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Predicting embodied carbon emissions from purchased electricity for United States counties

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HIGHLIGHTS

- Model predicts embodied lifecycle CO_2e for 60 U.S. balancing authorities.
- Novel method translates CO_2e balancing authority emissions down to the county level.
- 16 balancing authority consumption and generation emission factors deviate by >20%.
- County-level emission factor variations of 6 balancing authorities >0.3 MT-CO_2e/MWh.

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ABSTRACT

Predicting the embodied scope 3 carbon dioxide equivalent (CO_2e) emissions from purchased electricity for end users in the United States is challenging due to electricity transmission within interconnected power grids. Existing methods only focus on large aggregation areas, thereby ignoring potentially significant emission factor (EF) variations, so this study proposes a novel method to translate the CO_2e emissions from the balancing authority (BA)-level to the county-level by utilizing explicit finite-difference theory for electricity flow predictions, and then employing economic input–output theory to evaluate the scope 3 embodied lifecycle CO_2e emissions. Results show that the generation-based EFs at the BA-level range from 0.007 to 0.905 MT-CO_2e/MWh with a mean value of 0.400 MT-CO_2e/MWh and a standard deviation of 0.229 MT-CO_2e/MWh. The consumption-based EFs at the BA-level range from 0.008 to 0.836 MT-CO2e/MWh with a mean value of 0.378 MT-CO_2e/MWh and a standard deviation of 0.019 MT-CO_2e/MWh. Results also show that sixteen BA consumption-based EFs deviate by more than 20% compared to their generation-based EFs, which indicates the significance of accounting for electricity interchanges in emissions quantification processes. A larger range of possible consumption-based EFs is revealed at the county-level: 0.007 to 0.902 MT-CO_2e/MWh, with a mean value of 0.452 MT-CO_2e/MWh and a standard deviation of 0.123 MT-CO_2e/MWh. Results also indicate significant variations in EFs of counties within each BA: 20 BAs have county-level EFs range greater than 0.1 MT-CO_2e/MWh, 13 BAs have county-level EFs range greater than 0.2 MT-CO_2e/MWh and 6 BAs have county-level EFs range beyond 0.3 MT-CO_2e/MWh.

1. Introduction

Electricity generation is one of the largest producers of global carbon dioxide equivalent (CO_2e) emissions. The emissions are dominated by carbon dioxide (CO_2) but also include small amounts of other gases (e.g., methane (CH_4), nitrous oxide (N_2O) and F-gases) that stem from the three major lifecycle stages of electricity production: upstream (e.g., extraction and delivery), operation and downstream (e.g., disposal and recycling) [1]. Emission factors (EFs), which indicate the amount of emissions embodied in unitary electricity consumption (MT-CO_2e/MWh), are a common way to incorporate predictions from the life cycle impact assessment of electricity production [2].

In the United States, the end users of grid power often rely on their utility providers or other aggregated data sources such as the Emissions & Generation Resource Integrated Database (eGrid) [3] developed by United States Environmental Protection Agency (EPA) to retrieve their EFs, which are then used in developing carbon reduction strategies. One major drawback of the EFs provided by eGrid is that they neglect the impact of electricity exchanges across regional boundaries [4]. Furthermore, the EFs provided in the eGrid database do not stem from

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lifecycle analysis, thereby neglecting emissions from both upstream and downstream stages in the electricity production process [4].

There is currently a strong motivation to better quantitatively understand how electricity and emissions propagate. Dotzauer [5], for example, emphasized the need for improved reliability in electricity tracking. According to the greenhouse gas (GHG) emissions inventory [6] and the GHG footprint reduction targets developed by the EPA, existing studies can be classified into three scopes. Scope 1 GHG emissions measure the direct emissions from sources, such as onsite fossil fuel combustion. Notably, the eGrid database established by EPA fits into this scope since it estimates GHG emission rates at different levels [3] using the regional electricity production portfolio. However, electricity transfers among regions and some low-carbon electricity generation sources (i.e., nuclear power, hydropower, solar energy and wind energy) are neglected.

Scope 2 GHG emissions include the impact of generating the purchased electricity. Marriott and Matthews [7] estimated the U.S. state-level EFs by treating most of the states as either a net importer or exporter using net electricity interchange data from year 2000. A transportation optimization model that assumes “minimized travel distance” predicts where electricity flows to net exporters. The resultant EFs are calculated based on the predicted values of direct imports or exports, which could be inconsistent with actual electricity trades. Similarly, Colett et al. [8] conducted a case study of U.S. GHG emissions in primary aluminum production by proposing “nested average allocation protocols” that only consider bilateral electricity trades to estimate the emissions interchanges at the power control area (PCA)-level.

Scope 3 GHG emissions measure both direct and indirect electricity-related emissions resulting from the transportation and distribution of purchased electricity. Qu et al. [9] examined the virtual CO_2 emission flows in the global electricity trade network. Sjödin and Grönkvist [10] acknowledged the significance of electricity cross-border trade between countries in the Nordic region and discussed different ways to account for GHG emissions variations due to corresponding electricity demand and supply changes. Kang et al. [11] introduced the “carbon emission flow in networks” concept and developed a method to trace GHG emissions through a virtual network using an actual analysis of China’s energy pattern. In their study, the country is divided into 6 regions that act as both electricity consumers and producers. Qu et al. [12] examined the CO_2 emissions embodied in interprovincial electricity transmissions in China. Wei et al. [13] conducted a case study in Shanghai, China by comparing the different scopes of GHG emissions caused by electricity consuming activities. Their results show that Shanghai has high scope 3 GHG emissions due to large net inflows of electricity embodied GHG emissions, which emphasizes the significance of scope 3 GHG emissions accounting. St-Jacques et al. [14] demonstrated a case study of GHG emissions embodied in building electricity use in Ontario, Canada. Finally, Chaparro et al. [15] assessed the marginal carbon emissions of hydrothermal systems of Chile.

In the U.S., the entire power grid consists of thousands of miles of power transmission lines that connect power plants and deliver electricity to consumers all over the country [16]. The vast amount of electricity interchanges between regions and various regional electricity production methods could significantly alter the EFs. Following the “carbon emission flow in networks” concept introduced by Kang et al. [11], Kodra et al. [17] employed an iterative method to track the electricity interchanges and associated emissions transfers in the U.S. at the PCA-level. At each time step, each PCA transmits a portion of its available electricity to other PCAs who trade with it directly. The iteration stops when the available electricity of each PCA becomes extremely small. Based on Kodra’s work, Qu et al. [18] proposed the quasi-input–output (QIO) model that improves the accuracy of the iterative method by utilizing the idea of input–output theory from economics, and they applied it to the Eurasian Continent. Interestingly, de Chalendar et al. [19] implemented a fully coupled multiregional input–output model to trace the emission flows at the BA-level over multiple time period sizes, and Koffler et al. [20] developed the regional life cycle inventory of scope 3 GHG emissions at the eGrid subregion-level.

The above studies indicate that the spatial resolution of scope 3 emissions in the U.S. has been restricted to the PCA-level due to the lack of consistent and high-resolution data. However, Siddique et al. [21] recognized that the carbon footprints of electricity are sensitive to geographical attribution methods and spatial resolution. Therefore, this study fills an important knowledge gap by introducing a novel method that that predicts GHG emissions at a much finer scale – the county level – which enables the first known assessment of the spatial variation of scope 3 EFs within balancing authorities. This assessment therefore tests the hypothesis that the spatial variation of EFs within balancing authority areas can be significant and therefore should be incorporated into building scope 3 GHG emissions calculations.

2. Methodology

The approach here first traces the electricity generation and its associated lifecycle emissions within the U.S. at the BA-level using data published in the hourly electric grid monitoring system developed by the U.S. Energy Information Administration (EIA) [22]. The published daily data are collected and cleaned, and the annual EF values are determined by summing daily data over the entire year. In 2019, the 64 BAs in the U.S. that consistently reported power data to the EIA are considered. Five BAs based in Canada [23] and one BA based in Mexico [24] are also included to properly address the effects of international electricity interchanges. The EFs at the BA-level are determined using the QIO model.

The second step is the translation of BA-level data down to the county-level. A novel approach was developed to translate the EFs at the BA-level to the county-level resolution with the aid of an explicit finite difference method to predict county-level electricity flows. This approach predicts the variation in scope 3 emissions within BAs and achieves the needed finer level of granularity in consumption-based EF predictions.

2.1. The network approach: QIO model

Qu et al. [18] proposed the QIO model, which is a network approach that evaluates the embodied CO_2e emissions from purchased electricity using economic input–output theory. Traditional input–output theory is used to describe the interrelationship of supply and demand between different sectors in an economy. The two major branches of traditional input–output theory are the Leontief model, which is a demand driven model, and the Ghosh model, which is a supply driven model [25]. The mathematical equivalence of the two branches in this case and the differences between the traditional input–output model with the QIO model are discussed in Qu et al. [18] The QIO model connects direct emissions from regional power generation to power consumption in other regions, which allows the model to capture both direct and indirect electricity transfers. The indirect electricity transfers occur when a region transfers electricity to other regions through one or more transit region(s) within the entire power grid.

In the QIO model, each region is represented as a node that connects to other nodes. Each node can either be an importer, an exporter or both. The electricity interchanges of each node (i) must be conserved, therefore

$$G_i + \sum_{j=1}^{n} E_{ji} = C_i + \sum_{j=1}^{n} E_{ij} = X_i \tag{1}$$

where $\mathbf{G}$ and $\mathbf{C}$ are 1 by n matrices. G_i and C_i represent the power generation and consumption of node i, respectively. $\mathbf{E}$ is the $n \times n$ matrix that represents the electricity transmission network with n nodes. E_{ij} indicates the amount of direct electricity transmission from node i to node j. $\mathbf{X}$ is defined here as the total electricity flows of all n nodes. Taking a four-node electric grid as an example, Fig. 1 shows that Node 1

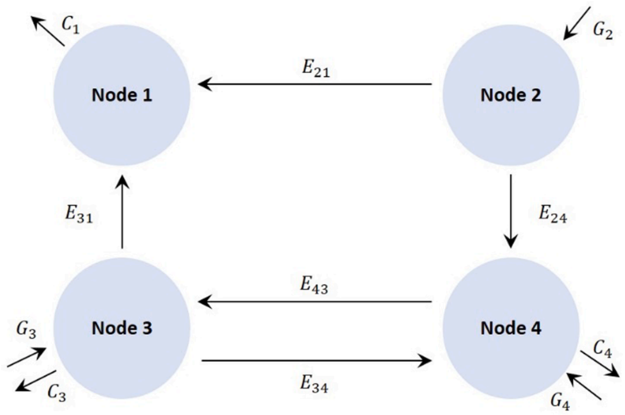

Fig. 1. Example of electricity conservation in a four-node grid.

imports electricity from both Node 2 (E_{21}) and Node 3 (E_{31}) as inflows, and local consumption (C_1) is the only outflow, indicating that node 1 is acting as an importer only. On the other hand, Node 2 exports electricity to Node 1 (E_{21}) and Node 4 (E_{24}) as electricity outflows, and local generation (G_2) is the only inflow, indicating that Node 2 serves as an exporter only. Both Nodes 3 and 4 have inflows and outflows connecting to other nodes, indicating that Nodes 3 and 4 are both importers and exporters.

The emissions associated with **X** in Eq. (1) can be written as

$$e_i^X = e_i^G + \sum\nolimits_{j=1}^{n} B_{ji} e_j^X = e_i^C + \sum\nolimits_{j=1}^{n} B_{ij} e_i^X \tag{2}$$

where e_j^X is the emissions in total electricity flows of node j. e_i^G and $e_i^C$are the emissions associated with electricity generation and electricity consumption, respectively, in node i. In this study, the lifecycle emissions associated with power generation e_i^G is determined by considering the unique power production portfolio using following equation:

$$e_i^G = \sum\nolimits_{k=1}^{n} G_k r_k \tag{3}$$

where k represents a specific power production technology, G_k is the electricity generation from technology k in MWh, and r_k is the lifecycle emission rates associated with electricity generation technology k [26].

A considerable amount of lifecycle assessment (LCA) research has been performed to evaluate the emission rates for different types of electricity generation technologies, but significant discrepancies exist. However, in project Life Cycle Assessment Harmonization [26], the National Renewable Energy Laboratory (NREL) analyzed and harmonized the LCA of multiple electricity generation methods to reduce the variability from more than 2,000 published results, so this study quantifies the lifecycle generation-based EFs at the BA-level by incorporating the harmonized median lifecycle emission rates of multiple power generation technologies into e_i^G. More discussion on this topic can be found in Supporting Information (SI).

B, shown in Eq. (2), is defined here as the direct outflow coefficient matrix and can be calculated using

$$B = \widehat{\mathbf{X}}^{-1} E = \begin{bmatrix} 0 & \frac{E_{12}}{X_1} & \cdots & \frac{E_{1n}}{X_1} \\ \frac{E_{21}}{X_2} & 0 & \ddots & \frac{E_{2n}}{X_2} \\ \vdots & \ddots & \ddots & \vdots \\ \frac{E_{n1}}{X_n} & \frac{E_{n2}}{X_n} & \cdots & 0 \end{bmatrix} \tag{4}$$

where $\widehat{\mathbf{X}}$ is the diagonal matrix of **X**, and B_{ij} represents the fraction of total electricity flows of node i that is exported to node j. By its definition, $B_{ij} = 0$ when $i = j$. Eq. (2) can be rearranged into matrix form:

$$\mathbf{e^X} = \mathbf{e^G}(\mathbf{I} - \mathbf{B})^{-1} = \mathbf{e^G} T \tag{5}$$

where $\mathbf{T} = (\mathbf{I} - \mathbf{B})^{-1}$ is referred to as the total outflow coefficient matrix in input–output theory [18]. Therefore, **T** captures all electricity transfers through infinite paths within the grid, and T_{ij} represents the proportion of aggregated electricity transfers to node j that is generated by node i. Furthermore, the EF for purchased electricity in each node can be determined:

$$EF = \mathbf{e^X} \widehat{\mathbf{X}}^{-1} = \mathbf{e^G} T \widehat{\mathbf{X}}^{-1} \tag{6}$$

In addition, all the emissions due to electricity transfers through infinite paths from generating grids to consuming grids can be traced using

$$W = \widehat{\mathbf{e^G}} T \mathbf{B^C} \tag{7}$$

where $\widehat{\mathbf{e^G}}$ is the matrix of diagonal components of $\mathbf{e^G}$ and $\mathbf{B^C} = \widehat{\mathbf{C}}\widehat{\mathbf{X}}^{-1}$, which is a diagonal matrix that represents the fraction of electricity consumption in total electricity flow. W_{ij} represents the total embodied GHG emissions that transferred from generating grid i to consuming grid j.

2.2. The EF translation approach

The QIO model provides accurate results for scope 3 GHG emissions estimation provided that data such as regional power generation, consumption and cross-regional electricity transfers are available. Therefore, the spatial precision of the QIO model is currently limited to the BA-level. The translation approach proposed here uses an explicit finite-difference method to enable the application of the QIO method for scope 3 GHG emissions predictions with higher spatial precision (e.g., at the state-level and county-level) in order to assess the variation in EFs within BAs. This section illustrates how to apply the QIO method at the county-level using existing data at the BA-level.

First, each county is assigned to a BA based on the coverage areas of each BA to utilize existing data at the BA-level [27]. Since the boundaries of BAs are often fuzzy and overlapping, the smaller BAs are preserved when they are covered by larger BAs entirely. For the counties that are covered by two or more BAs, geographic centroids are used to determine which BA they are assigned to. Second, the known data, including power generation, consumption, and interregional electricity transfers, of each BA are translated to the county-level. The EIA published power plant data in 2020 for all power plants operating with a combined nameplate capacity of 1 MW or more [28]. This information is used to determine the total power generation in each county. Due to data consistency issues, the total electricity generation calculated as the sum total of all power plants within each BA is not always identical to the BA-level generation data provided in the electric grid monitor [22]. Therefore, county-level electricity generation is predicted using

$$G_{i,m} = \frac{\sum_k g_{i,m,k}}{\sum_m \sum_k g_{i,m,k}} \times G_i \tag{8}$$

where $G_{i,m}$ represents the adjusted electricity generation of county m in BA i, and $g_{i,m,k}$ indicates the electricity generation of power plant k in county m of BA i, which is acquired from EIA-923 [29]. G_i is the electricity generation of BA i reported by the EIA in the hourly electric grid monitor [22].

The electricity consumption of counties could in theory be calculated in a similar manner, but detailed power plants' sales data are not available. Thus, we propose using Gross Domestic Product (GDP) as an indicator of electricity consumption. To verify our assumption, the correlation between GDP, found as the sum of all counties' GDP within a BA, and electricity consumption at the BA-level has been determined. Fig. 2 shows that the GDP and consumption can reasonably be approximated as proportional. Therefore, following equation is used to estimate the electricity consumption at the county-level:

$$C_{i,m} = \frac{\mathrm{GDP}_{i,m}}{\sum_m \mathrm{GDP}_{i,m}} \times C_i \tag{9}$$

where $C_{i,m}$ represents the electricity consumption of county m in BA i, $\mathrm{GDP}_{i,m}$ indicates the GDP of county m in BA i, and C_i is the electricity consumption of BA i reported by the EIA in the hourly electric grid monitor [22].

The electricity transfer between BAs is traced back to counties within each BA. Between two BAs with electricity transfers (E_{ij}), it is assumed for all counties in the destination BAj that a county with high electricity consumption is more likely to import electricity. Since consumption is roughly proportional to GDP per Fig. 2, the distribution of electricity that comes from BA i to all counties in BA j is

$$E_{ij-n} = \frac{\mathrm{GDP}_{j,n}}{\sum_n \mathrm{GDP}_{j,n}} \times E_{ij} \tag{10}$$

where subscript n represents the county in destination BA j. For all counties in BA i, it is assumed that a county with more electricity generation is more likely to export electricity, so the electricity to county n in BA j is traced back to each county m in BA i as

$$E_{ij-mn} = \frac{\sum_k g_{i,m,k}}{\sum_m \sum_k g_{i,m,k}} \times E_{ij-n} \tag{11}$$

where k indicates an electricity generation technology.

Eqs. (10) and (11) provide a mechanism to predict electricity transfers between counties in different BAs, but additional modeling is required to predict the direct electricity interchanges between counties within the same BA. However, a lack of electricity interchange data at the county-level exists, so an approximate model is developed here based on applying reasonable assumptions about electricity flows. This novel geographical electricity flow model is inspired by, and uses concepts from, thermal finite volume and explicit finite-difference methods to estimate the direct electricity interchange between counties within the same BA. In this model, each county is treated as a control volume and the model begins with an electricity balance equation:

$$\frac{dE_c}{dt} = \dot{E}_{in} - \dot{E}_{out} - \dot{E}_{nf} \tag{12}$$

where dE_c/dt is the total rate of electricity change in the county of interest, and $\dot{E}_{in}$ and $\dot{E}_{out}$ represent the electricity flow into and out of the control volume, respectively. $\dot{E}_{nf}$ is the net electricity flow rate of the control volume. By taking electricity going out of the control volume as positive, $\dot{E}_{nf}$ can be determined as

$$\dot{E}_{nf,m} = g_m - c_m - f_{out,m} \tag{13}$$

where $f_{out,m}$ indicates the net electricity flow between county m and other BAs. Discretizing the equation over time for county m within a BA with N counties, Eq. (12) becomes

$$\frac{\left(\phi_m^{p+1} - \phi_m^p\right)}{\Delta t} = \sum_{n \neq m}^{N} f_{mn}\left(\phi_n^p - \phi_m^p\right) - \dot{E}_{nf,m} \tag{14}$$

where p and Δt represent the time step number and time step value, respectively, f_{mn} is the weighing factor, and ϕ_m^p is a scalar potential that indicates the electricity remaining that are available for transfer at time step p in county m. The above model assumes that each county only imports or exports electricity. It is assumed that the electricity interchange is more likely to happen between counties with more generation and consumption, so f_{mn} is defined here as

$$f_{mn} = \frac{|g_m c_n - g_n c_m|}{\sum_m \sum_n |g_m c_n - g_n c_m|} \tag{15}$$

Eq. (14) is solved iteratively for ϕ at the subsequent time step as

$$\phi_m^{p+1} = \left(1 - \Delta t \sum_n f_{mn}\right)\phi_m^p + \Delta t \sum_n \left(f_{mn}\phi_n^p\right) - \dot{E}_{nf,m}\Delta t \tag{16}$$

At steady state, $\phi_i^{p+1} = \phi_i^p$, with convergence criterion set at $\left|\phi_m^{p+1} - \phi_m^p\right| \langle 10^{-6}$. Eq. (14) becomes

$$\sum_n f_{mn}(\phi_m - \phi_n) - \dot{E}_{nf,m} = 0 \tag{17}$$

where the time step number designation is removed since ϕ is independent of time step at steady state. Eq. (17) provides a basis for the electricity flow model since the general governing equation for

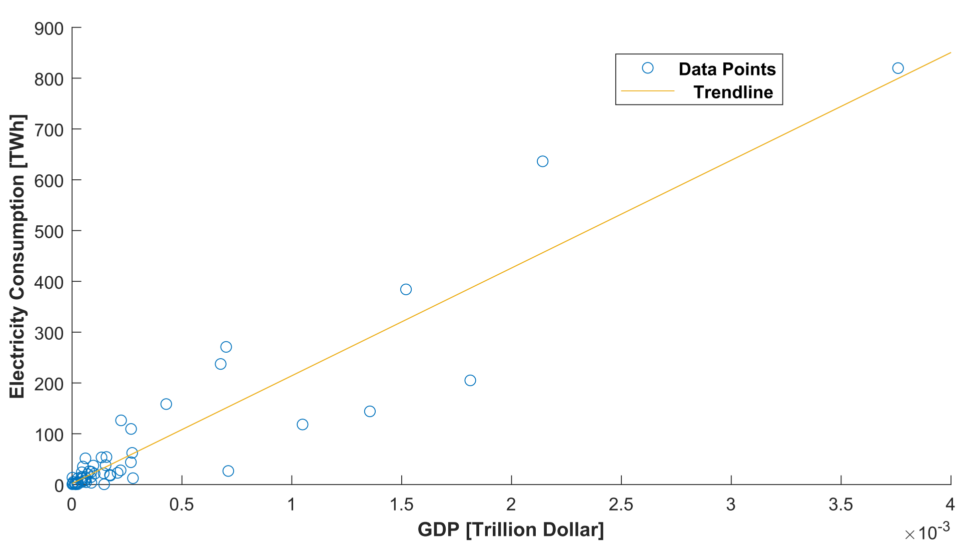

Fig. 2. Correlation between GDP and electricity consumption at the BA-level.

electricity flows at steady state is

$$\dot{E}_{nf,m} = \sum_{n \neq m}^{N} \dot{E}_{mn} \tag{18}$$

where $\dot{E}_{mn}$ is the electricity transfer from county m to county n, determined as

$$\dot{E}_{mn} = f_{mn}(\phi_m - \phi_n) \tag{19}$$

The QIO model can then be applied at the county-level with knowledge of county-level electricity generation, consumption, and intercounty electricity transfers.

3. Verification

Kodra et al. [17] estimated the EF values for over 134 PCAs in North America using an iterative method and available data from 2012. Qu et al. [18] pointed out that the iterative method is a mathematically equivalent approach to the QIO model if infinite iterations were performed. To verify the QIO model implementation here, we compared results using both the iterative method and the QIO model using 2019 data. The convergence criterion for the iterative method is an available electricity in 'tank T' at or below 10^{-9} MWh as suggested by Kodra et al. [17] Results show that the maximum absolute error is 1.85×10^{-17} MT-CO_2e/MWh and the mean absolute error is 1.00×10^{-17} MT-CO_2e/MWh when comparing EFs derived from two methods, which again shows the equivalence between the two approaches and provides confidence in the implementation of the QIO model in this study.

4. Results

4.1. BA-level EF

Fig. 3 shows some BAs that provide electricity directly to end users in the power grid network. The figure uses 2019 data. Generation-only BAs – those that do not directly serve retail customers (e.g., Electric Energy, Inc. (EEI), Gridforce Energy Management, LLC (GRID)) – are not included. Each node in the figure, covered by a pie chart, represents a BA. The colors on the pie chart represent different electricity generation technologies, and the size of the pie chart indicates the amount of electricity generated in MWh. PJM Interconnection, LLC (PJM), which produced over 821 TWh electricity in 2019, was the biggest electricity producer within the country at 15.3% of national total electricity generation. It should be noted that around 60% and 34% of electricity generated from PJM is fossil-fuel and nuclear-based, respectively.

Fig. 4 demonstrates how electricity interchanges affect EFs at the BA-level. A total of 64 markers shown in the figure represent the 64 BAs operating in the U.S. electricity network in 2019. Horizontal and vertical axes indicate generation-based EFs and consumption-based EFs, respectively. The generation-based EFs are determined by only considering CO_2e emissions in power generation processes within each BA using the lifecycle emission rates published by NREL. The calculated BA generation-based EFs range from 0 to 0.978 MT-CO_2e/MWh, and the consumption-based EFs range from 0 to 0.836 MT-CO_2e/MWh. Ten BAs (brown triangles) have consumption-based EFs of 0, indicating that they are generation-only BAs that do not directly provide electricity to customers. One BA (red square) has a generation-based EF of 0, which means that 100% of its electricity sold to end users is from other BAs. Results also show that 30 BAs with nonzero generation- and consumption-based EFs have smaller consumption-based EFs than generation-based EFs. Portland General Electric Company (PGE), which has a generation-based EF of 0.316 MT-CO_2e/MWh (65% of natural gas and around 35% of hydro power) and a consumption-based EF of 0.171 MT-CO_2e/MWh, is the BA with the largest reduction in GHG emissions (-59.6%) after considering electricity interchanges between regions. On the other hand, the EF of Western Area Power Administration-Upper Great Plains West (WAUW) has a generation-based EF (0.007 MT-CO_2e/MWh) which is much smaller than its consumption-based EF (0.372 MT-CO_2e/MWh, or 193%). Overall, in addition to the generation-only and non-generation BAs, 16 BAs' consumption-based EFs deviate from their respective generation-based EFs by over 20%, which indicates the significance of accounting electricity interchanges in the CO_2e emissions quantification processes.

Fig. 5 reveals the largest CO_2e emission transmissions within the grid. Due to space limits, only emission transmissions at least 10^6 MT are shown. Specifically, the Salt River Project Agricultural Improvement and Power District (SRP) transmitted the most CO_2e emissions to other BAs in 2019, which occupies 59.7% of total local CO_2e production. The two largest customers who receive electricity from SRP are the Arizona Public Service Company (AZPS) and the California Independent System Operator (CISO). Interestingly, CISO is the BA that receives the most CO_2e emissions from other BAs due to large electricity imports, whereas the Los Angeles Department of Water and Power (LDWP), the Balancing Authority of Northern California (BANC), AZPS and SRP are the biggest contributors. Furthermore, PJM, Midcontinent Independent System

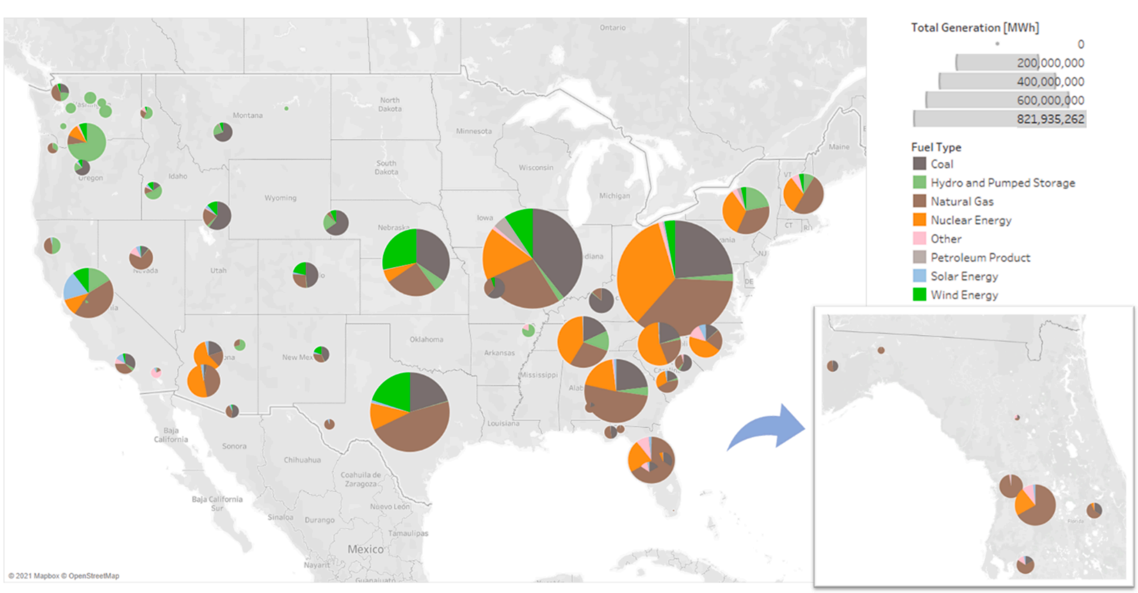

Fig. 3. Power generation portfolio of BAs that serve directly to end users.

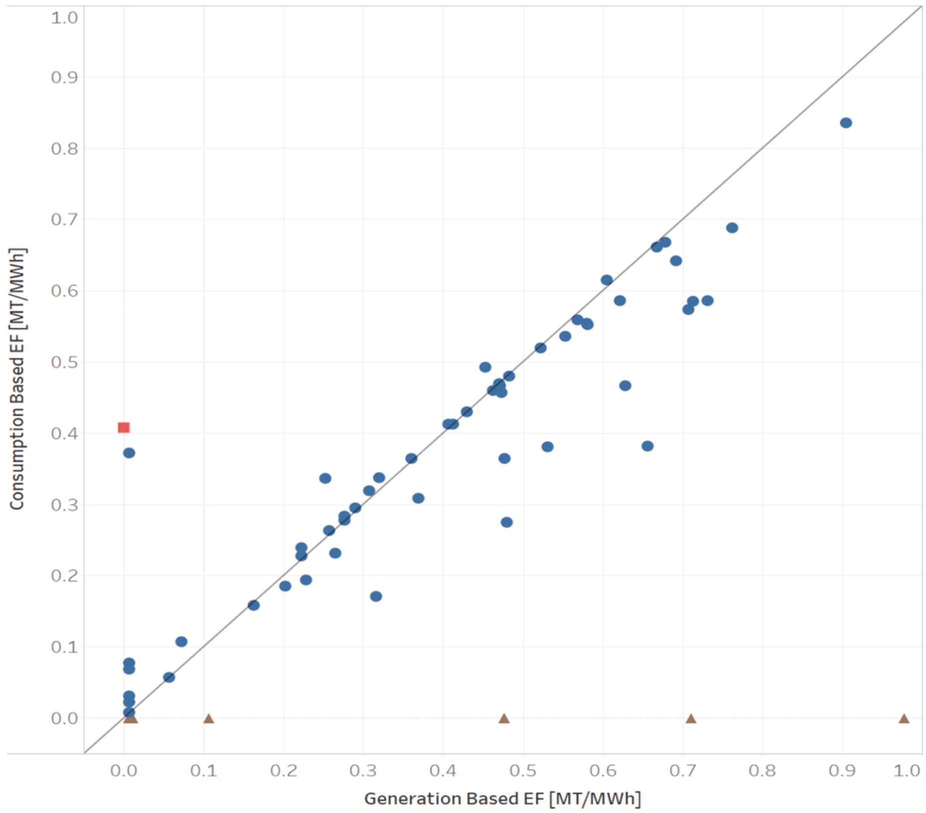

Fig. 4. Comparison between generation-based EFs and consumption-based EFs at the BA-level.

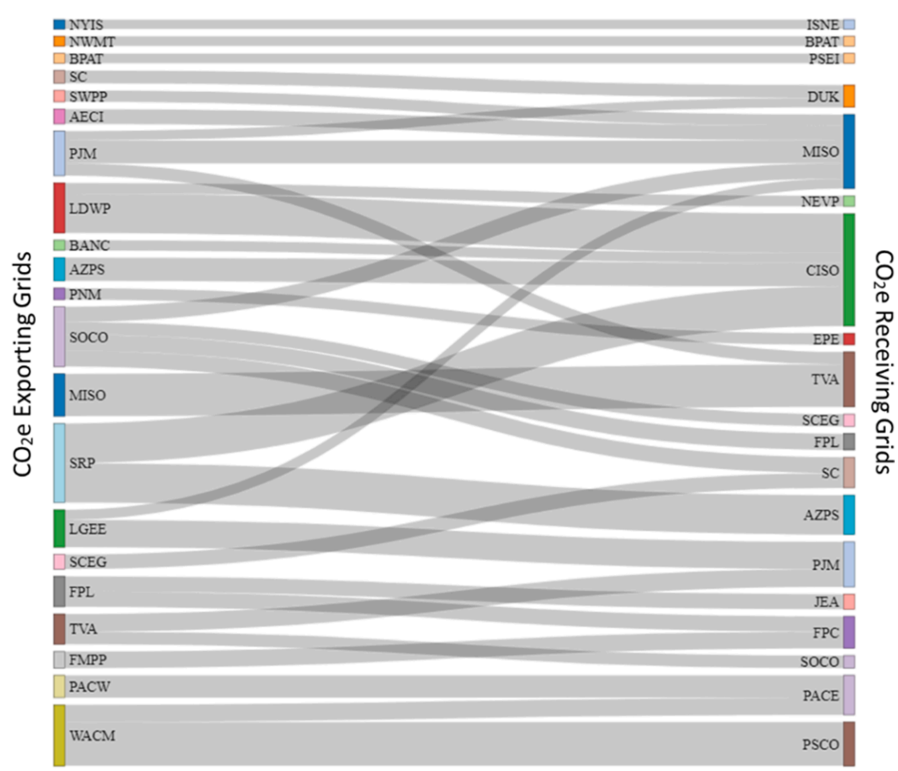

Fig. 5. Largest CO_2e emissions transmissions (>1,000,000 MT) between grids.

Operator, Inc. (MISO), the Electric Reliability Council of Texas, Inc. (ERCO) and the Southwest Power Pool (SWPP) are the biggest CO_2e producers in the country. On the contrary, 10 BAs (e.g. WAUW and the City of Tacoma, Department of Public Utilities (TPWR), etc.) in the U.S. achieved 100% renewable energy in 2019, which gives these BAs the distinction of having the least CO_2e emissions from electricity generation. Notably, 92.4% of total GHG emissions from electricity production in the Southwestern Power Administration (SPA) is transmitted to other BAs. Furthermore, over 99% of GHG emissions associated with electricity consumption in HST is generated from other BAs.

4.2. County-level EF

The predicted county-level consumption-based EFs are shown in Fig. 6. Results reveal that the consumption-based EFs at the county-level (0.007–0.902 MT-CO_2e/MWh) vary more broadly than at the BA-level (0.008–0.836 MT-CO_2e/MWh). Specifically, Chelan County and Grant County, WA are reported to have the lowest EFs (0.007 and 0.013 MT-CO_2e/MWh, respectively) among all counties in contiguous United States. The electricity market of those two counties are operated by Public Utility District No. 1 of Chelan County (CHPD) and Public Utility District No. 2 of Grant County (GCPD), respectively, who have achieved 100% renewable energy (hydropower and pumped storage) in electricity production. On the contrast, Mason County, KY, which is operated by LG&E and KU Services Company (LGEE), is reported to have the highest EF (0.902 MT-CO_2e/MWh) among all counties. One reason for the large EF is that the electricity production in LGEE is still dominated by fossil fuels (99%), where coal and natural gas produce 83% and 16% of electricity, respectively. Though electricity interchanges with other low EF counties help to reduce the consumption-based EF, the EFs of most of the counties within LGEE remains high. Counties in California and Pacific Northwest regions generally have low EFs due to high renewable energy usage. Counties in New England also show relatively low EFs because of international electricity transfers (electricity imports from Canada are dominated by hydropower). However, some counties within the Rocky Mountains and Midwest show some of the highest EFs in the U.S. because fossil fuels are still their largest electricity generation sources [30].

Fig. 7 reveals the remarkable variances in consumption-based EFs at the county-level within each BA. Red lines represent county-level EFs within a certain BA, and the green dots indicate BA-level EFs. Results suggest that using a BA-level EF as an emissions indicator for counties can be extremely inaccurate. One example of such inaccuracy can be found comparing EFs at the county-level and the BA-level in LGEE. The QIO model reveals that LGEE possesses a consumption-based EF of 0.836 MT-CO_2e/MWh, which makes it one of the most emission intensive BAs in the country. However, wide-ranging county-level EFs are found in counties within LGEE (0.287–0.902 MT-CO_2e/MWh) due to the diversity of power origins. Results also show that the BA-level EF is very close to county-level EFs if the BA contains few counties.

Fig. 8 reveals the variations in county-level EFs within each BA. Specifically, 20 BAs have county-level EFs vary greater than 0.1 MT-CO_2e/MWh, 13 BAs have EFs range greater than 0.2 MT-CO_2e/MWh, and 6 BAs have an EF variation exceeding 0.3 MT-CO_2e/MWh. The diagram re-emphasizes the large level of county-level EF variations within some BAs.

For comparison purposes, county-level EFs estimated in this study have been gathered at the state-level. The top half of Fig. 9 thoroughly characterizes the variances of county-level EFs within each state, as shown in the red lines. Green dots indicate the state-level EFs published in the eGrid database. Specifically, 12 eGrid estimates are smaller than the lower bound of county-level EFs within the same state, and 11 estimates are larger than the higher bound of county-level EFs within the same state. The bottom half of Fig. 9 shows the standard deviation of county-level EFs of each state. Specifically, taking California as an example, the EFs of counties within California range widely from 0.200 to 0.531 MT-CO_2e/MWh with a standard deviation of 0.05 MT-CO_2e/MWh, indicating that all data points are close to the mean, whereas the California-wide EF of 0.191 MT-CO_2e/MWh is reported in eGrid database. Overall, eGrid estimates range from 0.026 to 0.936 MT-CO_2e/MWh, while the county-level estimations range from 0.007 to 0.902 MT-CO_2e/MWh. One crucial reason that leads to such discrepancy is that neither electricity interchanges nor lifecycle analysis were considered in eGrid predictions.

A simplified uncertainty analysis, shown as Supplementary Information, was performed to quantify the possible range of both generation-based and consumption-based emission factors at the balancing authority-level due to the uncertainty in data inputs. These uncertainties stem from discrepancies and inconsistencies in the self-reported electricity generation values at the BA level provided by the Energy Information Administration. Furthermore, inconsistent methodologies and assumptions in thousands of life cycle assessment studies to predict life cycle emissions by various power generation sources have led to additional uncertainties. It was found that balancing authorities with extensive coal use led to the largest EF range, while consumption-based EFs tend to have smaller ranges than generation-based EFs because of fuel mixing.

The improved model provides an important step to determining the scope 3 greenhouse gas emissions from electric consumers, which could drive climate-change related policies and regulations. For example, the

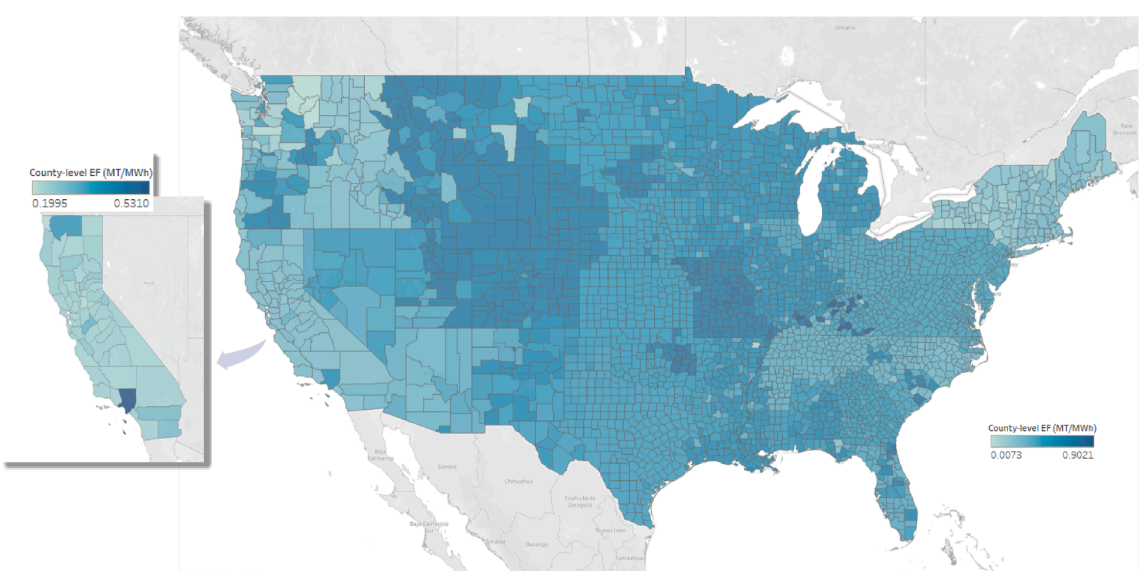

Fig. 6. Consumption-based EFs at the county-level.

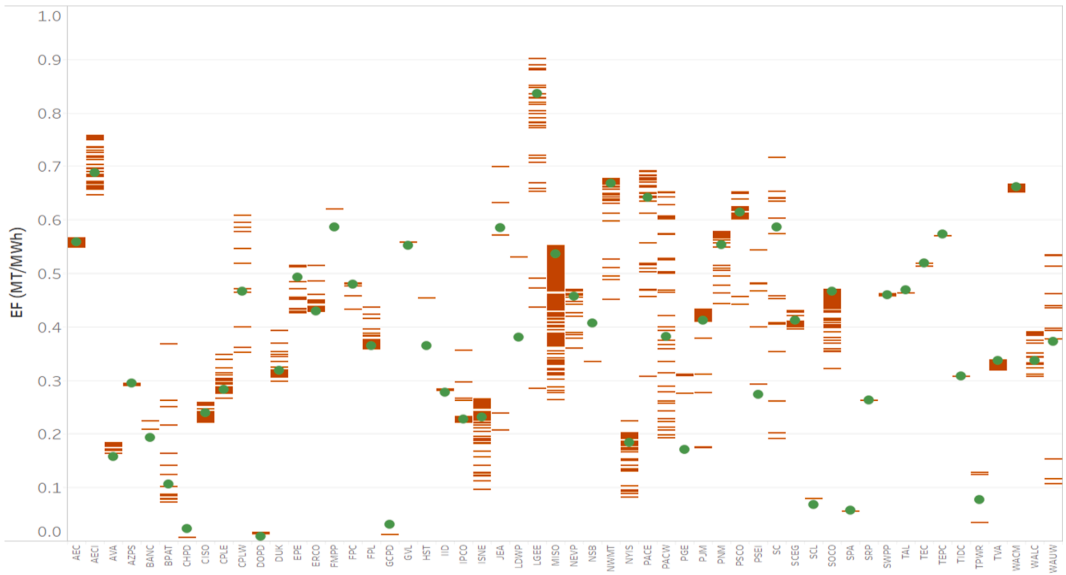

Fig. 7. Variations in consumption-based EFs at the county-level.

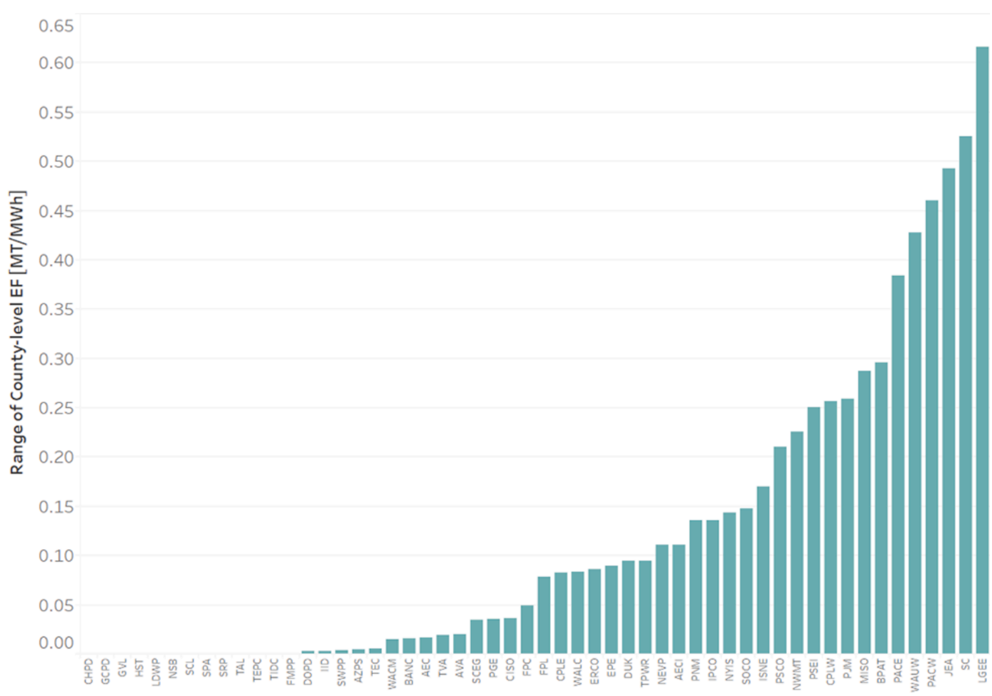

Fig. 8. Range of county-level EFs within a given BA.

carbon usage effectiveness (CUE) metric, which is defined as the mass of CO_2e per kWh of IT load [31], is used in the data center industry and can be estimated as the product of emission factor and the commonly-used power usage effectiveness (PUE), which is the total data center power consumption divided by IT load. The improved model can also be applied to determine the emission factors for any international region where electricity generation and transfer data are available.

5. Conclusions

This study confirms the hypothesis that scope 3 greenhouse gas emissions vary significantly within a large aggregation area (i.e., balancing authority region) by presenting a framework to estimate and track the local greenhouse gas emissions within the complex North American power grid. This study demonstrates that the new framework provides plausible data at a high spatial resolution (i.e., the county level), so the framework could be adapted to deduce the life cycle consumption-based emission factors at other spatial resolutions (e.g., state-level and region-level, etc.). Predictions that 16 balancing authorities have differences between consumption and generation-based EFs that exceed 20%, which suggests that consumption and generation-based emission factors may be significantly different for a given region and should not be used interchangeably. The results also reveal that large (>0.1 MT-CO_2e/MWh) county-level consumption-based emission factor variations exist in 37% of balancing authorities due to electricity interchanges, which supports the hypothesis that significant spatial emission factor variations exist within balancing authority regions.

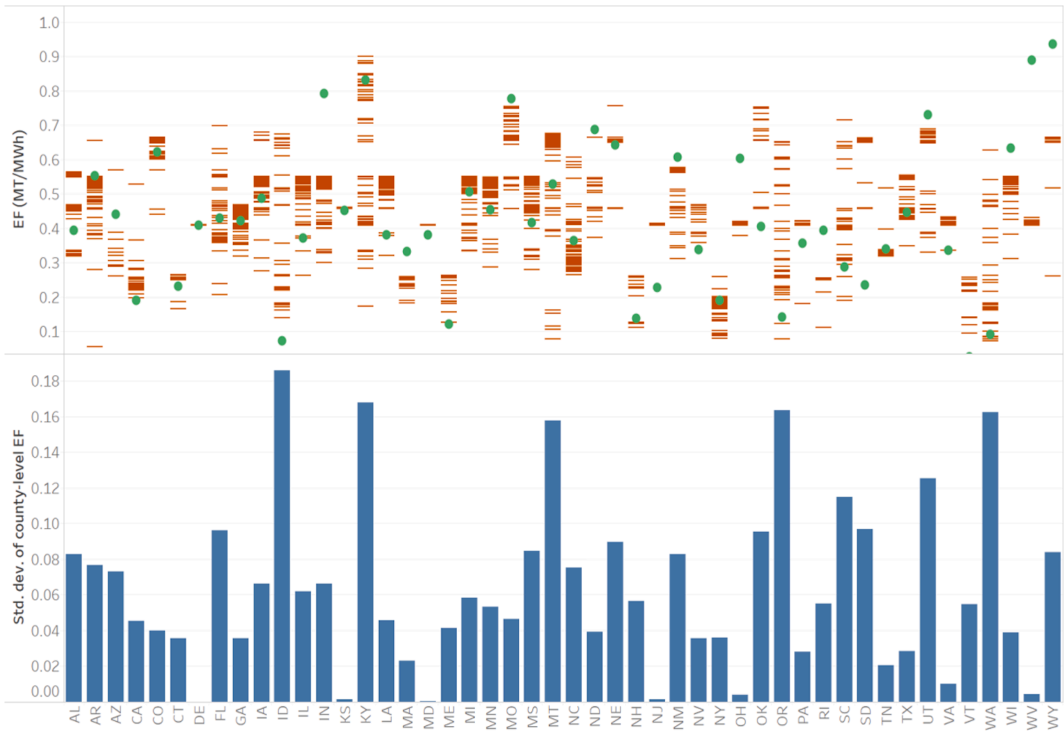

Fig. 9. Comparison between county-level EFs and eGrid state-level EF.

CRediT authorship contribution statement

Li Chen: Methodology, Formal analysis, Investigation, Writing - original draft, Visualization. **Aaron P. Wemhoff:** Conceptualization, Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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