Environmental Science & Technology
pubs.acs.org/est
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Water and Carbon Footprints of Electricity Are Sensitive to Geographical Attribution Methods

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Cite This: Environ. Sci. Technol. 2020, 54, 7533−7541
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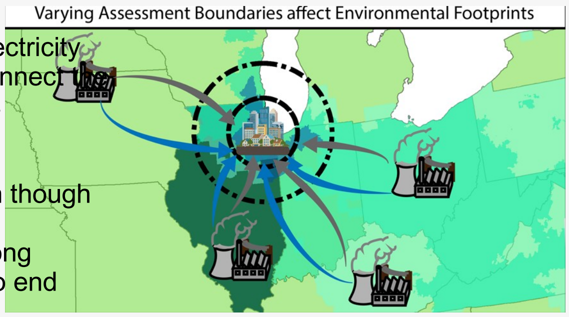

ABSTRACT: Environmental footprinting methods provide a means to relate the environmental externalities of electricity production to electricity consumers. Although several methods have been developed to connect the environmental footprint of electricity generation to end users, estimates produced by these methods are inherently uncertain due to the impossibility of actually tracing electricity from the point of generation to utilization. Previous studies rarely quantify this uncertainty, even though it may fundamentally alter their findings and recommendations. Here, we evaluate the sensitivity of water and carbon footprints estimates among seven commonly used methods to attribute electricity production to end users. We assess how sensitive water and carbon electricity footprint estimates are to attribution methods, how these estimates change over time, and the main factors contributing to the variability between methods. We evaluate and make available the water and carbon footprints of electricity consumption for every city across the contiguous United States for all assessed methods. We find significant but spatially heterogeneous variability in water and carbon footprint estimates across attribution methods. No method consistently overestimated or underestimated water and carbon footprints for every city. The variation between attribution methods suggests that future studies need to consider how the method selected to attribute environmental impacts through the electrical grid may affect their findings.

INTRODUCTION

Electricity production is the largest emitter of greenhouse gases (GHGs)[1] and the second largest water consumer globally.[2,3] Environmental footprinting methods, as defined by Hoekstra and Wiedmann,[4] offer one way of understanding and quantifying the direct and indirect pressures of electricity.[5] However, data uncertainty, incongruent scale of production and consumption, and traceability within the electric grid challenge robust attribution of environmental footprint of electricity production to the final consumer. Researchers have developed numerous environmental footprint attribution methods to overcome some of these challenges within both the water footprint[6−8] and carbon footprint[9−11] communities. Yet, there remains a great deal of uncertainty as to how sensitive results are to attribution methods and how this sensitivity differs between different footprint indicators.

Here, we conduct a comparative study of common approaches to estimate the environmental footprint of electricity consumption to test how sensitive water and carbon footprints of electricity consumption are to geographical attribution methods. While previous studies often focus on the uncertainty of the underlying data used to calculate environmental footprints,[12,13] we demonstrate the importance of also considering the impact of the method selected to attribute environmental footprints of electricity production to consumers. We focus on commonly used bottom-up approaches to estimating different footprints (as opposed to top-down approaches, such as environmentally extended multiregional input−output models, e.g., Mo et al.[14] and Tian et al.[15]). Environmental footprints associated with electricity production are assigned to end consumers with the same or connected geopolitical, infrastructure, or natural boundaries (e.g., state, electricity grid, or watershed). Henceforth, we refer to geographical attribution boundaries simply as "attribution boundaries". We ask and answer the following three questions: (i) how sensitive are water and carbon footprints of electricity estimates to attribution method? (ii) does variance between attribution methods differ between areas and within an area over time? and (iii) what factors contribute to variability between attribution methods and do these factors differ by environmental footprint type?

Attribution methods can be classified into two general types: (i) empirical data models and (ii) power system optimization models.[16] Empirical models use historical observations to

Received: January 9, 2020
Revised: May 7, 2020
Accepted: May 7, 2020
Published: May 7, 2020

Table 1. Evaluation of Seven Common Empirically Based Methods to Attribute the Environmental Footprint of Electricity to End Users. Advantages and Disadvantages of Each Method, as well as Studies that Have Employed Each Method, Are Shown below

Method	Advantage	Disadvantage	Employed by
Interconnections	Conforms to electricity infrastructure; minimum data requirements and calculations	Large area; does not prioritize local impacts	Ruddell et al.[6]
Balancing authority	Geographically smaller than interconnect	Pass-through nodes; nonspecific geographical areas	Cohen and Ramaswami[23]
Balancing authority with transfers	Conforms to electricity infrastructure; illustrates burden shift of resources	Time-consuming; disparate datasets	Chini et al.,[7] Kodra et al.,[33] and Djehdian et al.[34]
EPA eGRID boundaries	Conforms to data used for emission assessments and electricity infrastructure	Data only available every two years; requires integration with EIA data for water resources	Peer et al.[35]
Basin scale	Conforms to natural hydrology	Does not consider infrastructure	Tidwell et al.,[8] Kelley and Pasqualetti[36]
Radius from city	Accounts for local impacts	Does not consider infrastructure	Chini et al.[37]
State	Policy and regulations often set at the state level; EIA aggregates data at the state level	Cities in some states are supplied by different providers (e.g., Chicago, IL)	Chini et al.,[27] Bartos and Chester,[38] DeNooyer et al.,[39] Grubert and Webber,[40] and Stillwell et al.[41]

calculate emission factors, trading models, or statistical relationships to connect environmental footprints of electricity production to electricity consumption. Trading models incorporate additional data to account for imports and exports of electricity across specified boundaries.[10,17,18] Power system optimization models determine embedded resources based on power distribution networks and economic optimization. In this study, we compare empirical methods that use both simple emission factors and trading models as these are the most commonly used environmental footprint attribution methods. Moreover, many power system optimization models are proprietary, making comparison of these methods infeasible. The empirical methods evaluated rely on different geographical, infrastructure, and political boundaries, including interconnections, balancing authorities, Environmental Protection Agency (EPA) eGRID, river basins, state, and radius from cities (see Table 1). Regardless of the attribution boundary, all methods utilize the same underlying data.

We calculate the water and carbon footprints associated with electricity consumption in each metropolitan statistical area (MSA; as defined by the U.S. Census Bureau) within the contiguous United States using the most common empirically based attribution methods. Although any electricity consumer could be used in this study, MSAs provide a clearly defined and diverse set of electricity end users. Further, cities are integral in achieving environmental sustainability and climate change mitigation targets as they are central points of consumption and account for a significant portion of energy use and emissions.[19,20] Urban areas consume around three-fourths of global energy, with electricity being the second largest energy source, as well as the fastest growing energy use.[21,22] Nearly two-thirds of the 43 cities evaluated by Cohen and Ramaswami[23] imported over half of their electricity, demonstrating how metropolitan areas' resource consumption and environmental impact stretch well beyond their geopolitical boundaries. While some studies have evaluated the carbon footprint of a city's electricity consumption,[24−26] we have a more limited understanding of how cities draw on local and nonlocal water resources to fulfill their electricity demand.[27]

The following section provides background on environmental footprints of electricity production and how these footprints are assigned to end consumers. Next, we describe the methodology employed in this study, followed by our results. Lastly, we discuss our findings and the implications they have on future research as well as cities, companies, and other groups that want to determine their water and carbon footprints of electricity consumption. Importantly, all water and carbon footprint estimates for every US MSA are published with this study to support future research and aid electricity consumers in determining the water and carbon footprints of their electricity use.

BACKGROUND

The electric grid in the United States is divided into three main interconnects: Western Interconnection, Eastern Interconnection, and the Electric Reliability Council of Texas (ERCOT). The Eastern and Western Interconnect are composed of 31 and 37 balancing authorities, respectively.[28] ERCOT consists of a single balancing authority. Each balancing authority balances electricity supply and demand in real-time to ensure system reliability. Power plants are distributed across each of these interconnections, supplying electricity to the grid. Depending on the fuel source and technology employed, power plants emit significant amounts of GHGs. Further, power plants impact local water resources through their large water withdrawals. A portion of water withdrawals are evaporated and removed from the local water system, while the rest are returned to the water body at elevated temperatures leading to thermal pollution and ecological damage.[29,30] Attributing these local impacts to end consumption shows the burden shift of electricity demand to production locations.

The transmission of electricity through the electric grid creates difficulties associated with attributing water and carbon footprints of electricity generation to end users. Previous works[16,31] have explored how these inherent challenges may impact the attribution of carbon footprints to different electricity users, but no study has evaluated the impact on water footprint estimates. Further, no studies, to our knowledge, have evaluated carbon and water footprints together to understand the resource demands of all urban areas across an entire nation. Ryan et al.[16] and Weber et al.[31] highlight the variation and assumption of multiple attribution methods with respect to emissions, concluding that the study objective often motivates the method choice. Within the United States, all empirically based methods rely on power plant level data reported by the Energy Information Administration (EIA). Each power plant is mapped to the particular attribution boundary of interest. The data within the

https://dx.doi.org/10.1021/acs.est.0c00176
Environ. Sci. Technol. 2020, 54, 7533−7541

EIA are self-reported via Form 923 and come with their own sets of uncertainty (although data quality has improved markedly in recent years[32]). Quantifying the uncertainty of the underlying reported data has been evaluated by others[12,32] and is outside the scope of this study.

Here, we highlight seven different methodologies for attributing electricity-related water consumption and carbon emissions to electricity consumers within each US MSA. The complexity of the electrical grid and the impossibility of tracing an electron through it means there is no "correct" attribution method, and it is impractical to consider one estimate better than others. Instead, each environmental footprint attribution method of electricity has distinct advantages and disadvantages (Table 1). Each empirical method employs different geographic boundaries, which draw on a different collection of power plants (Figure S1). Approaches using interconnections, balancing authorities, or eGRID boundaries consider, to varying degrees, the physical infrastructure of the electrical grid. The interconnect boundary represents the largest geographic scale and is the simplest to calculate, while methods utilizing the balancing authority scale are more computationally intensive and require integration across multiple databases (EIA, EPA, and the Federal Energy Regulatory Commission (FERC)). The eGRID scale also offers some smaller scale regional attribution and varies slightly from the boundaries of balancing authorities. The eGRID boundary was designed to promote consumer-scale or regional decision-making capability. The basin scale and geographical radius boundaries attempt to localize impacts of the water footprint of electricity production by evaluating the removal of water resources from the immediate environment. The state scale method has advantages in that it follows policy boundaries for water discharge permits and thermal pollution. However, basin, radius, and state boundary methods can overlook some of physical constraints of electricity distribution through the grid.

In this study, we consider the water consumed and carbon and carbon equivalents emitted (henceforth, denoted simply as "carbon") during the operational stage of electricity generation. Roughly two-thirds of water consumption in the life cycle of electricity production occurs during the operational stage of electricity generation.[3,35] Similarly, the operational stage of electricity generation constitutes 83−99% of the total GHG emissions associated with fossil-fuel-based electricity production.[42] Environmental footprint assessments use physical or monetary units to normalize the footprint in terms of production (e.g., Marston et al.[43] use both units). When determining the water or carbon footprint of electricity, water consumption or GHG emissions are most often normalized by energy units, which we adopt in this study. Our analysis evaluates how sensitive our results are to temporal dynamics by using available water consumption data (years 2014 to 2017) and GHG emission data (years 2014 and 2016).

MATERIALS AND METHODS

Attributing water and carbon footprints of electricity requires two steps. First, it is necessary to determine the water or carbon footprint per kWh of delivered electricity, i.e., volume of water per kWh and mass of carbon per kWh (intensity). The water or carbon footprint per unit of delivered electricity is largely a function of the power plants assumed to service the area of interest. Second, one must determine the electricity demand of the city or entity of interest. In this study, we focus on the first step and the various methods to estimate water and carbon footprints per unit of electricity generation. The following sections describe the methods and data needed to replicate each of the seven attribution approaches most commonly employed in the literature.

Electricity Generation and Environmental Footprint Data. Electricity generation and water consumption data were taken from self-reported generator observations, which are collected and tabulated by the Department of Energy's EIA.[44] While the quality of EIA data has been questioned, it provides detailed data at a fine spatial resolution and is the data set most commonly used in studies aiming to estimate the environmental footprint of electricity production and consumption. Besides, the purpose of this study is to compare different attribution methods, meaning it is of greater importance that each attribution method utilizes the same data across all methods. Power plants with generation capacity greater than 100 MW are required to report their water consumption to EIA.[46] These large power plants contribute almost 75% of the United States total electricity generation.[47] Smaller power plants (generation capacity less than 100 MW) are required to report their energy production but not their water consumption to the EIA. These smaller power plants are included within our study by assigning the median value of water consumption calculated from the reporting power plants to all small power plants with similar fuel type and generation capacity less than 100 MW. EIA does not have water consumption data for renewable energy sources, such as wind, solar, or hydropower. Average water consumption values based on detailed engineering studies were used for solar and wind operated renewable power plants.[3,48] Water consumption attributed to hydroelectric power is related to reservoir evaporation and is often many times the magnitude of other types of power plants.[3] Water footprints of hydroelectric power plants are taken from,[49] which considers the multiple users of a reservoir (e.g., irrigation, flood control, hydropower) and allocates the evaporative losses across these users so to avoid the overestimation of hydropower water consumption.

We utilize the most recent versions of the EIA Form 923 (annual values from 2014−2017) and the EPA tabulated emissions from power generating facilities[50] to analyze the temporal variability of water consumption and carbon emissions within each metropolitan area for a given attribution method. We utilize EPA's Clean Air Markets Division data[50] on observed emissions from stack monitoring, as opposed to EIA's modeled emission estimates,[51] to estimate carbon footprints. Carbon footprints are calculated using equivalent carbon dioxide weights, CO_{2e}.

With respect to water resources, we take a water footprinting approach to assess water intensity of electricity based on attribution methods. We recognize that there are other approaches to assess the environmental impacts of water resources, specifically with respect to water scarcity (e.g., International Organization of Standards ISO 14046). This life cycle assessment (LCA) method is outside the scope of the current study.

Attribution of Electricity Source to Consumers. Following Kodra et al.,[33] we aggregate power flow among the electricity-generating units within the attribution boundaries under analysis. In general, there are two different types of data-driven attribution methods (1) those based on grid infrastructure and (2) those based on geographical boundaries. Attribution methods based on grid infrastructure better

https://dx.doi.org/10.1021/acs.est.0c00176
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constrain the production, transfer, and consumption of electricity to the underlying grid infrastructure and the companies that operate them, but these methods are limited by data and require a higher order of computation. Grid infrastructure boundaries, including interconnections, balancing authorities, and eGRID, are defined by the Department of Homeland Security, North American Electric Reliability Corporation, and EPA.

Geopolitical or geophysical boundaries do not match the actual flow of electricity along the grid, but national and state regulations and policies concerning water and GHG emissions are often mandated based on these boundaries. This makes geopolitical and geophysical boundaries particularly important when analyzing the burden they exert on the environment. For geopolitical and geophysical boundary-based attribution methods, an attribution boundary may have few or no power plants within its border. The electricity demand within that attribution boundary may well exceed the generation. To overcome this issue, we used an energy balance approach to match excess electricity generation to unmet electricity demand following the approach of Ruddell et al.[6] Areas with electricity generation exceeding the demand will make their excess electricity available to a "collective pool" of surplus electricity that deficit areas can pull from the grid.

Both the grid-based and geographic boundary methods utilize the same generalizable equations to estimate the environmental resources or emissions intensity of electricity production (EIP).

$$\mathrm{EIP}_i = \frac{\sum_x E_x}{\sum_x P_x} \tag{1}$$

$$\mathrm{EIP}_{i^*} = (\mathrm{EIP}_i \times \alpha_i) + \mathrm{EIP}_{i-\mathrm{interconnect}} \times (1 - \alpha_i) \tag{2}$$

Here, EIP_i is the weighted averaged embedded environmental resources or emissions (E) of electricity production (P) of the power plants (x) within attribution boundary i. EIP_{i^*} recalculates the embedded environmental resource or emissions intensity of electricity production within a geographical attribution boundary (e.g., state boundaries) when electricity transfers between attribution boundaries are considered. Since it is infeasible to consider actual electricity transfers across the grid with geographical attribution boundaries, electricity demand that cannot be supplied by power plants within the specified boundary will be fulfilled from excess electricity produced within the interconnect to which the attribution boundary i is nested within (i − interconnect). α_i is the ratio of electricity generation and consumption within attribution boundary i. α_i is capped at 1, which signifies that power plants within the attribution boundary are capable of fully meeting the electricity demand within the attribution boundary (i.e., no electricity transfers occur). If electricity transfers across grid-based attribution boundaries are considered, the previous equation can be updated as follows:

$$\mathrm{EIP}_{i^*} = (\mathrm{EIP}_i \times \beta_i) + \sum_j \mathrm{EIP}_j \times (1 - \beta_{i,j}) \tag{3}$$

where β_i is the fraction of electricity produced within attribution boundary i to total production plus net imports of attribution boundary i. $\beta_{i,j}$ is the fraction of electricity imported into attribution boundary i from j to total production and net imports of attribution boundary i.

Finally, the embedded environmental resources or emissions of electricity consumption of MSA m (EIC_m) is determined by summing the product of each overlapping attribution boundary's EIP_{i^*} and the proportion of MSA m geographical area (A_i) covered by the area of the attribution boundary ($A_{i,m}$).

$$\mathrm{EIC}_m = \frac{\sum_i (\mathrm{EIP}_i \times A_{i,m})}{A_m} \tag{4}$$

We used this general approach to estimate both water and carbon footprints and intensities of each MSA for all attribution methods. Further discussion on the individual methods and their underlying assumptions and data can be found in the Supporting Information.

Due to data limitations, our study focuses on the annual scale to assess both carbon and water footprints. While the EIA provides data at a monthly scale for several environmental impacts, we are limited in our study by datasets from the EPA (eGRID) and FERC. These datasets are only at the annual scale. We recognize that there are variations in renewables intra-annually, which might affect the results, to an extent; however, for uniform comparison across methods, we aggregate EIA data and conduct the study on the annual scale.

RESULTS

Sensitivity of Carbon and Water Intensities to Attribution Method. Each metropolitan area demonstrates different levels of sensitivity to the attribution method for water and carbon footprints of electricity. The sensitivity of each metropolitan area to water and carbon attribution methods is quantified by the coefficient of variation (CV) and presented in Figure 1a,b, respectively. For water intensities, higher CV in urban areas of the Southwestern United States suggest that water intensity of delivered electricity is highly sensitive to the attribution method (denoted by an orange or red color in Figure 1). This variation indicates diverse electricity production technologies (e.g., presence of large number of hydro and solar power plants in the same region) in the surrounding areas. Although water consumption of nuclear power generation is higher than those of other thermoelectric generations, the difference is insignificant when compared with hydroelectricity. The amount of water consumed in the production of electricity can vary based on several factors, including fuel type, combustion method, and type of cooling technology. Macknick et al.,[45] Peer and Sanders,[52] and others provide breakdowns of the water intensity based on these factors. Variability arises from changes in energy generation mix portfolios of MSA for different geographic attribution boundaries (shown in Table S4 of the Supporting Information) based on the geographic location of the generating units.

The mid-Atlantic and northwestern regions of the United States have smaller CV, indicating that the water intensity values are not as sensitive to the attribution method. The relative consistency between estimates produced by different methods in these regions is due to a largely homogeneous electricity generation portfolio across all the attribution boundaries. Hydroelectric power plants are ubiquitous in the northwestern US, resulting in a high but consistent water intensity for MSAs in the region. Large amounts of electricity, and therefore embedded water, are transferred between the states of California, Arizona, Colorado, Utah, and New Mexico

https://dx.doi.org/10.1021/acs.est.0c00176
Environ. Sci. Technol. 2020, 54, 7533−7541

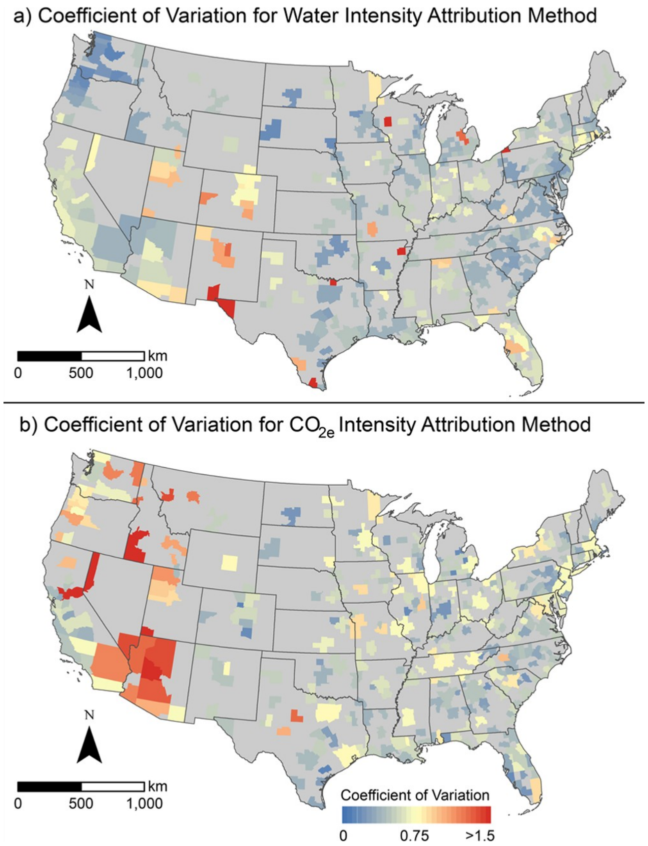

Figure 1. Variability between attribution methods (represented here as the coefficient of variation, computed based on the results from each of the methods) for water intensity (a) and CO_{2e} intensity (b) is not constant across the country. A lower coefficient of variation (represented by blue) signifies agreement in estimates among the attribution methods, while a higher coefficient of variation (represented by orange or red) signifies a divergence between estimates produced by each method. The mid-Atlantic and northwestern regions show greater homogeneity in water and carbon footprints and are not as sensitive to the attribution method as other regions of the country.

within the Western Interconnect creating geographical dispersed dependencies on water resources.[6,7]

Using the same attribution methods, we substitute water consumption for greenhouse gas emissions, represented by CO_2 equivalents (Figure 1b). These carbon intensity equivalents provide another way to evaluate these attribution methods. When evaluating the coefficient of variation of each attribution method across the country, there are localized areas of high variation between methods in the southwestern and northwestern United States. The mid-Atlantic region's sensitivity of emission intensity, like water intensity calculations, has a relatively low coefficient of variation. However, in general, there was no correlation between the coefficient of variation of water intensities and emission intensities. Further comparison of the coefficients of variation between water and carbon intensities can be found in the Supporting Information (Figure S2).

To further compare the attribution methods and their impact on water and carbon intensity calculations, we investigate the effect of electricity transfers between attribution boundaries on environmental footprints. We evaluated the impact of electricity transfers for three attribution methods: HUC-4, PCA/balancing authority, and state scales. Balancing the electricity demand from the surrounding interconnect changes the embedded resource intensity. In general, water intensity remained constant or increased for each of the three methods when including energy balancing (Figure S3). Conversely, the carbon intensity of MSA's electricity use demonstrated a much wider range of change, with no clear increasing or decreasing trend when electricity transfers were considered. Carbon intensities vary more widely across power plants and attribution boundaries than water intensities, and this greater variation is the primary reason why carbon intensities exhibit greater heterogeneity in response to electricity transfers than water intensities (Figure S3). Moreover, we found that the carbon footprints of electricity consumption are more sensitive to the attribution method selected compared to the water intensities (95% confidence level). In general, the CV of carbon intensities are larger than that of water intensities. The CV of water and carbon follow a gamma distribution with a long right tail, signifying that some MSAs exhibit much greater sensitivity to the attribution method than their peers (Figure S2).

Trends across Attribution Methods. Analysis of the water intensity for the top 50 most populous MSAs shows significant variation across different MSAs for the same attribution method and within the same MSA with different attribution methods (Figure 2). Table S3 of the Supporting Information provides a list of the top 50 MSAs by population. For many of the most populous cities, the majority of the attribution methods produce similar results. However, for some of these cities, there is a much wider spread of the estimated water intensity values. For example, the mean estimated water intensity of Buffalo, NY is approximately 40 m^3/MWh, nearly 7 times the average US city, and ranged from approximately 5−80 m^3/MWh, which is the second largest spread of water intensities across all MSAs. Numerous MSAs have one or more attribution methods that produce water or carbon intesnity estimates that are much higher than the average, although there is no singular method or set of methods that consistently results in larger or smaller water or carbon intensity estimations. The 50 km radius attribution method has the smallest water footprint for about one-third of MSAs, while one-third of MSAs had the interconnection as the largest water footprint. Interestingly, the HUC-4 boundary method produced the largest carbon intensity value for nearly half (48.7%) of all MSAs.

Although the selected urban areas show high sensitivity to the attribution method selected, the temporal variation of water intensity of delivered electricity is relatively constant across all urban areas (Figure 3 shows the 50 most populous US cities). In general, there is no significant difference between the four years within each MSA. This finding supports previous research[35] showing that temporal variability of regional water intensity is minimal compared to changes in fuel and technology mixes. Therefore, any changes seen are most likely due to an addition or retirement of a power plant included in the spatial boundary.

Factors Contributing to Variability between Attribution Methods. To further illustrate why different attribution methods may produce variation in environmental footprint estimates, we re-examine Buffalo, NY, which has a large spread in water intensity estimates by different attribution methods (approximately 5−80 m^3/MWh). We also investigate Chicago, IL, which has a relatively small spread of water intensities

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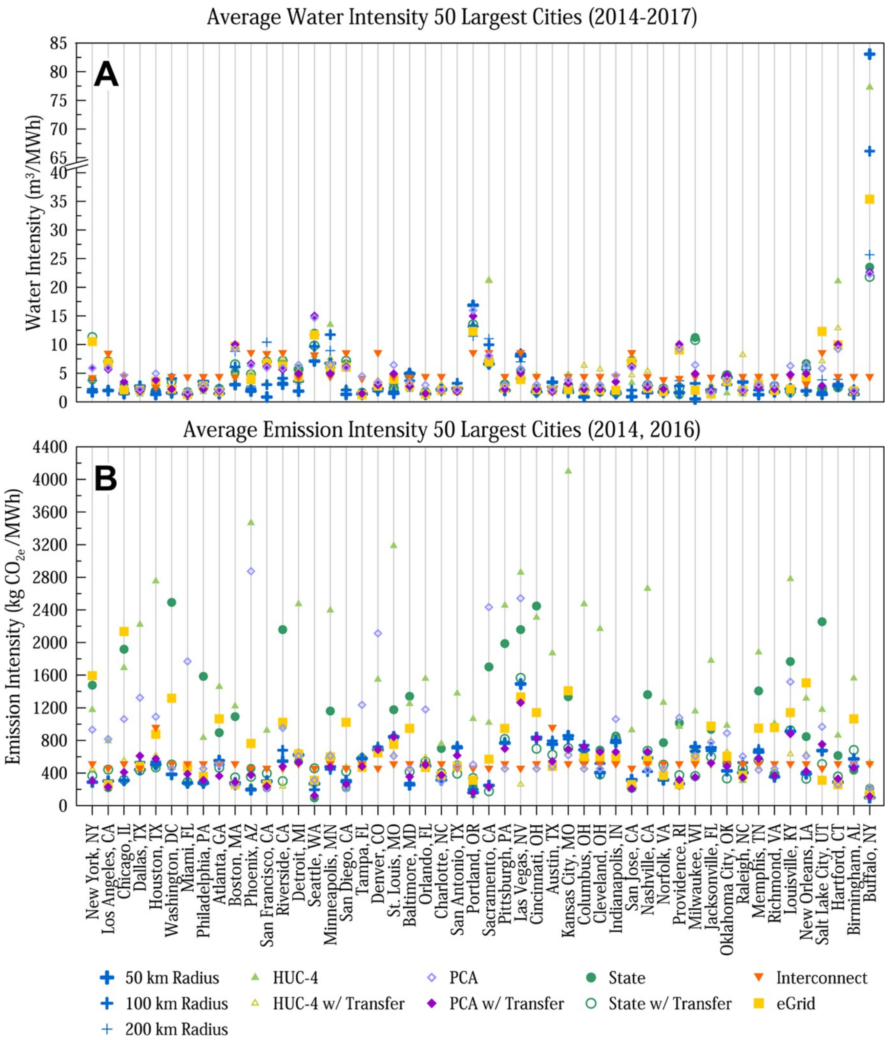

Figure 2. Comparing the average values of (A) water and (B) carbon intensity across the 50 largest metropolitan statistical areas shows nonstandard variation between the attribution methods. In many of these cities, the attribution method does not significantly change the value of water intensity (i.e., Dallas, TX; Philadelphia, PA; and Norfolk, VA). Other cities, such as Seattle, WA and Buffalo, NY, have a much larger spread of water intensities based on attribution methods. The emission intensities for the 50 largest cities vary widely depending on the attribution method. Additionally, methods that utilize HUC-4, PCA, and state boundaries generally produce larger estimates than other attribution methods.

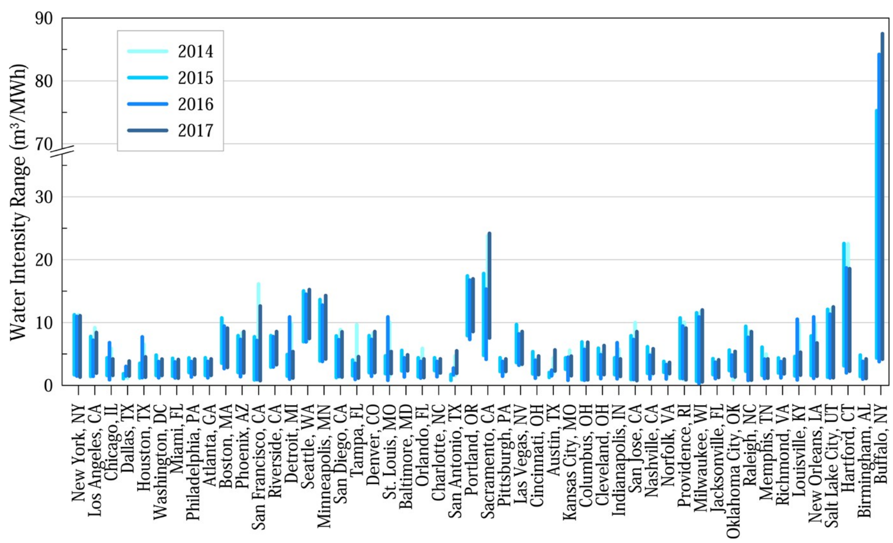

Figure 3. Water intensities for the largest 50 metropolitan areas in the United States show little variation between years.

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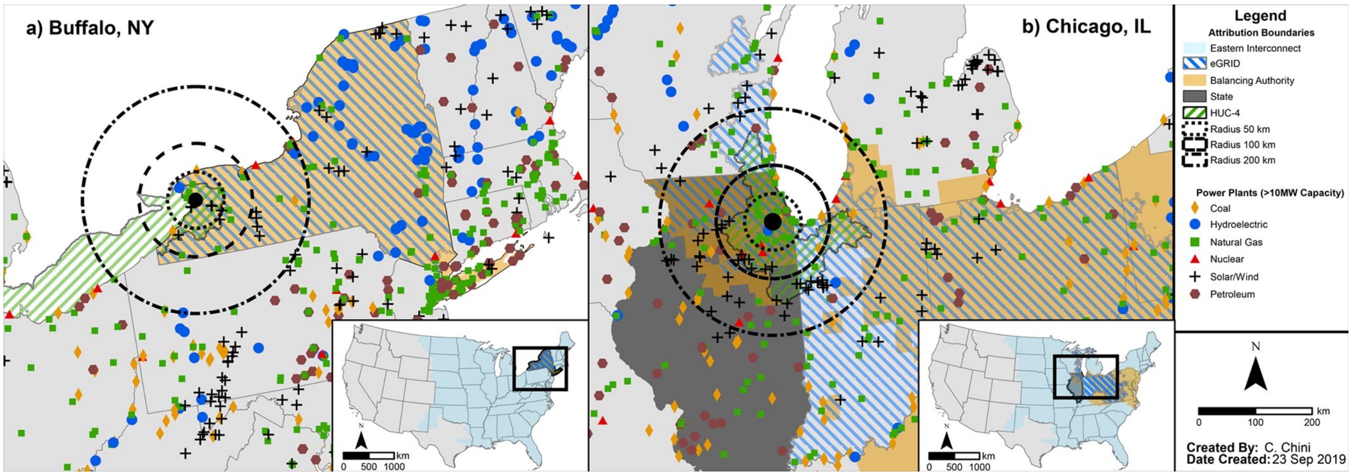

Figure 4. (a) Buffalo, NY and (b) Chicago, IL demonstrate among the greatest and least variance in water intensities of electricity deliveries between attribution methods, respectively. Water intensity estimates for Buffalo are more sensitive to the attribution method due to the misalignment of attribution boundaries and the clustering of certain power plant types (namely, hydropower) within some attribution boundaries but not others. Conversely, attribution boundaries used to determine Chicago's water intensity have largely the same collection of power plant types, all producing similar water intensity estimates.

across attribution methods (approximately 1−5 m^3/MWh). Each of these MSAs is located on the borders of their respective state and at the intersection of multiple hydrologic boundaries. Buffalo is located on Lake Erie on the western edge of New York, while Chicago is on Lake Michigan at the northeast edge of Illinois.

The large variance in water intensity for Buffalo comes from the diverging attribution boundaries and the diverse forms of power generation types clustered throughout the state (Figure 4a). In more general terms, when attribution boundaries do not significantly overlap, it means a different set of power plants is assumed to supply an MSA's electricity. This assumption is particularly consequential in places like western New York, where a clustering of electricity generation technologies can dramatically shift estimates of water intensities depending on the set of power plants within the respective attribution boundary. For example, Figure 4a depicts solar/wind (low water intensity) and hydroelectric (very high water intensity) power facilities in northern New York, which are excluded in the HUC-4 boundary and the radii attribution methods but captured by other boundaries. Chicago shares many similarities to Buffalo (it also lies on the boundary of its state at the edge of the Great Lakes, with greatly diverging attribution boundaries); yet, Chicago has a much smaller variation in estimated water intensities across all attribution methods. Chicago's small variation can largely be explained by the relatively uniform distribution of different power plant types throughout the surrounding area (Figure 4b). Unlike Buffalo, there is not a clustering of particular types of power production that might sharply skew water intensity estimates upon inclusion of this area within an attribution method.

DISCUSSION

We do not suggest a "best" or "correct" attribution method for environmental footprints of electricity. Instead, we contend that it is important to understand the inherent assumptions associated with each attribution method and the degree that these methods produce different estimates. We suggest that the chosen method for attributing environmental footprints of electricity production to end users be selected based on the research problem posed. If the study, for example, aims to assess the impacts of state regulations or grid operation, a state or grid-based attribution boundary may be most appropriate. However, if the study is focused on local hydrologic impacts of electricity consumption or the opportunity cost of local water withdrawal, then the radius or HUC-4 attribution boundaries provide a better localized context of analysis. With that said, the methods most commonly employed in the literature to relate environmental footprints of electricity production to consumers do not explicitly consider the environmental impacts of freshwater appropriations (i.e., they do not follow the LCA approach set forth by ISO 14046). Future studies would benefit from assessing the environmental consequences of water consumption and GHG emissions, including water scarcity.[53−55]

Regardless of what attribution method is deemed the most appropriate for a particular study, the potential large variations in environmental footprint estimates (as demonstrated in this study) highlight the need to use multiple attribution methods to quantify the sensitivity associated with the primary attribution method selected. In areas that have a high sensitivity to attribution methods, it is particularly important to characterize this variability and the assumptions associated with the chosen attribution method. Data uncertainty and sensitivity have previously been shown to have a nontrivial impact on estimates of environmental footprints.[43] Here, we demonstrate that the method selected to attribute the footprint of electricity generation to end users can also significantly shape estimates of a consumer's water and carbon footprints. Therefore, future studies relating the environmental impacts of electricity production to end users should incorporate some measure of variability associated with the selected attribution method. The differences in water and carbon intensity calculations produced by each method demonstrate the difficulty in formulating sound policy and decision-making based on one attribution method, as each can yield very different conclusions. An ensemble approach that balances these tradeoffs presents an opportunity to avoid bias associated with a selection of one methodology over another.

https://dx.doi.org/10.1021/acs.est.0c00176
Environ. Sci. Technol. 2020, 54, 7533−7541

As urbanization and overexploitation of natural resources intensify in the future, assessing and attributing the environmental footprint of electricity generation to cities will be critical to understand the telecoupling between production and consumption of electricity within the water−energy−carbon nexus. However, it is important that the scientific community converges on a means to attribute the environmental impacts of electricity production to end users so comparisons can be made across different studies and decision-making is based on robust findings. For example, a standardized approach for determining the carbon footprint of electricity use that quantifies uncertainty or variability of the estimates will be important as voluntary and mandatory carbon offset markets become more common. Cities, corporations, and other groups aiming to determine the environmental footprint of their electricity consumption should present sound reasoning for the attribution method they select and this methodology should be consistently applied across all environmental footprint types, regions, and industries that the entity operates so that different attribution methods are not selected merely to produce the most favorable results. While we do not settle the debate on which method is "best", we do make it clear that future studies should assess the sensitivity of their key conclusions to their selection of attribution methodology.

ASSOCIATED CONTENT

* Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.0c00176.

Additional discussion on methods and supporting figures (PDF)

Water intensity values for each method for all MSAs, years 2014−2017 and carbon intensity values for each method for all MSAs, years 2014 and 2016 (XLSX)

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Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

C.M.C. and L.M. conceived the study. M.A.B.S. conducted the analysis. C.M.C. created the figures and visualizations. All authors contributed to the writing of the manuscript. L.M. acknowledges support by the National Science Foundation Grant No. ACI-1639529 (INFEWS/T1: Mesoscale Data Fusion to Map and Model the US Food, Energy, and Water (FEW) system). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. All data used in this study come from public sources. Data produced through this research can be found in the Supporting Information.

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https://dx.doi.org/10.1021/acs.est.0c00176
Environ. Sci. Technol. 2020, 54, 7533−7541