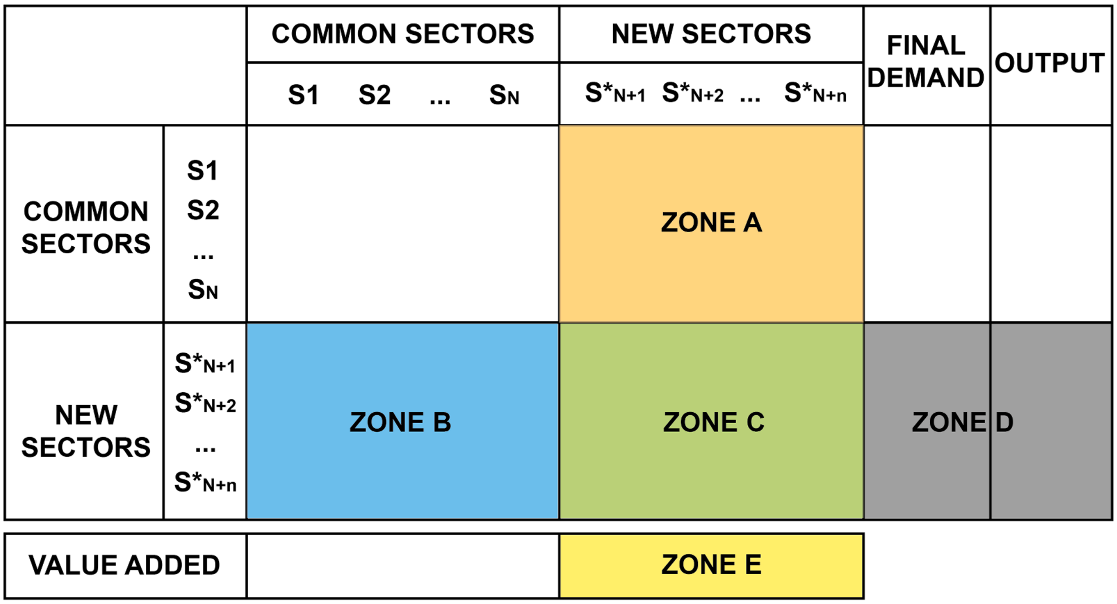

Figure 3. Schematic framework for the disaggregation of the electricity sector

Schematic illustration of the electricity-sector disaggregation within the input-output table. The original electricity sector is expanded into 14 subsectors, and the disaggregation process is implemented across five zones (zones A–E).

(+2.1%) and decreasing in cleaner-energy economies such as Laos (−14.8%). At the sectoral level, footprints decline notably in agriculture (−12.1%) and textiles (−10.1%) but rise in electricity supply (+12.4%) and construction (+4.1%). This highlights that technology-specific disaggregation of the electricity sector (EMERGING-E) enhances the quantitative representation of sectoral electricity use and improves the accuracy of consumption-based carbon footprint estimates. As electricity is a key input across sectors, from manufacturing to transport and buildings, decarbonizing power systems is fundamental to broader low-carbon transitions.[25,28] The EMERGING-E model supports more targeted, evidence-based policymaking by enabling governments to evaluate renewable integration, monitor embodied emissions, and track progress toward sustainability goals.

Renewable electricity plays a central role in national climate strategies, especially in emerging economies with rapid energy transitions and infrastructure development.[29,30] EMERGING-E fills a critical gap by offering a transparent, country-specific modeling framework that reflects local energy realities. This not only strengthens the technical basis for emissions accounting but also provides strategic support for achieving nationally determined contributions (NDCs).[31,32] By enhancing data availability and analytical capacity, EMERGING-E empowers emerging economies to develop and implement more autonomous, equitable, and effective climate policies.

Future and broader applications

EMERGING-E demonstrates valuable potential in two key directions: enabling fine-grained, facility-level supply chain modeling and offering a transferable disaggregation approach applicable to a wider range of sectors in global sustainability assessments. Beyond the electricity sector, the methodological framework of EMERGING-E has strong potential for application in other sectors with complex and heterogeneous structures, such as transport and agriculture. Such disaggregation would help reveal the heterogeneity in specific supply chains and their associated social and environmental impacts across sectors, which will strengthen the ability of MRIO models to support more targeted, equitable, and effective sustainability assessments.[33,34]

A key direction for future development of EMERGING-E lies in its integration with point-source power plant data to enable disaggregation at the facility level. This would allow the construction of plant-level MRIO models that capture electricity flows and emissions with much greater spatial resolution.[35] When combined with data on mitigation technologies, technical potentials, and abatement costs, such models could support the design of more precise and cost-effective decarbonization pathways.[36]

METHODS

EMERGING-E electricity sector disaggregation framework

Figure 3 shows the basic disaggregation methodology. We have used the approach proposed by Sören Linder et al.,[16] which is an advanced Wolsky's approach. As shown in the schematic, the sectors are divided into two parts: common sectors and new sectors. So, we have 5 matrix zones that need to be split, and we need to obtain 5 zone weight factor matrices.

For zones D and E, firstly, we use the transmission and distribution share $Invest_{N+t}$ of the total non-tax value of electricity generation from different economies based on the data sources from the Energy Information Administration,[19] Eurostat,[20] National Electric Energy Agency, IEA,[18] and World Bank,[21] power transmission and distribution networks in the current year, to split the transmission and distribution sectors from the remaining 12 power generation sectors. We then split the final demand and

Table 2. Economies with regional industrial structure data in EMERGING-E

Number	Country	ISO3	Region
17	Australia	AUS	Oceania
18	Austria	AUT	Europe
25	Bulgaria	BGR	Europe
34	Brazil	BRA	South America
41	Canada	CAN	North America
45	China	CHN	Asia
70	Spain	ESP	Europe
71	Estonia	EST	Europe
82	United Kingdom	GBR	Europe
91	Greece	GRC	Europe
101	Croatia	HRV	Europe
115	Japan	JPN	Asia
117	Kenya	KEN	Africa
122	Korea, Rep.	KOR	Asia
177	Poland	POL	Europe
206	Slovak Republic	SVK	Europe
207	Slovenia	SVN	Europe
231	United States	USA	North America
243	South Africa	ZAF	Africa

sectoral output of 12 new generation sectors based on the share of annual electricity generation output of the new sectors P_{N+k}:

$$X^*_{N+t} = X_N \times \left(Invest_{N+t} \Big/ \sum_{t=1}^{3} Invest_{N+t} \right), \quad \text{(Equation 1)}$$

$$F^*_{N+t} = F_N \times \left(Invest_{N+t} \Big/ \sum_{t=1}^{3} Invest_{N+t} \right), \quad \text{(Equation 2)}$$

$$VA^*_{N+t} = VA_N \times \left(Invest_{N+t} \Big/ \sum_{t=1}^{3} Invest_{N+t} \right), \quad \text{(Equation 3)}$$

$$X^*_{N+k} = X^*_{N+3} \times \left(P_{N+k} \Big/ \sum_{k=1}^{12} P_{N+k} \right), \quad \text{(Equation 4)}$$

$$F^*_{N+k} = F^*_{N+3} \times \left(P_{N+k} \Big/ \sum_{k=1}^{12} P_{N+k} \right), \quad \text{(Equation 5)}$$

and

$$VA^*_{i,N+k} = VA^*_{i,N+3} \times \left(P_{N+k} \Big/ \sum_{k=1}^{12} P_{N+k} \right), \quad \text{(Equation 6)}$$

where X_N, F_N, and VA_N are the original output, final demand, and value added of the electricity sector N in EMERGING; X^*_{N+t}, F^*_{N+t}, and VA^*_{N+t} are the new output, final demand, and value added of the new transmission ($t = 1$), distribution sectors ($t = 2$), and total 12 power generation sectors ($t = 3$) in EMERGING-E; and X^*_{N+k}, F^*_{N+k}, and $VA^*_{i,N+k}$ are the output, final demand, and value added of the new k-type power generation sector in EMERGING-E.

For zone A, we introduce the input weight factors I_{N+k}. The allocation of industry input to the new power generation sectors is based on the weighted sum of the power plant LCOE costs $LCOE_{N+k}$ from the IEA[22] (if LCOE cost data are unavailable, use the Energy Public Investment data EPI_{N+k} from the International Renewable Energy Agency[23] instead) and the annual electricity generation output of the new sectors P_{N+k}, collected from Electricity Statistical Yearbook or Electricity Statistics Bureau in each economy, and the weighting coefficient of the two indicators is 1:3.

$$I_{N+k} = (3 \times P_{N+k} + LCOE_{N+k}) \Big/ \sum_{k=1}^{12} (3 \times P_{N+k} + LCOE_{N+k}) \quad \text{(Equation 7)}$$

Moreover, for zone A, the mix of product offerings required to operate and maintain different energy generation plants is different. Therefore, the allocation of industry inputs to a new power generation sector should not be based solely on the electricity output of the new sector but rather on the type of power plant.[37] For example, fossil energy power plants (e.g., coal-fired plants) require fuel, while new energy plants (e.g., wind plants) do not. We therefore add to the original input factor the constraint that fossil energy sources (coal, oil, gas, and their products) supply only the corresponding generation sector:

$$Z^*_{i,N+t} = Z_{i,N} \times \left(Invest_{N+t} \Big/ \sum_{t=1}^{3} Invest_{N+t} \right) \quad \text{(Equation 8)}$$

and

$$Z^*_{i,N+k} = Z^*_{i,N+3} \times \left(I_{N+k} \Big/ \sum_{k=1}^{12} I_{N+k} \right), \quad \text{(Equation 9)}$$

where $Z_{i,N}$ is the intermediate supply of common sector i in the electricity sector N; $Z^*_{i,N+t}$ is the intermediate supply of common sector i in the new transmission ($t = 1$), distribution sectors ($t = 2$), and total 12 power generation sectors ($t = 3$); and $Z^*_{i,N+k}$ is the intermediate supply of sector i in the new k-type power generation sector in EMERGING-E.

For zone B, we introduce the output weight factors R_i^k. We derive the unknown technical coefficients in zone B by considering regional electricity generation mixes and industry clusters.[38] The national proportion of new electricity sectors consumed by the common sectors is based on the regionally weighted industry coefficient method in each economy, which is the sum weighted of common sector output in each region from the National Bureau of Statistics, and the mix of installed capacity of different types of point-source power plants in the region comes from the WEPP database. The supply proportion from new transmission and distribution sectors to common sectors is only based on their total output X_{N+t}, and we assume that the supply structure is the same as the original electricity sector in EMERGING:

$$Z^*_{N+t,i} = Z_{N,i} \times \left(X_{N+t} \Big/ \sum_{n=1}^{14} X_{N+n} \right), \quad \text{(Equation 10)}$$

$$R_i^k = \sum_r S_r^i \Big/ \sum_i S_r^i \times \left(\sum_r E_r^k \Big/ \sum_k E_r^k \right), \quad \text{(Equation 11)}$$

and

$$Z^{*}_{N+k,i} = Z^{*}_{N+3,i} \times R^{k}_{i}, \qquad \text{(Equation 12)}$$

where $Z^{*}_{N+t,i}$ is the intermediate supply of new transmission ($t = 1$), distribution sectors ($t = 2$), and total 12 power generation sectors ($t = 3$) in common sector i; $Z_{N,i}$ is the original intermediate supply of electricity sector N in common sector i; S^{i}_{r} is the output of common sector i in region r; E^{k}_{r} is the k-type total installed capacity in region r; and $Z^{*}_{N+k,i}$ is the intermediate supply from new k-type power generation sectors to common sector i in EMERGING-E.

Finally, for zone C, we assume that the consumption of different power generation sectors by the power supply sector is determined based on the output weights of different power generation sectors, w_{N+n}, and we introduce the intra-matrix in order to split the intra-industry value in the new intra-matrix for the new power generation sectors by using the proportion of output in 14 new electricity sectors X_{N+n}, which is based on Wolsky's method[39]:

$$w_{N+n} = X_{N+n} \Big/ \sum_{n=1}^{14} X_{N+n} \qquad \text{(Equation 13)}$$

and

$$\begin{pmatrix} Z^{*}_{N+1,N+1} & Z^{*}_{N+1,N+n} \\ Z^{*}_{N+n,N+1} & Z^{*}_{N+n,N+n} \end{pmatrix} = Z_{N,N} \times \begin{pmatrix} w_{N+1} & w_{N+1} \\ w_{N+n} & w_{N+n} \end{pmatrix}, \qquad \text{(Equation 14)}$$

where $Z^{*}_{N+1,N+n}$ is the new intermediate supply of sector N+1 in the electricity sector $N + n$ and $Z_{N,N}$ is the original intra-industry value of electricity sector N in EMERGING.

Given the multiple sources of data in the disaggregated table, inconsistencies may arise, resulting in initial results that are not balanced. To address this, we apply the RAS method, a biproportional matrix balancing procedure, to balance the table. The RAS method is used for balancing the columns and rows of IOTs when updating or revising them.[40] Since the sectoral output (X), final demand (F), and intermediate transaction (Z) derived from the initial estimates may not reflect real values, we use the RAS method to correct these less reliable values and balance the EMERGING-E MRIO tables.

Since there are 245 economies included in the EMERGING model and many emerging economies do not publish relevant information on their regional electricity structure and industrial structure, in EMERGING-E, we only collected data from representative developed countries and selected emerging economies in the five regions (listed in Table 2) and obtained an approximate regional IOT with 146 sectors. Based on the regional electricity structure, we performed electricity sector splits for the economies with missing data.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for data resources should be directed to and will be fulfilled by the lead contact, Dabo Guan (guandabo@tsinghua.edu.cn).

Materials availability

This study generated a new MRIO database, EMERGING-E. The 2018 EMERGING-E MRIO table has been deposited on Zenodo (https://doi.org/10.5281/zenodo.18303090) and is publicly available without restriction.

Data and code availability

The EMERGING-E MRIO table in 2018, the MATLAB code for the validation analysis, and source data for the main figures presented in this study have been deposited on Zenodo at https://doi.org/10.5281/zenodo.18303090.

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AUTHOR CONTRIBUTIONS

D.G. designed the study. J.H., R.G., and Z.W. performed the analysis. J.H. prepared the manuscript. J.H., R.G., and J.L. collected the relevant macroeconomic data. Y.H. processed the point-source power plant data. J.H., J.M., D.G., and S.L. interpreted the data. All authors participated in writing the manuscript.

DECLARATION OF INTERESTS

The authors declare no conflict of interest.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT in order to improve language fluency and correct grammatical errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

SUPPLEMENTAL INFORMATION

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REFERENCES

1. Wiedmann, T. (2009). A review of recent multi-region input–output models used for consumption-based emission and resource accounting. Ecol. Econ. *69*, 211–222.
2. Davis, S.J., and Caldeira, K. (2010). Consumption-based accounting of CO2 emissions. Proc. Natl. Acad. Sci. USA *107*, 5687–5692. https://doi.org/10.1073/pnas.0906974107.
3. Ma, Z., Zhang, S., Hou, F., Tan, X., Zhang, F., Yang, F., and Guo, F. (2020). Exploring the driving factors and their mitigation potential in global energy-related CO2 emission. Global Energy Interconnection *3*, 413–422.
4. Bouckaert, S., Pales, A.F., McGlade, C., Remme, U., Wanner, B., Varro, L., D'Ambrosio, D., and Spencer, T. (2021). Net zero by 2050: A roadmap for the global energy (International Energy Agency). https://iea.blob.core.windows.net/assets/063ae08a-7114-4b58-a34e-39db2112d0a2/NetZeroby2050-ARoadmapfortheGlobalEnergySector.pdf.
5. Burnard, K., Jiang, J., Li, B., Brunet, G., and Bauer, F. (2014). Emissions Reduction through Upgrade of Coal-Fired Power Plants: Learning from Chinese Experience (Paris: International Energy Agency: Partner Country Series). https://iea.blob.core.windows.net/assets/9ed014cf-ed30-44a0-a1d4-7a112506c6df/PartnerCountrySeriesEmissionsReductionthroughUpgradeofCoalFiredPowerPlants.pdf.

6. Amponsah, N.Y., Troldborg, M., Kington, B., Aalders, I., and Hough, R.L. (2014). Greenhouse gas emissions from renewable energy sources: A review of lifecycle considerations. Renew. Sustain. Energy Rev. *39*, 461–475.
7. Asmelash, E., Prakash, G., Gorini, R., and Gielen, D. (2020). Role of IRENA for global transition to 100% renewable energy. Accelerating the Transition to a 100% Renewable Energy Era, T. Uyar, ed. (2020). Lecture Notes in Energy, 74 (Springer, Cham), pp. 51–71. https://doi.org/10.1007/978-3-030-40738-4_2.
8. Shahsavari, A., and Akbari, M. (2018). Potential of solar energy in developing countries for reducing energy-related emissions. Renew. Sustain. Energy Rev. *90*, 275–291.
9. Gielen, D., Boshell, F., Saygin, D., Bazilian, M.D., Wagner, N., and Gorini, R. (2019). The role of renewable energy in the global energy transformation. Energy Strategy Rev. *24*, 38–50. https://doi.org/10.1016/j.esr.2019.01.006.
10. Černý, M., Bruckner, M., Weinzettel, J., Wiebe, K., Kimmich, C., Kerschner, C., and Hubacek, K. (2021). Employment Effects of the Renewable Energy Transition in the Electricity Sector: An Input-Output Approach (ETUI Research Paper-Working Paper).
11. Wood, R., Stadler, K., Bulavskaya, T., Lutter, S., Giljum, S., De Koning, A., Kuenen, J., Schütz, H., Acosta-Fernández, J., Usubiaga, A., et al. (2014). Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. Sustainability *7*, 138–163.
12. Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., et al. (2018). EXIOBASE 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. J. Ind. Ecol. *22*, 502–515.
13. Peters, J.C. (2016). The GTAP-Power Data Base: Disaggregating the Electricity Sector in the GTAP Data Base. J. Glob. Econ. Anal. *1*, 209–250. https://doi.org/10.21642/JGEA.010104AF.
14. Chepeliev, M. (2020). GTAP-Power Data Base: Version 10. J. Glob. Econ. Anal. *5*, 110–137.
15. Chepeliev, M. (2023). GTAP-Power Data Base: Version 11. J. Glob. Econ. Anal. *8*, 101–135. https://doi.org/10.21642/JGEA.080203AF.
16. Lindner, S., Legault, J., and Guan, D. (2013). DISAGGREGATING THE ELECTRICITY SECTOR OF CHINA'S INPUT–OUTPUT TABLE FOR IMPROVED ENVIRONMENTAL LIFE-CYCLE ASSESSMENT. Econ. Syst. Res. *25*, 300–320. https://doi.org/10.1080/09535314.2012.746646.
17. Huo, J., Chen, P., Hubacek, K., Zheng, H., Meng, J., and Guan, D. (2022). Full-scale, near real-time multi-regional input–output table for the global emerging economies (EMERGING). Journal of Industrial Ecology *n/a*. J. Ind. Ecol. *26*, 1218–1232. https://doi.org/10.1111/jiec.13264.
18. IEA (2024). World - Electricity/heat supply and consumption. https://www.iea.org/data-and-statistics/data-product/electricity-information.
19. EIA (2023). Electric Power Annual 2022. United States Energy Information Administration. https://www.eia.gov/electricity/annual/.
20. Eurostat (2024). Energy statistics – natural gas and electricity prices (from 2007 onwards). https://ec.europa.eu/eurostat/databrowser/view/nrg_pc_206/default/table?lang=en&category=nrg.nrg_price.nrg_pc.
21. Bank, W. (2024). Electric power transmission and distribution losses (% of output). https://data.worldbank.org/indicator/EG.ELC.LOSS.ZS.
22. IEA (2020). Projected Costs of Generating Electricity 2020. IEA, Paris. https://www.iea.org/reports/projected-costs-of-generating-electricity-2020, Licence: CC BY 4.0.
23. Cpl, I.a. (2023). Global landscape of renewable energy finance. International Renewable EnergyAgency, Abu Dhabi. https://www,irena.org/Publications/2023/Feb/Global-landsenergy-hinance-2023.
24. Division, U.N.S. (2020). National Accounts Statistics: Analysis of Main Aggregates, 2019. http://data.un.org/Data.aspx?d=SNA&f=group_code%3A203.
25. Kabeyi, M.J.B., and Olanrewaju, O.A. (2022). Sustainable energy transition for renewable and low carbon grid electricity generation and supply. Front. Energy Res. *9*, 743114.
26. Davis, S.J., Lewis, N.S., Shaner, M., Aggarwal, S., Arent, D., Azevedo, I.L., Benson, S.M., Bradley, T., Brouwer, J., Chiang, Y.-M., et al. (2018). Net-zero emissions energy systems. Science *360*, eaas9793. https://doi.org/10.1126/science.aas9793.
27. Shaikh, M.A., Kucukvar, M., Onat, N.C., and Kirkil, G. (2017). A framework for water and carbon footprint analysis of national electricity production scenarios. Energy *139*, 406–421.
28. McPherson, M., Rhodes, E., Stanislaw, L., Arjmand, R., Saffari, M., Xu, R., Hoicka, C., and Esfahlani, M. (2023). Modeling the transition to a zero emission energy system: A cross-sectoral review of building, transportation, and electricity system models in Canada. Energy Rep. *9*, 4380–4400.
29. Aleluia, J., Tharakan, P., Chikkatur, A.P., Shrimali, G., and Chen, X. (2022). Accelerating a clean energy transition in Southeast Asia: Role of governments and public policy. Renew. Sustain. Energy Rev. *159*, 112226.
30. Vanegas Cantarero, M.M. (2020). Of renewable energy, energy democracy, and sustainable development: A roadmap to accelerate the energy transition in developing countries. Energy Res. Social Sci. *70*, 101716.
31. Höhne, N., Kuramochi, T., Warnecke, C., Röser, F., Fekete, H., Hagemann, M., Day, T., Tewari, R., Kurdziel, M., and Sterl, S. (2021). The Paris Agreement: Resolving the Inconsistency between Global Goals and National Contributions (Routledge)), pp. 30–46.
32. Huo, J., Meng, J., Zheng, H., Parikh, P., and Guan, D. (2023). Achieving decent living standards in emerging economies challenges national mitigation goals for CO2 emissions. Nat. Commun. *14*, 6342. https://doi.org/10.1038/s41467-023-42079-8.
33. de Koning, A., Bruckner, M., Lutter, S., Wood, R., Stadler, K., and Tukker, A. (2015). Effect of aggregation and disaggregation on embodied material use of products in input–output analysis. Ecol. Econ. *116*, 289–299.
34. Wenz, L., Willner, S.N., Radebach, A., Bierkandt, R., Steckel, J.C., and Levermann, A. (2015). Regional and sectoral disaggregation of multi-regional input–output tables–a flexible algorithm. Econ. Syst. Res. *27*, 194–212.
35. Brinkerink, M., Mayfield, E., and Deane, P. (2024). The role of spatial resolution in global electricity systems modelling. Energy Strategy Rev. *53*, 101370.
36. Meng, J., Way, R., Verdolini, E., and Diaz Anadon, L. (2021). Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. Proc. Natl. Acad. Sci. USA *118*, e1917165118.
37. Marriott, J. (2007). An electricity-focused economic input-output model: Life-cycle assessment and policy implications of future electricity generation scenarios (Carnegie Mellon University, Pittsburgh, PA: PhD dissertation). https://www.cmu.edu/ceic/assets/docs/publications/phd-dissertations/2007/joe-marriott-phd-thesis-2007.pdf.
38. Lindner, S., Legault, J., and Guan, D. (2012). DISAGGREGATING INPUT–OUTPUT MODELS WITH INCOMPLETE INFORMATION. Econ. Syst. Res. *24*, 329–347. https://doi.org/10.1080/09535314.2012.689954.
39. Wolsky, A.M. (1984). Disaggregating input-output models. Rev. Econ. Stat. *66*, 283–291.
40. Trinh, B.a.P., N.V. (2013). A Short Note on RAS Method. Adv. Manag. Appl. Econ. *3*, 133–137.