

Validating and Comparing Energy Estimation Methods at Water Resource Recovery Facilities

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Abstract

Water resource recovery facilities play a crucial role in the water-energy nexus, consuming a substantial amount of energy in the United States. Growing treatment volumes and more stringent water quality standards are expected to increase the amount of energy needed to treat wastewater, but accurately estimating energy consumption and potential remains challenging due to variability in scale, treatment methods, and effluent standards. In this study, we used publicly available data to evaluate the accuracy of methods for estimating energy consumption, then quantified uncertainty based on key factors like flow rate, treatment level, and geographic location. To validate methods, we estimated energy consumption at the facility-level, then compared estimates to self-reported data from utilities in major U.S. cities. We found that methods based on effluent treatment level and flow rate performed well for estimating electricity consumption, and process models of treatment trains were accurate relative to other methods for estimating total energy consumption. Applying the evaluated methods to a national inventory of treatment facilities, we estimate that annual energy consumption ranged from 50,900 to 77,100 TJ in 2012 and will increase to between 81,100 and 123,000 TJ in 2042. By quantifying the variability of existing estimation methods and highlighting their advantages and disadvantages, this work enables more data-driven water-energy management in the future.

Keywords: wastewater, electricity, energy, energy recovery

1. Introduction

Water and wastewater utility operations comprise 30-40% of their local governments' energy budgets,¹ but are often overlooked in decarbonization research and planning. Water resource recovery facilities (WRRFs), commonly referred to as wastewater treatment plants, can consume a substantial amount of energy, particularly large, centralized facilities. In the United States, WRRFs have been estimated to consume between 0.8% and 3% of electricity^{2,3} and 0.1 to 0.3% of total energy,⁴ nationally. Previous studies approximate that wastewater systems consume between 15.1 and 30.2 TWh of electricity per year,^{2,5,6,7} a wide range which highlights the uncertainty in current energy demand estimates. The average energy intensity of WRRFs which employ aerobic activated sludge treatment and anaerobic sludge digestion in the United States is 0.6 kWh/m³,⁸ approximately 10-15% of which is typically attributed to collection and pumping.² However, there is considerable variability based on local geography and system design. Energy requirements for wastewater disposal are typically negligible, though coastal areas can be an important exception.⁹

The Electric Power Research Institute (EPRI) estimates that electricity use for wastewater treatment increased by 74% between 1996 and 2013,² a trend expected to continue due to population growth, treatment consolidation, and more stringent requirements for removing nutrients and emerging contaminants from wastewater.¹⁰ More specifically, nitrification and nitrogen removal plants require additional energy for increased aeration compared to conventional biological treatment.^{6,10,11,12} As estimated by El Abbadi et al.¹³ and Song et al.,¹⁴ electricity use accounts for approximately 23% of wastewater treatment emissions overall. Consequently, new discharge requirements necessary for protecting public and environmental health may complicate decarbonizing the wastewater sector in some regions.

While energy use by WRRFs is anticipated to increase, the potential of WRRFs as energy producers is an increasingly recognized strategy for reducing dependency on the largely fossil-based electricity grid.^{7,8,12,15} Wastewater contains roughly nine times more energy than is required for its treatment, indicating that even a small amount of energy recovery could make the entire wastewater treatment process energy-neutral or even energy-positive.¹⁶ As demonstrated by East Bay Municipal Utilities District (EBMUD), a net supplier of power,¹⁷ generating electricity from anaerobic digester biogas, along with capturing and reusing heat, can be a substantial source of renewable energy that is cost-competitive and qualifies for renewable energy credits under some states' Renewable Fuel Standard. However, a comprehensive summary of the state of energy recovery from biogas found that only 10% of WRRFs use biogas for heat or power generation in the United States,¹⁸ likely due to high interconnection costs and/or tariffs from electric utilities, as well as inconsistent standards for biogas purity.¹⁹

Wastewater utilities, on average, comprise a meaningful portion of the national energy budget; however, estimates of regional and national energy requirements for WRRFs in the United States from previous studies, as summarized in Table S1 of the Supporting Information (SI) section, vary widely. Differences in treatment goals, effluent water quality standards, unit processes, economies of scale, energy sources, and site-specific conditions, among other factors, contribute to the uncertainty reflected in the range of existing estimates. While these estimates were made using the best available data at the time, the methods employed in these studies have yet to be validated against empirical data. To address this knowledge gap, we used self-reported electricity consumption, natural gas consumption, and biogas collection data from WRRFs to evaluate a selection of energy estimation methods cited in previous studies.^{2,13,20,21,22,23,24} In addition to quantifying the accuracy of previously applied methods, we apply them to a national inventory of WRRFs to develop bounds on energy consumption and offer recommendations for method selection based on data availability and desired computational intensity, encouraging better informed water-energy estimations by researchers and practitioners in the future.

2. Methods

We applied each of the selected estimation methods to a comprehensive inventory of WRRFs in the United States generated using data from the Clean Watersheds Needs Survey (CWNS), an assessment of publicly-owned wastewater collection and treatment facilities typically conducted by the Environmental Protection Agency (EPA) every four years. For WRRFs located in 66 major U.S. cities, we validated estimates using published energy data from Chini and Stillwell,²⁵ assessing the accuracy of each method based on flow rate, effluent treatment level, and location. Lastly, we used each method to project national energy use by WRRFs, providing bounds on uncertainty for the future energy needs of wastewater treatment.

2.1. Defining the validation set

In an effort to support water-energy nexus research grounded in real-world data, Chini and Stillwell²⁵ collected wastewater flow and energy data from utilities serving 110 major U.S. cities in 2012 and aggregated by city based on service area, referred to throughout as the original dataset. Because facility-level flow, treatment process, and location data is available for the same year in the CWNS, we validated different energy estimation methods by using CWNS data to estimate electricity consumption, energy consumption, and electricity generation at individual

WRRFs, aggregating to the city level, then comparing estimated and reported energy intensity values for a subset of cities referred to throughout as the validation set.

We used data from 66 of the 110 cities that responded to information requests to validate WRRF energy estimation methods. Of the 44 cities excepted from the validation set, we excluded 21 because they did not report complete energy and flow data; three because they did not report any electricity consumption data; and two due to validity concerns (i.e., a reported energy intensity orders of magnitude greater than other cities in the validation set). Lastly, we excluded 18 cities due to deficiencies in the 2012 CWNS (i.e., no reported data for the state of South Carolina or insufficient unit process data). For a full breakdown of exclusion criteria from the validation set, as well as minor corrections to the published original dataset based on unprocessed utility records requested from Chini and Stillwell,²⁵ please see Tables S3 and S4 in the SI.

Though the final subset of WRRFs used for energy estimation method validation (Table S2) is biased toward major metropolitan areas, it represents a wide range of locations and WRRF sizes, approximately 2,700-3,000,000 m³/day, throughout the United States while also covering a large portion of the country's population (Figure 1). Because only a subset of these cities (21) leverage biogas for electricity generation, we were unable to provide as rigorous a validation for the energy recovery estimation methods; however, we include the preliminary validation results herein to emphasize the uncertainty regarding the reliability of these methods and echo the need for greater data availability and transparency called upon by other researchers.²⁶

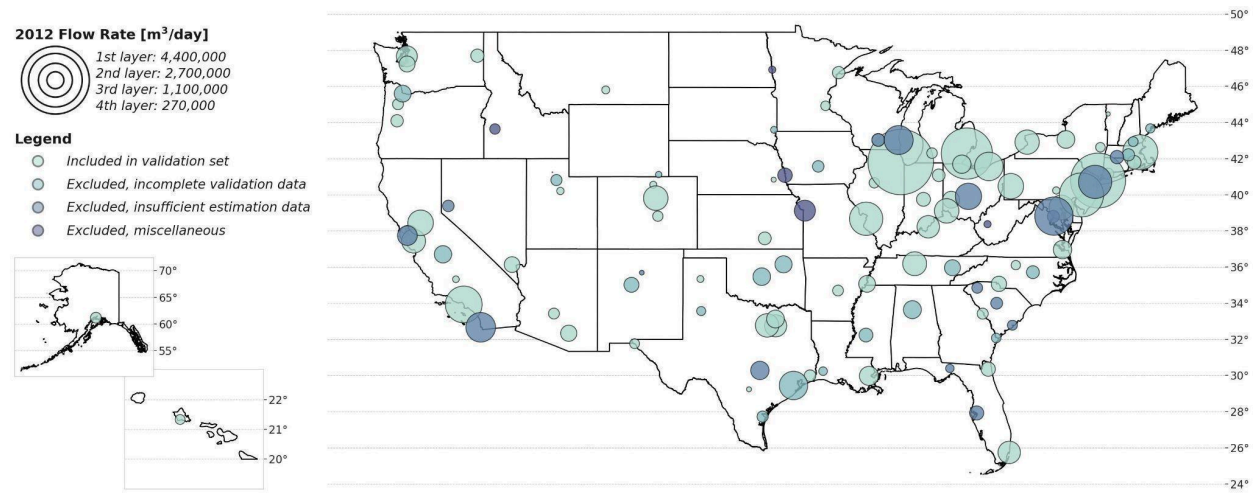


Figure 1: Method validation set summary; cities included in the validation set are indicated by light green circles. Of the excluded data, “incomplete validation data” refers to utilities included in the original Chini and Stillwell²⁵ dataset that did not provide sufficient information on wastewater volumes processed and/or energy consumption by WRRFs for method validation; “insufficient estimation data” refers to WRRFs that did not report any data in the 2012 CWNS (i.e., the state of South Carolina) or did not provide sufficient unit process data to use estimation methods based on treatment trains; and “excluded, miscellaneous” refers to utilities that either did not report any electricity consumption or were flagged as unreliable due to unreasonably high energy consumption intensities reported in Chini and Stillwell.²⁵

Though the datasets underpinning this analysis are both from 2012, we observed discrepancies in reported flow between CWNS and the validation set. More specifically, the percent difference in flow rate varied between 0.32 and 150% (standard deviation of 28%). While counterintuitive, this discrepancy could occur for several reasons, including different reporting periods (fiscal year

versus calendar year), reporting entities (utility representatives versus state liaisons), and reporting metrics (average daily flow rate versus annual volume processed). To minimize the impact of these discrepancies on our validation efforts, we assessed method accuracy based on energy consumption intensity, normalizing total energy consumption by annual volume of wastewater processed.

2.2. Overviewing energy estimation methods

For WRRFs in the validation set, we estimated electricity consumption, energy consumption (both electricity and natural gas use), and electricity generation from biogas utilization, when applicable, using a total of 11 different published methods. As summarized in Table 1, each method varies in terms of inputs, complexity, and results, and two methods account for variations in energy use between typical (T) and best practice (BP) operating conditions. However, most rely on energy intensities associated with different aspects of WRRFs, including facility size, effluent treatment level, and treatment technology selection. Because we reference the methods as the bolded portion of their full name throughout this study, we recommend readers use Table 1 as a quick reference for interpreting results. For a summary of the limitations of each estimation method, see Table S5.

Table 1: Summary of Energy Use and Potential Estimation Methods

Method Name*	Source	Complexity	Method Inputs				Resulting Estimate		
			Flow	Effluent Treatment Level	Technology Selection	Local Climate	Electricity Use	Energy Use	Electricity Generation
Flow Rate Method	Pabi et al. 2013 ²	Low	Yes	No	No	No	Yes	No	No
Effluent Treatment Level A Method	Pabi et al. 2013 ²	Low	Yes	Yes	No	No	Yes	No	No
Effluent Treatment Level B Method	Li et al. 2025 ²⁰	Low	Yes	Yes	No	No	Yes	No	No
Treatment Train Configuration A (T/BP) Method ⁺	Tarallo et al. 2015 ²¹	High	Yes	No	Yes	No	Yes	Yes	Yes
Treatment Train Configuration B (T/BP) Method ⁺	El Abbadi et al. 2025 ¹³	High	Yes	No	Yes	No	Yes	Yes	Yes
Unit Process A Method	Plappally and Leinhard 2012 ²²	Medium	Yes	No	Yes	No	Yes	No	No
Unit Process B Method	Pabi et al. 2013 ²	Medium	Yes	No	Yes	No	Yes	No	No

Regression Method	Carlson and Walburger 2007 ²³	Medium	Yes	No	Yes	Yes	No	Yes	No
Biogas A Method	ERG and RDC 2011 ²⁴	Low	Yes	No	No	No	No	No	Yes
Biogas B Method	ERG and RDC 2011 ²⁴	Low	Yes	No	Yes	No	No	No	Yes
Biogas C Method	Li et al. 2025 ²⁰	Low	Yes	No	No	No	No	No	Yes
<p>*Methods are referenced throughout this study as the bolded portion of the method name.</p> <p>*Method includes variations for typical (T) and best practice (BP) configurations.</p> <p>*Methods which require no or minimal unit process data handling were ranked as low complexity, methods which require some unit process data handling were ranked as medium complexity, and methods which require a high degree of unit process data handling, for instance, to form treatment train assignments, were ranked as high complexity.</p>									

Using facility flow and characteristic data, primarily obtained through the 2012 CWNS, we assigned each WRRF in the validation set a method-specific energy intensity, then estimated annual electricity use, energy use, and electricity generation from biogas by multiplying intensity with the annual volume of wastewater processed in 2012. Though not all methods analyzed in this study are designed to estimate all three energy parameters, we grouped method descriptions below based on the logic for assigning energy intensity. Most of the methods can be categorized based on how energy intensity is derived, but the Regression method diverges from the convention of using energy intensities by relating energy consumption to a variety of WRRF characteristics through a regression analysis.

2.2.1 Methods based on plantwide characteristics

Flow and effluent methods: Estimation methods based on simple plantwide characteristics tend to be easier to implement because they do not require cleaning and compiling often inconsistent and unavailable unit process information. Using flow rate and effluent treatment level (raw discharge, primary, advanced primary, secondary, or advanced treatment) data reported in the CWNS, we used three methods (Flow, Effluent A, and Effluent B) to estimate total annual electricity consumption [kWh/year] for each WRRF i using the same basic equation (Equation 1), where we determined electricity consumption intensity [kWh/m³] for each WRRF based on either daily flow rate or effluent treatment level, then multiplied by annual flow rate (Q_{annual}) [m³/year]. For facilities that did not specify a current or projected effluent treatment level in the 2012 or 2022 CWNS (three and 12, respectively), we assumed secondary treatment.

$$\text{Equation 1: Annual Electricity Consumption}_i = \text{Electricity Consumption Intensity}_i * Q_{\text{annual}, i}$$

Originally published in 1996 and revised in 2013, EPRI² developed electricity consumption intensities categorized by daily flow rate (Table S6) and effluent treatment level (Table S7), respectively, referred to as the Flow and Effluent A methods in this study. The Effluent B method updates effluent treatment level-based electricity consumption intensities developed by EPRI using data from more recent studies in the United States (Table S8).¹⁸ While these methods do

not incorporate electricity consumption intensities specific to treatment processes employed at individual WRRFs, they leverage the likelihood that WRRFs of similar sizes and effluent treatment levels may have similar energy requirements. In the Flow method, electricity consumption intensity decreases as facility size increases, likely resulting from economies of scale. In the Effluent A and B methods, electricity consumption intensity increases with treatment level because higher levels of treatment, particularly nutrient removal, require more energy to achieve. The Effluent A method was applied by Tidwell, Moreland, and Zemlick,²⁷ however, they used design flow rather than observed flow to apply the electricity consumption intensities developed by EPRI to WRRFs in the Western United States.

Regression method: Originally published by Carlson and Walburger,²³ the Regression method diverges from the standard formula of multiplying intensity with flow rate to obtain total consumption. Instead, this logarithmic method relates total energy use [MJ/year] to WRRF characteristics that correlate strongly with energy use, including: average daily flow rate (Q_{daily}) in million gallons per day [MGD], design flow rate (Q_{design}) [MGD], influent biochemical oxygen demand (BOD) concentration (BOD_{in}) [mg/L], effluent BOD concentration (BOD_{out}) [mg/L], the total number of local annual heating and cooling degree days (HDD, CDD), and the use of trickling filters (TF) and nutrient removal processes (NR). Using daily observed and design flow rates as well as unit process data reported in the CWNS, an assumed BOD_{in} and BOD_{out} of 190 and 10 mg/L, respectively,²¹ and average HDD and CDD by state for 2012 from the National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Survey,²⁸ we estimated annual energy consumption for each WRRF i using Equation 2.

$$\begin{aligned} \text{Equation 2: Annual Energy Consumption}_i = & \exp(12.5398 + 0.8966*\ln(Q_{\text{daily},i}) + \\ & 0.4920*\ln(\text{BOD}_{\text{in}}) - 0.1962*\ln(\text{BOD}_{\text{out}}) - 0.4314*\ln(Q_{\text{daily},i}/Q_{\text{design},i}*100) - 0.3363*\text{TF}_i + \\ & 0.1587*\text{NR}_i + 0.2421*\ln(\text{HDD}_i) + 0.1587*\ln(\text{CDD}_i)) * 1.055056 \end{aligned}$$

This method is unique from others analyzed in this study in that the authors developed a logarithmic model of energy consumption based on a variety of characteristics using a statistically representative sample of WRRFs. Note that TF and NR are binary values, with a value of one indicating an active trickling filter or nutrient removal system. For locations which experienced either no HDD (Honolulu, HI) or CDD (Anchorage, AK) in 2012, we dropped the entire HDD or CDD term. For WRRFs without a reported design flow, we assumed design flow to be equivalent to reported flow.

2.2.2 Methods based on treatment processes

Though more computationally intensive, methods that consider treatment technology selection at individual WRRFs can provide more specific energy estimates than those reliant on plantwide characteristics and enable exploring how energy demands change as unit processes evolve. The majority of these methods function by either assigning energy intensities to individual unit processes and summing to calculate a cumulative intensity for each WRRF (Process A, Process B), or by using key unit processes to assign a prototypical treatment train with a modeled intensity to each WRRF (Configuration A, Configuration B).

Process A and B methods: For the Process A and Process B methods, we used flow rate and unit process data reported in the CWNS to estimate annual electricity consumption by assigning an

electricity consumption intensity to each unit process k reported at individual WRRF i , then summing to generate a cumulative intensity and multiplying by annual flow rate (Equation 3).

$$\text{Equation 3: Annual Electricity Consumption}_i = \sum_{k=1}^n \text{Electricity Consumption Intensity} * Q_{\text{annual}, i}$$

The key difference between the Process A and B methods is that the Process A method uses average electricity consumption intensities from a variety of published studies (Table S9), while the Process B method uses electricity consumption intensities from grey literature categorized by both unit process and flow rate (Table S10). We assigned unit processes not included in these tables an electricity consumption intensity of zero, and we included a baseload (energy required for wastewater pumping, odor control, non-process loads, etc.) in the cumulative electricity consumption intensity for all WRRFs, regardless of unit process reporting, in the Process B method. If multiple forms of activated sludge treatment were reported for a particular plant, we used the average intensity for all the reported activated sludge configurations. The Process A method was used by Gingerich and Mauter⁷ and Stillwell et al.,⁵ with slight modifications to the methodology used to compile unit process data.

Configuration A and B methods: Because reported unit process data is often incomplete or inconsistent, an alternative approach to using technology-specific intensities is to use key unit processes to assign a treatment train with a modeled energy intensity to each WRRF. We used two methods, both of which can be employed assuming either typical or best practice operating conditions, to estimate annual electricity consumption: the Configuration A and B methods. Originally defined by Tarallo et al.,²¹ the Configuration A method models the electricity consumption intensity of 18 common treatment trains, while the Configuration B method expands upon the Configuration A method to include a wider range of possible treatment configurations by extrapolating results from Tarallo et al.²¹ Because the electricity consumption intensities provided in Tarallo et al.²¹ (Tables S11a and S11b) and El Abbadi et al.¹³ (Tables S12a and S12b) are specific to treatment trains, we used unit process information, primarily reported in various releases of the CWNS, to assign each WRRF i one or more treatment trains based on secondary treatment, nutrient removal, and biosolids management practices. We then estimated annual electricity consumption by multiplying the corresponding electricity consumption intensity by annual flow rate (Equation 4). When multiple treatment trains were equally well-matched, we averaged the electricity consumption intensities for all identified treatment trains.

$$\text{Equation 4: Annual Electricity Consumption}_i = \text{Electricity Consumption Intensity}_i * Q_{\text{annual}, i}$$

Because these methods also provide energy consumption intensity and electricity generation intensity, we used them to estimate total annual energy consumption and electricity generation from biogas utilization in addition to electricity consumption. A key differentiating factor between the Configuration A and Configuration B methods is that the original Configuration A method does not provide instructions for assigning WRRFs a treatment train, whereas the Configuration B method does. Because transforming unit process data into a treatment train assignment is a critical intermediate step to using both methods, we modified the treatment train assignment methodology used in El Abbadi et al.¹³ to assign treatment trains in the Configuration A method. Another important distinction between these methods is that not all WRRFs were able to be assigned a treatment train and associated energy use in the Configuration A method due to

either that facility using a treatment configuration not modeled by Tarallo et al.²¹ or a paucity of unit process data. However, the Configuration B method addresses this limitation by providing energy intensities for an expanded range of treatment trains and, in the absence of sufficient unit process information, assigning a treatment train by making assumptions based on common configurations for similarly sized WRRFs in the area. These methods are reported to be only applicable to facilities with an average daily flow greater than 18,927 m³/day (5 MGD) and secondary treatment, at a minimum, but lacking a better alternative we applied them to the entire national inventory. For the code used to assign WRRFs treatment trains based on reported unit process data, please see `tt_assignment.ipynb` in our public GitHub repository. For the treatment train assignments used in national baseline estimates, please see Supplementary Files A and B.

Biogas A, B, and C methods: For WRRFs that produce electricity using biogas captured from anaerobic digestion, we used unit process data from the U.S. Department of Energy's (DOE) Combined Heat and Power (CHP) Installation Database,²⁹ the Water Environment Federation's (WEF) Water Resource Recovery Facilities Biogas Database,³⁰ the Energy Information Administration's (EIA) 2012 Survey Form EIA-923,³¹ and the CWNS to estimate electricity generation [kWh/year] via three methods (Biogas A, Biogas B, and Biogas C). The first, less complex method (Biogas A) assumes a fixed electricity generation intensity of 0.13 kWh/m³ based on an average observed electricity generation of 26 kW/MGD and an 80% capacity factor. The second method (Biogas B) uses electricity generation intensities specific to the prime mover, the engine or turbine that converts the chemical energy stored in biogas into mechanical power (Table S13). The third method (Biogas C) uses an electricity generation intensity based on assumed influent total suspended solids and 5-day BOD concentrations detailed in Li et al.²⁰ For each WRRF i flagged as producing electricity, we estimated annual electricity generation by multiplying either the fixed or prime mover-specific electricity generation intensity with annual flow rate (Equation 5). Because the WEF database used to identify prime movers at WRRFs lists both turbines and microturbines, we made the simplifying assumption that turbines have the same intensity as microturbines for the Biogas B method. Additionally, we assumed that facilities without a specified prime mover use reciprocating engines.

$$\text{Equation 5: Annual Electricity Generation}_i = \text{Electricity Generation Intensity}_i * Q_{\text{annual}, i}$$

2.3. Compiling a national WRRF inventory

Prior to applying the aforementioned estimation methods to WRRFs in the validation set, we first compiled an inventory of WRRFs in the United States, excluding its territories, using data from the CWNS^{32,33,34,35} on location, average daily flow rate, design capacity, effluent treatment level, and treatment processes. We considered WRRFs which reported a non-zero flow in the 2012 CWNS, 14,559 facilities, the foundation of our baseline inventory for national estimates and method validation (Figure 2). For energy use and generation projections, we developed a 2042 national inventory based on facilities that project a non-zero flow in the 2022 CWNS (Figure S1). We estimated national electricity consumption, energy consumption, and electricity generation in 2012 and 2042 by applying the aforementioned methods to the baseline and projected WRRF inventories developed above.

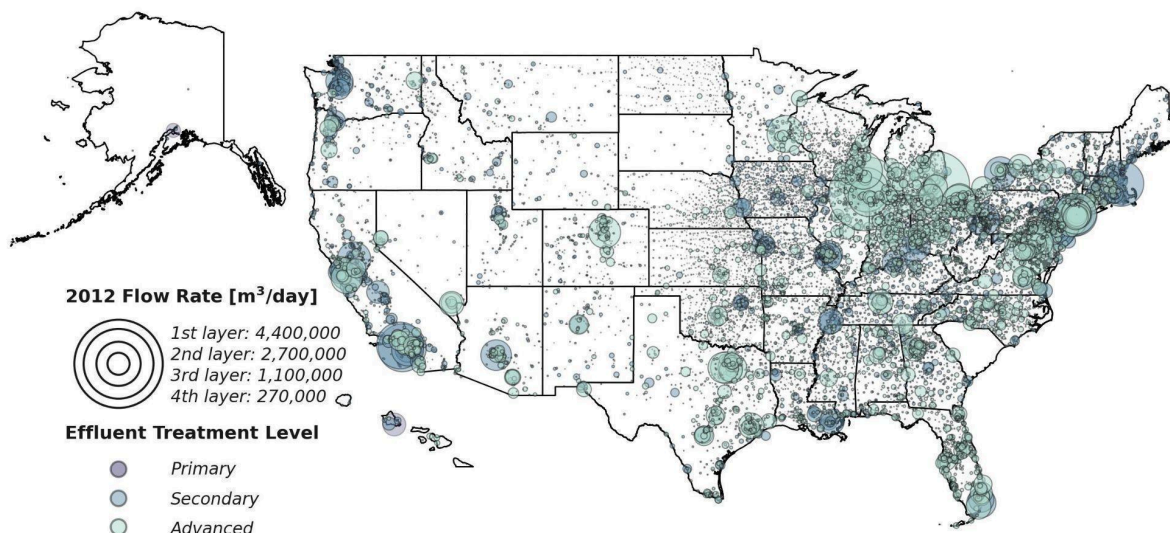


Figure 2: Baseline national WRRF inventory, compiled using location, flow rate, and effluent treatment level data from the 2012 CWNS. This figure illustrates how WRRF size and effluent treatment standards vary widely across the United States. Note that facilities in the state of South Carolina did not report data to the 2012 CWNS.

Because some methods require unit process data to estimate energy use and recovery, we developed a cumulative unit process list representative of the treatment processes that were active in 2012 by aggregating unit processes reported in the 2004, 2008, and 2012 CWNS. If a facility was flagged as performing nitrogen, ammonia, or phosphorus removal in the CWNS, we added the corresponding unit process to the cumulative unit process list. We removed duplicate unit processes and unit processes from 2008 and 2012 flagged for abandonment. Additionally, if multiple secondary and/or solids treatment processes were reported across the three surveys, we retained only the most recently reported process(es). For national energy use projections, we developed a cumulative, projected unit process list using the same methodology, but with added data from the 2022 CWNS. The methodology for creating the cumulative unit process list is similar to that of prior studies (e.g., Gingerich and Mauter⁷ and El Abbadi et al.¹³) and detailed in the `create_unit_process_lists.ipynb` script of our GitHub repository.

Because the 2012 CWNS does not specify whether biogas is used for heating to offset natural gas combustion, a biogenic fuel to produce electricity, or both, we used three additional data sources to identify electricity-producing WRRFs: the U.S. DOE's CHP Database,²⁹ the WEF's Water Resource Recovery Facilities Biogas Database,³⁰ and the U.S. EIA's 2012 Survey Form EIA-923.³¹ We used the same strategy as El Abbadi et al.¹³ to integrate these databases into the cumulative unit process lists, with the exception that we assumed all WRRF facilities in the WEF database were active in 2012, though the WEF data was published in 2013. For a summary of the biogas data sources, see Table S14.

3. Results

3.1. Validating electricity consumption estimation methods

Table 2 compares the root mean square error (RMSE), mean absolute percent error (MAPE), and mean percent error (MPE) of each method for estimating electricity consumption intensity, averaged across all cities in the validation set. The distribution of percent error in terms of electricity consumption intensity for each method is also visualized in the form of kernel density estimation (KDE) plots in Figure 3. Note that electricity consumption, in this case, is considered the sum of electricity imported from the grid and electricity produced on-site from biogas utilization.

Table 2: Summary Error Statistics for Electricity Consumption Estimation Methods

Method	RMSE, Electricity Consumption Intensity [kWh/m ³]	MAPE, Electricity Consumption Intensity [%]	MPE, Electricity Consumption Intensity [%]
Flow	0.37	44	12
Effluent A	0.36	63	51
Effluent B	0.37	37	-0.76
Configuration A (T)	0.39	44	-5.3
Configuration A (BP)	0.47	51	-38
Configuration B (T)	0.41	46	-7.7
Configuration B (BP)	0.50	54	-42
Process A	0.55	110	108
Process B	0.41	64	50

*Note, RMSE = root mean squared error, MAPE = mean absolute percent error, and MPE = mean percent error.

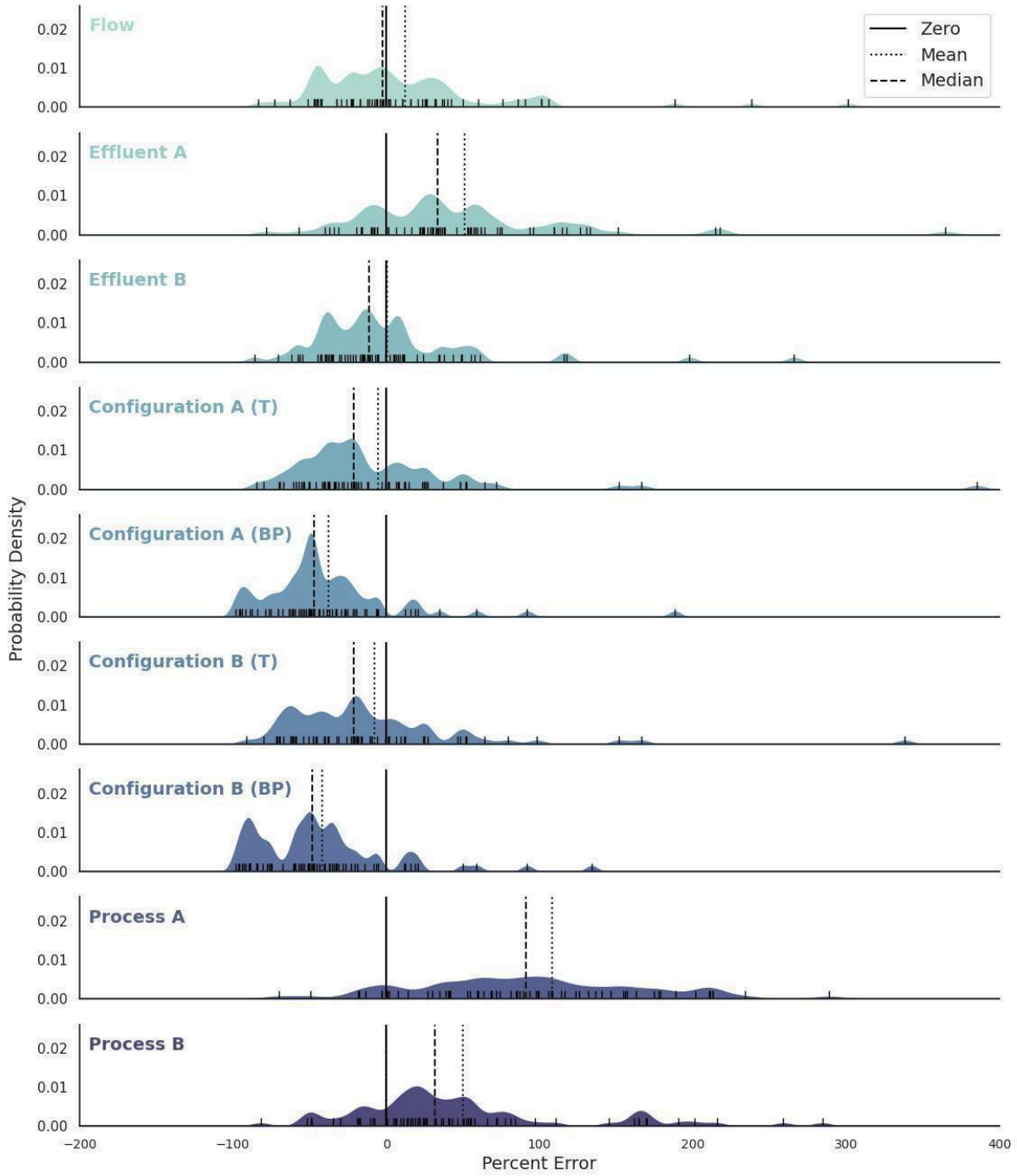


Figure 3: KDE of percent error for city-wide electricity consumption intensity estimates. Each tick mark on the x-axis represents the percent error for an individual city, where percent error was calculated by comparing the total electricity consumption intensity of all WRRFs in that city with the electricity consumption intensity reported in the original dataset.²⁵ The ridgeline plots show the smoothed distribution of percent error across all cities in the validation set for each electricity consumption estimation method. Note that Eugene, OR, and Little Rock, AR, are excluded for ease of viewing the error distribution.

We find method performance varies with error metric. The Effluent A and Flow/Effluent B methods perform best in terms of RMSE (0.36 and 0.37 kWh/m³), the Effluent B and Flow/Configuration A (T) methods perform best in terms of MAPE (37% and 44%), and the Effluent B and Configuration A (T) methods perform best in terms of MPE (-0.76 and -5.3%). Of these methods, the Effluent B method exhibits the most normal error distribution, estimating electricity usage within 50% of the reported value for the majority of WRRFs in the validation set. Based on the mean and median percent error shown in Figure 3, the Effluent A, Process A, and Process B methods tend to overestimate electricity consumption intensity, with the Process A method consistently overestimating electricity consumption, up to 700%, despite accounting for a limited number of energy-consuming processes at WRRFs. Conversely, the Configuration A and B methods tend to underestimate electricity consumption, particularly under the best practice configuration assumption.

3.2. Validating energy consumption estimation methods

Table 3 compares the RMSE, MAPE, and MPE of each method for estimating energy use intensity, inclusive of both electricity and natural gas use, averaged across all cities in the validation set. The distribution of percent error in terms of energy consumption intensity for each method is also visualized in the form of KDE plots in Figure 4.

Table 3: Summary Error Statistics for Energy Consumption Estimation Methods

Method	RMSE, Energy Consumption Intensity [MJ/m ³]	MAPE, Energy Consumption Intensity [%]	MPE, Energy Consumption Intensity [%]
Configuration A (T)	1.5	50	5.0
Configuration A (BP)	1.7	50	-30
Configuration B (T)	1.5	53	7.5
Configuration B (BP)	1.7	48	-29
Regression	2.7	150	150

*Note, RMSE = root mean squared error, MAPE = mean absolute percent error, and MPE = mean percent error.

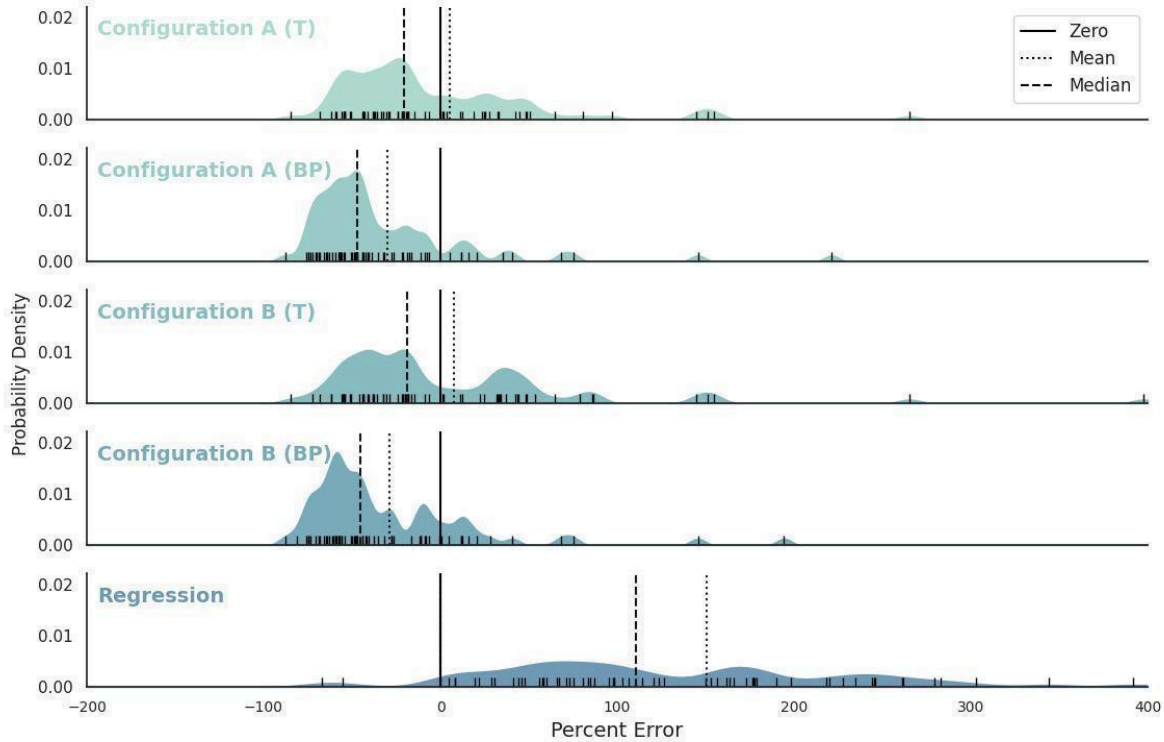


Figure 4: KDE of percent error for city-wide total energy consumption intensity estimates. Each tick mark on the x-axis represents the percent error for an individual city, where percent error was calculated by comparing the total energy consumption intensity of all WRRFs in that city with the energy consumption intensity reported by Chini and Stillwell.²⁵ The ridgeline plots show the smoothed distribution of percent error across all cities in the validation set for each energy consumption estimation method. Note that Little Rock, AR, and Eugene, OR, are excluded for ease of viewing the error distribution.

In terms of RMSE, the Configuration A and B methods under the typical configuration assumption performed best (1.5 MJ/m^3). We observe a similar trend in terms of MPE in which the Configuration A and B methods perform better under the typical assumption (5.0 and 7.5%); however, the Configuration B method under the best practice configuration assumption slightly outperforms the other methods in terms of MAPE (48%). The Configuration methods exhibited a mix of over- and underestimation, trending towards underestimation when the best practice assumption is employed. These methods could be performing irregularly for a variety of reasons, including misassignment of treatment trains and/or inaccurate process modeling or application of models from Tarallo et al.,²¹ but we cannot separate these sources of error without manually confirming which treatment train assignments are correct. The original Configuration A and expanded Configuration B treatment train methods performed similarly on the validation set; however, it is important to note that, for the purpose of drawing a fair comparison between methods, WRRFs that were not able to be assigned a treatment train via the Configuration A method (2,282 facilities) were dropped from the validation set. Because it depends heavily on unit process data and only models energy intensity of a subset of treatment trains, the Configuration A method cannot be applied to all WRRFs, a notable limitation of the method that is not reflected in the above statistics. Despite adjusting for changed heating and cooling needs associated with climate, the Regression method consistently overestimated the energy

consumption by an average of 150%. This method was developed more as a benchmarking tool than an estimation method, which may help explain this bias.

3.3. Validating electricity generation estimation methods

Table 4 compares the RMSE, MAPE, and MPE of each method for estimating hypothetical energy recovery at eligible facilities, averaged across the 21 cities which reported electricity generation from biogas utilization in both Chini and Stillwell²⁵ and any of the biogas utilization datasets.^{29,30,31} Note that, within the validation set, 12 cities reported electricity generation in Chini and Stillwell²⁵ but not the biogas databases, and one city reported electricity generation in the biogas databases but not Chini and Stillwell.²⁵ To avoid introducing error due to differences in how electricity-producing facilities were identified, these cities were excluded from this portion of the analysis. The distribution of percent error in terms of electricity generation intensity for each method is visualized in the form of KDE plots in Figure 5.

Table 4: Summary Error Statistics for Energy Recovery Estimation Methods

Method	RMSE, Electricity Generation Intensity [kWh/m ³]	MAPE, Electricity Generation Intensity [%]	MPE, Electricity Generation Intensity [%]
Configuration A (T)	0.34	87	-72
Configuration A (BP)	0.33	88	-63
Configuration B (T)	0.29	59	-16
Configuration B (BP)	0.28	69	9.9
Biogas A	0.30	61	-1.5
Biogas B	0.30	68	9.8
Biogas C	0.31	250	240

*Note, RMSE = root mean squared error, MAPE = mean absolute percent error, and MPE = mean percent error.

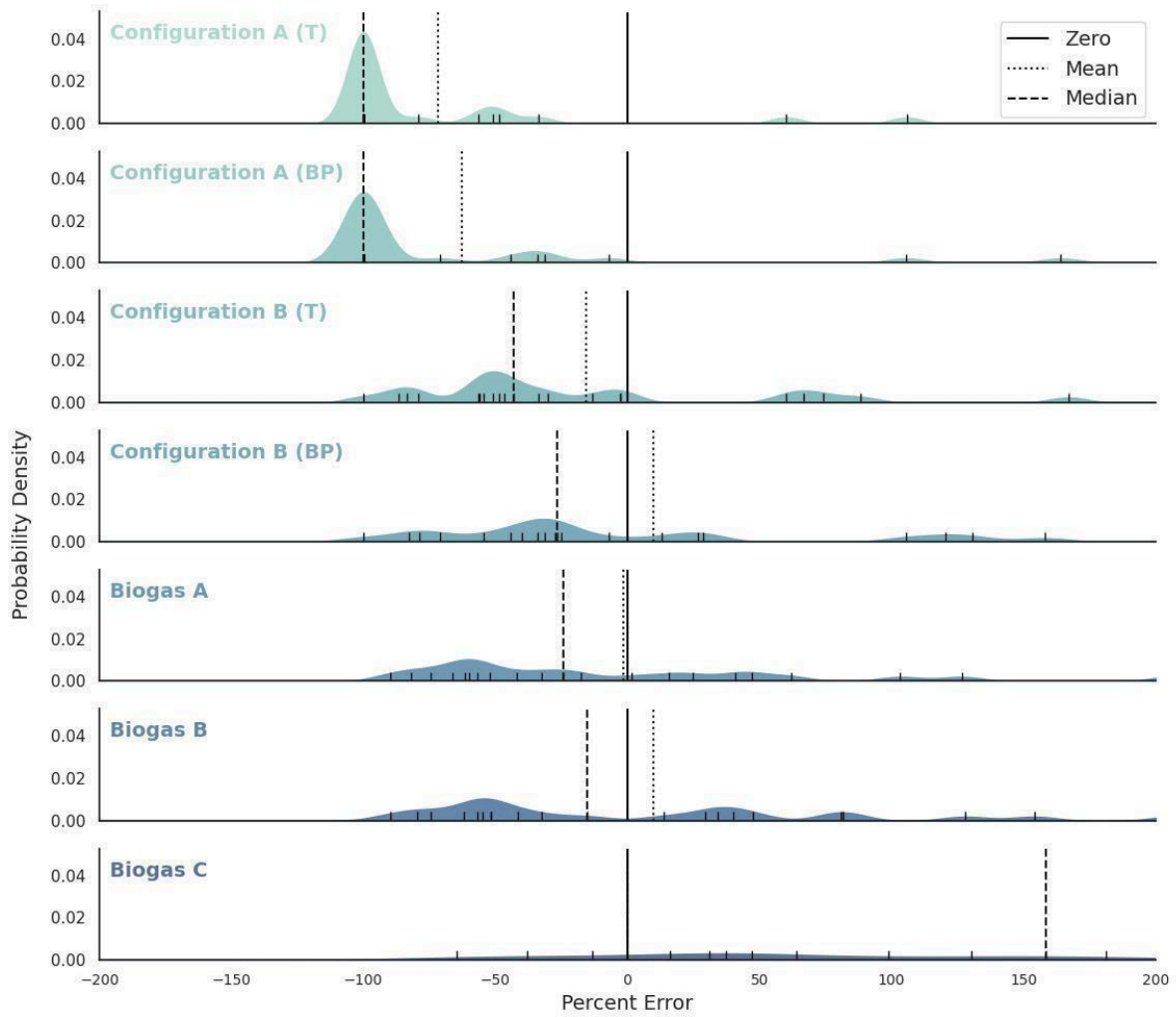


Figure 5: KDE of percent error for city-wide total electricity generation intensity estimates. Each tick mark on the x-axis represents the percent error for an individual city, where percent error was calculated by comparing the total electricity generation intensity of all WRRFs in that city with the electricity generation intensity reported by Chini and Stillwell.²⁵ The ridgeline plots show the smoothed distribution of percent error across all cities in the validation set for each electricity generation estimation method. Note that eight cities (Tucson, AZ; Bakersfield, CA; St. Louis, MO; New York, NY; Syracuse, NY; Toledo, OH; Harrisburg, PA; and Fort Worth, TX) are excluded from the Biogas C plot for ease of viewing the error distribution.

Because not all WRRFs in the validation set utilize biogas for electricity generation, there are fewer reported values to validate the electricity generation estimation methods with (21 cities total). Additionally, to convert reported volume of biogas collected in Chini and Stillwell²⁵ to power, we assumed that 70% of biogas collected was used for electricity generation and that generators have an efficiency of 37% based on the EIA's 2012 Survey Form EIA-923.³¹ Subsequently, the smaller validation set, in addition to ambiguity as to the ratio of biogas used for heating versus electricity generation, makes it difficult to draw conclusions about the accuracy of the energy recovery estimation methods. Of these 21 cities, only seven contain

facilities that were assigned an electricity-producing treatment train in the original Configuration A method, resulting in several cities with -100% error. Because the Configuration B method is capable of assigning more of these WRRFs an electricity-producing treatment train, it outperforms the Configuration A method for energy recovery estimations. With this in mind, the Biogas A method performs well across the three error metrics.

3.4 Method accuracy by different WRRF characteristics

Some estimation methods may be unintentionally biased towards WRRFs with certain characteristics. We assessed the accuracy of each method for different subsets of WRRFs in the validation set, grouped by flow rate (three size categories), effluent treatment level, and latitude (three categories, as shown in Figure 1), which is a rough proxy for climate and heating demands. Table 5 compares the accuracy of the electricity consumption estimation methods by WRRF characteristics. For each subset of WRRFs by plant characteristic, the most accurate method in terms of percent of reported electricity consumption intensity is bolded. Similar tables for energy consumption intensity and electricity generation intensity are included in the SI (Tables S15 and S16).

Table 5: Percent of Reported Electricity Consumption Intensity by Plant Characteristics

		Number of Cities	Percent of Reported Electricity Consumption Intensity [%]								
			Flow	Effluent A	Effluent B	Configuration A (T)	Configuration A (BP)	Configuration B (T)	Configuration B (BP)	Process A	Process B
Flow Rate [10 ³ m ³ /day]	43.8-126	19	127	153	101	101	68	103	69	216	166
	126-274	16	106	160	109	94	59	84	48	210	149
	274+	27	101	144	96	91	61	91	58	202	138
Effluent Treatment Level	Primary	1	288	127	70	252	192	252	192	313	291
	Secondary	22	131	158	101	99	67	103	69	205	131
	Advanced	39	100	152	104	90	57	83	50	213	161
	Multiple	4	83	108	70	84	54	80	49	163	112
Latitude	< 35°	15	134	184	122	108	71	106	68	236	159
	35-42.5°	37	94	133	89	80	53	78	50	191	145
	> 42.5°	14	137	164	109	120	77	116	70	226	154

*Note, bolded values represent the most accurate estimation method for the given subset of cities in the validation set.

On average, the evaluated electricity estimation methods performed better on high-flow, secondary/advanced treatment, and midlatitude facilities. The Flow method performed best for midsize and large facilities, but was outperformed by the Effluent B/Configuration A (T) methods for smaller WRRFs. While only one city (Anchorage, AK) used solely primary treatment, electricity consumption intensity estimates were notably less accurate for this city, overestimating city-wide electricity usage across almost all methods. For most energy consumption estimation methods, the estimated energy consumption intensity tends to decrease as plant size increases.

4. Discussion

4.1. Sensitivity analysis on validation set

To assess estimation method accuracy, we compared electricity consumption intensity estimates to reported values for 66 cities in Chini and Stillwell;²⁵ however, several outliers in our results indicate that method accuracy can vary substantially depending on what cities are included in the validation set. To evaluate the sensitivity of our results to the validation set composition, we applied repeated k-fold cross-validation and assessed how each electricity consumption estimation method varies in accuracy when validated using different subsets of cities. We randomly split the full validation set (66 cities total) into two groups of 33, recalculated MAPE for each subset, then repeated this process 50 times (Figure 6).

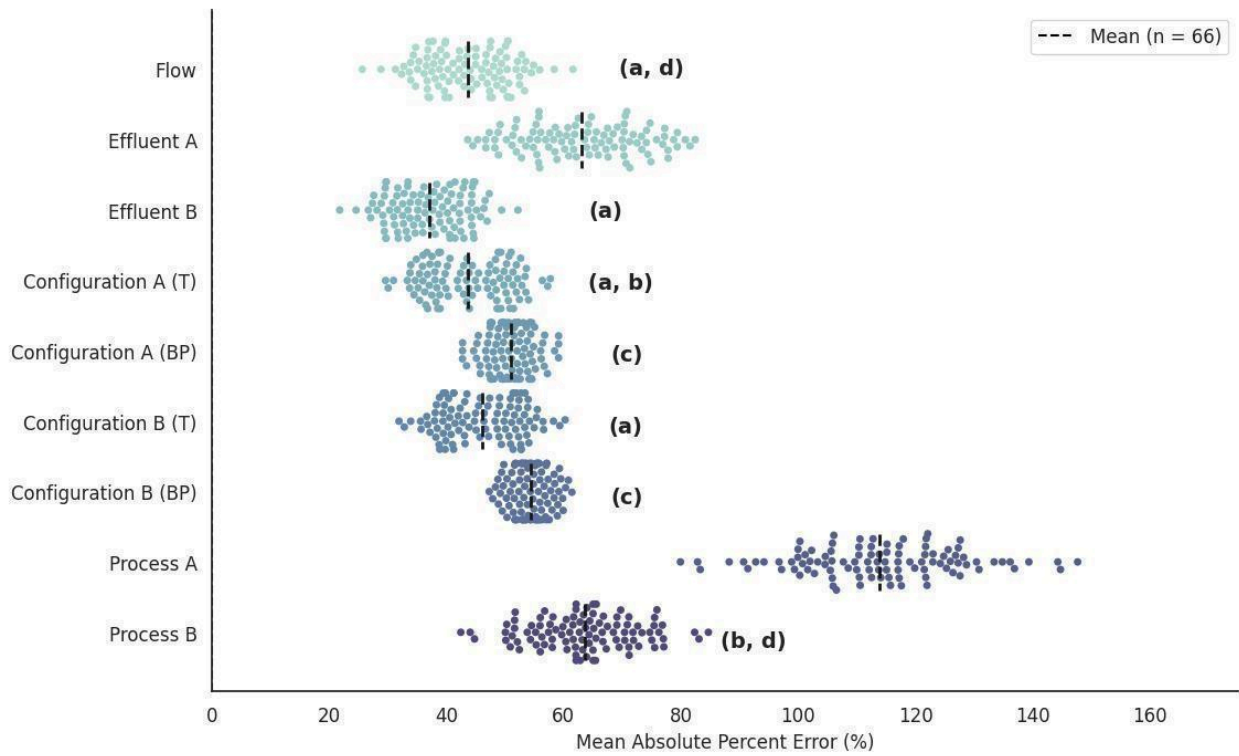


Figure 6: Distribution of mean absolute percent error (MAPE) for repeated k-fold cross-validation. For 50 repetitions, we randomly split the validation set (66 cities) into two groups and recalculated the mean absolute percent error for each group. Each point on this plot represents the MAPE for a unique subset of cities in the validation set in terms of estimating electricity consumption intensity. The Flow, Effluent A, Effluent B, Configuration A (T), Configuration A (BP), Configuration B (T), Configuration B (BP), Process A, and Process B methods, respectively, exhibit the following ranges in MAPE: 26-62%, 44-82%, 22-52%, 30-58%, 43-59%, 32-60%, 47-61%, 80-148%, and 42-85%. Letters indicate groups of methods that are equally sensitive to changes in the validation set, as detailed by the p-value matrix in Table S17.

As visualized in Figure 6, the impact of changes to the validation set differs across electricity consumption estimation methods. A wider range in MAPE values indicates our evaluation of method accuracy is more sensitive to what cities are included in the validation set, thus reducing

confidence in our evaluation of method performance. In contrast, a narrower distribution of MAPE values indicates the method is robust to changes in the validation set. We observe the following ranges in potential MAPE values for each method: Flow (36%), Effluent A (38%), Effluent B (30%), Configuration A (T) (28%), Configuration A (BP) (16%), Configuration B (T) (28%), Configuration B (BP) (14%), Process A (68%), and Process B (43%). To identify which methods were most sensitive to changes in the validation set, we applied Levene's test to each possible combination of methods ($n=64$) and obtained the p-values detailed in (Table S17). These results indicate that the Flow, Effluent B, Configuration A (T), and Configuration B (T) methods can be considered equally sensitive to changes in the validation set.

To investigate how the variance in error fluctuates based on the size of the validation set, we used bootstrapping to randomly sample the full set in groups of $n = 5$ to 65, 1,000 times each. For each sample size, we calculated the standard deviation of MAPE. We observed that standard deviation of MAPE tends to decrease as sample size increases, indicating that smaller validation samples exhibit wider ranges of error in this analysis (Figure S2). This has important implications for our assessment of electricity generation methods in particular, as these results are grounded in a smaller validation set (21 cities total). This validation set is likely too small and, subsequently, sensitive to the validation sample to confidently rank the accuracy of each method. However, we include the results in this analysis because the wide range in accuracy is in and of itself a finding, especially as the wastewater industry focuses more heavily on resource recovery. This preliminary result demonstrates the need for additional data collection and method validation.

4.2. National energy consumption estimations

Previous studies have estimated national electricity consumption to be between 18.1 and 30.2 TWh per year.^{2,5,6,7} By applying the evaluated methods to all 14,559 WRRFs in the baseline national inventory, we obtained ranges for the total national electricity and energy use from wastewater treatment in 2012 (Table S18) that partially align with previous estimates, with the exception of the Configuration A and B and Process A methods.

However, we exclude the Effluent A, Configuration A, Process A, Process B, and Regression methods from our final range of national electricity and energy consumption values with the following justifications:

- Because we assigned only 3,065 out of 14,559 WRRFs a treatment train and, subsequently, an energy use via the Configuration A method, the national baseline estimates for the original treatment train method only represent 60.6% of facilities by volume in the United States and should not be considered a comprehensive estimate of national energy use.
- As discussed in the sensitivity analysis, the accuracy of the Effluent A, Process A, and Process B methods fluctuates substantially depending on what cities are included in the validation set, reducing our confidence in these estimations.
- The Regression method consistently scored the worst in terms of all error metrics, overestimating energy consumption by an average of 150%.

Excluding these five methods, our final estimates of national electricity consumption in 2012 range from 11.1 to 24.4 TWh and, for total energy consumption, range from 50,900 to 77,100 TJ. Our results indicate that WRRF's comprised between 0.27% and 0.59% of total national electricity consumption and between 0.05% and 0.08% of energy consumption in 2012.³⁶ These ranges are lower and narrower than those of previous studies which estimated WRRFs to consume between 0.8% and 3% of electricity^{2,3} and 0.1 to 0.3% of primary energy,⁴ nationally. For the 16,181 WRRFs in the projected national inventory, we forecasted total national electricity and energy use from wastewater treatment in 2042 (Table S19). Excluding the same five methods from our projections, we estimate that national electricity consumption in 2042 will increase to between 16.5 and 39.6 TWh and that national energy consumption will increase to between 81,100 and 123,000 TJ. National electricity use is expected to increase between 47% and 73%, supporting the hypothesis that rising populations and more stringent effluent water quality requirements will increase energy demand.

It is important to note that 90% of our validation set is greater than 18,927 m³/day (5 MGD), and these methods may perform differently on small WRRFs. However, considering that the majority of flow in the national inventory (78%) is processed by large WRRFs, we apply them to the entire inventory herein. Note that we included the national estimates for electricity generation to demonstrate the wide range in theoretical energy recovery but, due to a paucity of validation data, were unable to assess the accuracy of these methods.

4.3. Limitations

This analysis depends heavily on the CWNS, the most comprehensive data source for wastewater infrastructure in the United States. The CWNS is an invaluable resource for wastewater-related research, but it also has limitations that may have had variable impacts on our assessment of method accuracy. For instance, as shown in Figure 6, the Process A and B methods exhibit wider ranges of MAPE than the Configuration A and B methods despite relying on the same unit process data from CWNS. A notable difference between these methods is that the Process A and B methods assign electricity consumption intensities to individual unit processes and sum to create a cumulative intensity, whereas the Configuration A and B methods use only key unit processes to assign WRRFs treatment trains with modeled intensities. The sensitivity of the Process A and B methods to the validation set, coupled with relatively consistent overestimation of electricity consumption, suggests inaccuracies in unit process reporting and/or flaws in our methodology for compiling unit process data and illustrates how uncertainty regarding unit process reporting can propagate through an analysis.

Due to the survey's evolving structure and requirements, not all active WRRFs report updated information every year of the CWNS. For example, in 2012, the state of South Carolina did not submit any WRRF data, and in 2022 only 12% of WRRFs reported updated unit processes. Rather than have every WRRF report updated unit processes in 2008 and 2012, these surveys requested that respondents report changes (e.g., abandonment, expansion, new process) to their facilities. These change codes proved challenging to interpret, as respondents sometimes selected multiple, conflicting change codes for unit processes. These data limitations resulted in 11,494 WRRFs not having enough unit process information available to assign a treatment train via the Configuration A method and 12,040 WRRFs not having enough information to assign an electricity consumption via the Process A method. Additionally, in the 2022 CWNS, respondents reported only one flow rate and did not specify if the value was design or observed flow, values

which were reported separately in prior releases of the CWNS. Therefore, the energy projections based on forecasted flow reported in the 2022 CWNS are likely overestimations. Future research efforts could improve these projections by exploring strategies for separating actual and design flow rates in the 2022 CWNS, or using an alternative source for flow rate data. Additionally, future projections could be improved by exploring ways to supplement or reduce inconsistencies in unit process data from the CWNS.

The 2004, 2008, and 2012 CWNS also do not specify whether biogas is used for electricity generation or heating, meaning we had to reference additional datasets^{29,30,31} for energy recovery estimates that are accompanied by their own limitations. The main shortcoming of the WEF database is that it does not distinguish between rich and lean-burn reciprocating engines, a necessary distinction for the Biogas B method. Consequently, because most of the engines installed today are rich-burn,²⁴ we assumed that all combustion engines reported in the WEF database are rich-burn. Because not every WRRF identified what kind of prime mover is used to convert biogas to electricity, we assumed WRRFs without a specified prime mover used reciprocating engines. Lastly, some WRRFs may generate electricity using other methods (e.g., photovoltaic cells³⁷) but estimating electricity generation from sources other than biogas ultimately falls outside the scope of this research.

In addition to the limitations related to input data, the data used for validation collected by Chini and Stillwell²⁵ likely includes energy demand from collection systems and other auxiliary needs like office and laboratory spaces for some WRRFs. Energy use for pumping in the collection system is typically negligible compared to the energy required for wastewater treatment² and most of the methods evaluated in this study do not include energy use by collection systems. Some methods like the Configuration and Process B methods do, however, include the energy cost of providing the final lift pumping from the sewers to the hydraulic grade of the WRRF. Similarly, some (Configuration and Process B methods) but not all methods include the energy costs of auxiliary needs. Another complication related to the validation set is that Chini and Stillwell²⁵ does not specify how much of the collected biogas is used for electricity generation versus heating. Consequently, we assumed that 70% of biogas collected was used for electricity generation and that generators have an efficiency of 37% based on the EIA's 2012 Survey Form EIA-923.³¹

Of the 107 WRRFs in the final validation set, 30 reported using combined sewer systems. Because combined sewer systems direct stormwater in addition to wastewater into WRRFs, influent water quality composition and, therefore, energy efficiency at WRRFs, can be affected by irregular temperature and precipitation patterns.³⁸ Considering that several cities in the validation set experienced an abnormally dry or wet year in 2012,³⁹ our validation efforts may have been influenced by extreme weather patterns and/or climate change. Lastly, because the validation set used in this study is composed entirely of WRRFs in urban areas, typically large cities, methods that produce accurate estimations herein may perform differently if applied to WRRFs with different characteristics than those of the validation set (e.g., rural or smaller, suburban wastewater treatment systems).

4.4. Comparing estimation methods

Our results demonstrate that not all energy consumption and potential estimation methods are appropriate for every use case. Calibrating the methods using the results of our validation has the potential to yield a more robust approach for energy accounting at WRRFs, but given the aforementioned limitations of this work, we recommend this for future research and highlight the advantages and disadvantages of each method as originally published below.

Electricity consumption: In our analysis, the Effluent B and Flow methods demonstrated low error relative to others in terms of estimating electricity consumption intensity. The Configuration (T) methods also performed well, but less consistently across all the evaluated metrics. The Flow, Effluent B, and Configuration (T) methods exhibit relatively low sensitivity to changes in the validation set, but the Flow method is slightly less robust. The Flow and Effluent B methods only require flow rate and effluent treatment level data, both of which are relatively consistently collected metrics for WRRFs; therefore, these methods are well-suited for large-scale analysis of many WRRFs or when limited data is available on treatment practices. However, the Effluent B method is more appropriate for analyses in which changing effluent water quality requirements are a consideration, as their impacts on energy use may not be captured by the Flow method. The Configuration methods model energy intensities specific to a variety of treatment trains, and therefore would be more appropriate for comparing different configurations. However, because they require ample unit process data, the Configuration methods are also more time-intensive to implement. For a summary of our recommendations for selecting an electricity consumption estimation method, please see Figure 7.

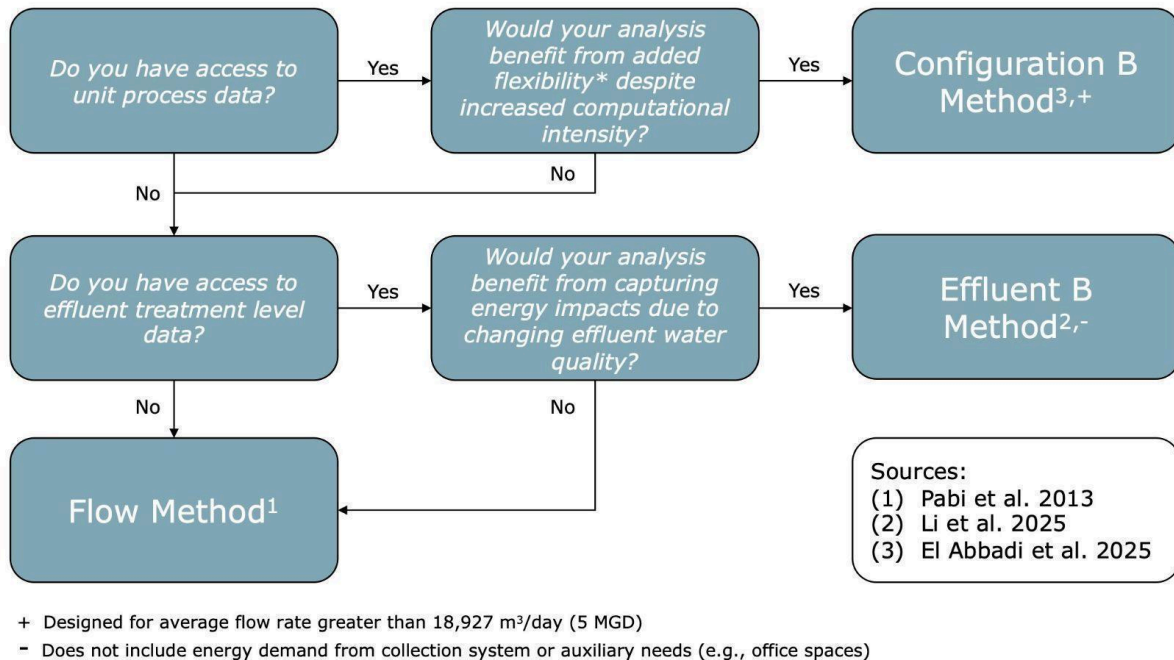


Figure 7: Summary of recommendations for selecting an electricity consumption estimation method based on accuracy, sensitivity to the validation set, and data availability / computational intensity constraints. *Added flexibility refers to the ability to: estimate natural gas use and energy recovery in addition to electricity use; break down energy consumption by unit process; compare energy impacts of different

kinds of treatment technologies; and analyze energy requirements of future technology adoption (e.g., nutrient removal, biogas utilization).

Energy consumption: For any estimate of total energy consumption, we recommend the Configuration B method, as the Regression method consistently overestimates energy consumption. The Configuration A and B methods under the typical assumption performed best across the evaluated error metrics, but were slightly more sensitive to changes to the validation set than their best practice counterparts which tended more strongly towards underestimation of energy use. However, it is important to note that this study was conducted using data from over a decade ago, and some WRRFs may have adapted their technology and operating practices to be more efficient and, therefore, similar to the best practice treatment trains since then. Both treatment train-based methods depend heavily on high quality unit process data, but because the Configuration B method includes methodology for assigning a treatment train, flexibility to assign a treatment train with little or inconsistent unit process data available, and a wider range of possible treatment trains, we ultimately recommend this method over the original Configuration A method.

Energy recovery: Due to the limited number of electricity-generating facilities and ambiguity as to how much biogas is used for electricity generation versus heating in the validation data, it is difficult to conclude the optimal method for estimating electricity generation. However, the wide range of accuracy and high sensitivity to the validation set exhibited by the electricity generation estimation methods in this analysis underscores how little is known about the reliability of energy recovery estimates at WRRFs. As academic and industry focus shifts to energy recovery as a means of reducing the economic burden on and energy independence of WRRFs,^{7,8,12,15} the ability to accurately estimate current and projected energy recovery is becoming increasingly critical for researchers and practitioners alike. Researchers require reliable methods for estimating energy recovery with limited access to empirical data, particularly for large-scale water-energy nexus studies, and practitioners with facility-specific energy and flow data may still require tools to understand how changing flow rates, water quality regulations, and technology upgrades impact their energy use. However, without more data from utilities regarding biogas collection and the amount of electricity produced, reported separately from electricity purchased from the grid, we cannot perform the more rigorous validation of these methods that is necessary to employ them with confidence.

5. Conclusion

In this study, we used publicly available data to compare the accuracy of methods for estimating WRRF electricity and energy consumption. When applied to baseline and projected inventories of WRRFs in the United States, these methods produced a wide range of estimated energy demands, highlighting the uncertainty regarding how much energy is and will be required by the wastewater treatment sector. However, through highlighting the advantages and disadvantages of each method, this work enables researchers and practitioners to make more informed estimations in the absence of empirical data. Because the methods evaluated in this study rely on different aspects of large and often inconsistent datasets, improving the coverage and quality of wastewater flow rate and unit process data is essential to strengthening estimates of energy use and potential. Changes to the CWNS like requiring updated reporting of unit processes, distinguishing between observed and design flow, and reporting the portion of biogas for electricity production versus heating would substantially improve the reliability of the dataset

and, subsequently, energy estimates dependent on it. This work also emphasizes the need for total energy consumption estimation methods that can function independently of unit process data, as accurate energy consumption estimates play a key role in reducing dependency on natural gas. Lastly, because increased data availability enables stronger method validation and, therefore, more confident recommendations to industry, we advocate for increased transparency from water and wastewater utilities regarding energy consumption and generation data.

Wastewater treatment in the United States is changing as the result of rising demand, degrading infrastructure, evolving water quality regulations, and fluctuating levels of investment in the water sector. However, without proper consideration of the energy impacts of WRRFs, these changes have the potential to undermine decarbonization efforts and shift risk to the consequences of relying on a carbon-intensive energy grid. Subsequently, understanding current and future energy requirements of WRRFs is key to adapting to changing conditions in a sustainable manner. By providing situation-specific suggestions for energy estimation methods and bounds for uncertainty in existing estimates, this research can be used to enhance the accuracy of future WRRF energy estimations and underscores the importance of accurate energy accounting in the wastewater sector.

6. Acknowledgements

We would like to acknowledge the utilities that made this work possible through sharing their water-energy data, the researchers who compiled and published this data in a publicly accessible database, and the researchers who previously published methods for estimating energy use and potential at WRRFs. We would also like to commend the U.S. EPA on their efforts in collecting WRRF data on a national scale through the CWNS, a critical dataset for us and many other researchers.

Funding statement: This manuscript has been authored by an author at Lawrence Berkeley National Laboratory under Contract No. 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.

Author contributions: Conceptualization was performed by AH and JSD. Methodology was developed by AH, SEA, RL, and JSD. Validation was conducted by AH, SEA, RL, and JSD. Data curation and formal analysis was performed by AH, JSD, SEA, and CC. Software development and visualization was done by AH. The original draft was written by AH and JSD. Writing – reviewing and editing was performed by all authors. Funding acquisition was conducted by JSD. Supervision was performed by JSD.

Code availability: Code supporting this study is available at https://github.com/AbbyHodson/wwtp_energy_comparison.

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

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Supplementary Information (SI) for “Validating and Comparing Energy Estimation Methods at Water Resource Recovery Facilities”

Supplementary Files:

- supplementary_file_a.csv: Treatment train assignments for all WRRFs in the United States (2012) (Treatment Train Configuration A Method)
- supplementary_file_b.csv: Treatment train assignments for all WRRFs in the United States (2012) (Treatment Train Configuration B Method)
- supplementary_file_c.csv: Annual electricity consumption, energy consumption, and electricity generation estimates for all WRRFs in the United States (2012)
- supplementary_file_d.csv: Annual electricity consumption, energy consumption, and electricity generation estimates for all WRRFs in the United States (2042)

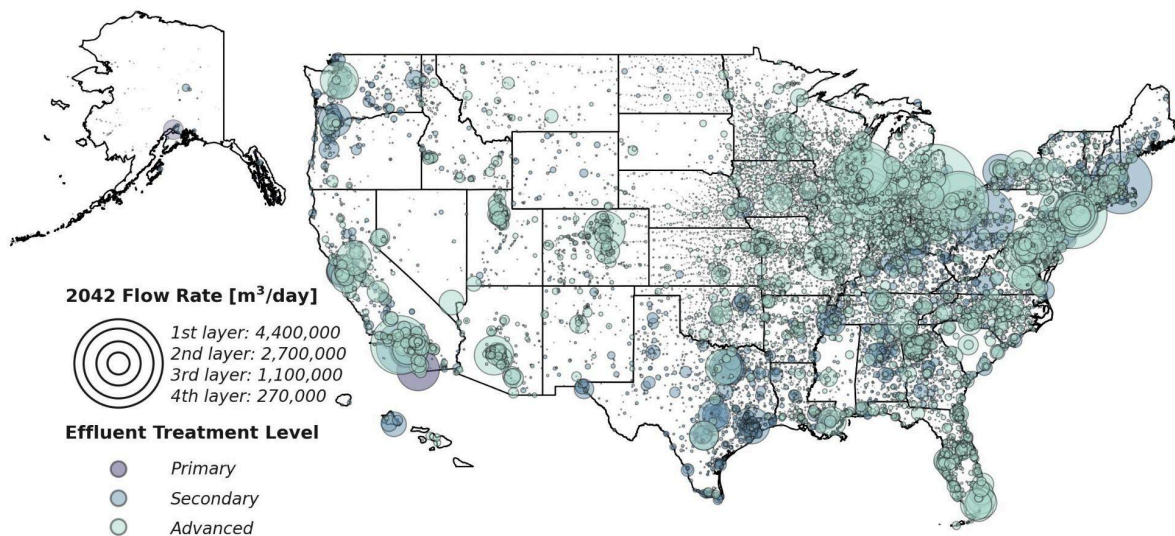


Figure S1: Projected national WRRF inventory, compiled using location, flow rate, and effluent treatment level data from the 2022 CWNS. Note that, because the 2022 CWNS does not distinguish between design and observed flow, the projected annual flow rate shown here is likely an overestimate.

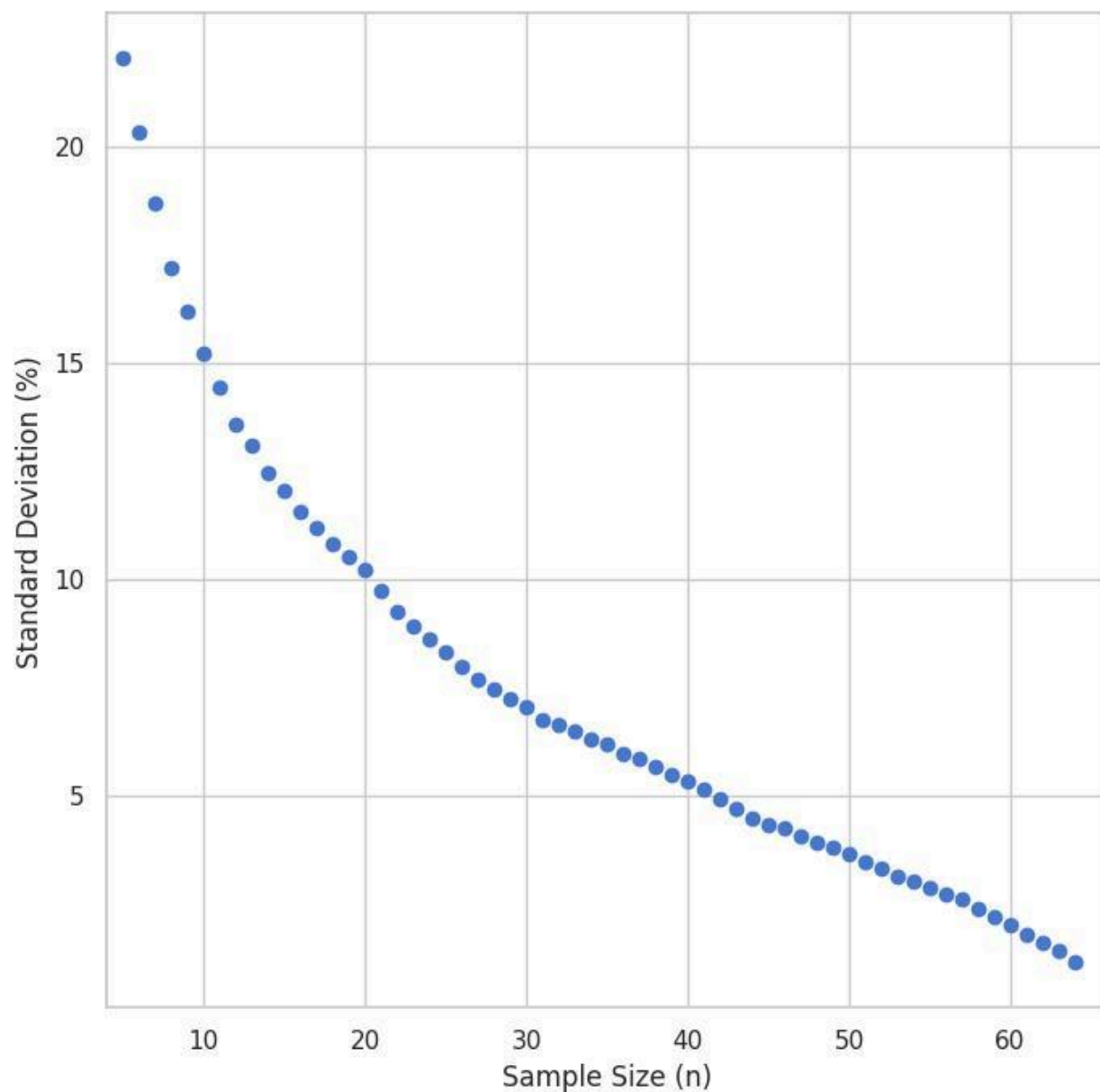


Figure S2: Standard deviation of mean absolute percent error for different samples ($n = 5$ to 65) of the validation set. As the sample size increases, the standard deviation of error tends to decrease, affirming that the size of the validation set does significantly impact our assessment of error for each method.

Table S1: Summary of Existing U.S. WRRF Electricity Consumption Estimations

Primary Authors	Publication Date	Scale	Electricity Consumption [TWh]
Gingerich and	2018	National	19.5

Mauter ¹			
Tarallo ²	2014	National	22.0
Tidwell, Moreland, and Zemlick ³	2014	Western U.S.	9.0
Pabi et al. ⁴	2013	National	30.2
Stillwell et al. ⁵	2010	National	18.1-23.8

Table S2: Summary of WRRFs Used for Method Validation

CWNS ID	Location	Latitude	Longitude	Annual Flow Rate, 2012 [Mm³/year]	Effluent Treatment Level, 2012
36004064002	Albany, NY	42.63	-73.76	31.61	Secondary
48000105001	Amarillo, TX	35.34	-101.83	16.59	Advanced
02000106001	Anchorage, AK	61.20	-150.02	40.98	Primary
13000054001	Augusta, GA	33.42	-82.02	42.33	Advanced
06005010002	Bakersfield, CA	35.28	-119.07	15.61	Secondary
24000001001	Baltimore, MD	39.30	-76.49	214.83	Advanced
48006001001	Beaumont, TX	29.99	-94.13	46.98	Advanced
30000060001	Billings, MT	45.80	-108.47	21.83	Secondary
25000128001	Boston, MA	42.35	-70.96	428.32	Secondary
09000150001	Bridgeport, CT	41.16	-73.21	33.29	Advanced
09000150002	Bridgeport, CT	41.17	-73.17	11.09	Advanced
36009071001	Buffalo, NY	42.92	-78.90	205.87	Secondary
50000016001	Burlington, VT	44.47	-73.22	6.59	Advanced
37006001002	Charlotte, NC	35.07	-80.88	39.63	Advanced
37006001003	Charlotte, NC	35.19	-80.90	15.86	Advanced
37006001005	Charlotte, NC	35.15	-80.85	18.38	Advanced
37006001008	Charlotte, NC	35.38	-80.94	5.68	Advanced
37006001009	Charlotte, NC	35.34	-80.70	2.25	Advanced
17000721001	Chicago, IL	41.81	-87.77	1121.92	Advanced

17000721002	Chicago, IL	42.00	-88.14	12.44	Advanced
17000721005	Chicago, IL	42.02	-88.04	37.31	Advanced
17000721009	Chicago, IL	41.66	-87.61	321.35	Advanced
39003369002	Cincinnati, OH	39.11	-84.55	208.63	Secondary
39001666002	Cleveland, OH	41.40	-81.63	234.88	Advanced
39001666003	Cleveland, OH	41.49	-81.73	48.36	Advanced
08000001001	Colorado Springs, CO	38.82	-104.81	37.31	Advanced
48004026001	Dallas, TX	32.75	-96.55	170.92	Advanced
39002093001	Dayton, OH	39.73	-84.23	99.48	Advanced
08000070001	Denver, CO	39.81	-104.96	210.01	Advanced
26000596001	Detroit, MI	42.28	-83.13	912.60	Advanced
27000002001	Duluth, MN	46.76	-92.13	53.47	Advanced
48001009001	El Paso, TX	31.76	-106.44	23.20	Secondary
48001009007	El Paso, TX	31.79	-106.53	10.18	Advanced
41000045001	Eugene, OR	44.10	-123.11	53.19	Advanced
08000037001	Fort Collins, CO	40.55	-105.13	17.41	Advanced
18000225001	Fort Wayne, IN	41.08	-85.10	55.27	Advanced
48004122001	Fort Worth, TX	32.77	-97.14	191.91	Advanced
37004102003	Greensboro, NC	36.11	-79.69	30.26	Advanced
42001006001	Harrisburg, PA	40.24	-76.86	18.24	Advanced
15000003010	Honolulu, HI	21.33	-158.04	33.99	Secondary
18000061002	Indianapolis, IN	39.75	-86.17	67.70	Advanced
12000016001	Jacksonville, FL	30.35	-81.63	52.45	Advanced
12000016002	Jacksonville, FL	30.11	-81.63	0.83	Advanced
12000016003	Jacksonville, FL	30.35	-81.54	17.82	Advanced
26000108001	Kalamazoo, MI	42.31	-85.57	38.69	Advanced
32000011001	Las Vegas, NV	36.14	-115.04	85.66	Advanced
31001425002	Lincoln, NE	40.88	-96.62	9.05	Secondary
05000001001	Little Rock, AR	34.70	-92.17	12.43	Secondary
05000001008	Little Rock, AR	34.74	-92.22	27.92	Secondary

06004010001	Los Angeles, CA	33.93	-118.43	449.04	Secondary
06004010002	Los Angeles, CA	33.75	-118.26	22.80	Advanced
21000025001	Louisville, KY	38.23	-85.84	134.71	Secondary
21000025011	Louisville, KY	38.09	-85.90	41.06	Secondary
55002781001	Madison, WI	43.03	-89.35	56.65	Advanced
47000940001	Memphis, TN	35.07	-90.13	97.41	Secondary
12000017004	Miami, FL	25.75	-80.15	175.47	Secondary
27000001003	Minneapolis, MN	44.83	-93.21	25.16	Advanced
27000001012	Minneapolis, MN	44.75	-92.85	2.10	Advanced
27000001026	Minneapolis, MN	44.66	-93.10	4.89	Advanced
47001016001	Nashville, TN	36.19	-86.79	126.98	Advanced
47001016002	Nashville, TN	36.29	-86.69	24.32	Advanced
47001016006	Nashville, TN	36.18	-86.86	48.27	Advanced
22009071001	New Orleans, LA	29.98	-90.00	127.25	Secondary
36002001007	New York, NY	40.71	-73.98	82.90	Secondary
36002001008	New York, NY	40.64	-74.13	47.02	Secondary
36002001009	New York, NY	40.59	-73.93	128.62	Advanced
36002001010	New York, NY	40.64	-74.04	120.33	Secondary
36002001011	New York, NY	40.73	-73.95	374.79	Secondary
36002001012	New York, NY	40.83	-73.96	234.88	Secondary
36002001013	New York, NY	40.55	-74.11	33.19	Secondary
36002001014	New York, NY	40.58	-73.83	29.04	Secondary
51000308001	Norfolk, VA	36.96	-76.42	27.88	Secondary
51000308002	Norfolk, VA	37.08	-76.53	19.33	Advanced
51000308011	Norfolk, VA	36.90	-76.43	23.49	Secondary
51000308012	Norfolk, VA	36.77	-75.97	47.88	Secondary
48004354001	North Texas	33.13	-96.56	25.68	Advanced
48004354004	North Texas	33.00	-96.55	29.22	Advanced
48004354009	North Texas	33.13	-96.56	55.27	Advanced
06002036001	Oakland, CA	37.82	-122.30	110.53	Secondary
17000430001	Peoria, IL	40.66	-89.62	37.31	Advanced

42000094001	Philadelphia, PA	39.99	-75.09	271.78	Secondary
42000094002	Philadelphia, PA	39.89	-75.22	274.26	Secondary
42000094003	Philadelphia, PA	39.90	-75.15	130.98	Secondary
04001316001	Phoenix, AZ	33.43	-112.11	41.45	Advanced
42005016001	Pittsburgh, PA	40.47	-80.04	226.59	Secondary
44000022001	Providence, RI	41.79	-71.39	65.91	Secondary
49000064001	Provo, UT	40.21	-111.65	18.65	Advanced
06005009001	Sacramento, CA	38.45	-121.46	227.98	Secondary
41000031001	Salem, OR	45.01	-123.05	41.04	Secondary
48008015004	San Antonio, TX	29.24	-98.42	8.70	Advanced
06002041001	San Jose, CA	37.43	-121.95	197.99	Advanced
53000776002	Seattle, WA	47.66	-122.43	151.98	Secondary
53001220001	Spokane, WA	47.70	-117.48	60.79	Advanced
29001023001	St Louis, MO	38.67	-90.20	153.37	Secondary
29001023002	St Louis, MO	38.53	-90.27	157.51	Secondary
29001023003	St Louis, MO	38.81	-90.28	38.12	Secondary
29001023004	St Louis, MO	38.75	-90.50	37.03	Secondary
36007136001	Syracuse, NY	43.06	-76.18	98.31	Advanced
36007136005	Syracuse, NY	43.21	-76.21	7.71	Advanced
36007136007	Syracuse, NY	43.15	-76.24	3.70	Advanced
53001280001	Tacoma, WA	47.24	-122.41	82.90	Secondary
53001280003	Tacoma, WA	47.29	-122.49	6.22	Secondary
39008260001	Toledo, OH	41.69	-83.48	117.44	Advanced
04001903001	Tucson, AZ	32.34	-111.07	38.00	Advanced
04001904001	Tucson, AZ	32.28	-111.02	53.33	Advanced
20000193001	Wichita, KS	37.59	-97.31	56.12	Advanced
20000193002	Wichita, KS	37.62	-97.50	0.83	Advanced

Table S3: Summary of Cities Excluded from Validation Set

Location	Sufficient Data in Chini and Stillwell? ⁶	Sufficient Data in CWNS? ^{7,13,14}
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Albuquerque, NM	No; did not report both energy and flow	No; insufficient unit process data*
Alexandria, VA	Yes	No; insufficient unit process data*
Austin, TX	Yes	No; insufficient unit process data*
Birmingham, AL	No; did not report both energy and flow	Yes
Boise, ID	No; did not report electricity	Yes
Charleston, SC	Yes	No; SC did not report any data to CWNS in 2012 ⁷
Charleston, WV	No; did not report electricity	Yes
Cheyenne, WY	No; did not report both energy and flow	No; insufficient unit process data*
Columbia, SC	Yes	No; SC did not report any data to CWNS in 2012 ⁷
Columbus, OH	Yes	No; insufficient unit process data*
Corpus Christi, TX	No; did not report both energy and flow	Yes
Des Moines, IA	No; did not report both energy and flow	Yes
Fargo, ND	No; did not report electricity	Yes
Fresno, CA	No; did not report both energy and flow	Yes
Greenville, SC	Yes	No; SC did not report any data to CWNS in 2012 ⁷
Houston, TX	No; did not report both energy and flow	Yes
Jackson, MS	No; did not report both energy and flow	Yes
Kansas City, MO	No; flagged as unreliable by Chini and Stillwell ⁶	Yes
Knoxville, TN	No; did not report both energy and flow	Yes

Lake Charles, LA	No; did not report both energy and flow	Yes
Lubbock, TX	No; did not report both energy and flow	Yes
Madison, WI	Yes	No; insufficient unit process data*
Manchester, NH	No; did not report natural gas	Yes
Milwaukee, WI	Yes	No; insufficient unit process data*
Newark, NJ	Yes	No; insufficient unit process data*
Oklahoma City, OK	No; did not report natural gas use	Yes
Omaha, NE	No; flagged as unreliable due to unusually high energy intensity	Yes
Ogden, UT	Yes	No; unable to identify WRRF in 2012 CWNS ⁷
Portland, ME	No; energy and flow data incomplete	No; insufficient unit process data*
Portland, OR	No; energy and flow data incomplete	Yes
Raleigh, NC	No; did not report both energy and flow	Yes
Reno, NV	Yes	No; insufficient unit process data*
Salt Lake City, UT	No; energy and flow data incomplete	Yes
San Diego, CA	Yes	No; insufficient unit process data*
San Francisco, CA	Yes	No; insufficient unit process data*
Santa Fe, NM	Yes	No; insufficient unit process data*
Savannah, GA	No; did not report both	Yes

	energy and flow	
Sioux Falls, SD	No; did not report both energy and flow	Yes
Springfield, MA	Yes	No; insufficient unit process data*
Tallahassee, FL	Yes	No; insufficient unit process data*
Tampa, FL	Yes	No; insufficient unit process data*
Tulsa, OK	No; did not report both energy and flow	Yes
Washington, DC	Yes	No; insufficient unit process data*
Worcester, MA	No; did not report both energy and flow	No; insufficient unit process data*

*Note, insufficient unit process data is considered not enough unit process data reported in the 2004, 2008, and 2012 CWNS^{13,14,7} to assign a treatment train in the Configuration A Method. Please see `tt_assignment.ipynb` in the project's [github](#) for more details on what unit processes are used to assign treatment trains in this method.

Table S4: Summary of Manual Corrections to Published Chini and Stillwell⁶ Dataset

Location	Adjustments
Alexandria, VA	Separated total and imported electricity consumption
Bakersfield, CA	Separated total and imported electricity consumption; corrected biogas values
Baltimore, MD	Separated total and imported electricity consumption; corrected biogas values
Eugene, OR	Separated total and imported electricity consumption
Oakland, CA	Separated total and imported electricity consumption
Salem, OR	Separated total and imported electricity

	consumption; corrected biogas values
San Francisco, CA	Modified to just include Oceanside Water Pollution Control Plant, as this is the only plant that sent complete flow and energy data
St. Louis, MO	Separated total and imported electricity consumption; corrected biogas values
Tacoma, WA	Separated total and imported electricity consumption
Toledo, OH	Corrected biogas values; substituted landfill gas for natural gas, assuming one standard cubic foot of landfill gas is equivalent to 0.005 therms
Tucson, AZ	Separated total and imported electricity consumption; corrected natural gas values

Table S5: Limitations of Energy Estimation Methods

Method Name*	Source	Limitations
Flow Rate Method	Pabi et al. 2013 ⁴	Does not specify whether the collection system or auxiliary needs are considered.
Effluent Treatment Level A Method	Pabi et al. 2013 ⁴	Does not account for the collection system. Does not specify whether auxiliary needs are considered.
Effluent Treatment Level B Method	Li et al. 2025 ⁸	Does not account for the collection system or auxiliary needs.
Treatment Train Configuration A (T/BP) Method⁺	Tarallo et al. 2015 ¹⁰	Requires sufficient unit process data to form a treatment train assignment. Does not provide a methodology for transforming unit process data into a treatment train assignment. Possible treatment train assignments are limited to the 25 most common configurations in North America, as of 2008. Designed for WRRFs that treat over 18,927 m ³ /day (5 MGD). Does not account for the collection system, aside from the influent pump station. Assumes medium-strength domestic wastewater.

Treatment Train Configuration B (T/BP) Method⁺	El Abbadi et al. 2025 ¹¹	Does not account for the collection system, aside from the influent pump station. Designed for WRRFs that treat over 18,927 m ³ /day (5 MGD). Assumes medium-strength domestic wastewater.
Unit Process A Method	Plappally and Leinhard 2012 ⁹	Requires detailed unit process data. Does not account for the collection system and auxiliary needs.
Unit Process B Method	Pabi et al. 2013 ⁴	Does not account for the collection system. Requires detailed unit process data.
Regression Method	Carlson and Walburger 2007 ¹⁹	Designed for WRRFs with a design flow over 6,819 m ³ /day (1.5 MGD) and WRRFs serving a population of 10,000 or more.
Biogas A Method	ERG and RDC 2011 ¹²	Assumes a mesophilic digester.
Biogas B Method	ERG and RDC 2011 ¹²	Assumes a mesophilic digester.
Biogas C Method	Li et al. 2025 ⁸	Assumes idealized medium-strength domestic wastewater and a uniform CHP efficiency (30%) across all WRRFs.
<p>*Methods are referenced throughout this study as the bolded portion of the method name.</p> <p>⁺Method includes variations for typical (T) and best practice (BP) configurations.</p>		

Table S6: Electricity Consumption Intensity by Flow Category (Flow Rate Method)⁴

Flow Category [MGD]	Electricity Consumption Intensity [kWh/m³]
Less than 2	0.870
2 - 4	0.790
4 - 7	0.630
7 - 16	0.530
16 - 46	0.450
46 - 100	0.450
100 and above	0.420

Table S7: Electricity Consumption Intensity by Effluent Treatment Level (Effluent Treatment Level A Method)⁴

Effluent Treatment Level	Electricity Intensity [kWh/m³]
Raw Discharge	0.000
Primary	0.198
Advanced Primary	0.198
Secondary	0.550
Advanced	0.711

Table S8: Electricity Consumption Intensity for Effluent Treatment Level (Effluent Treatment Level B Method)⁸

Effluent Treatment Level	Electricity Intensity [kWh/m³]
Raw Discharge	0
Primary	0.110
Advanced Primary	0.141
Secondary	0.352
Advanced	0.487

Table S9: Electricity Consumption Intensity for Key Unit Processes (Unit Process A Method)⁹

Unit Process Name	Average Electricity Consumption Intensity [kWh/m³]
Activated Sludge, Anaerobic/Anoxic	0.465
Activated Sludge, Anaerobic/Anoxic/Oxic	0.465
Activated Sludge, Complete Mix	0.465
Activated Sludge, Contact Stabilization	0.465
Activated Sludge, Conventional	0.465
Activated Sludge, Extended Aeration	0.465
Activated Sludge, High Rate	0.465
Activated Sludge, Other Mode	0.465
Activated Sludge, Pure Oxygen	0.465
Activated Sludge, Step Aeration	0.465
Activated Sludge, With Biological Denitrification	0.550
Aerated Grit Chambers	0.015
Aeration (Post-treatment)	0.009

Aeration (Pre-treatment)	0.009
Biological Nitrification - Separate Stage	0.085
Biological Phosphorus Removal	0.100
Biosolids Aerobic Digestion, Air	0.175
Biosolids Aerobic Digestion, Autothermal Thermophilic	0.175
Biosolids Aerobic Digestion, Oxygen	0.175
Biosolids Anaerobic Digestion, Other	0.265
Biosolids Anaerobic Digestion, Thermophilic	0.265
Biosolids Chemical Addition (Polymer)	0.150
Biosolids Mechanical Dewatering (Centrifuge)	0.015
Biosolids Mechanical Dewatering (Filter Press)	0.015
Biosolids Mechanical Dewatering (Pressure Filter)	0.015
Biosolids Mechanical Dewatering (Vacuum Filter)	0.015
Clarification, In-Channel	0.010
Clarification, Intermediate	0.010
Clarification, Secondary	0.010
Clarification, Tube Settlers	0.010
Dechlorination	0.090
Disinfection, Chlorination	0.000
Disinfection, Gaseous Chloride	0.000
Disinfection, Liquid Chloride	0.000
Disinfection, Ultraviolet	0.041
Disinfection, UV Radiation	0.041
Filter, Denitrification with Coarse Media	0.010
Filter, Denitrification with Fine Media	0.010
Filter, Mixed Media	0.010
Filter, Other	0.010
Filter, Pressure	0.010
Filter, Rapid Sand	0.010
Filter, Rock	0.010

Filter, Slow Sand	0.010
Grit Removal	0.015
Lagoon, Aerated	0.199
Lagoon, Polishing	0.190
Nitrification, Biological (Combined and BOD Reduction)	0.085
Nitrification, Biological (Separate Stage)	0.085
Phosphorus Removal, Biological	0.100
Phosphorus Removal, Biological (Modified Bardenpho)	0.100
Pond, Stabilization	0.009
Reactor (Oxidation Ditch)	0.330
Reactor, Sequencing Batch (SBR)	0.465
Sedimentation	0.009
Sedimentation, Chemical Precipitation	0.009
Sedimentation, Primary	0.009
Trickling Filter, Other Media	0.321
Trickling Filter, Plastic Media	0.321
Trickling Filter, Redwood Slats	0.321
Trickling Filter, Rock Media	0.321
Filter, Moving Bed	0.010
Biological Nutrient Removal (BNR) Membrane Bio-Reactor (MBR)	0.085
Biological Nutrient Removal	0.650
Activated Sludge, with Phosphorus Removal	0.565
Disinfection, Sodium Hypochlorite	0.000
Clarification, Other	0.010
Phosphorus Removal, Biological (Phostrip)	0.100
Trickling Filter, Biofilter	0.321
Aerobic Unit	0.009

Table S10: Electricity Consumption Intensity for Key Unit Processes (Unit Process B Method)⁴

Unit Process	Annual Flow [Mm ³]						
	1.38	6.91	13.8	27.6	69.1	138	346
Wastewater Pumping	0.058	0.058	0.058	0.058	0.058	0.058	0.059
Odor Control	0.040	0.032	0.041	0.066	0.063	0.058	0.055
Grit Removal, Aerated	0.034	0.008	0.007	0.004	0.004	0.004	0.004
Grit Removal, Forced Vortex	0.042	0.011	0.006	0.003	0.002	0.002	0.002
Primary Clarifiers	0.008	0.007	0.008	0.008	0.008	0.008	0.006
Ballasted Sedimentation	0.020	0.020	0.020	0.020	0.020	0.020	0.018
Trickling Filters	0.166	0.134	0.134	0.134	0.134	0.134	0.134
Biological Nutrient Removal (BNR) Mixing	0.029	0.029	0.029	0.028	0.027	0.029	0.025
Aeration without Nitrification	0.190	0.190	0.190	0.183	0.177	0.168	0.162
Aeration with Nitrification	0.285	0.285	0.285	0.273	0.265	0.251	0.243
Aeration with BNR	0.314	0.314	0.314	0.301	0.292	0.280	0.268
Secondary Clarifiers	0.022	0.018	0.018	0.018	0.019	0.018	0.019
Sequencing Batch Reactors	0.288	0.288	0.288	0.277	0.268	N/A	N/A
Membrane Bioreactors	0.713	0.715	0.715	0.715	0.715	N/A	N/A
Aerobic Digestion	0.264	0.264	0.264	N/A	N/A	N/A	N/A
Anaerobic Digestion	N/A	0.029	0.029	0.028	0.026	0.026	0.026
Gravity Belt Thickener	0.008	0.007	0.006	0.006	0.006	0.006	0.006
Dissolved Air Flotation	N/A	N/A	0.048	0.039	0.033	0.031	0.047
Centrifuge	0.021	0.015	0.010	0.010	0.010	0.010	0.010

Thickening							
Belt Filter Press	N/A	0.012	0.012	0.009	0.007	0.007	0.005
Screw Press	0.005	0.005	0.004	0.004	0.003	0.003	0.003
Centrifuge Dewatering	0.069	0.069	0.069	0.069	0.069	0.069	0.069
Thermal Drying	0.058	0.058	0.058	0.058	N/A	N/A	N/A
UV Disinfection	0.059	0.062	0.062	0.062	0.062	0.062	0.062
Depth Filtration	0.026	0.018	0.015	0.015	0.015	0.015	0.015
Surface Filtration	0.013	0.009	0.008	0.008	0.008	0.008	0.008
Plant Utility Water	0.012	0.012	0.011	0.011	0.011	0.011	0.011
Nonprocess Loads (Buildings, Lighting, Computers, Pneumatics, etc.)	0.079	0.063	0.055	0.048	0.048	0.048	0.048
Energy Recovery	N/A	-0.076	-0.076	-0.076	-0.076	-0.076	-0.076
Total Baseload (Wastewater Pumping, Odor Control, Utility Water, Non-process Loads)	0.189	0.165	0.166	0.182	0.180	0.174	0.172

Table S11a: Electricity Consumption, Electricity Generation, and Natural Gas Consumption Intensity by Treatment Train (Typical) (Treatment Train Configuration A Method)¹⁰

Treatment Train	Electricity Consumption Intensity [kWh/m³]	Electricity Generation Intensity [kWh/m³]	Natural Gas Consumption Intensity [MJ/m³]
B1	0.37	0.00	0.00
B1E	0.37	0.17	0.00
B4	0.42	0.00	0.73
B5	0.41	0.00	1.78
B6	0.38	0.00	0.68
C3	0.41	0.00	0.40
D1	0.31	0.00	0.00

E2	0.56	0.00	0.17
E2P	0.55	0.00	0.17
F1	0.46	0.00	0.00
G1	0.60	0.00	2.18
G1E	0.60	0.15	2.22
H1	0.53	0.00	0.89
I2	0.66	0.00	0.17
I3	0.62	0.00	0.35
N1	1.74	0.00	5.81
N2	1.76	0.00	4.52
O1	0.41	0.00	0.00

Table S11b: Electricity Consumption, Electricity Generation, and Natural Gas Consumption Intensity by Treatment Train (Best Practice) (Treatment Train Configuration A Method)¹⁰

Treatment Train	Electricity Consumption Intensity [kWh/m³]	Electricity Generation Intensity [kWh/m³]	Natural Gas Consumption Intensity [MJ/m³]
B1	0.25	0.00	0.00
B1E	0.25	0.21	0.00
B4	0.28	0.00	0.00
B5	0.32	0.00	1.12
B6	0.29	0.00	0.16
C3	0.29	0.00	0.40
D1	0.24	0.00	0.00
E2	0.38	0.00	0.16
E2P	0.36	0.00	0.16
F1	0.30	0.00	0.00
G1	0.41	0.00	2.54
G1E	0.41	0.21	2.54
H1	0.35	0.00	1.10
I2	0.40	0.00	0.16
I3	0.38	0.00	0.35
N1	0.98	0.00	5.81
N2	0.97	0.00	3.79
O1	0.32	0.00	0.00

Table S12a: Electricity Consumption, Electricity Generation, and Natural Gas Consumption Intensity by Treatment Train (Typical) (Treatment Train Configuration B Method)¹¹

Treatment Train	Electricity Consumption Intensity [kWh/m³]	Electricity Generation Intensity [kWh/m³]	Natural Gas Consumption Intensity [MJ/m³]
*A1	0.37	0.00	0.00
*A1e	0.37	0.17	0.00
*A2	0.42	0.00	0.72
*A5	0.41	0.00	1.78
*A6	0.38	0.00	0.68
A4	0.41	0.00	0.40
*C1	0.30	0.00	0.00
E3	0.56	0.00	0.16
*E3	0.55	0.00	0.16
*E1	0.46	0.00	0.00
*G1	0.59	0.00	2.17
*G1e	0.59	0.15	2.21
*G1-p	0.53	0.00	0.89
F3	0.66	0.00	0.16
F4	0.62	0.00	0.35
*D1	1.73	0.00	5.79
*D3	1.75	0.00	4.51
*B1	0.41	0.00	0.00
*A3	0.48	0.00	0.16
*A4	0.35	0.00	0.36
A1	0.44	0.00	0.00
A1e	0.44	0.14	0.00
A3	0.52	0.00	0.16
A5	0.47	0.00	1.78
A6	0.44	0.00	0.68
*C1E	0.30	0.12	0.00
*C3	0.38	0.00	0.16
*C4	0.28	0.00	0.36
*C5	0.34	0.00	1.78

*C6	0.31	0.00	0.68
*E1e	0.46	0.15	0.00
*G3	0.69	0.00	2.34
*G4	0.56	0.00	2.53
*G5	0.62	0.00	3.95
*G6	0.59	0.00	2.85
*G1e-p	0.53	0.15	0.89
F1	0.65	0.00	0.00
F1e	0.65	0.11	0.00
F5	0.68	0.00	1.78
F6	0.65	0.00	0.68
*D1e	1.73	0.17	5.79
*B1e	0.41	0.17	0.00
*B3	0.52	0.00	0.16
*B4	0.38	0.00	0.36
*B5	0.44	0.00	1.78
*B6	0.41	0.00	0.68
L-u	0.00	0.00	0.00
L-a	0.00	0.00	0.00
L-n	0.00	0.00	0.00
L-f	0.00	0.00	0.00

Table S12b: Electricity Consumption, Electricity Generation, and Natural Gas Consumption Intensity by Treatment Train (Best Practice) (Treatment Train Configuration B Method)¹¹

Treatment Train	Electricity Consumption Intensity [kWh/m³]	Electricity Generation Intensity [kWh/m³]	Natural Gas Consumption Intensity [MJ/m³]
*A1	0.25	0.00	0.00
*A1e	0.25	0.21	0.00
*A2	0.28	0.00	0.00
*A5	0.32	0.00	1.12

*A6	0.28	0.00	0.16
A4	0.29	0.00	0.40
*C1	0.23	0.00	0.00
E3	0.38	0.00	0.16
*E3	0.36	0.00	0.16
*E1	0.30	0.00	0.00
*G1	0.41	0.00	2.53
*G1e	0.41	0.21	2.53
*G1-p	0.35	0.00	1.09
F3	0.40	0.00	0.16
F4	0.38	0.00	0.35
*D1	0.98	0.00	5.79
*D3	0.97	0.00	3.78
*B1	0.32	0.00	0.00
*A3	0.32	0.00	0.16
*A4	0.25	0.00	0.35
A1	0.29	0.00	0.00
A1e	0.29	0.17	0.00
A3	0.35	0.00	0.16
A5	0.36	0.00	1.12
A6	0.32	0.00	0.16
*C1E	0.23	0.16	0.00
*C3	0.30	0.00	0.16
*C4	0.24	0.00	0.35
*C5	0.30	0.00	1.12
*C6	0.27	0.00	0.16
*E1e	0.30	0.20	0.00
*G3	0.49	0.00	2.69
*G4	0.41	0.00	2.88
*G5	0.48	0.00	3.65
*G6	0.44	0.00	2.69

*G1e-p	0.35	0.20	1.09
F1	0.37	0.00	0.00
F1e	0.37	0.12	0.00
F5	0.44	0.00	1.12
F6	0.41	0.00	0.16
*D1e	0.98	0.23	5.79
*B1e	0.32	0.22	0.00
*B3	0.40	0.00	0.16
*B4	0.33	0.00	0.35
*B5	0.39	0.00	1.12
*B6	0.36	0.00	0.16
L-u	0.00	0.00	0.00
L-a	0.00	0.00	0.00
L-n	0.00	0.00	0.00
L-f	0.00	0.00	0.00

Table S13: Electricity Generation Intensity by Prime Mover (Biogas B Method)¹²

Prime Mover	Electricity Generation Intensity [kWh/m ³]
Reciprocating Engine	0.146
Microturbine	0.130
Fuel Cell	0.212

Table S14: Summary of Biogas Data Sources

Source	Biogas Dataset	Reporting Year(s)	Notes
U.S. Environmental Protection Agency ^{13,14,7,15}	Clean Watersheds Needs Survey	2004, 2008, 2012, and 2022	2004-2012 releases do not specify whether biogas is used for electricity production; not used for electricity generation baseline estimations.
U.S. Department of Energy ¹⁶	Combined Heat and Power	1961-2024	Specifies whether biogas is used for electricity production and

	Installation Database		prime mover type; used for Configuration A and B, Process A and B, and Biogas A, B, and C methods.
Water Environment Federation ¹⁷	Water Resource Recovery Facilities Biogas Database	2013	Specifies whether biogas is used for electricity production and prime mover type; used for Configuration A and B, Process A and B, and Biogas A, B, and C methods. Assumed that electricity-producing facilities identified in this dataset were producing electricity in 2012.
U.S. Energy Information Administration ¹⁸	Survey Form EIA-923	2012	Only applicable for large facilities, but specifies whether biogas is used for electricity production and prime mover; used for Configuration A and B, Process A and B, and Biogas A, B, and C methods.

Table S15: Percent of Reported Energy Consumption Intensity by Plant Characteristics

			Percent of Reported Energy Consumption Intensity [%]				
		Number of Cities	Configuration A (T)	Configuration A (BP)	Configuration B (T)	Configuration B (BP)	Regression
Flow Rate [10 ³ m ³ /day]	43.8-126	19	117	78	122	81	300
	126-274	16	112	75	107	70	239
	274+	27	95	63	101	67	209
Effluent Treatment Level	Primary	1	245	168	245	168	221
	Secondary	22	124	84	133	89	275
	Advanced	39	93	61	93	60	242
	Multiple	4	79	52	81	52	201
Latitude	< 35°	15	127	84	131	87	289
	35-42.5°	37	86	57	89	59	217
	> 42.5°	14	132	87	133	87	297

*Note, bolded values represent the most accurate estimation method for the given subset of cities in the validation set.

Table S16: Percent of Reported Electricity Generation Intensity by Plant Characteristics

		Percent of Reported Electricity Generation Intensity [%]							
		Number of Cities	Configuration A (T)	Configuration A (BP)	Configuration B (T)	Configuration B (BP)	Biogas A	Biogas B	Biogas C
Flow Rate [10 ³ m ³ /day]	43.8-126	2	22	28	57	64	98	110	335
	126-274	6	62	82	94	122	89	98	306
	274+	12	15	20	75	99	94	106	323
Effluent Treatment Level	Secondary	7	14	17	66	88	72	80	35
	Advanced	13	39	51	87	113	109	120	29
Latitude	< 35°	3	83	107	162	212	136	147	1,394
	35-42.5°	12	6	8	65	85	99	113	4,067
	> 42.5°	6	46	61	84	109	78	85	1,608

*Note, bolded values represent the most accurate estimation method for the given subset of cities in the validation set.

Table S17: p-values for Levene's Test on Each Combination of Electricity Consumption Estimation Methods

	Flow	Effluent A	Effluent B	Configuration A (T)	Configuration A (BP)	Configuration B (T)	Configuration B (BP)	Process A	Process B
Flow	N/A	0.0002*	0.2042	0.7947	0.0000*	0.8103	0.0000*	0.0000*	0.1583*
Effluent A	0.0002*	N/A	0.0000*	0.0002*	0.0000*	0.0000*	0.0000*	0.0195*	0.0371*
Effluent B	0.2042	0.0000*	N/A	0.1037	0.0000*	0.2631	0.0000*	0.0000*	0.0136*
Configuration A (T)	0.7947	0.0002*	0.1037	N/A	0.0000*	0.5912	0.0000*	0.0000*	0.2097
Configuration A (BP)	0.0000*	0.0000*	0.0000*	0.0000*	N/A	0.0000*	0.1102	0.0000*	0.0000*
Configuration B (T)	0.8103	0.0000*	0.2631	0.5912	0.0000*	N/A	0.0000*	0.0000*	0.0958*
Configuration B (BP)	0.0000*	0.0000*	0.0000*	0.0000*	0.1102	0.0000*	N/A	0.0000*	0.0000*
Process A	0.0000*	0.0195*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	N/A	0.0001*
Process B	0.1583	0.0371*	0.0136*	0.2097	0.0000*	0.0958*	0.0000*	0.0001*	N/A

Note: p-values with a * indicate that, at the 10% significance level, the two methods have a statistically significant difference in variance of mean absolute percent error; in this instance, a statistically significant difference indicates that the methods are not equally sensitive to changes in the validation set.

Table S18: Estimated National Electricity Consumption, Energy Consumption, and Electricity Generation in 2012 Using All Methods

Method	National Electricity Consumption [TWh/year]	National Energy Consumption [TJ/year]	National Electricity Generation [TWh/year]
Flow	24.4	N/A	N/A
Effluent A	29.0*	N/A	N/A
Effluent B	19.5	N/A	N/A
Configuration A (T)	10.6*	46.5 x 10 ³ *	0.39*
Configuration B (T)	17.5	77.1 x 10 ³	0.90*
Configuration A (BP)	7.0*	31.0 x 10 ³ *	0.51*
Configuration B (BP)	11.1	50.9 x 10 ³	1.15*
Process A	36.0*	N/A	N/A
Process B	29.7*	N/A	N/A
Biogas A	N/A	N/A	1.24*
Biogas B	N/A	N/A	1.42*
Biogas C	N/A	N/A	4.23*
Regression	N/A	221 x 10 ³ *	N/A
*Excluded from the final range of national energy use and potential estimates.			

Table S19: Estimated National Electricity Consumption, Energy Consumption, and Electricity Generation in 2042 Using All Methods

Method	National Electricity Consumption [TWh/year]	National Energy Consumption [TJ/year]	National Electricity Generation [TWh/year]
Flow	39.6	N/A	N/A
Effluent A	49.9*	N/A	N/A
Effluent B	33.6	N/A	N/A
Configuration A (T)	17.0*	71.63 x 10 ³ *	0.82*
Configuration B (T)	27.9	123 x 10 ³	3.07*
Configuration A (BP)	10.9*	47.6 x 10 ³ *	1.07*
Configuration B (BP)	16.5	81.14 x 10 ³	3.94*
Process A	60.4*	N/A	N/A
Process B	48.8*	N/A	N/A
Biogas A	N/A	N/A	2.62*
Biogas B	N/A	N/A	2.96*
Biogas C	N/A	N/A	8.97*

Regression	N/A	304 x 10 ³ *	N/A
*Excluded from the final range of national energy use and potential estimates.			

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