Decision Support Algorithm for Evaluating Carbon Dioxide Emissions from Electricity Generation in the United States

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Summary

This article presents an algorithm to aid practitioners in determining the most appropriate method to estimate carbon dioxide emissions from an electricity load. Applications include sustainability assessments of products, processes, energy efficiency improvements, changes in generation infrastructure, and changes in electricity demand. Currently, there is no consensus on appropriate methods for calculating greenhouse gas emissions resulting from specific electricity loads. Previous research revealed significant differences in emissions when different methods were used, a situation that could result in divergent sustainability or policy recommendations. In this article, we illustrate the distribution of emissions estimates based on method characteristics such as region size, temporal resolution, average or marginal approaches, and time scales. Informed by these findings, a decision support algorithm is presented that uses a load's key features and an analyst's research question to provide recommendations on appropriate method types. We defined four different cases to demonstrate the utility of the algorithm and to illustrate the variability of methods used in previous studies. Prior research often employed simplifying assumptions, which, in some cases, can result in electricity being allocated to the incorrect generating resources and improper calculation of emissions. This algorithm could reduce inappropriate allocation, variability in assumptions, and increase appropriateness of electricity emissions estimates.

Introduction

Accounting for carbon dioxide (CO_2) emissions from electricity production is an essential aspect of many environmental impact studies and use of proper methods is essential when assessing avoided emissions from energy efficiency improvements, renewable generation, and changes in electricity demand. A number of methods exist to estimate greenhouse gas emissions associated with electricity consumption. This work focuses on those that account for combustion emissions, rather than emissions from upstream processes. There are methods developed in academia, industry, and government that are variously proprietary, open source, or developed for use within an organization (e.g., the U.S. Environmental Protection Agency's [US EPA] Integrated Planning Model). Approaches vary widely; they incorporate different variables, make different assumptions, and range in sophistication from simple look-up tables to sophisticated recursive optimizations. Such differences are a product

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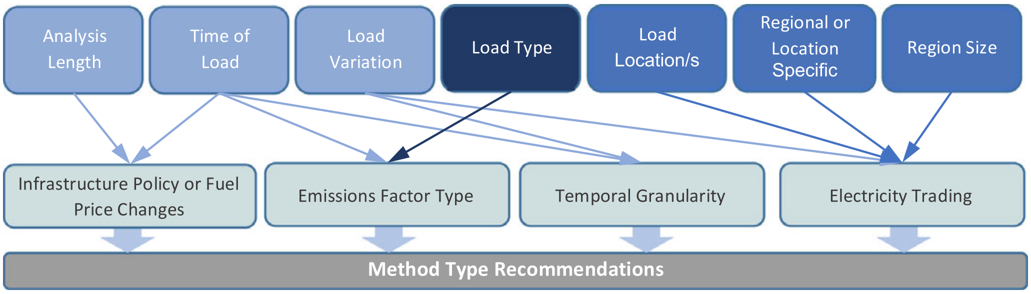

Figure 1 Conceptual illustration of how each load feature (top row) impacts specific method characteristics (middle row) recommended when estimating emissions. Load features relate to time (light blue), location (medium blue), and load type (consequential or attributional) (dark blue).

of the complexity of the electricity grid, which makes quantifying emissions from specific electricity loads challenging, and tracing electricity back to one generator often impossible (Yang 2013a; Weber et al. 2010). The grid's continuously changing mix of generation assets, which causes variation in emissions with time, adds to this complexity (Soimakallio et al. 2011; Yang 2013b).

Due to the grid's complexity, selecting an appropriate method to estimate emissions requires careful consideration of available methods' assumptions and characteristics. It is essential to align the method used with the specific load and research question (Ryan et al. 2016). The goal of the algorithm described in this paper is to foster this alignment by providing guidance to practitioners (e.g., researchers, policy analysts, life cycle assessment analysts, and consultants) in selecting a method that will appropriately allocate electricity CO_2 emissions to a load of interest based on the load's key features and the practitioner's research question. Although this algorithm focuses on CO_2 emissions, practitioners could use a similar approach for other greenhouse gas (GHG) emissions. Due to the large number of available methods, selection can be a daunting task. The algorithm provides assistance by determining what simplifying assumptions about the physical grid operation, which requires significant knowledge, time, and data to model properly, will and will not significantly change a load's emissions estimates. It then provides guidance on what types of methods make appropriate simplifying assumptions. Different methods can result in different emissions factors when examining an identical change in demand for a given location (Weber et al. 2010; Ryan et al. 2016), making it extremely important for practitioners to "exercise caution and sensitivity" when modeling electricity supply scenarios (Amor et al. 2014). This article describes the algorithm's logic and structure, and presents the algorithm's recommended method types for particular loads alongside those used in previous literature.

There is currently no consensus on the appropriate methods for estimating emissions from grid electricity for specific loads (Yang 2013a; Weber et al. 2010). Contention also exists over the 'best' method to estimate emissions, even from well-studied loads, like electric vehicles (EVs) (Graff Zivin et al. 2014; Soimakallio et al. 2011). Several examples of method variation are highlighted in the discussion and results section, where our algorithm is applied to four loads. Loads utilizing electricity from microgrids or off-grid applications are outside the scope of the algorithm, and are generally much simpler to model with tools such as HOMER (HOMER Energy 2016).

Methods

The relationships between load features (e.g., diurnal variability) and a method's characteristics are based on recommendations from our previous review (Ryan et al. 2016). In this paper, we show the effects of a method characteristics' (e.g., region size, temporal resolution, average or marginal approach, and the study duration) on emissions factor variation. The algorithm we present in this section determines the key features of an electricity load and an analyst's corresponding research question through a series of inquiries. Key features relate to time, location, and load type (consequential or attributional). These features are closely linked and all affect the way emissions for the load should be calculated.

Figure 1 is a conceptual representation of the connections between load features (top row) and method characteristics (middle row). The Supporting Information available on the Journal's website includes flow diagrams illustrating all of the connections between load features and method characteristics needed to operate the algorithm (figures S1 to S6 in the supporting information), as well as reference tables to assist in answering the algorithm's questions or to look up results for the relative importance of trading. The *Determining Method Characteristics* section explains in more detail the methods for determining the load features and how features are connected to recommended method characteristics.

Determining Method Characteristics

In this section, we explore the range of impacts on emissions factors stemming from decisions on the method characteristics. Using recent historical data, we illustrate the relative impacts of region size, inter-regional trading, temporal variation, the type of emissions factor, and multiyear changes. This analysis provides new insights into the range and relative impacts of model choice and simplification.

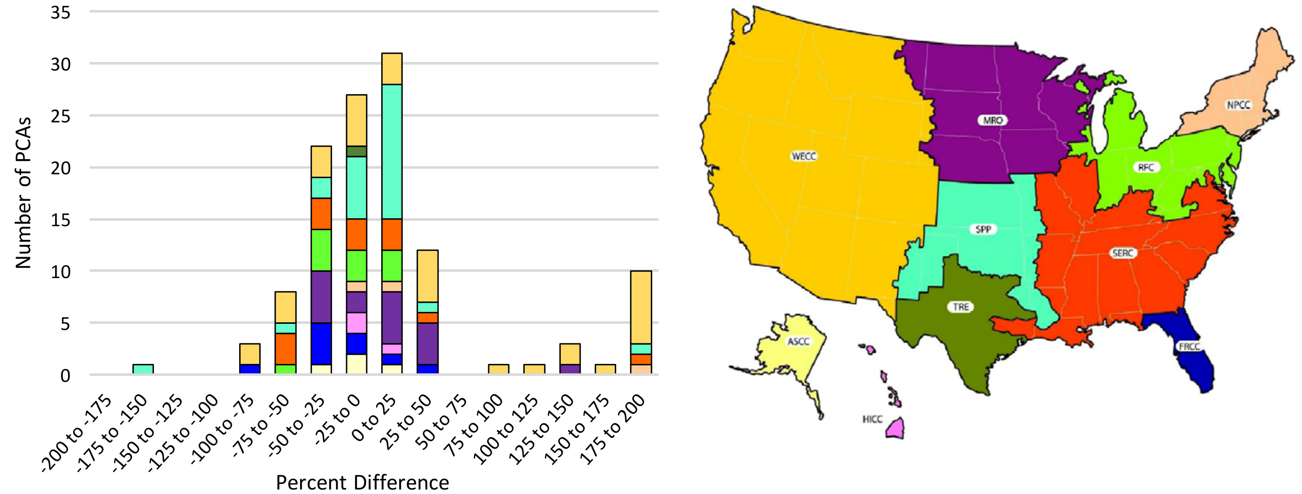

Figure 2 Frequency distribution of the percent difference between each Power Control Area's (PCA) emissions factor (lbs CO_2/kWh) and its surrounding North American Electric Reliability Corporation (NERC) region's emissions factor, color coded by NERC region. Emissions factors are based on eGRID 2012 data (US EPA 2012a, 2014). eGRID = Emissions & Generation Resource Integrated Database; lbs CO_2/kWh = pounds of carbon dioxide per kilowatt-hour.

Region Size

Previous work found significant variation in results when using different geographic regional boundaries to estimate CO_2 emissions from the same load, highlighting the importance of selecting an appropriate regional boundary (Ryan et al. 2016). Figure 2 illustrates the difference in emissions factor between each power control area (PCA) and its surrounding North American Electric Reliability Corporation (NERC) region. Many vary by less than 25% and some regions (e.g., Texas Reliability Entity) are more homogenous than others (e.g., Western Electricity Coordinating Council), but the average absolute value percent difference is 47%. Despite these strong differences, existing literature does not provide consistent guidance on appropriate region sizes or geographical boundaries (Weber et al. 2010), beyond the repeated theme that politically defined entities (e.g., states) are not appropriate regions to use in electricity studies (Kim and Rahimi 2014; Tamayao et al. 2015).

In determining suitable regional boundaries, the algorithm considers whether a load is regionally dispersed or occurs in a specific location(s). Regional, in this context, means that a load is roughly evenly distributed across a geographical area (i.e., consists of a large number of roughly homogeneous and evenly distributed locations within a given regional boundary). The region sizes used in this algorithm range from PCAs at the small end of the scale to the entire United States at the large end. The size and location of the region selected can affect the losses due to transmission. If the method selected does not include transmission losses, they may need to be added based on the region size selected. Values for select region sizes are available through the Emissions & Generation Resource Integrated Database (eGRID) and the U.S. Energy Information Administration (US EIA) (US EPA 2014; US EIA 2016a).

In the algorithm, the location(s) of electricity loads are categorized as "known locations" (e.g., factories) if they are specific and known, the number of loads is manageable for the analyst, and the locations are not homogeneous and evenly distributed within a region. In this case, the location(s), ZIP code(s), and data from the US EPA's *Power Profiler eGRID Subregion and GHG emissions finder tool* together determine the loads' eGRID subregion (US EPA 2012b). If the locations' PCAs are known, those PCAs are recommended as boundaries for loads with known locations. If the PCAs are unknown, eGRID subregions are recommended. We employed eGRID subregion boundaries due to their frequent use, because their boundaries are based on grid topology and not political geography, and for their ability to be delineated based on ZIP code. Grid operating decisions are made at the PCA level, making PCAs an appropriate basis for analyzing the electricity system. However, electricity trading can become vastly more important at this scale. We discuss this further in the *Incorporation of Electricity Trading* section. In general, if the location of production is known and data are available, our recommended best practice is that a smaller region be used when estimating emissions from electricity consumption. Electricity on the grid will follow the path of least resistance, which will be the shortest distance since resistance increases with line length (Chen 2005), so it is logical that the generators in the PCA/Balancing Authorities (BA) (i.e., the smallest electrical region) would be the most probable to serve the load.

Incorporation of Electricity Trading

A variety of methods have been developed to estimate regional imports and exports of electricity in an attempt to better estimate average electricity GHG emissions. Marriott and Matthews (2005) modeled interstate trading to improve their emissions estimates for particular industries, and found that incorporating trading brought state average emissions factors closer to the U.S. average. Colett and colleagues (2015) included trading in their nested average emissions modeling applied to aluminum production. They examined trading between each location's PCA and the surrounding NERC region (Colett et al. 2015). Ji and colleagues used an input-output model to determine the indirect electricity trading in interconnected grid networks (e.g., North Europe, Eurasia, and China) and to better estimate GHG emissions (Ji et al. 2016).

The method used in our analysis to determine the importance of trading, as in the other studies discussed, employs annual average trading values. These methods are only appropriate for attributional loads without temporal variation. The necessity of including traded electricity when estimating emissions depends on multiple factors. The factors used in the algorithm are emissions factor type, region type, percentage of total electricity consumption that was imported, and percentage difference in emission factor between the importing region and the surrounding region. How the algorithm uses these factors to estimate the importance of including trading is discussed below.

Factors not included (e.g., locational marginal price, load size, and available regional capacity) are important when assessing marginal emissions but are not as necessary for average emissions. Estimating marginal emissions requires determining the effects of a change in demand on electricity trading. This is both regionally and temporally specific and requires significantly more data.

Changes in demand (i.e., a consequential load calling for an estimation of marginal emissions) could cause an increase or decrease in electricity trading depending on the region's capacity, existing load, and the marginal price of the region's electricity, as well as of those it is interconnected with. A region that currently experiences no imports could begin importing electricity if the addition of an electricity load increased demand beyond regional supply or influenced marginal electricity price enough to make it economical to begin trading. In this case, the emissions from the traded electricity should be allocated to the load along with emissions from any change in generation caused within the region. The regional importance of trading (RIT) method, discussed in equations 1 and 2, does not incorporate these details and is not appropriate for estimating the importance of including marginal trading. Only prospective dispatch methods are appropriate to estimate emissions in this situation (Ryan et al. 2016).

Factors that should be considered when estimating marginal emissions affect trading on an hourly basis. Figure S8 of the supporting information on the Web illustrates hourly changes in demand and hourly variation in imports and exports from Florida for 6 months of 2015. The data show a trend across the day where greater imports occur during hours of higher demand and that the differences between hours within a day and among days are nontrivial. We only provide general recommendations on trading and marginal emissions, as we do not have the data to complete a quantitative analysis (similar to the calculation of RIT values in the proceeding paragraphs) on an hourly basis or for consequential loads. In these situations, we advise practitioners to examine the hourly trading values in their region of interest before proceeding. The "U.S. Electric System Operating Data" from the US EIA is a useful reference in this area (US EIA 2017).

The algorithm recommends the inclusion of electricity trading when estimating marginal emissions for region types other than the largest: NERC, AVoided Emissions and geneRation Tool (AVERT), US EPA, interconnection, and the entire United States. The inclusion of trading is also generally not a necessary method characteristic for average emissions in the aforementioned region types. Based on 2013 data, each NERC region's summer and winter imports were less than 3% of their annual net load (NERC 2015). In 2014, imports from Canada made up only 1.6% of U.S. electricity retail sales (US EIA 2015), and U.S. electricity trade with Mexico in 2013 was less than 0.01% of total U.S. electricity consumption (US EIA 2013).

If the region under consideration is a state, then it is important to incorporate electricity trading. Exceptions are Texas (since the vast majority is within the Electric Reliability Council of Texas [ERCOT] interconnection) and the Hawaiian and Alaskan grids. In most cases, state borders have no relationship to power system operational boundaries; electricity frequently flows across state borders.

If the region under analysis is a PCA and the emissions factor type is average, the necessity of including trading is determined by the percent difference between the PCA's emission factors and its corresponding eGRID subregion emissions factor and by the percent of electricity consumed in the PCA that is imported. Each NERC region is made up of one or more eGRID subregions, and each subregion is made up of one or more PCAs. The emission factors for each PCA and subregion used in this determination are total CO_2 emissions from the US EPA's eGRID database (US EPA 2014). Data for imports into BAs are from Federal Energy Regulatory Commission (FERC) form 714 (FERC 2010). The BAs are matched to PCA regions by their US EIA code. Not all regions match and both emissions data and trading data were not available for every PCA/BA set. We define the relative importance of trading, $RIT_{\mathrm{PCA/BA}}$ for the PCAs as (equation 1):

$$RIT_{\mathrm{PCA/BA}} = \left(\frac{EF_{\mathrm{PCA}} - EF_{Subregion}}{0.5(EF_{\mathrm{PCA}} + EF_{Subregion})}\right) \times \left(\frac{net\_actual_{\mathrm{BA}}}{net\_energy\_load_{\mathrm{BA}}}\right). \quad (1)$$

where net_actual_{BA}, is the BA's "net actual" imports (imports minus exports) and $net\_energy\_load_{\mathrm{BA}}$ is its load. EF_{PCA} is the average emissions factor of the PCA and $EF_{Subregion}$ is the emissions factor of the subregion. The $RIT_{subregion}$ values for eGRID subregions are (for $actual\_rec_i \geq actual\_del_i$) (equation 2):

$$RIT_{subregion} = \left(\frac{EF_{subregion} - EF_{nerc}}{0.5(EF_{subregion} + EF_{nerc})}\right) \times \left(\frac{\sum_i^N actual\_rec_i - \sum_i^N actual\_del_i}{\sum_i^N net\_energy\_load_i}\right), \quad (2)$$

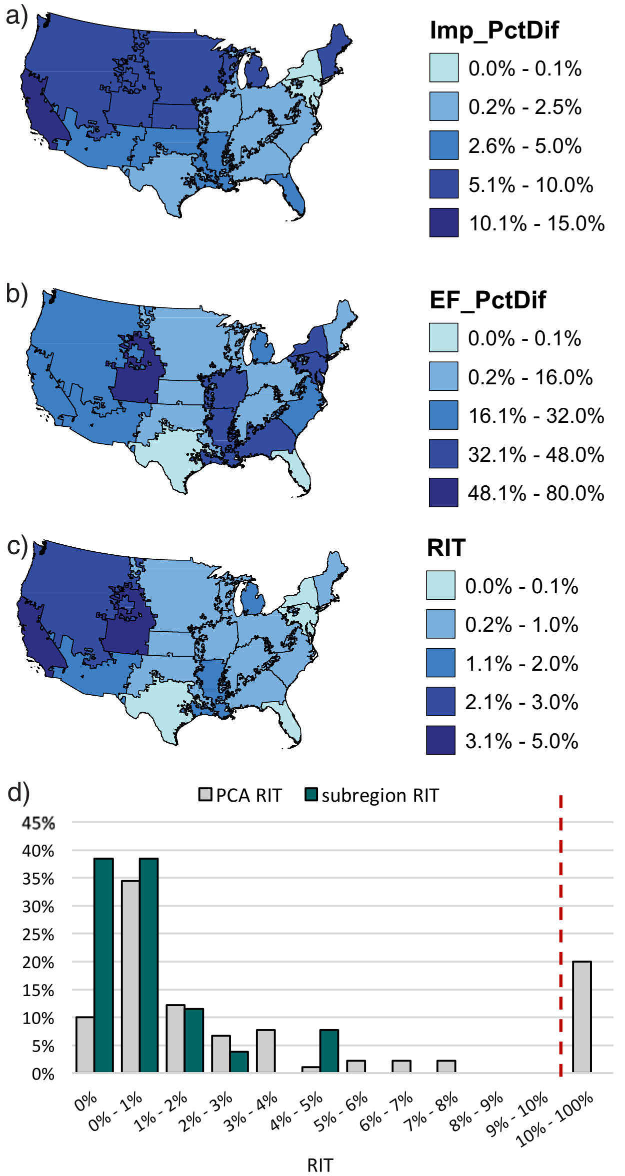

Figure 3 Spatial distribution by subregion of: (a) annual net imports as a percentage of the total demand (Imp_Pct); (b) percent difference between subregion emissions factors and NERC emissions factor (EF_PctDif); (c) relative importance of trading (RIT); (d) frequency distribution of relative importance of trading (RIT) values for each Power Control Authority (PCA) and subregion. NERC = North American Electric Reliability Corporation.

where $actual\_rec_i$ is the import into each PCA/BA, $actual\_del_i$ is the export out of each PCA, i is each PCA/BA within the subregion, N is the number of PCA/BAs in the subregion for which $RIT_{subregion}$ is being calculated, and EF_{nerc} is the average emission factor for the NERC region, from the US EPA's eGRID database (US EPA 2014). Other data sources and regional boundaries could be used in this analysis (e.g., US EPA regions), but we selected eGRID boundaries due to their frequent use, the public accessibility of their data, and because their boundaries are based on grid topology and not political geography. Figure 3a to 3c shows the $RIT_{subregion}$ values and the impacts of the percent difference in emissions factor and percent imports. In some regions (e.g., Florida), there is a large percentage of imported electricity, but the percent difference between the emissions factor of the subregion and of the NERC region is zero, making the $RIT_{subregion}$ value zero. The opposite is seen in New York, for example. Figure 3d shows the spread of $RIT_{subregion}$ and RIT_{PCA} values. An analyst should examine where their region falls in this distribution to determine if it is important to include electricity trading when their region is a PCA or a subregion.

RIT does not represent the actual change in emission factors when trading is included, but is intended to indicate the relative importance of including electricity trading in an analysis when using average emissions factors. There are limitations to this approach, namely that the time of trading is not included and average emissions factor are used. These exclusions limit the application of RIT values to determining methods for estimating annual average emissions factors for attributional loads in the near term. Emissions factors and the amount of trading will vary from year to year, so RIT should not be used in analyses with future time frames. Tables S4 and S5 of the supporting information on the Web present the values of *RIT* for each subregion and PCA/BA. Table 1 lists general recommendations based on region type.

Table 1 Importance of electricity trading based on analysis region and emissions factor type

Region	*Average emissions factor*	*Marginal emissions factor*
Entire U.S., interconnection, NERC, EPA, AVERT	Unlikely to have significant impacts	Unlikely to have significant impacts
eGRID subregion	Based on RIT value	Important to consider
State	Important to consider except for Alaska, Hawaii, and Texas	Important to consider except for Alaska, Hawaii, and Texas
PCA/BA	Based on RIT value	Important to consider

Note: NERC = North American Electric Reliability Corporation; EPA = U.S. Environmental Protection Agency; AVERT = AVoided Emissions and geneRation Tool; eGRID = Emissions & Generation Resource Integrated Database; PCA = power control area; BA = Balancing Authorities; RIT = relative importance of trading.

Emissions Variation with Time

The importance of accounting for CO_2 emissions variation over time is highly dependent on temporal variation in load, temporal variation in regional generation mix, and emission factor type. Ignoring temporal variation can reduce the

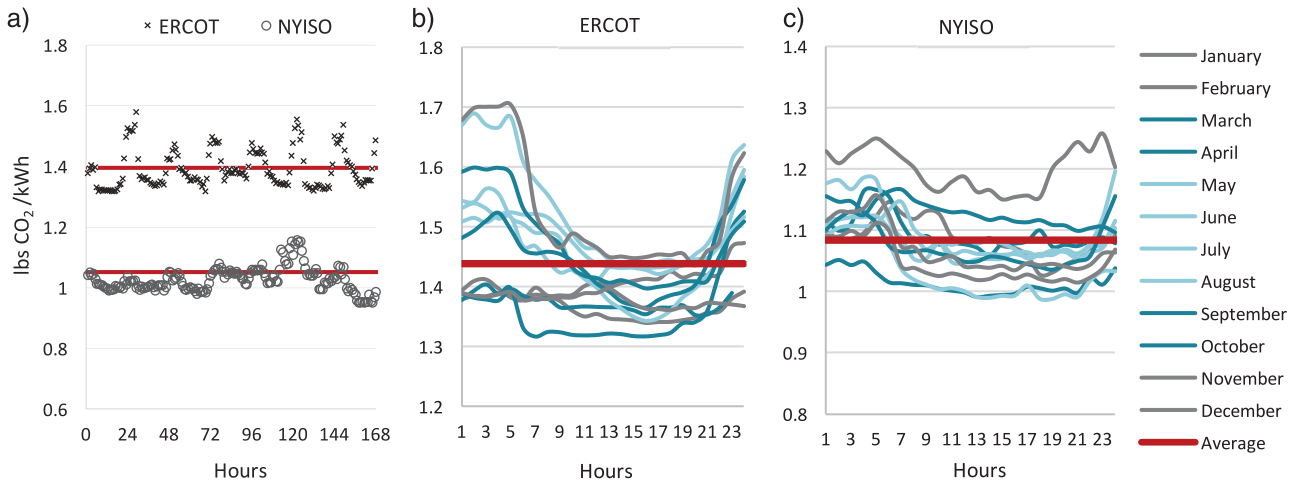

Figure 4 Differences in diurnal and seasonal impacts on average emissions factors between NYISO and ERCOT: (a) average hourly CO_2 emissions factors for NYISO and ERCOT spanning the first week in April 2015 (SNL 2016); (b) hourly average emissions factors for the first weekday of each month in 2015 compared to the annual average in ERCOT and (c) in NYISO (SNL 2016). CO_2 = carbon dioxide; ERCOT = Electric Reliability Council of Texas; lbs CO_2/kWh = pounds of carbon dioxide per kilowatt-hour; NYISO = New York Independent System Operator.

relevance of a study if a load varies substantially with time (Amor et al. 2014). It can make a significant difference in emissions if a load occurs during on-peak or off-peak hours (Mathiesen et al. 2009). Typically, a region's electricity generation mix varies by year, season, and time of day (Soimakallio et al. 2011), but this variation is not consistent across different regions.

Figure 4a shows hourly average CO_2 emission factors for ERCOT and the New York Independent System Operator (NYISO) for the first week of April 2015, illustrating that the difference in diurnal variation between the two regions (SNL 2016). Figure 4b and 4c illustrates the monthly difference in diurnal CO_2 emission factor for ERCOT and NYISO (using the first day of each month). In ERCOT, there is a stronger diurnal variation in a number of months, but the trend is not seasonal. In general, emissions in NYISO do not have as much diurnal variation as in ERCOT, but there is significant monthly variation. Additionally, there is significant difference between the annual average emissions factor in each region and the hourly values, showing again the importance of including temporal variation for temporally varying loads.

To determine the importance of including temporal variation, the algorithm considers the time granularity and duration of the analysis, seasonal and daily variation in load, and emission factor type. Time granularity can vary from a particular hour to multiple years. Typically, the simpler methods cannot account for seasonal or daily load variation because they report emissions on a yearly basis, but emissions reporting intervals vary over a wide range. Figures S1 to S3 in the supporting information on the Web provide more detail on how temporal load features will affect the algorithm's recommendations. In some cases, the need to include emissions variation in an analysis is also dependent on how much the regional generation mix changes throughout the year or day, as shown in figure 4.

When using a marginal emissions factor, not only are the load profile (i.e., variation in electricity load versus time of day) and regional generation mix variation important in determining the need for emissions variation with time, but so is the importance of including trading. When using a marginal emissions factor in an analysis where the algorithm recommends the inclusion of trading, hourly temporal variation should be incorporated whether or not the load has strong diurnal or seasonal shapes. If trading occurs as a result of the load, the trading could have strong temporal variation, seen in figure S8 of the supporting information on the Web, even if the load is relatively constant in magnitude.

Type of Emissions Factor

Emissions can be categorized as either marginal or average. Emissions from all generators operating at a given time constitute average emissions, while marginal emissions are produced by generators that adjust their output in response to a change. Marginal generators, as with average, can be a mix of types using a variety of fuels. The distinction between marginal and average emission factors is important due to the significant differences in emissions estimates that can result. Twelve of the 26 eGRID subregions have a 25% or larger difference between their eGRID subregion annual CO_2 nonbaseload output emission rate (pounds per megawatt-hour lbs/MWh) (i.e., marginal) and their eGRID subregion annual CO_2 total output emission rate (lbs/MWh) (i.e., average) (US EPA 2014). These differences are likely to have a significant effect on a study's recommendations. Note that eGRID's nonbaseload emissions factor is not a true marginal emission factor as it includes all combustion units with a capacity factor of less than 0.8, but it is often used as an estimate of the marginal emission factor. The nonbaseload rate is provided by the US EPA primarily to estimate emissions for energy efficiency and clean

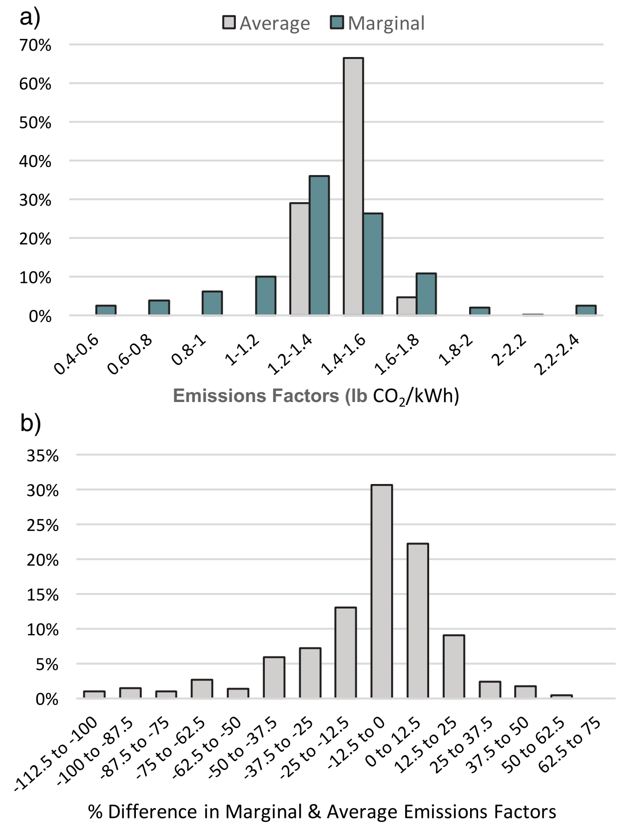

Figure 5 Frequency distribution of emissions factors: (a) hourly marginal and average CO_2 emissions factors (lbs. CO_2/kWh) for ERCOT in 2015; (b) percent difference between marginal and average emissions factors in each hour. Marginal values were calculated from AVERT's Texas region, and average emissions were calculated from SNL gross generation and CO_2 emissions data for ERCOT. AVERT = AVoided Emissions and geneRation Tool; ERCOT = Electric Reliability Council of Texas; lbs CO_2/kWh = pounds of carbon dioxide per kilowatt-hour.

energy projects (US EPA 2014). Additionally, our analysis of ERCOT's hourly average and marginal emissions, shown in figure 5, showcase the significant differences seen in each individual hour between average and marginal emissions, as well as the differences overall. While the annual average difference between the emissions factor types was only 8%, the hourly difference between the average and marginal emission factors was 19% and for a given hour differ by up to 1.2 pounds of CO_2 per kilowatt-hour (lbs CO_2/kWh). The data used to calculate the average and marginal emissions were from different sources, but were from the same year and had the same regional boundary.

Information required to estimate which specific generators are marginal, such as price bids, are typically not publicly available (Amor et al. 2014). Even when necessary data are available (possibly from regional transmission organizations or independent system operators [ISOs]), identifying the marginal generators is difficult and greatly increases analysis time (Mathiesen et al. 2009).

In order to determine whether a marginal or average factor should be used, the algorithm considers whether a load is new, existing, existing but changing, or simply a change in generation mix. Methods should use an average emissions factor if a load is existing because it is part of the current demand. If the load is specified as a change or new, and is not a small commercial or residential load, the algorithm recommends the load be treated as marginal because it is not part of the existing demand and will cause a change in the generation mix. If the load is a small commercial or residential load, the algorithm recommends the use of an average emissions factor. Small loads are defined as a change smaller than typical demand variation, which is balanced through ancillary services, so marginal generators will not necessarily be dispatched to meet the change. It is important to note that this question refers to the aggregation of all loads a user is interested in analyzing within a region. If the aggregation is larger than the regulation load, then the new load or change in load should be treated as marginal. In PJM, regulation services, which make up for the mismatch in demand and supply, constitutes 0.7% of the total load, based on 2016 PJM hourly load (PJM 2016a) and ancillary services market data (PJM 2016b). This percentage will likely vary by region. The logic for this section is presented in figure S1 of the supporting information on the Web.

Changes in Infrastructure, Fuel Price, or Energy-Related Policy

Electricity demand, technology portfolio (i.e., infrastructure), resource availability, and imports determine the electricity generation mix. Fuel price, regulations, and the economic climate can drive changes in these characteristics, which can significantly affect average and marginal emission factors, thus making it important to consider them when analyzing emissions as part of sustainability assessments with future time frames. Predictions for changes in fuel prices and regulations can affect not only predicted generator operation, but also planned capacity additions, retirements, and implementation of emissions control measures. Even if significant changes in existing infrastructure are not expected, a method that can account for changes in fuel price demand or regulations needs to be used to accurately address possible changes in generation mix when analyzing future electricity emissions impacts.

Using annual average CO_2 emissions factors for each year from 1973 to 2015 (calculated from US EIA data), we show in figure 6 the relative change in emissions factors over the following 10 years. From 1973 to 1999, this value steadily increased, and from 1999 to 2015, it began to decrease. On average, the emissions factor changed 6% in 3 years and 9% after 5 years.

Informed by the results shown in figure 6, we classify future loads into three time spans: less than 3 years, from 3 to 5 years, and more than 5 years. These delineations are used to provide recommendations on method type. Figure S4 of the supporting information on the Web illustrates this logic.

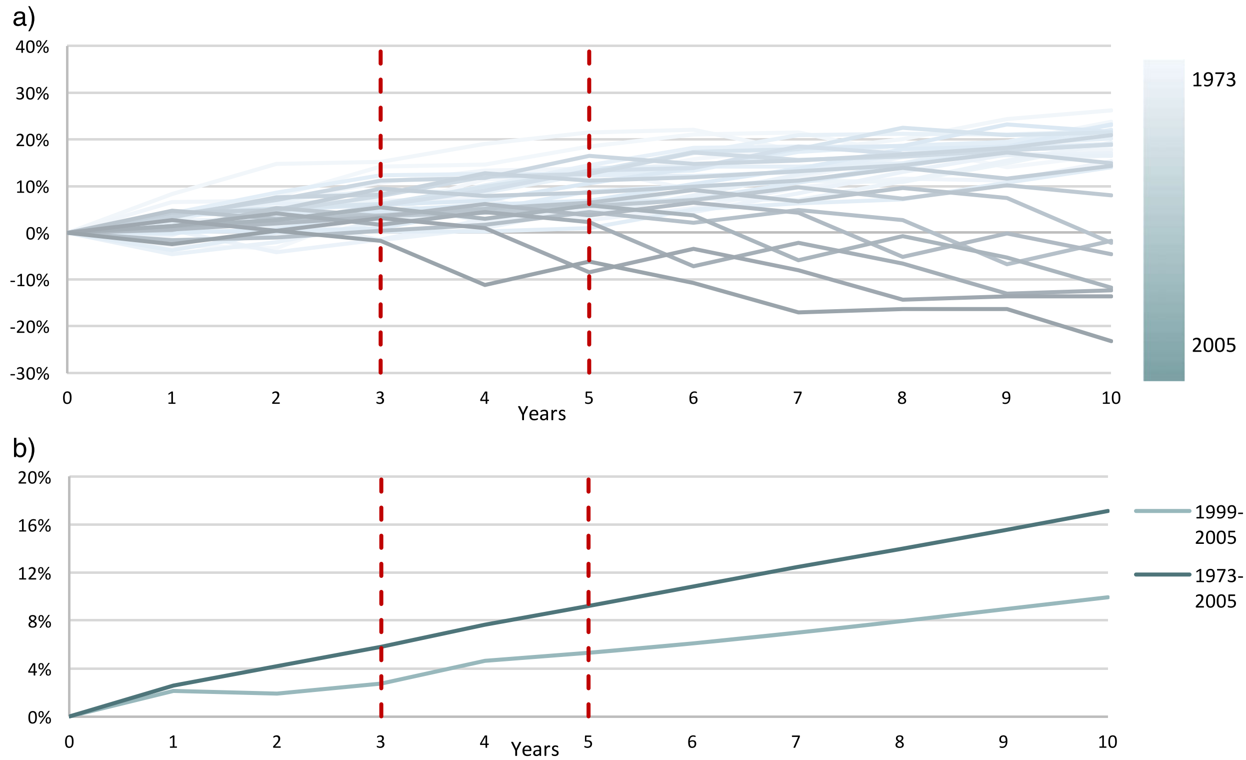

Figure 6 Percent change in annual average emissions factor (lbs CO_2/kWh) across 10 years: (a) with base years from 1973 to 2005; (b) average magnitude of the percent change in the annual average emissions factors (lbs CO_2/kWh) across 10 years, for base years from 1973 to 2005 and 1999 to 2005. The data are calculated from US EIA CO_2 emissions from energy consumption in the electric power sector (US EIA 2016b) and net electricity generation from the power sector (US EIA 2016c). Vertical dashed lines separate future load time periods used to recommend whether possible methods should incorporate fuel, price, policy, or infrastructure changes. lbs CO_2/kWh = pounds of carbon dioxide per kilowatt-hour.

Excel Tool

The algorithm is coded into an Excel tool (available at http://css.umich.edu/page/selecting-electricity-emissions-models-seem) that includes additional capabilities such as specific method recommendations and the ability to weight the importance of method characteristics. The algorithm Excel tool was tested by practitioners including 12 individuals with expertise in the field, fellow researchers, faculty, and industry partners. Each practitioner was provided three scenarios from a set of seven. Refinements to the tool were made based on practitioner feedback, much of which related to question phrasing. There is some subjectivity inherent in the algorithm, in that not all practitioners' results were identical for the same load. This subjectivity allows the algorithm to better match method characteristics to the chosen load and research question being considered, while enabling exploration of the impact of different responses on the algorithm's recommendations.

Illustrative Case Discussion

Illustrative recommendations based on the algorithm's results are presented for four hypothetical electricity loads: a household air conditioner; an EV fleet; a grid-connected solar photovoltaic (PV) installation; and aluminum smelters. Emissions from these types of electricity loads, most predominantly the EV fleet and aluminum smelters, have been assessed in multiple studies (discussed below). The EV and aluminum smelter cases are presented here, and the air-conditioner and PV cases are located in the Supporting Information on the Web. We present the methods used in these studies alongside the algorithm's recommendations to illustrate the variation in assumptions made among studies and by the algorithm. While we propose the algorithm's recommendations as current best practices, this should not be taken as an implication that there is one "best" method to use for all electricity loads and research questions. Our intention is not to highlight shortcomings in the methods used in previous studies, but to emphasize the variability and inconsistency among them and the need for the kind of guidance our algorithm provides. *Key results that vary across the methods are presented in italics throughout the case study sections*. The case study loads were selected not only because they have been previously studied in detail, but also because they highlight how the algorithm's recommendations are affected by differences in key load features, that is, variable vs. constant load, demand reduction vs. addition, regional vs. location-specific, and historical vs. future. In most cases, there are differences among the literature methods and between the literature

Table 2 Algorithm recommendations on method characteristics for estimating electricity emissions resulting from the electricity consumption of a household air conditioner an EV fleet, a grid connected solar PV installation, and aluminum smelters

	Electricity Loads			
Characteristic	*Household Air Conditioner*	*EV Fleet*	*Solar PV*	*Aluminum Smelters*
Emissions factor type:	Average emissions factor	Marginal emissions factor	Marginal emissions factor	Average emissions factor
Temporal variation:	An hourly time interval should be considered to capture daily variation.	The method needs to incorporate hourly variation.	The method needs to incorporate hourly variation.	The method does not need to incorporate variation with time.
Time granularity:	Monthly	Hourly	Hourly	Yearly
Time scale:	Time scale does not need to be considered because you are interested in a historical load.	Method may need to account for future infrastructure, fuel price, or energy policy changes. Select methods in the Economic Dispatch or Unit Commitment categories may be appropriate.	Method may need to account for future infrastructure, fuel price, or energy policy changes. Select methods in the Economic Dispatch or Unit Commitment categories may be appropriate.	Time scale does not need to be considered because you are interested in a historical load.
Region size:	PCA	State	PCA	PCA, but location/s are still specific.
Region:	ISO New England	CA	Nevada Power Company	Big Rivers Electric Corporation, South Carolina Public Services Authority
Inclusion of trading:	The relative importance of trading is estimated to be 0.1%.	The method should incorporate electricity trading.	The method should incorporate electricity trading.	In consecutive order based on location, the relative importance of trading is estimated to be: 2%, 16%.
Top ranked method types:	Empirical Data & Relationship Methods: Simple Emissions Factors, Statistical Relationship Model & Power System Optimization: Economic Dispatch	Power System Optimization Methods: Economic Dispatch, Unit Commitment	Power System Optimization Methods: Economic Dispatch, Unit Commitment	Empirical Data & Relationship Methods: Simple Emissions Factors or Emissions Factor Methods with Trading/Imports

Note: EV = electric vehicles; PV = photovoltaics; PCA = power control area; CA = California.

methods and the algorithm's recommended method characteristics, which are collected in table 2.

Fleet of Electric Vehicles

A researcher is interested in estimating the change in hourly CO_2 emissions resulting from the electricity consumed by a new fleet of electric taxis deployed in major cities across California over the next 5 years. The algorithm's recommendations are presented in table 2. Heterogeneous daily charging patterns drive the algorithm's recommendation to *incorporate hourly variation*, and because the fleet is new (i.e., an added load), the algorithm recommends the use of *marginal* emissions factors. The researcher's assumptions include a constant fleet size and likely changes in electricity infrastructure, fuel prices, or energy policy. As a result, the algorithm recommends that the selected method *may need to account for these changes* over the time period of the analysis. These characteristics drove the recommendation for an economic dispatch and unit commitment model.

There is a large amount of literature on estimating emissions from EV electricity consumption. Ryan and colleagues (2016) compared the emissions factors for EV charging using a variety of methods. In this section, we will mention just a few of the many studies that model fleets of EVs. In these studies, the emissions factor type, time scale, and temporal variation used varied among studies. Other characteristics also varied, but differences in study scale and location drove those differences.

When comparing well-to-wheels CO_2 emissions from EVs to internal combustion engine vehicles in the United Staes, UK, and France, Holdway and colleagues (2010) applied country-level *average* emissions factors and fuel-specific emission factors. Despite Holdway and colleagues' (2010) major simplifying assumptions, they were able to illustrate the importance of grid decarbonization in EVs effectively reducing emissions in the transportation sector. Instead of directly modeling the electricity grid for their comparison of vehicle drivetrains, Meinrenken and Lackner (2015) used a wide range of carbon intensities (50 to 1,200 grams of CO_2 equivalent per kWh) by employing a variety of average grid mixes, from all wind-solar to all coal, similar to Holdway and colleagues' approach. Meinrenken and Lackner (2015) were able to determine under what grid conditions each drivetrain type would reduce overall emissions. These two studies do not align with the algorithm's recommendations for current best practices, but they are asking different research questions than the one posed in our case. They are presenting comparative scenarios whereas the case study focuses on modeling a specific electricity grid.

Jansen and colleagues (2010) included temporal variation when analyzing EV penetration scenarios in the western U.S. grid by developing a dispatch model using historical data to correlate system load with resource capacity factors. Blumsack and colleagues (2008) also incorporated hourly variation when assessing environmental impacts of replacing 73% of the light-duty vehicle fleet with plug-in hybrid electric vehicles. Blumsack and colleagues (2008) used marginal emissions factors that were developed with an economic dispatch method for three ISOs. These methods align closely with our algorithm's recommendations, in that *temporal variation* was taken into account and *marginal* emissions factors were used (Jansen et al. 2010; Blumsack et al. 2008). Because of their use of historical data, however, these studies are only applicable in the near term, prior to any significant changes in infrastructure or fuel price.

Kim and Rahimi (2014) studied long-term emissions impacts of an EV fleet for 2020 and 2030 in Los Angeles. Their study aligns with all of the recommendations laid out by the algorithm (Kim and Rahimi 2014). They used an economic dispatch method that incorporated *temporal variation* and *marginal* emissions factors, and they accounted for *infrastructure changes* and renewable energy portfolio standard changes (ibid.).

Although Kim and Rahimi's (2014) study aligned well with our algorithm's recommendations, the other studies relied on simplifying assumptions that do not align with the algorithm's recommended current best practices for emissions estimation. Due to their assumptions, they are not able to describe EV emissions based on future grid topology. However, these studies were able to answer their research questions successfully and their assumptions do not invalidate their results as they pertain to these research questions in any way. The results of studies with large differences in baseline assumptions cannot be effectively compared, however, and policy makers and consumers might be uncertain how to respond should they encounter divergent results.

Material Production: Aluminum

An analyst is interested in CO_2 emissions attributed to the production of a kilogram of aluminum ingot at two aluminum smelters, the Hawesville Smelter in Hawesville, Kentucky, and the Alumax Smelter in Mount Holly, South Carolina. In order to determine these emissions, it is necessary to calculate the CO_2 emissions per kWh of electricity consumed at the facilities. The algorithm's recommendations are presented in table 2. The smelters are assumed to run at constant load throughout the year, resulting in the recommendation that the *method does not need to include emissions variation with time*.

The algorithm's recommendation to use yearly *average* emissions factors aligns well with past studies completed on emissions from aluminum production. Colett and colleagues (2015), McMillan and Keoleian (2009), and an Aluminum Association study (2013) all used annual *average* electricity mixes. Although these studies use the same type of emissions factor, they vary in their inclusion of trading and regional granularity. In the Big Rivers Electric Corporation PCA region hypothetical smelter case (Hawesville), trading is estimated to have an *RIT* of 2%, implying that trading is of little importance. In the South Carolina Public Services Authority PCA, trading is estimated to have an *RIT* of 16%, implying nontrivial effects of trading. These results show that the importance of trading is very location-specific. Of the studies mentioned, Colett and colleagues (2015) is the only one that includes trading, and they also used the recommended *PCA* region size when estimating the emissions from producing aluminum ingot. It is not surprising that the inclusion of trading varies across studies, considering the varying region sizes used and the location-specific nature of the importance of trading. However, inconsistency in this assumption limits an objective comparison of results.

The Aluminum Association (2013) used a very specific regional boundary, based on power contracts and on-site generation, for determining emissions from electricity consumed in the smelting and ingot casting processes. For secondary metal production, either a U.S. or Canadian average electricity mix was used due to lack of facility-specific data (ibid.). McMillan and Keoleian (2009) looked at aluminum production on an even broader scale when completing a life cycle assessment of primary aluminum ingot, concentrating on six world regions and using each region's average electricity fuel mix and fuel carbon intensity to estimate emissions from electricity consumed. Although these regional boundaries are much larger than recommended by our algorithm, their method allowed them to estimate the potential implications regional differences and global trade of aluminum ingot could have on emissions (McMillan and Keoleian 2009). However, using different regional boundaries can significantly impact a study's results, as seen in Ryan and colleagues (2016), making a comparison with their results inappropriate.

The use of our algorithm not only aids practitioners in selecting an appropriate method, but also in determining what past study results are most relevant to their analysis and, over time, will hopefully increase consistency in the assumptions made in future studies.

Summary and Conclusion

Emissions allocation for electricity consumption is a complex task. A variety of assumptions can be made to simplify this task, but some of those assumptions can also drastically change the results of an analysis and even lead to divergent conclusions on the sustainability of a process, product, or policy. Our goal is for the algorithm is to provide guidance on the key assumptions that can be made without producing dramatically different results than a user would obtain by modeling all of the temporal and physical details of the power system.

When we compared the algorithm's recommendations to those used in the literature, we saw significant differences among methods used and between the literature methods and those we would recommend. Reasons for these differences include variation in research question, study timeline, study region, data availability, time constraints, and general difficulty in modeling the electricity grid. The structure and context of a study's research question has some of the greatest influence on the method used to estimate CO_2 emissions, as illustrated in the case studies. For example, by using constant emission factors in comparing drivetrains, in contrast to the algorithm's recommendation of a factor that varies with time, Meinrenken and Lackner (2015) were able to assess under what grid mixes different drivetrains would be optimal without incorporating current conditions. However, if the question were which drivetrain is currently optimal, temporal variation in emissions would need to be incorporated into the analysis.

Differing research questions, study timeline, and region validate many of the differences in study assumptions, while others varied from one another and our best practice recommendations without justification. In these cases, lack of consistency limits comparability and could cause results to vary significantly. The choice of emissions factors is important for determining the effectiveness of policies that drive changes in electricity consumption (Ji et al. 2016). If studies are to be used to inform policy or consumer decisions, consistency and transparency in assumptions is important.

In many cases, a method that encompasses all of the algorithm's recommendations and does not require a significant amount of time or data to employ may not exist. Therefore, it is important to determine the method characteristics that are essential. These characteristics are often based on the research question, but there are some general guidelines. If a region has strong diurnal changes in electricity mix and a load has strong diurnal changes in magnitude, it is essential to model emissions variation with temporal granularity matching that of variation in electricity mix. If a future load's emissions are being estimated and changes are anticipated in grid infrastructure, fuel price, or policy, the chosen method must incorporate these effects. The delineation between marginal and average emissions is also crucial, though there is still debate over which is appropriate for certain types of loads. Consideration and justification are required when employing either approach, and the decision between them should not be made only on the basis of a method's ease of use.

Policy studies often use more complex methods to estimate emissions resulting from electricity generation, but expecting an analyst assessing a product's life cycle emissions to model the electricity system in great detail could be unrealistic (Amor et al. 2014). Factors that make an analyst's task more challenging include temporal variation, electricity trading, and marginal emissions, which are all particularly difficult and data intensive to model. Our algorithm is particularly useful in assisting analysts in navigating these complexities and informing them of method assumptions that will not compromise their study.

The algorithm presented here has a number of limitations, both general and specific. In general, the algorithm as described here does not provide a list of methods that can be employed for a given load. This information is included in the algorithm's Excel tool version (available at http://css.umich.edu/page/selecting-electricity-emissions-models-seem), and a list of methods and types can be found in Ryan and colleagues (2016). More specifically, the algorithm does not provide regionally explicit guidance on the need to incorporate variation with time. Depending on the type of load variation, the algorithm stipulates that the need is dependent on the region's generation mix variation throughout the year, a statistic that would need to be investigated further by a practitioner before proceeding. Regional emissions variation with time is an area for further study. In certain cases, the algorithm is unable to provide definitive recommendations on the inclusion of electricity trading, temporal emissions variation, or the use of future projections. The algorithm also does not have sufficient data to provide recommendations on importance of trading for marginal emissions or for average emissions in all PCA regions, as discussed in the methods section. These limitations require the user to conduct further investigation for certain loads. In cases where one method does not fit all of the algorithm's recommendations, it is best to use multiple methods to develop an understanding of uncertainty in the emissions estimates. We are not able to quantify uncertainty for our recommendations due to the study specific nature of results, but each method will have its own level of uncertainty, which is important to understand.

Despite difficulties in modeling and a lack of data, it is important for practitioners to understand how they should estimate CO_2 emissions from electricity consumption. This algorithm provides a framework for practitioners to more carefully examine method assumptions that can be influential in realistically estimating electricity emissions from specific loads. It also aims to be a step toward building consensus on appropriate methods to estimate emissions for particular load types and to influence practitioners to examine more closely how they estimate emissions from electricity consumption in their work. This would allow for more transparency and greater comparability of study results.

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Supporting Information

Supporting information is linked to this article on the *JIE* website:

Supporting Information S1: This supporting information contains instructions on implementing the decision support algorithm presented in this article, two illustrative cases, and nine tables and eight figures.