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Water Resources Research®

DATA ARTICLE

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Spatially and Temporally Detailed Water and Carbon Footprints of U.S. Electricity Generation and Use

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Key Points:

- We offer hourly U.S. electricity mix, water, and $CO_{2\text{-eq}}$ intensities of end users, providing comprehensive local grid impact assessment
- The Water IMPACT tool provides modeling framework for historical and real-time estimates of electricity mix and environmental impacts
- The dataset and modeling framework support DOE's energyshed management initiative, helping users effectively reduce Scope 2 footprints

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Abstract Electricity generation in the United States entails significant water usage and greenhouse gas emissions. However, accurately estimating these impacts is complex due to the intricate nature of the electric grid and the dynamic electricity mix. Existing methods to estimate the environmental consequences of electricity use often generalize across large regions, neglecting spatial and temporal variations in water usage and emissions. Consequently, electric grid dynamics, such as temporal fluctuations in renewable energy resources, are often overlooked in efforts to mitigate environmental impacts. The U.S. Department of Energy (DOE) has initiated the development of resilient energyshed management systems, requiring detailed information on the local electricity mix and its environmental impacts. This study supports DOE's goal by incorporating geographic and temporal variations in the electricity mix of the local electric grid to better understand the environmental impacts of electricity end users. We offer hourly estimates of the U.S. electricity mix, detailing fuel types, water withdrawal intensity, and water consumption intensity for each grid balancing authority through our publicly accessible tool, the Water Integrated Mapping of Power and Carbon Tracker (Water IMPACT). While our primary focus is on evaluating water intensity factors, our dataset and programming scripts for historical and real-time analysis also include evaluations of carbon dioxide (equivalence) intensity within the same modeling framework. This integrated approach offers a comprehensive understanding of the environmental footprint associated with electricity generation and use, enabling informed decision-making to effectively reduce Scope 2 water usage and emissions.

1. Introduction

The use of electricity is a critical aspect of modern society, but electricity generation can have significant environmental impacts, particularly in terms of water usage and greenhouse gas (GHG) emissions (Laurent & Espinosa, 2015; Siddik et al., 2020). According to the U.S. Geographical Survey (USGS), thermoelectric power plants ranked as the highest water withdrawing sector in the U.S. in 2015, accounting for 41% of total freshwater withdrawals in the country (Dieter et al., 2018). Electricity generation was responsible for 25% of total U.S. GHG emissions in 2021, ranking second only after the transportation sector (EPA, 2023b).

The environmental impact of electricity generation is influenced by a range of factors, including the type of fuel used, the technology employed, and the location and time of generation. Accurately estimating the influence of these factors on the environmental impact of electricity use is a complex task due to the intricate nature of the electric grid and the constantly changing electricity mix by fuel type. To avoid this complexity, studies on environmental impact analysis often rely on average annual water intensity and carbon intensity metrics (i.e., the amount of water used or GHG emitted, respectively, per unit of electricity generated) for a given geographic area (Goldstein et al., 2020; Scown et al., 2011; Shehabi et al., 2016). Further, emissions reporting frameworks, such as those developed by the World Resources Institute and CDP (Sotos, 2015), allow for the use of annual national average emissions rates for determining Scope 2 emissions (i.e., emissions from power generation) associated with a facility/company.

There is an increasing demand from corporations, governments, and other institutions for accurate and comprehensive data to monitor the environmental footprint associated with electricity use and the fuel mix utilized. For example, California's 2023 SB-253 Climate Corporate Data Accountability Act mandated that large corporations divulge their Scope 2 emissions (SB-253, 2023). Concurrently, the U.S. Department of Energy is advancing an energyshed management system, an initiative aimed at promoting understanding and practical application of the "energyshed" concept, which pertains to segments of the electric grid where power is both consumed and generated (DOE, 2022). This project seeks to develop technologies, policies, and market mechanisms that enable informed energy choices, cost savings, carbon reduction, and resilience. Moreover, there is rising business and stakeholder interest in reducing environmental footprints, evidenced by enthusiasm for an "app" that allows users to view their local electricity mix by entering a zip code (DOE, 2022).

Detailed data on fuel mix and the associated environmental footprint will enable grid operators to understand the environmental footprint of their electricity imports. Providing spatially and temporally detailed data is crucial for understanding the impact of energy consumption patterns and supporting the transition to cleaner and more sustainable energy systems. The diurnal and seasonal variations in the mix of electricity sources contributing to the grid are well recognized (de Chalendar et al. (2019); Miller et al., 2023; Zohrabian et al., 2023). Studies have explored methods to reduce carbon footprints by optimizing operation hours, such as scheduling electric vehicle charging during low-emission periods (Huber et al., 2021) and taking advantage of temporal differences in the carbon footprint of the grid. Although existing studies acknowledge the impact of dominant fuel types in variations for carbon intensity, to our knowledge, no study has provided detailed information on electricity mix by fuel type in the supplied electricity within a local grid from end users perspective. Moreover, to our knowledge, no study has addressed and assessed the significant spatial and temporal variations in water usage associated with electricity use, which is often not given the same attention as GHG emissions in scientific studies or corporate reporting.

The composition of electricity generation sources varies greatly across regions, with the dominant sources of power generation ranging from hydroelectricity in the Northwest region to coal and natural gas in the Southeast. Furthermore, the energy mix can fluctuate significantly over the course of the day and across seasons, underscoring the need for a high level of spatial and temporal resolution in the assessment of the water and carbon footprint of electricity use for a community or facility. Moreover, specific circumstances can modify the daily and yearly electricity consumption pattern of a particular facility, as demonstrated by the shift in hourly and seasonal peaks of residential electricity usage due to the COVID-19 pandemic (Abdeen et al., 2021). These examples emphasize the significance of a high-resolution time-series database for electricity-embedded water use and GHG emissions to ensure precise environmental impact evaluations, as well as coordinated measures to reduce one's environmental footprint through better planning of electricity demand. Facilities with flexible electricity demand can plan their peak energy demand to align with times of the day or year when the electricity mix has the lowest emissions or the smallest impact on aquatic systems. While some studies have estimated the temporal variations in carbon emissions associated with local electric grids (de Chalendar et al., 2019; Zohrabian et al., 2023), their main focus on CO_2 overlooks total GHG emissions and water usage associated with electricity consumption. Furthermore, these studies do not detail the specific type of power plants contributing to the electricity sector's environmental footprint, making it challenging to determine how changes in the future energy mix might impact environmental footprints. Therefore, developing methods that provide fine spatial and temporal datasets of both water and carbon intensities of electricity generation and consumption are crucial to accurately assess the environmental footprint of electricity.

To effectively assess the environmental consequences of electricity usage by consumers, it is crucial to delineate the characteristics of the local electric grid. This involves examining the mix of electricity sources and evaluating the water and carbon intensities of the local grid, which together shape the environmental footprint of electricity use. The DOE has introduced the concept of an "energyshed," analogous to a watershed, where the boundaries of an energyshed vary in geographic scale, from regional grids to local communities or individual households (DOE, 2022). This tiered framework facilitates engagement at various levels, acknowledging that upstream decisions can impact downstream communities, though the effects are not always reciprocal. Various stakeholders have highlighted the importance of enhancing current tools to provide the detailed analysis required for energyshed evaluations. The DOE recommends leveraging existing resources from utilities and balancing authorities as a preliminary step for further development. Balancing authorities are responsible for managing the day-to-day operation of the electric system, ensuring that electricity demand and supply are balanced within their respective portions of the grid, as shown in Figure 1 (EPA, 2018). Balancing authorities undertake the responsibility for a specific portion of the power system, actively maintaining operating conditions by ensuring an adequate electricity supply to meet expected demand. This involves not only managing internal generation but also coordinating transfers of electricity, known as interchanges, with neighboring balancing authorities. The U.S. electric grid is broken into three components: Eastern Interconnection, Western Interconnection, and Electricity Reliability Council of Texas (ERCOT) Interconnection. As of 2023, there are 27 balancing authorities in the

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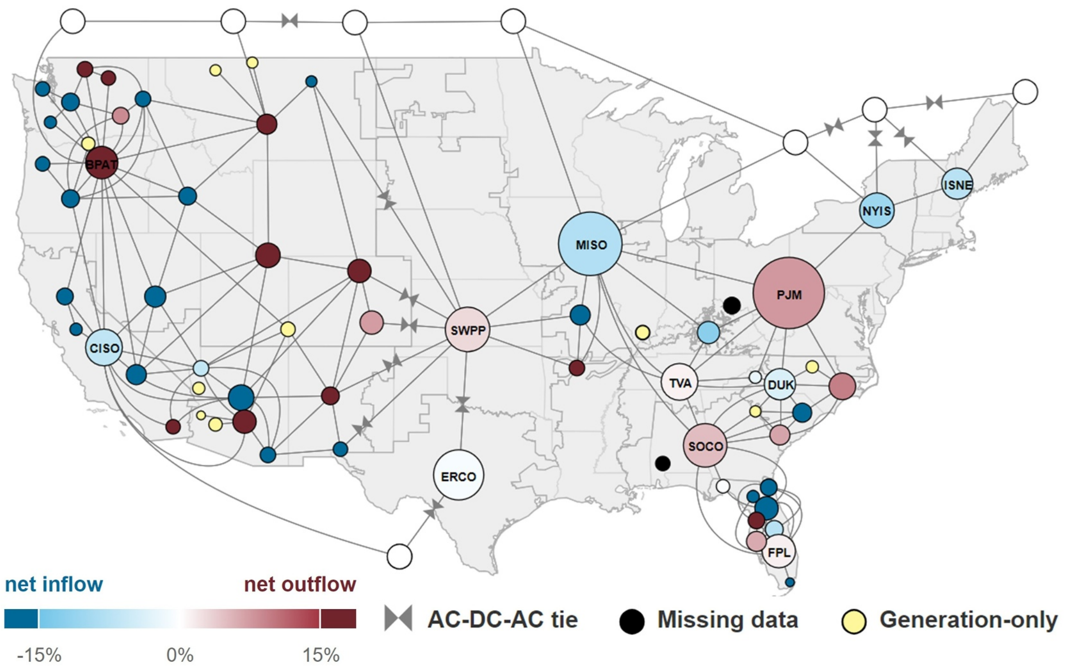

Figure 1. Electricity exchanges (lines) among balancing authorities for a randomly selected hour in 2022 [from EIA, 2023a]. Nodes represent balancing authorities, and their sizes are proportionate to the net electricity transferred with other balancing authorities.

Eastern Interconnection, 33 in the Western Interconnection, and just one in the ERCOT Interconnection operating within the U.S. The number of these balancing authorities changes over time as some entities cease operations or merge into larger systems, with eight retiring after 1 July 2015, and two new entities emerging (EIA, 2023a). The fuel-mix of electricity consumption and the associated environmental implications within a specific balancing authority is a composite result of its own operations and the dynamic interactions with neighboring balancing authorities through the strategic management of electricity transfers.

This study leverages recent advancements in monitoring and data reporting, which enables our calculations of embedded water and emission intensities associated with electricity generation from each balancing authority. Electricity exchange between balancing authorities influences the virtual water and emission intensity of electricity use, leading to virtual water and emission flows across the U.S. electric grid. These electricity transfers, which carry virtual water and emission to end users—sometimes over significant distances—exhibit spatial and temporal variations, often following notable seasonal trends (Nugent et al., 2023). Our method considers the geographic and temporal variations in electricity generation and transfers between balancing authorities, allowing us to examine the seasonal variation in water and carbon intensities, as well as the diurnal variations in water and carbon intensities of consumed electricity. Balancing authorities correspond to the physical organization that ensures the real-time matching of electricity demand and supply through internal electricity generation and transfers with other balancing authorities, making it the most granular representation of the electricity grid feasible without introducing several assumptions regarding electricity distributions within the balancing authority.

The goal of this study is to create a reproducible code and data product to elucidate the environmental footprint of electricity generation and consumption within the U.S. A key novelty of our methodology and corresponding open-source model, online visualization tool, and data product is the detailed spatial and temporal resolution of our analysis, which reveals information of electricity fuel mix and water footprint, alongside more commonly reported carbon emissions. We call our primary data product the Water Integrated Mapping of Power and Carbon Tracker (Water IMPACT) tool. This paper is accompanied by the following data, visualizations, and scripts: (a). Hourly estimates of electricity mix by fuel type, water withdrawal intensity (WWI), water consumption intensity (WCI), and GHG emission intensity (CI) expressed in carbon dioxide equivalent ($CO_{2\text{-eq}}$) of electricity generation and consumption for each balancing authority in the U.S. (Water IMPACT-Data); (b) A visualization tool to

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Table 1
Data Types, Data Sources, and Required Assumptions Used to Estimate the Water and Carbon Intensity of Electricity Generation and Consumption

Data type	Reference and description	Temporal and spatial granularity	Methodological assumptions
Electricity generation and transfers	EIA 930 Hourly and Daily Balancing Authority Operations Report: Electricity generation, electricity transfers between balancing authorities (EIA, 2023a)	EIA 930: Hourly; Balancing authority	
	EIA 923 Power Plant Operations Report: Net electricity generation (EIA, 2023b)	EIA 923: Monthly; Plant level	
Water withdrawals and consumption	EIA thermoelectric cooling data: water withdrawal and consumption (EIA, 2023c)	EIA thermoelectric cooling data: Monthly; Plant level; Thermoelectric power plant with generation capacity >100 megawatt (MW)	Water intensity of a balancing authority or a fuel type remains constant over the span of a month.
	Grubert (2020): Water consumption and withdrawals for hydroelectric power plants	Grubert (2020): Annual; Plant level	
	Meldrum et al. (2013): Water consumption and withdrawals for wind and solar power plants	Meldrum et al. (2013): Annual; Average by fuel type	
Greenhouse gas emissions	EPA's eGRID: $CO_{2\text{-eq}}$ emission	EPA's eGRID: Annual; Plant level	Emission intensity of a balancing authority or a fuel type remains constant over the span of a year.

facilitate the observation of the geospatial estimates (Water IMPACT-Viz); (c) A Python script to enable the reproduction of the dataset with future data as it becomes available (Water IMPACT-Script); (d) A Python script to produce a real-time hourly dataset of the aforementioned intensity factors.

In this data paper, we first detail the data used within our study and the methodology used (Section 2). Next, we describe Water IMPACT, as well as our validation efforts (Section 3). Finally, we discuss how Water IMPACT can be used.

2. Methods

2.1. Data Collection and Preparation

This study uses a diverse set of publicly available data and derived data products utilizing existing literature (e.g., water use by hydroelectric facilities) to estimate the hourly water usage and GHG emissions associated with electricity consumption within each balancing authority in the U.S. The spatial and temporal granularity, as well as the latency of estimates related to the electricity mix and water usage of consumed electricity, are among the chief novelties of this work. Table 1 details the key data products used in this study.

The United States has a large mix of power plants that generate electricity from various energy sources. According to the U.S. Energy Information Administration (EIA), there were more than 12,000 electric power plants in the U.S. as of 2022, with a total generation over four billion megawatt hours (MWh) (EIA, 2023b). The most common fuel types used by these power plants were fossil fuels (primarily natural gas and coal), nuclear, and renewables (including hydroelectric, wind, solar, biomass, and geothermal). Each of these power plants has distinct operations and environmental footprint.

Thermoelectric power plants produce significant heat, necessitating cooling which is often achieved through water use. This withdrawn water dissipates heat through processes like evaporative cooling or once-through-cooling before being returned to the environment. Water consumption refers to the portion of withdrawn water that does not return to its source due to irreversible losses, impacting local water availability. Together, these processes constitute "water use" in electricity generation, encompassing both withdrawals and consumption.

Detailed data describing electricity generation, GHG emissions, and water use come from publicly available federal sources. The EIA Form 923 provides monthly data on electricity generation and fuel type and relevant operational details for all power plants providing electricity to utilities in the U.S. The EPA's eGRID (EPA, 2023a) database monitors annual CO_2, NO_X, SO_2, N_2O, and CH_4 emissions from all U.S. utility-scale power plants with generation capacity greater than 1 MW using stack monitoring. Generators with less than

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1 MW capacity contribute around 1% of total electricity generation and they often exclusively serve specific facilities and don't significantly contribute to the electric grid. Therefore, this study excludes small-scale generation facilities. The EIA's thermoelectric cooling data (EIA, 2023c) provides water withdrawal and consumption data for larger power plants (generation capacity greater than 100 MW). While water data records from smaller plants are incomplete, the 850 largest thermoelectric power plants account for nearly 75% of the total electricity generated in the U.S. The remaining 2,500 smaller thermoelectric plants that do not report water withdrawals and consumption contribute a mere 6% to the overall energy production (with renewables making up the remaining 19%). While water cooling is used by most thermoelectric power plants, air cooling, though much less common (3% of generation capacity), can be used for heat dissipation.

We used the average monthly water use intensity (m^3/MWh; consumption and withdrawals) of all power plants of the same fuel type for small power plants that did not report their water usage. The water usage of wind and photovoltaic solar power stations is negligible compared to the water usage at thermoelectric facilities (Macknick et al., 2012) and is not available for individual facilities. Therefore, the average values from the research by Meldrum et al. (2013) were utilized as representative water usage values in this study.

Water consumption does not occur at the point of generation of hydroelectric facilities but upstream of the generation plant behind the dam where water is lost through evaporation from the reservoir surface. Various methods exist for estimating the water footprint of hydropower, and the choice of method can significantly impact assessments of water usage. Many studies allocate all reservoir evaporation from dams with multiple purposes (e.g., flood control, water supply) to hydroelectricity (Mekonnen & Hoekstra, 2012). Yet, others go to the other extreme and do not attribute any of the water evaporated from the reservoir upstream of the generator to hydroelectricity (Ruddell et al., 2014). In this study, we take a more balanced approach by using the primary purpose allocation method, as described by Grubert (2016), to assess the water footprint of hydroelectricity generation. Briefly, the primary purpose allocation method estimates the reservoir evaporation upstream of the hydropower dam and assigns all evaporation to the primary dam purpose (e.g., hydropower, irrigation, flood control). All secondary dam purpose(s) have none of the reservoir evaporation assigned to them. Grubert (2020) linked all the hydroelectric power plants from the U.S. Energy Information Administration (EIA) with the corresponding dams from the National Inventory of Dams (NID) dataset. This enables the use of open water evaporation rates from the U.S. Geological Survey (USGS) (Reitz et al., 2017) to estimate water consumption by hydroelectric power plants. Since there is no extraction of water directly from the source waterbody for hydroelectric facilities, we equate water withdrawals to the reservoir evaporation assigned to hydroelectric generation.

The estimation of carbon intensity relies on the methodology by de Chalendar et al. (2019), which was adopted by EIA's Hourly Electric Grid Monitor. The process involves assessing GHGs from power plants at a facility level using detailed information on electricity generation, fuel types, and emissions factors to estimate the emissions associated with each power plant as provided in the EPA's eGRID dataset. Despite the prevailing recognition of hydroelectricity as a prominent sustainable energy source, recent studies have uncovered that tropical reservoirs' conditions, high organic content, warmth, and anoxic layers can spur CO_2 and CH_4 emissions (Deemer et al., 2016). Notably, however, the EPA's eGRID dataset does not account for these emissions arising from hydroelectric generation. Given limited reservoir data and following contemporary studies on emissions embedded in electricity consumption, we have also disregarded hydroelectricity's emissions impact.

Through the integration of diverse data sources (as outlined in Table 2), we compiled the monthly electricity generation, water usage, and GHG emission at the power plant level for the period spanning from 2018 to 2022. Utilizing the reported monthly power plant level data, we also estimated the hourly water and carbon footprints associated with electricity consumption across all U.S. balancing authorities. The following sections describe how these estimates were made for both historical and real-time electricity generation and consumption.

2.2. Monthly Water and Carbon Intensities of Electricity by Balancing Authority: Generation

Each power plant is assigned to a balancing authority within the EIA 923 database. Upon compiling the plant-level monthly water usage and GHG emission dataset, the monthly water usage and carbon intensity by fuel type was calculated for each balancing authority. The water withdrawal, water consumption, and GHG emission intensity (referred to generally as the environmental intensity or footprint in Equation 1) of each balancing authority can be calculated individually.

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Table 2
Summary of Data Products Detailing the Water Withdrawal Intensity (WWI), Water Consumption Intensity (WCI), and Carbon Intensity (CI) of Electricity Generation and Consumption Across the U.S. From 2018 to 2022

Data products	Data description	Data type	Reference
Historical data (Water IMPACT-Data)	Hourly electricity mix, WWI, WCI, and CI	CSV	Siddik, M. A. B., Shehabi, A., Rao, P., & Marston L. (2024). Spatially and Temporally Detailed Water and Carbon Footprints of U.S. Electricity Generation and Use, HydroShare, http://www.hydroshare.org/resource/2f54448714554f83b9655da108f0fd3f
Code script 1 (Water IMPACT-Script)	Python script for historical data (Water IMPACT-Data) reproduction	IPYNB	
Code script 2	Python script for real-time data generation	IPYNB	
Data visualization (Water IMPACT-Viz)	Electricity mix, WWI, WCI, and CI	HTML	

Note. The code is also published to provide real-time estimates and reproduce historical data.

$$GEI_{b1,F,M} = \frac{\sum EF_{b1,P,F,M}}{\sum EG_{b1,P,F,M}} \tag{1}$$

In this equation, $GEI_{b1,F,M}$ $\left(\text{in m}^3/\text{MWh or tonnes}/\text{MWh}\right)$ represents the generation environmental intensity in balancing authority $b1$, specific to the fuel type F and the month M. $EG_{b1,P,F,M}$ $(in\ \text{MWh})$ denotes the total electricity generated by power plant P using fuel type F within balancing authority b1 during month M, and $EF_{b1,P,F,M}$ $\left(\text{in m}^3 \text{ or tonnes}\right)$ refers to the environmental footprint (either associated water withdrawal, water consumption, or GHG emissions) related to electricity generation by power plant P of fuel type F within balancing authority $b1$ for that specific month M.

2.3. Hourly Water and Carbon Intensities of Electricity by Balancing Authority: Consumption

2.3.1. Electricity Mix: Hourly Historical

Balancing authorities report their hourly electricity operating data to EIA as part of the EIA 930 hourly grid monitor database. In addition to near real-time information on hourly net generation by fuel type, the EIA 930 dataset includes the electricity transfers between balancing authorities. Since balancing authorities track hourly net generation by fuel type, whereas power plants only report monthly net generation data, we assume that each power plant's relative monthly contribution to a balancing authority's electricity generation and environmental footprint of the similar fuel type is representative of the power plant's hourly profile. We assume that the environmental intensity factor of electricity generation for a balancing authority with a specific fuel type remains constant within a month. For example, if the EIA's thermoelectric cooling database indicates that, in a particular month, coal-fired plants in a balancing authority used on average 1 m^3/MWh of water for generating electricity, this rate of water usage is applied to every hour of coal-generated electricity within that month by the balancing authority. Thus, the variability in a balancing authority's hourly environmental intensity factor reflects the reported hourly changes in electricity mix, not plant-level hourly changes in emission or water use intensity. While diurnal temperature fluctuations and operational changes can affect submonthly water withdrawal and consumption intensities (Tidwell et al., 2019), the hourly difference in the environmental intensity between fuel types (which we capture) is generally much greater than hourly differences between plants of the same type. Moreover, our approach uses all available data and includes the full range of power plants, not just large fossil-fuel fired power plants like previous studies (Miller et al., 2023).

The distribution of electricity between balancing authorities creates a transfer of virtual water and emissions between those balancing authorities. For example, importing electricity from a balancing authority with more carbon (or water) intensive electricity production effectively raises the carbon (or water) footprint of electricity consumers within the importing balancing authority. Using these data, we first estimated the ratio of electricity mix fuel type in the electricity consumption within each balancing authority for each hour.

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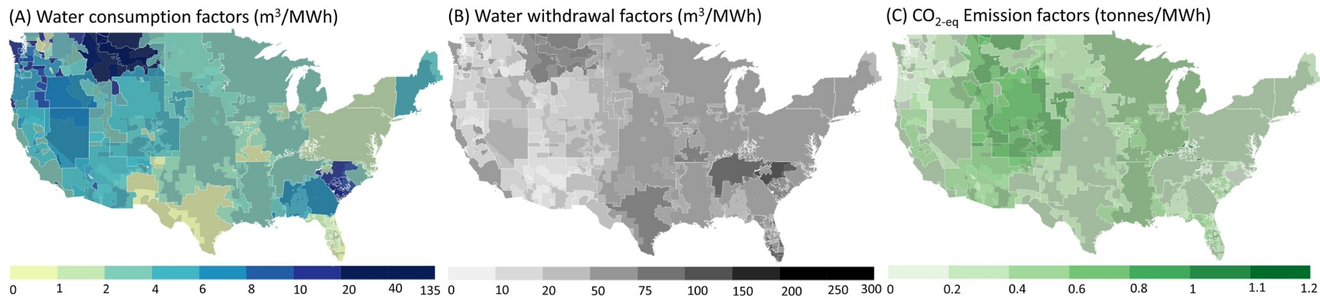

Figure 2. Spatial variation in annual average (a) water consumption (m^3/MWh) from electricity use considering primary purpose water consumption for hydroelectricity (b) water withdrawal (m^3/MWh) from electricity use (considering primary purpose water withdrawal for hydroelectric generation), and (c) GHG gas emitted (tonnes/MWh) from electricity use for each contiguous U.S. balancing authority for the year 2020.

$$CM_{b1,F} = \frac{\sum_{i=1}^{n} EG_{bi\to b1} \times R_{bi,F}}{EC_{b1}} \tag{2}$$

For a given hour, the electricity consumption mix, $CM_{b1,F}$ represents the percentage of consumed electricity from each fuel type F in the consuming balancing authority $b1$. $EG_{bi\to b1}$ represents the electricity consumption in balancing authority $b1$ that was generated within balancing authority bi. When bi is set to $b1$, it represents electricity that is produced and consumed in the same balancing authority. $R_{bi,F}$ represents the ratio of electricity generated by fuel type F in balancing authority bi. EC_{b1} represents the total electricity consumption within balancing authority $b1$ for the given hour.

2.3.2. Water and Carbon Intensities by Balancing Authority: Hourly Historical

Equation 3 presents the environmental intensity of electricity use (EIU), which details the water withdrawal (WWI in m^3/MWh), water consumption (WCI in m^3/MWh), or GHG emissions (CI in tonnes/MWh) associated with the use of electricity during a specific hour of the day accounting for electricity transfers between balancing authorities.

$$EIU_{b1} = \sum_{F} \frac{\sum_{i=1}^{n} EG_{bi\to b1} \times R_{bi,F} \times GEI_{bi,F,M}}{EC_{b1}} \tag{3}$$

Where $GEI_{bi,F,M}$ come from Equation 1 and denote the environmental intensity of electricity generation of balancing authority bi, respectively, with fuel type F. The remaining terms are the same as those used in Equation 2.

2.3.3. Water and Carbon Intensities: Hourly Real-Time

The environmental intensity of electricity generation or use cannot be calculated for the current month since power plant level data is not released until well after the month has concluded. Therefore, we use environmental intensities from the same month from the most recently available year to estimate the environmental footprint for the current month. Alternatively, the long-term average environmental intensity could have been used but these may be markedly different from the current environmental intensity since the electricity mix in the U.S. has significantly changed throughout the last decade. Our Python script extracts the latest hourly grid monitor data for the last 24 hr from the EIA 930 webpage to estimate the hourly electricity mix by fuel type for electricity consumption. The reported hourly electricity mix is then used to estimate the real-time hourly fuel mix, water withdrawal, water consumption, and carbon intensity for each balancing authority using Equation 3.

3. Results

3.1. Data Records

The visualization of the annual average WCI, WWI, and CI factors' spatial variation is presented in Figure 2. These can be replicated for any specific hour, day, month, or year within the 2018–2022 period. These data will be

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Table 3
Columns of the Data Products

Feature name	Feature description
Datetime	Date and hour of the reported data
Balancing authority	The entity or utility responsible for managing the operation of a portion of the U.S. electrical grid
Balancing authority code	A unique 3-letter code provided by EIA for each balancing authority
WWI (m^3/MWh)	Volume (m^3) of water withdrawn embedded in each unit of electricity consumption (MWh) considering primary purpose allocation of water withdrawal for hydroelectric generation.
WWI_NH (m^3/MWh)	Volume (m^3) of water withdrawn embedded in each unit of electricity consumption (MWh) considering no water allocation for hydroelectric generation.
WCI (m^3/MWh)	Volume (m^3) of water consumption embedded in each unit of electricity consumption (MWh) considering primary purpose allocation of water consumption for hydroelectric generation.
WCI_NH (m^3/MWh)	Volume (m^3) of water consumption embedded in each unit of electricity consumption (MWh) considering no water allocation for hydroelectric generation.
CI (tonnes/MWh)	Volume (tonnes) of GHG emissions ($CO_{2\text{-equivalent}}$) embedded in each unit of electricity consumption (MWh)
Coal share (%)	Percent share of coal-fueled generation in the electricity supplied by a balancing authority
Gas share (%)	Percent share of natural gas-fueled generation in the electricity supplied by a balancing authority
Oil share (%)	Percent share of petroleum oil-fueled generation in the electricity supplied by a balancing authority
Nuclear share (%)	Percent share of nuclear-fueled generation in the electricity supplied by a balancing authority
Hydro share (%)	Percent share of hydroelectric generation in the electricity supplied by a balancing authority
Solar share (%)	Percent share of solar-powered generation in the electricity supplied by a balancing authority
Wind share (%)	Percent share of wind-powered generation in the electricity supplied by a balancing authority
Other share (%)	Percent share of other generation techniques (e.g., biomass, geothermal) in the electricity supplied by a balancing authority

continually updated in near-real time on a web interface hosted at Lawrence Berkeley National Laboratory (https://waterimpacttool.lbl.gov). A description of the contents of the three datasets can be found in Table 2.

3.2. Data Structure

The Water IMPACT-database contains all data products and code scripts produced in this study. These data products consist of a tabular dataset (Water IMPACT-Data), a visualization tool (Water IMPACT-Viz), and a code script enabling hourly estimation of electricity mix by fuel type, water withdrawal intensity, water consumption intensity, and GHG emission intensity. Table 3 presents the features of the Water IMPACT data along wit descriptions of feature properties. The published data are available from 2018 to 2022. Importantly, the provided code script enables real-time estimates of the electricity mix and the embedded GHG, water withdrawals, and water consumption of both generation and consumption. During hours when a balancing authority does not import any electricity, the values in the generation tab remain consistent with those in the consumption tab. There exist generation-only balancing authorities that typically exhibit no electricity consumption for the majority of hours. Occasionally, the EIA 930 dataset may lack reports on hourly electricity interchange or mix, resulting in empty cells in the consumption dataset for hours with no consumption or missing data. The open-source code and data enhance the reproducibility and utility of our work.

3.3. Technical Validation

The datasets utilized in this research have been sourced from widely recognized databases, ensuring their reliability and robustness. To validate the accuracy of our datasets, we compare them with previously published works that have examined the operational water consumption intensity of electricity generation categorized by fuel type in the U.S. (Figure 3). These studies predominantly relied on mathematical and physics-based modeling

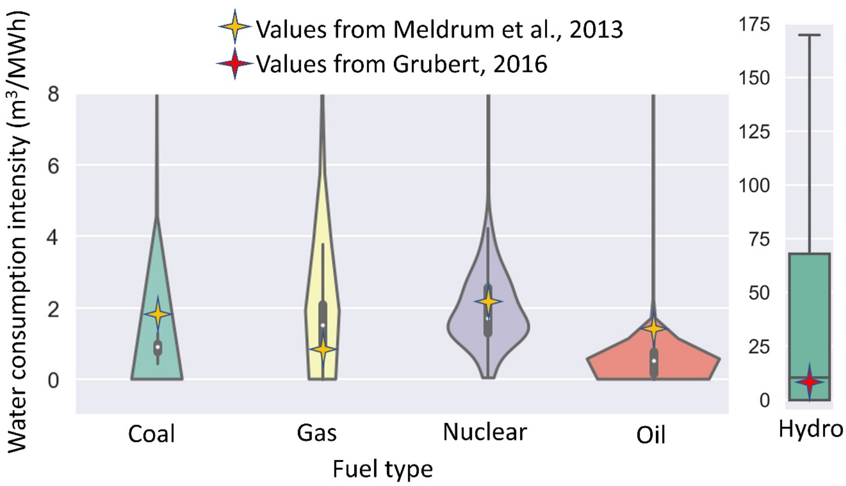

Figure 3. The range of water consumption intensity factors of non-hydro power plants from 2018 to 2022 were derived directly from reported water consumption and net electricity generation by each power plant in this study. Reported plant-level water consumption intensities allow us to capture the variance in water consumption intensities compared to average values provided by Meldrum et al. (2013). Still the average value by Meldrum et al. aligns with the central tendency of our empirical approach. Similarly, the estimated water consumption intensity factors of hydroelectric power plants align closely with the estimates reported by Grubert (2016) when allocated reservoir evaporation to the primary dam purpose.

approaches to estimate water usage in electricity generation. By comparing our data-based estimates with these previous studies, we can assess the validity of our research findings. It is reasonable to expect comparable, though different, values between our study's data-driven estimates and those derived from mathematical and physics-based modeling.

Chini et al. (2018) examined virtual water flows within the U.S. electric grid over the period of 2010–2016, utilizing an annual temporal resolution. Although the study period did not overlap between Chini et al. and this research, the water consumption intensity applied to electricity transfers were similar (Figure 4). As shown in Figure 4, water consumption intensity values remain relatively stable over time. The similarities in water consumption intensities found between our study and previous studies reinforce our methodological approach and data products.

Finally, the study by de Chalendar et al. (2019) estimated hourly CO_2 emission intensity of electricity consumption, offering an additional avenue to compare our research. Notably, we evaluate multiple GHG associated with electricity production (represented as CO_2-equivalent intensity), whereas de Chalendar et al. (2019) only evaluates CO_2. However, when we isolate and compare our CO_2 emission intensity values with those of EIA 930 grid monitor dataset, which is adopted from Chalendar et al. (2019), we find that they are almost identical for most balancing authorities, affirming the robustness of our model (as shown in Figure 5). Minor differences primarily result from rounding of the emission factors, while some balancing authorities exhibit more significant disparities. These differences arise from underlying assumptions regarding plant-level emission factors. For instance, the EIA 930 dataset uses either the same average CI factor or assumes zero emissions for all non-fossil fuel-fired power plants nationwide. However, the precise CI factor used by EIA is not available, challenging more detailed comparisons with our results. Additionally, the EIA relies on long-term averages of historical emission factors for power plants to estimate the emission factors of balancing authorities. In instances where there isn't sufficient historical data for a balancing authority, the U.S. average CI factor is substituted. For our comparison in Figure 5, we solely utilized power plant-level emission factors for 2021 to contrast the results of our model with the EIA 930 long-term average estimates of hourly CI factors.

4. Discussion

This study provides a comprehensive analysis of the spatial and temporal variations in the environmental footprint of electricity consumption in the United States. By developing a detailed dataset and the Water IMPACT tool, we offer a nuanced understanding of how electricity consumption by end users initiates virtual water use and GHG

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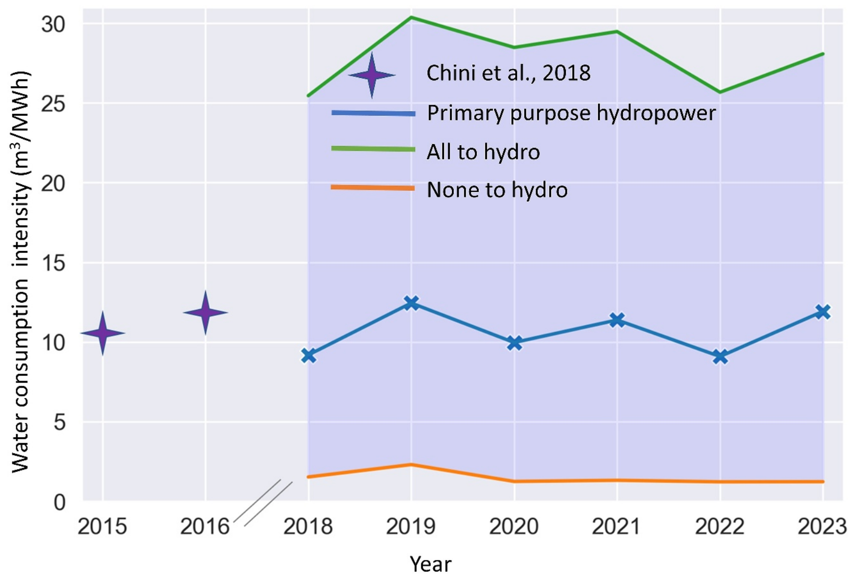

Figure 4. Water consumption intensity of electricity transferred between balancing authorities (orange, blue, and green lines) calculated in this study compared with Chini et al. (2018) (purple stars). Note that Chini et al. assumes that all evaporation from a reservoir is assigned to the primary purpose of the dam (e.g., all reservoir evaporation behind a dam whose primary purpose is hydropower is assigned to hydropower generation and not other dam purposes, such as public supply). This hydropower assumption corresponds to the blue line representing our results. More extreme assumptions on how to assign water consumption at hydropower facilities bound our results. The orange line assumes no reservoir evaporation is assigned to hydropower, while the green line assumes all reservoir evaporation is assigned to hydropower, irrespective of hydropower's priority among a dam's multiple purposes (e.g., water supply, flood control, navigation).

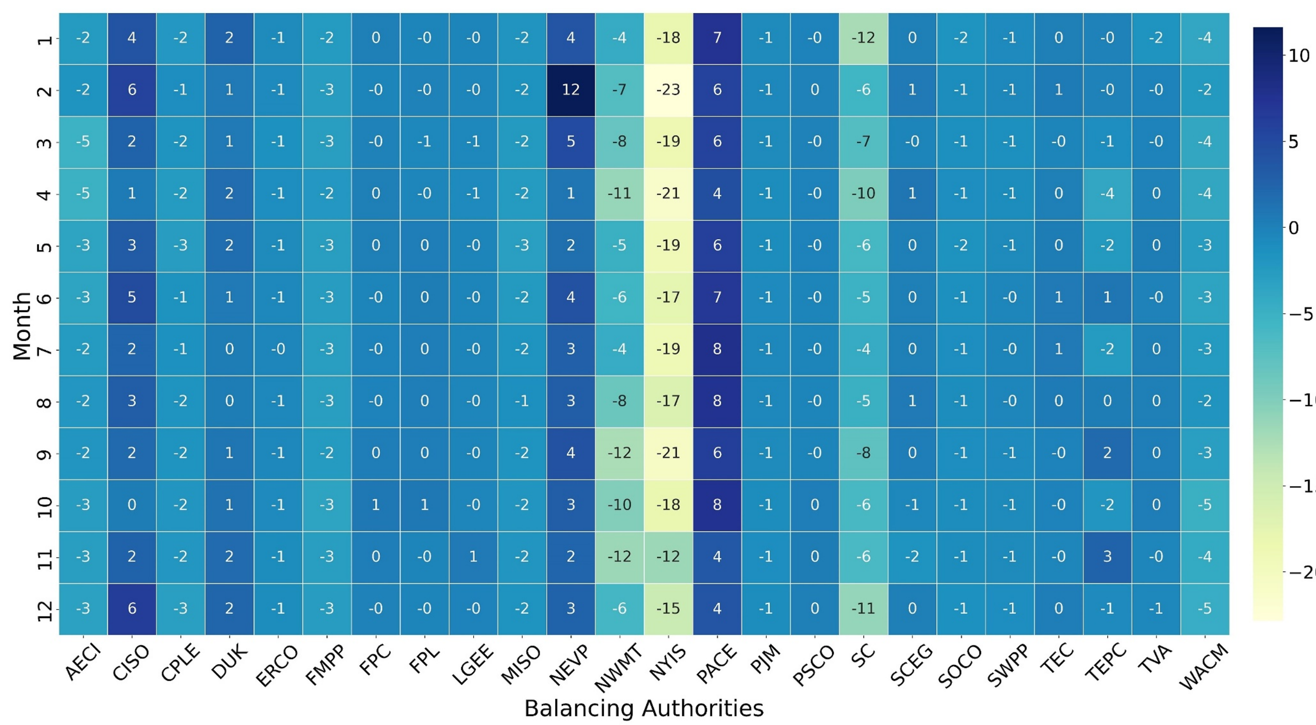

Figure 5. This figure illustrates the average percent difference in hourly CO_2 emission factors between our study and the EIA 930 grid monitor dataset for the top 25 balancing authorities with the highest GHG emissions, for the year 2021. Negative values indicate that our model's estimate is lower than those reported in the EIA 930 dataset, and vice versa. Smaller differences primarily stem from rounding of the emission factors, whereas more substantial disparities arise from underlying assumptions concerning plant-level emission factors, such as emission from non-fossil fuel fired power plants.

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emissions across different balancing authorities. Our research extends previous studies by incorporating both water and carbon intensities, offering a more comprehensive evaluation of environmental impacts. While prior studies focused solely on CO_2 emissions, our approach includes water usage and the fuel mix of consumed electricity. The robustness of our model is underscored by its ability to replicate CO_2 emission intensity values reported in the EIA 930 dataset, despite minor discrepancies. Our results demonstrate significant variations in water withdrawal and consumption intensities across different times and regions, emphasizing the need for integrated water-energy management strategies.

These findings have critical implications for policymakers and energy managers. Understanding these spatial and temporal dynamics allows for the estimation of the historical water and carbon footprints of facilities and the implementation of targeted strategies to reduce the environmental impact of electricity consumption. For instance, promoting electricity use during periods of low water and carbon intensities can significantly mitigate environmental footprints. This is particularly relevant for flexible energy demands, such as electric vehicle charging and industrial processes, which can be scheduled to align with cleaner and less water-intensive energy periods. By providing detailed, temporally, and spatially resolved data, our study offers valuable insights for optimizing energy use and reducing environmental impacts. Our study also aligns with the Department of Energy's concept of an "energyshed," which emphasizes the interconnectedness of electricity production and consumption within defined geographic boundaries. Our model provides a common framework for estimating both water and carbon intensity factors along with the electricity mix of the local grid, offering a valuable tool for researchers and stakeholders to simulate and optimize environmental impacts under different scenarios. Our findings advocate for integrated water-energy policies and underscore the need for continued research to support the transition to a sustainable energy future.

Despite the detailed spatial and temporal scope of our study, several limitations should be acknowledged. The primary limitation is the temporal resolution of power plant-level data, which may not capture hourly variations in water use and emissions. We assume that sub-monthly differences in water use and emissions are primarily driven by hourly shifts in electricity fuel type and source, which we account for in this study, not by plant-level changes in carbon or water intensities. Additionally, some power plant-level water usage and emission data, particularly for non-fossil fuel power plants, is not reported, requiring estimation methods. Due to the limited availability of reservoir data, our study does not account for emissions from hydropower. Emerging research, such as Jager et al. (2022), has started to uncover specific mechanisms by which hydropower affects carbon dynamics in reservoirs. However, the magnitude and timing of greenhouse gas emissions from reservoirs remain uncertain, particularly regarding how they fluctuate over time and across different reservoir functions. We also recognize that water withdrawal and consumption data from the EIA thermoelectric cooling dataset may contain erroneous data and outliers (Peer & Sanders, 2016). To address these limitations, we recommend the implementation of smart metering in power plants to obtain accurate, high-resolution temporal data on water use by thermoelectric facilities. As these technologies become more widespread, we anticipate that future datasets will allow for more precise assessments. Our study emphasizes the need for such advancements and encourages further research to explore the impacts of sub-monthly water use and carbon intensity variations within a power plant as better data becomes available.

Additional limitations stem from the quality of hourly electricity transfer data between balancing authorities and the assumption that balancing authorities' data can represent environmental footprints at finer spatial scales. The EIA 930 dataset publishes the electricity transfer data without modification, leading to occasional gaps or discrepancies when one of the balancing authorities fails to report data for a particular hour. These gaps can lead to mismatched transfer magnitudes between authorities, often resulting in empty cells in our dataset for hours with no recorded consumption or missing data. EIA's data management practices include employing basic imputation techniques to address gaps and correct manifest errors, along with ongoing collaborations with data providers to rectify anomalous historical values. Although our analysis does not account for these gaps, we have made our data and code publicly available to facilitate further investigation. Future iterations of Water IMPACT tool will incorporate new data as it becomes available or as additional insights into existing data emerge. While our approach is practical for a national-level study, local variations within balancing authorities may require more granular data for precise impact assessments. Still, the improved spatial detail of our study is an important first step in the DOE's energyshed initiative, acknowledging that even more spatially refined data and analysis would further improve our study.

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Future research can build on our work by enhancing data granularity and accuracy, integrating real-time monitoring systems, and incorporating power purchase agreements (PPAs) for local electric utilities to improve the precision of environmental footprint assessments. Exploring the potential of emerging technologies, such as smart grids and renewable energy storage, could offer practical pathways for sustainable energy management. Investigating the socioeconomic aspects of transitioning to cleaner energy sources, including cost-benefit analyses and equity considerations, would also be valuable. The modeling framework of this study and open-source data, Water IMPACT, will further our understanding and management of the environmental impacts associated with the electricity consumption of businesses, governments, and residents within the United States.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The codes and input data necessary for replicating the data products of this study can be found in Hydroshare (Siddik et al., 2024), a data sharing platform operated by the Consortium of Universities for the Advancement of Hydrologic Science Inc (CUAHSI) (www.HydroShare.org). The data visualization web interface is hosted by Lawrence Berkeley National Laboratory and can be accessed at https://waterimpacttool.lbl.gov. The programming was carried out utilizing the Python language and open-source packages. Additionally, the geospatial analysis packages of Python were employed to develop the visualization tool.

Versions and Packages:

Python: 3.10.

Pandas: 1.5.

Numpy: 1.19.

Datetime: 5.0.

Os: 2.1.

Folium: 0.14.

Geopandas: 0.12.

Acknowledgments

The code utilized to create this dataset, along with the resulting data, is available for download from Siddik et al. (2024) at https://www.hydroshare.org/resource/2f54448714554f83b9655da108f0fd3f/. The input data for this study are publicly accessible through the U.S. Energy Information Administration (EIA) and the Environmental Protection Agency (EPA) portals, as cited in the References section and Table 1. L.T.M. acknowledges support from the National Science Foundation Grant CBET- 2144169 ('CAREER: Advancing Water Sustainability and Economic Resilience through Research and Education: An Integrated Systems Approach'). 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. This manuscript has been authored by an author at Lawrence Berkeley National Laboratory under Contract DE-AC02-05CH11231 with the U.S. Department of Energy. The U.S. Government retains, and the publisher, by accepting the article for publication, acknowledges, that the U.S. Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for U.S. Government purposes. This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Industrial Efficiency and Decarbonization Office, of the U.S. Department of Energy under Contract DE-AC02-05CH11231.

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